Recent advances in calibration and coherent estimation

2nd Congress of Polish Statistics
Survey sampling and small area estimation

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This research was developed within the project
Research innovations for official and survey statistics (RIFOSS),
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The challenge of coherent estimation

Principle 14 of the *European Statstics Code of Practice* recommends *coherence and comparability* of statistics. The following kinds of coherence shall be considered:

- Internal coherence
- Coherence between regions, by subject, and by time
- Coherence with respect to definitions and surveys

Household surveys Coherence of individual and household data

Census 2011 Estimation at different regional levels, likely with different estimation methods
... and with different times of publication

New integrated household surveys Estimates of the master sample (Germany: microcensus) versus additional surveys (LFS, SILC, ICT, ...)

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Seminal work Deville and Särndal (1992)

Model calibration Wu and Sitter (2001), Montanari and Ranalli (2005)

Hybrid calibration Lehtonen and Veijanen (2015, 2017)

Ridge calibration Chambers (1996)

Multi-source calibration Guandalini and Tillé (2017)

Current overviews Särndal (2007), Kim and Park (2010), Kott (2016), Haziza and Beaumont (2017)

Do individual and household weights have to coincide?

- How to ensure consistent estimates at person- and household-level?
- In practice, Statistical Offices often use integrated weighting which produces one single weight for all persons within the same household by substituting the original auxiliary information by its corresponding household mean values
- This single integrated person weight is assigned one-to-one to the household the person belongs
- Consistency is ensured by the same weights used to estimate person- as well as household-level characteristics
- Current *best methods* propose to use integrated weights, i.e. constant within households
  E.g. for SILC: European Commission (2014)

The Integrated GREG Estimator

The integrated GREG estimator at person-level can be obtained by

$$\hat{T}_{y_p}^{INT} = \hat{T}_{y_p}^{HT} + \hat{\mathbf{B}}^{\mathbf{INT}\,T}(\mathbf{T_x} - \hat{\mathbf{T}}_{\mathbf{x}}^{\mathbf{HT}})$$

where $\hat{\mathbf{B}}^{\mathbf{INT}} = (\sum_{i \in s_p} \bar{\mathbf{x}}_\mathbf{i} \bar{\mathbf{x}}_\mathbf{i}^T / \pi_i v_i)^{-1} \sum_{i \in s_p} \bar{\mathbf{x}}_\mathbf{i} y_i / \pi_i v_i$. The corresponding integrated person-level weights are given by

$$w_i^{INT} = \frac{1}{\pi_i} + \sum_{i \in s_p} \frac{\bar{\mathbf{x}}_\mathbf{i}^T}{\pi_i v_i} \left(\sum_{i \in s_p} \frac{\bar{\mathbf{x}}_\mathbf{i} \bar{\mathbf{x}}_\mathbf{i}^T}{\pi_i v_i} \right)^{-1} (\mathbf{T_x} - \hat{\mathbf{T}}_{\mathbf{x}}^{\mathbf{HT}}).$$

Inserting a scale factor of $v_i = 1$ results in the integrated GREG estimator proposed by Lemaître and Dufour (1987). Inserting $v_i = N_g^{-1}$, in turn, results in the integrated GREG estimator proposed by Nieuwenbroek (1993).

Consequences of Integrated Weighting

- Utilization of constructed household mean values instead of the original auxiliaries
- Increased number of factor values
- Ignoring the heterogeneity within a household (only the between variance is taken into account)
- Ecological fallacy

Alternative Weighting Strategies

- We propose two alternative estimators which are capable of both ensuring consistent person and household estimates and allowing for different weights for persons within a household
- **Idea**: Constrain the consistency requirements to variables that are common to both the person- and the household data set. By incorporating these common variables as additional auxiliaries into the weighting step our alternative weighting strategies produce consistent estimates
- Thereby, consistency is ensured more directly and only for the relevant variables, instead of indirectly by aggregating the individual information per household
- For that purpose, we modify a method suggested by Renssen and Nieuwenbroek (1997) which originally aim at combining information from multiple independent surveys

