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Effect of register errors on quality of survey estimates

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Outline

- Study variable from sample survey
 - combined with other data from registers (personal ID)
 - are registers reliable?
- Regional means
 - errors in auxiliary register variables
 - sensitivity of estimators
- Class means of the survey variable
 - classes defined in the register
 - misclassification causes bias



What is a register?

- Administrative register
 - unit-level data
 - maintained by state administration, for example
 - updated whenever a change occurs in population
 - e.g. information from a person
- Statistical register
 - constructed from administrative registers
 - screening and editing
 - applied in this study



Errors in register

- Registers are usually perceived as reliable
- But error rates of 10 % have been observed
- Literature: Wallgren & Wallgren, Zhang, Zhang & Fosen
- Typical errors in register
 - coding errors
 - reporting errors by a person
 - delayed update
 - may cause misclassification



Point of view

- The effect of register errors on estimators
- Compare two sets of estimates
 - results with errors in register
 - results with error-free register (inaccessible)



Regional means involving auxiliary variables

Estimators incorporating auxiliary variables

- ordinary calibration without a model
- model-assisted and model-dependent methods
- Problem: auxiliary register variable X contains errors
- "Contamination" produces outliers

- observed $X^* = X + e$ e independent of Y

- Regression model:

 $\hat{\beta}_{X^*} \rightarrow 0$, as $Var(e) \rightarrow \infty$

- Effects on calibration, GREG, EBLUP?



Impact of misclassification on class means

- Means of response Y over classes of a register variable
 - example: small area estimation with errors in area codes
- Misclassification:
 - class label C* not always same as true class C
- Estimator of class mean is biased
- How large can this bias be?



Domain estimators of population means

- (1) No auxiliary data, domain sizes known
 - HT, Hajek
- (2) Auxiliary data from registers
 - (a) no explicit model in model-free "ordinary" calibration
 - (b) model fitted to whole sample
 - GREG
 - EBLUP
 - model calibration



Notation

- Domain in sample s_d
- Domain in population $\,U_{\!\scriptscriptstyle d}$
- Domain size in population N_d
- Design weights a_k



Definitions of domain estimators of means

$$\begin{split} & - \text{ HT } \hat{\bar{Y}}_{d;HT} = \frac{1}{N_d} \sum_{k \in S_d} a_k y_k \\ & - \text{ Hajek } \hat{\bar{Y}}_{d;Hajek} = \frac{\sum_{k \in S_d} a_k y_k}{\sum_{k \in S_d} a_k} \\ & - \text{ GREG } \hat{\bar{Y}}_{d;GREG} = \frac{1}{N_d} \left(\sum_{k \in U_d} \hat{y}_k + \sum_{k \in S_d} a_k \left(y_k - \hat{y}_k \right) \right) \\ & - \text{ EBLUP } \hat{\bar{Y}}_{d;EBLUP} = \frac{1}{N_d} \left(\sum_{k \in U_d - S_d} \hat{y}_k + \sum_{k \in S_d} y_k \right). \end{split}$$

Model-free domain level calibration

- Estimator
$$\hat{\overline{Y}}_{d;CAL} = \frac{1}{N_d} \sum_{k \in S_d} W_{dk} y_k.$$

minimize distance to design weights

- Conditions on weights
 - calibration equation

$$\sum_{k \in S_{d}} W_{dk} \begin{pmatrix} 1 \\ X_{1k} \\ \vdots \\ X_{pk} \end{pmatrix} = \sum_{k \in U_{d}} \begin{pmatrix} 1 \\ X_{1k} \\ \vdots \\ X_{pk} \end{pmatrix}$$

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$$\sum_{k \in s_d} \frac{\left(w_{dk} - a_k\right)^2}{a_k}$$

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Model-free calibration weights

$$w_{dk} = a_k \left(1 + \left(\sum_{i \in U_d} \boldsymbol{x}_i - \sum_{i \in s_d} a_i \boldsymbol{x}_i \right)' \left(\sum_{i \in s_d} a_i \boldsymbol{x}_i \boldsymbol{x}_i' \right)^{-1} \boldsymbol{x}_k \right)$$



Model calibration

- Model predictions instead of auxiliary variables
- Calibration equations

$$\sum_{k \in s_d} w_{dk} \begin{pmatrix} 1 \\ \hat{y}_k \end{pmatrix} = \sum_{k \in U_d} \begin{pmatrix} 1 \\ \hat{y}_k \end{pmatrix}.$$



Simulation experiments

- Auxiliary data in a synthetic register
 - continuous X,Z
 - categorical C
 - 40 regions D
- Response Y depends on the values of X, Z and C
 - mixed model: regional random intercepts, random slopes
- Errors in X and C are generated after creating Y
- Design-based simulation: 1000 SRSWOR samples
 - model fitted: mixed model, regional random effects



Experiment 1. Effects of contamination

- Contaminate 1% randomly chosen units in the population

 $X_k^* = X_k + M$

- M=20 or M=500 (note: X* ranges from -10 to 26)
- Estimation uses X*,Z and C
- Sample size n=4000



Absolute relative bias (ARB)

Domain estimates from 1000 simulated samples

- estimated bias

bias = (mean of estimates) - (true value)

- absolute relative bias
$$ARB = \left| \frac{bias}{true \, value} \right|$$



Mean squared error (MSE)

$$\mathsf{MSE}(\hat{\theta}) = \frac{1}{1000} \sum_{k=1}^{1000} (\hat{\theta}(s_k) - \theta)^2$$