Modified Extended GREG Estimator

Consider $\mathbf{c_i}$ as vector of the common variables at person-level with $\sum_{i \in U_g} \mathbf{c_i} = \mathbf{c_g}$. Then, the modified extended GREG estimator for the unknown person-level total is given by

$$\hat{T}_{y_p}^{ME} = \hat{T}_{y_p}^{GREG} + \hat{\mathbf{D}}_{\mathbf{c}}^{T} (\tilde{\mathbf{T}}_{\mathbf{c}} - \hat{\mathbf{T}}_{\mathbf{c_p}}^{\mathbf{GREG}})$$

and for the unknown household-level total

$$\hat{T}_{y_h}^{ME} = \hat{T}_{y_h}^{GREG} + \hat{\mathbf{E}}_{\mathbf{c}}^{T} (\tilde{\mathbf{T}}_{\mathbf{c}} - \hat{\mathbf{T}}_{\mathbf{c_h}}^{\mathbf{GREG}})$$

The auxiliaries at person- and at household-level can differ.

The unknown totals of the common variables have to be estimated by $\tilde{\mathbf{T}}_{\mathbf{c}}$. We propose two different choices of $\tilde{\mathbf{T}}_{\mathbf{c}}$.

At first, we propose to use the same auxiliaries $\mathbf{x_i}$ to estimate the variable of interest and the common variables.

First Proposed Modified Extended GREG Estimator

The first modified extended GREG estimator with $\tilde{\mathbf{T}}_{\mathbf{c}} = \hat{\mathbf{T}}_{\mathbf{c_p}}^{\mathbf{GREG}}$ as common variable total estimator at person-level is obtained by

$$\hat{T}_{y_p}^{ME1} = \hat{T}_{y_p}^{GREG}$$

and at the household-level by

$$\hat{T}_{y_h}^{ME1} = \hat{T}_{y_h}^{GREG} + \hat{\mathbf{E}}_{\mathbf{c}}{}^{T}(\hat{\mathbf{T}}_{\mathbf{c_p}}^{\mathbf{GREG}} - \hat{\mathbf{T}}_{\mathbf{c_h}}^{\mathbf{GREG}})$$

where $\hat{\mathbf{T}}_{\mathbf{c_p}}^{\mathbf{GREG}}$ and $\hat{\mathbf{T}}_{\mathbf{c_h}}^{\mathbf{GREG}}$ are respectively the person- and the household-level GREG estimator for the common totals.

Thus, the person-level estimator remains unaffected, consistency is solely ensured by the household-level estimator. This proceeding considerably facilitates the application for Statistical Offices.

Secondly, we argue that every common variable c_{il} can be modeled by a separate set of auxiliaries, which may contain some of the auxiliaries $\mathbf{x_i}$, but can also contain further auxiliaries.

Second Proposed Modified Extended GREG Estimator

Let $\mathbf{\hat{T}^{GREG}_{c^*_p}} = (\hat{T}^{GREG}_{c^*_{p,1}}, \ldots, \hat{T}^{GREG}_{c^*_{p,l}}, \ldots, \hat{T}^{GREG}_{c^*_{p,L}})^T$ be the vector of estimates for the common variable totals, where $\hat{T}^{GREG}_{c^*_{p,l}}$ is estimated by $\mathbf{z_l}$. Then, our second modified extended GREG estimator with $\mathbf{\tilde{T}_c} = \mathbf{\hat{T}^{GREG}_{c^*_p}}$ at person-level is given by

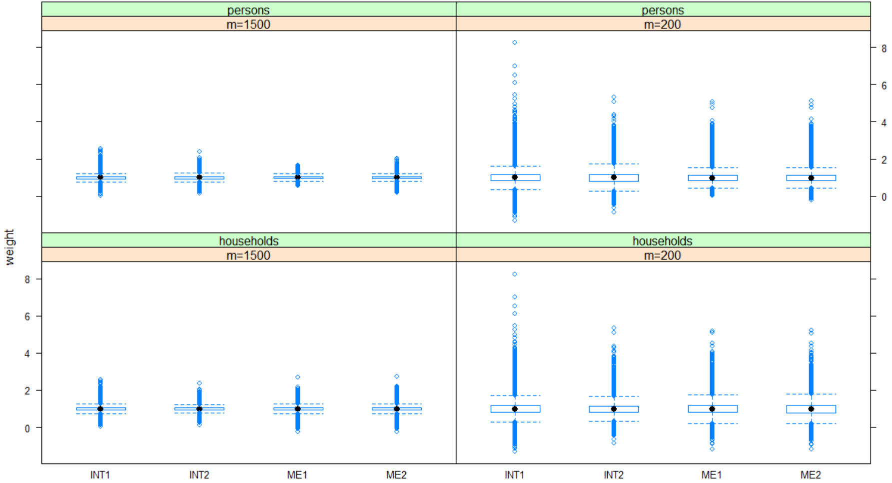
$$\hat{T}^{ME2}_{y_p} = \hat{T}^{GREG}_{y_p} + \mathbf{\hat{D}_c}^T(\mathbf{\hat{T}^{GREG}_{c^*_p}} - \mathbf{\hat{T}^{GREG}_{c_p}})$$

and at household-level it is given by

$$\hat{T}^{ME2}_{y_h} = \hat{T}^{GREG}_{y_h} + \mathbf{\hat{E}_c}^T(\mathbf{\hat{T}^{GREG}_{c^*_p}} - \mathbf{\hat{T}^{GREG}_{c_h}}).$$

Separate modeling allows to use of the best available estimates for $\mathbf{\tilde{T}_c}$.

Graphical presentation of weights



Relative efficiency on person-level ($R = 1,000$)

	Relative improvement in RRMSE							
	m=1500				m=200			
	$\frac{INT1}{ME1}$	$\frac{INT2}{ME1}$	$\frac{INT1}{ME2}$	$\frac{INT2}{ME2}$	$\frac{INT1}{ME1}$	$\frac{INT2}{ME1}$	$\frac{INT1}{ME2}$	$\frac{INT2}{ME2}$
inc	1.00	1.00	1.70	1.70	1.02	1.02	1.73	1.73
soc	1.01	1.01	1.22	1.22	1.01	1.02	1.23	1.24
sel	1.00	1.00	1.04	1.04	1.00	1.01	1.04	1.04
act1	1.00	1.00	1.30	1.30	1.01	1.01	1.32	1.32
act2	1.00	1.00	1.05	1.05	1.01	1.02	1.07	1.08
act3	1.00	1.00	1.15	1.15	1.01	1.01	1.17	1.18
inc_hs1	1.13	1.08	1.17	1.12	1.24	1.10	1.26	1.11
inc_hs2	1.30	1.28	1.38	1.35	1.33	1.26	1.34	1.27
inc_hs3	1.38	1.36	1.47	1.46	1.45	1.44	1.51	1.50
inc_hs4	1.49	1.49	1.64	1.64	1.45	1.48	1.56	1.60
inc_hs5	1.10	1.11	1.11	1.12	1.07	1.11	1.11	1.16
inc_hs6	1.11	1.07	1.13	1.09	1.12	1.15	1.14	1.16
bene_age1	1.00	1.01	1.03	1.03	1.01	1.00	1.05	1.04
bene_age2	1.00	1.00	1.10	1.10	1.01	1.02	1.15	1.17
bene_age3	1.00	1.00	1.07	1.07	0.99	1.00	1.11	1.12
bene_age4	1.00	1.00	1.02	1.02	1.01	1.02	1.05	1.06

Relative efficiency on household-level ($R = 1,000$)

	Relative improvement in RRMSE							
	m=1500				m=200			
	$\frac{INT1}{ME1}$	$\frac{INT2}{ME1}$	$\frac{INT1}{ME2}$	$\frac{INT2}{ME2}$	$\frac{INT1}{ME1}$	$\frac{INT2}{ME1}$	$\frac{INT1}{ME2}$	$\frac{INT2}{ME2}$
inc	1.00	1.00	1.70	1.70	1.02	1.02	1.73	1.73
soc	1.01	1.01	1.22	1.22	1.01	1.02	1.23	1.24
gross_inc	1.00	1.00	1.65	1.65	1.02	1.02	1.69	1.68
cap_inc	1.00	1.01	1.00	1.01	0.96	0.98	0.96	0.98
taxes	1.00	1.01	1.01	1.01	1.12	1.12	1.11	1.11

Change of paradigm in the German Census

- Register-assisted census (since 2011)
  - Use of administrative registers
    – population register
    – unemployment register (and others)
  - Sample of approx. 10% of the population
- Two goals have to be considered
  Goal 1 Estimation of over- and undercounts $\longrightarrow$ size of population
  Goal 2 Estimation of *other variables of interest*
- The challenge: Sample design and estimation method
- The problem (press debate) in Flensburg:
  Considerable gender disproportion in the age group under 8 years

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Problem of coherent census estimates

- Core estimates

  Goal 1 GREG estimates
  Goal 2 (NUTS3) GREG preferred
  Goal 2 (LAU) GREG likely to be inaccurate: SAE
- *Legal* RRMSE constraints on population on SMP level
- Many estimates on different levels
- Eurostat hypercubes:
  - Marginals from different hypercubes may overlap
  - Different estimation methods may be optimal
  - ... *are likely to be incoherent*

The aim of the German Federal Statistical Office is to gain coherent estimates, preferably via one *vector of weights*: **one number census**!

SMPs in Germany

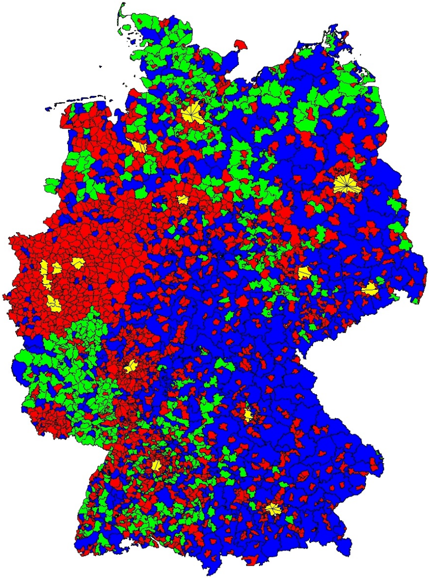
SMP 0 Parts of large towns (ab 200,000 inh.)

SMP 1 Community (GEM) from 10,000 inh.

SMP 2 Groups of comm. (if not 1) from 10,000 inh.

SMP 3 If not 1 or 2: rest in districts

In total 2,391 SMPs



Census, weights, and estimation

- The German register-assisted census is drawn via box-constraint optimal allocation which allows to include minimal and maximal sampling fractions
- This allows to constrain the variation of weights (here: 25) referring to the critique of Gelman (2007)
- However, the weights also have to be considered using small area estimation methods
- Negative or extreme weights shall be *cut*
- GREG and calibration-based estimators allow adequate accuracy estimates even if possible model-assumptions are violated (part of the German census law)

Generalized calibration with penalties (cf. Münnich, Sachs and Wagner, 2011) allows coherent benchmarking with small area estimates

Benchmark for the census I

- Goal 1: Combined GREG for each relevant regions (SMP 0/1)
  $\Rightarrow$ exact control (Condition I)
- Goal 2: Combined GREG on NUTS3
  $\Rightarrow$ little (or no) tolerance (Condition IIa)
  (alternative estimates are possible)
- Goal 2: You/Rao estimator on LAU-level
  $\Rightarrow$ larger tolerance needed (Condition IIb)

Note: Tolerated perturbation depends on the importance of the auxiliary variable for the census estimates. The solution (including weight variation control) can be obtained using complex solvers but has very large and sparse design matrices and suffers from zigzagging effects (non-smoothness introduced by the constraints).

Benchmark conditions for the census II

- By showing the semismoothness of the problem, we can obtain an optimal solution by applying the semismooth Newton method (with step control)
- Additionally: too large deviations from the registers to the final estimates on goal 1 (subgroups in subregions) urged the need for adding further constraints
  additional constraint on AGE x GEN for goal 1 (condition III)

The methodology must allow an easy and sophisticated control of the efficacy of the different calibration constraints that enables the user to set the (needed) tolerances individually!

Generalized calibration using penalties

$$\min_{(g,\epsilon^I_{KRS},\epsilon^I_{SMP},\epsilon^{II})} \sum_{k\in s} d_k \frac{(g_k-1)^2}{2} + \sum_{k\in I} \delta_k^{KRS} \frac{(\epsilon^I_{KRS_k}-1)^2}{2} + \sum_{k\in J} \delta_k^{SMP} \frac{(\epsilon^I_{SMP_k}-1)^2}{2} + \sum_{k\in K} \gamma_k \frac{(\epsilon^{II}_k-1)^2}{2}$$

$$\begin{aligned}
s.t.\ & \hat{\tau}^{CAL}_{SMP,ZEN} := X^{CAL}_{I,SMP,ZEN} \cdot g = \hat{\tau}^{GREG}_{SMP,ZEN} && \text{(I)}\\
& \hat{\tau}^{CAL}_{KRS,Cal} := X^{CAL}_{IIa,KRS,Cal} \cdot g = diag(\hat{\tau}^{YR}_{KRS,Cal}) \cdot \epsilon^I_{KRS} && \text{(IIa)}\\
& \hat{\tau}^{CAL}_{SMP,Cal} := X^{CAL}_{IIb,SMP,Cal} \cdot g = diag(\hat{\tau}^{YR}_{SMP,Cal}) \cdot \epsilon^I_{SMP} && \text{(IIb)}\\
& \tau^{CAL}_{KRS,A\times G} := \hat{X}^{CAL}_{III,KRS,A\times G} \cdot g = diag(\tau^{\mathbf{REG}}_{KRS,A\times G}) \cdot \epsilon^{II} && \\
& g \in \Omega && \\
& \epsilon^I_{KRS} \in \Omega^I_{KRS} && \\
& \epsilon^I_{SMP} \in \Omega^I_{SMP} && \\
& \epsilon^{II} \in \Omega^{II} && \text{(weight variation control)}
\end{aligned}$$

The solution is obtained via *semismooth Newton calibration* (cf. Münnich, Sachs, and Wagner, 2011)

Generalized constraint calibration

Generalized smooth calibration (P*)

$$\min_{(\mathbf{g},\boldsymbol{\epsilon})\in\mathbb{R}^{n+p^{\mathrm{rel}}}} \sum_{i\in\mathcal{S}} d_i \frac{(g_i-1)^2}{2} + \sum_{k\in J} \delta_k \frac{(\epsilon_k-1)^2}{2}$$

$$s.t. \sum_{i\in\mathcal{S}} d_i g_i \mathbf{x}_\mathbf{i}^\mathbf{I} = \boldsymbol{\tau}_{\mathbf{X}^\mathbf{I}}$$

$$\sum_{i\in\mathcal{S}} d_i g_i \mathbf{x}_\mathbf{i}^\mathbf{II} - \boldsymbol{\epsilon}\cdot\boldsymbol{\tau}_{\mathbf{X}^\mathbf{II}} = \mathbf{0}$$

$$\mathbf{m} \leq \mathbf{g} \leq \mathbf{M}$$

$$\mathbf{L} \leq \boldsymbol{\epsilon} \leq \mathbf{U}$$

- No closed-form solution, hence iterative semismooth Newton
- Other calibration functionals can also be used
- Model-calibration and hybrid calibration are special cases

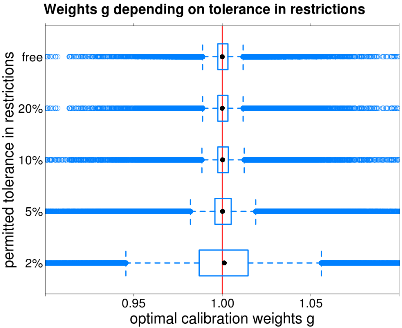
Simulation study - Overview

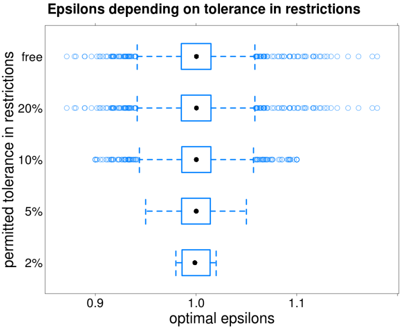
Census of Rhineland-Palatinate and Saarland:

- Goal 1 restrictions on SMP level
- Goal 2 restrictions on KRS level: e.g. EF117 classes
  $\Rightarrow$ Permitted tolerance per KRS: ϵ^{I}_{KRS}
- Goal 2 restrictions on KRS level: e.g. EF117 classes
  $\Rightarrow$ Permitted tolerance per SMP: ϵ^{I}_{SMP}
- Age $\times$ Gender classes:
  $\Rightarrow$ Permitted tolerance per SMP: ϵ^{II}
- Box-Constraints for calibration weights g
- Box-Constraints for deviation of ϵ^{I}_{KRS}, ϵ^{I}_{SMP} and ϵ^{II}

Distribution of weights and deviation from benchmarks

- Tolerance for AxG decreases from *free* to 2%

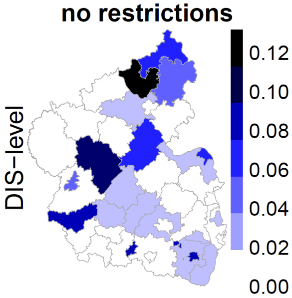


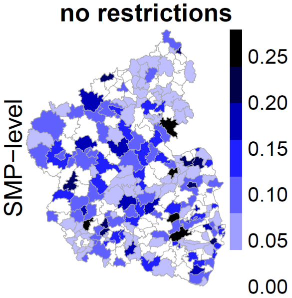


- Variation of weights *increases* while tolerance *decreases*
- Deviations from the benchmarks are pushed into the box of given tolerance

Deviation of estimated totals from registers (I)

- Estimated totals for AGExGENDER classes per stratum differ from known register totals
- Differences are higher in SMP-strata than in DIS-strata (due to the size of the strata) - exemplarily shown for one sample





Deviation of estimated totals from registers (II)

- Estimated totals for AGExGENDER classes per stratum differ from known register totals
- Differences are higher in SMP-strata than in DIS-strata (due to the size of the strata)
- Percentage of estimated totals (over 1000 MC-replications) which differ over $> 100\%$, $> 50\%$, $> 20\%$, $> 10\%$, and $> 5\%$ from register totals

Deviation	$> 100\%$	$> 50\%$	$> 20\%$	$> 10\%$	$> 5\%$
DIS	0.00%	0.00%	0.05%	3.43%	9.80%
SMP	0.00%	0.04%	1.96%	16.96%	34.00%

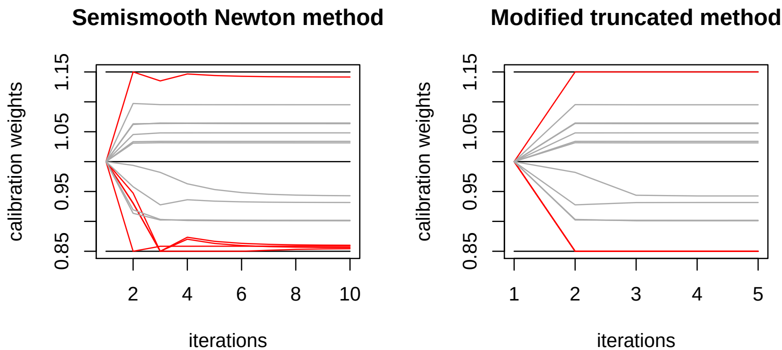
- In some samples, there are differences of more than 50% on SMP-level - occured in the Census 2011 (Cf. Flensburg problem)

Semismooth Newton method vs. truncated methods

- **Truncated algorithms**, e.g. within **R**-packages *sampling* (Tillé, Matei, 2011) and *survey* (Lumley, 2011):
  - Calibration with box-constraints (no relaxation)
  - Issues with (extreme) high dimensions
  - Reaches *very good approximation* of optimal solution
- **Modified truncated algorithms**:
  - Includes relaxation
  - Very efficient due to *sparse*-structure
  - Reaches *very good approximation* of optimal solution
- **Semismooth Newton method:**
  - Includes relaxation an *sparse*-structure due to efficiency
  - Reaches the **unique optimum** of the calibration problem
  - Higher computing time, potentially unstable in high dimensions
  - Sensitivity analysis via Lagrange multipliers

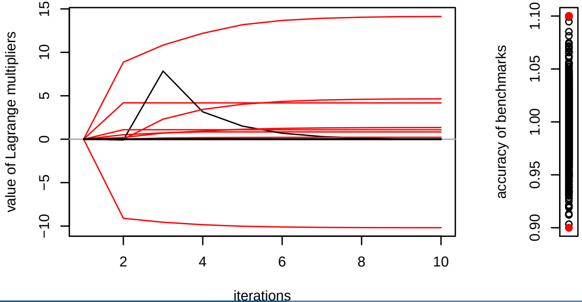
Differences in solutions computed by the modified truncated algorithm and the semismooth Newton method

- Plot of 15 calibrations weights depending on the iterations
- **Red:** Weights, which reach the box-constraints in truncated method
- Not necessarily on the box using the semismooth Newton method



Sensitivity analysis using Lagrange multipliers

- Left: Approx. 2000 Lagrange multipliers depending on the iteration
- Right: All estimations (differences from given totals)
- **Red:** Lagrange multiplier and estimations related to benchmarks which uses the maximum of the given tolerance
- Lagrange multipliers are all near to zero, except those that are related to *extreme* benchmarks



Semismooth Newton method vs. truncated methods

- Better results using the semismooth Newton method in contrast to a (modified) TRUNC
  (in scenarios with harder constraints)

  Value of objective function

tolerance / AxG	SSN	TRUNC
free	59.24	59.24
20%	59.24	59.24
10%	102.11	103.23
5%	495.72	517.00
2%	1653.45	1747.27

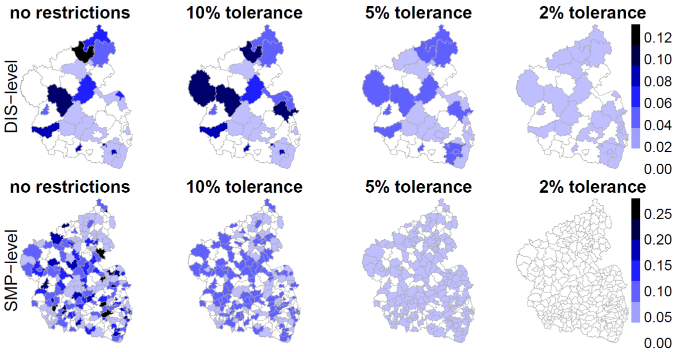
Semismooth Newton method vs. truncated methods

- Computing time for $n = 155840$ variables and $p \approx 5000$ benchmarks

tolerance	IT SSN	IT TRUNC	Time SSN	Time TRUNC
free	2	1	2.5 *sec*.	1.3 *sec*.
20%	2	1	2.5 *sec*.	1.3 *sec*.
10%	9	2	13.4 *sec*.	2.5 *sec*.
5%	13	3	21.0 *sec*.	3.8 *sec*.
2%	75	5	243.0 *sec*.	7.0 *sec*.

Deviation of estimated totals from registers

- Estimated totals for AGExGENDER classes per stratum differ from known register totals
- Differences shrink if we use relaxed benchmarks

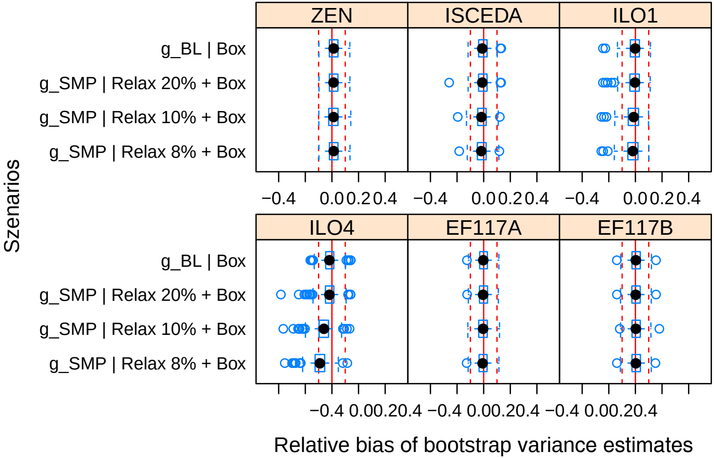


Variance estimation

- Linearisation variance estimator for the GREG (see Deville and Särndal, 1992, or D'Arrigo and Skinner, 2010) not applicable to (P*) due to box constraints and relaxation
  The reason is that only one part of the variability is covered (especially the estimated constraints)
- Rescaling Bootstrap (cf. Chipperfield and Preston, 2007) yields valuable results
  see next slide
- This allows to construct resampling weights
- And these allow improved inferences for regression models

Variance estimation (per SMP)

- Result per SMP: $\dfrac{E\left(V^{\text{boot}}(\hat{\tau}_Y)\right) - V^{\text{MC}}(\hat{\tau}_Y)}{V^{\text{MC}}(\hat{\tau}_Y)}$



Summary and outlook

- Coherence of individual and household weights
  - Loss of efficiency using integrated weights
  - Extended approach yields promising results
  - Sensible selection of variables is needed
  - Individual patterns still available
- Generalized calibration with flexible penalties
  - Is a very flexible tool in survey practice considering model estimates (incl. model and hybrid calibration)
  - Allows easily to add soft and hard constraints
  - Enables post-editing and evaluation in terms of areas, efficacy of constraints, variables and their outcomes
- Extension to integrated household surveys straight forward

Thank you for your attention!

This talk was developed within the project
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Literatur I

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