- Relative root mean squared error (RRMSE)

$$\mathsf{RRMSE}(\hat{\theta}) = \frac{\sqrt{\mathsf{MSE}(\hat{\theta})}}{\theta}$$

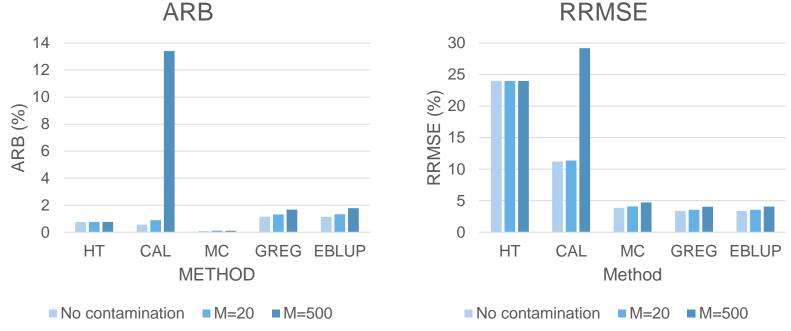


Averages over a domain size class

- Averages of ARB and RRMSE calculated over
 - small domains (expected sample size smaller than 30)
 - large domains (larger than 100)



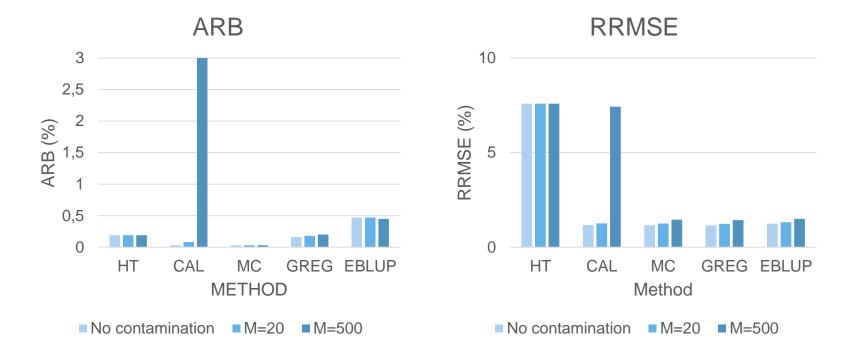
Effects of contamination in small domains



RRMSE



Effects of contamination in large domains



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Comparison of methods

- HT is not affected (no auxiliary data)
- Model-free calibration is sensitive (direct estimator)
- Model calibration less sensitive (indirect estimator)
- GREG remains design unbiased
- MSE of GREG and EBLUP increases slightly



Effect of contamination on GREG and EBLUP

- Extreme contamination with M=500
- Estimated slope for X* close to zero
- Most predictions almost as in a model that excludes X*

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GREG(X^*,Z,C) \approx GREG(Z,C)
EBLUP(X*,Z,C) \approx EBLUP(Z,C)
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Robust methods could be used

- Effect of outliers is reduced
 - robust EBLUP estimator (Sinha and Rao, 2009)
 - robust GREG (Lee and Patak, 1998)
- These handle outliers in both Y and in X
- Not commonly found in statistical packages



Experiment 2. Effects of misclassification on class means

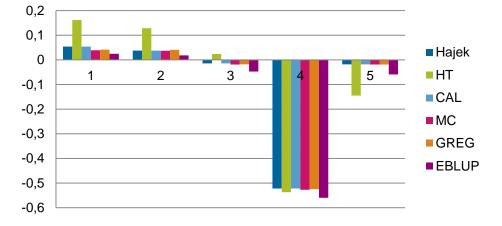
Means of Y in classes of C

Class	1	2	3	4	5
Share (%)	6.7	13.3	20.0	26.7	33.3
Mean of Y	17.3	23.2	28.8	34.8	40.5



Biased class mean estimators

- 10% of units in class 2 classified to class 4
- Observed mean in class 4 decreases, relative bias -1.5%



Bias of class mean estimators



Upper bound for bias

- Impose superpopulation model
 - random variables: response Y, true class C, observed class C*
 - assume that classification does not depend on Y given C
- Estimator for class mean converges to $E(Y|C^*)$, not E(Y|C)
- Asymptotic bias $E(Y|C^*)-E(Y|C)$



Difference between expectations

$$\begin{aligned} &\left| \mathsf{E} \big(\mathsf{Y} \, | \, \mathsf{C}^* = \mathsf{b} \big) - \mathsf{E} \big(\mathsf{Y} \, | \, \mathsf{C} = \mathsf{b} \big) \right| \\ &\leq \big(\mathsf{1} - \mathsf{P} \big\{ \mathsf{C} = \mathsf{b} \, | \, \mathsf{C}^* = \mathsf{b} \big\} \big) \mathsf{max}_{\mathsf{i}} \, \left| \mu_{\mathsf{i}} - \mu_{\mathsf{b}} \right| \qquad \left(\mu_{\mathsf{i}} = \mathsf{E} \big(\mathsf{Y} \, | \, \mathsf{C} = \mathsf{i} \big) \right) \end{aligned}$$

$$(1 - P\{C = b \mid C^* = b\}) \le 1 - \frac{1}{Qmax_t \frac{\pi_t p_{tb}}{\pi_b p_{bb}}}$$

- Q classes
- Class probabilities (proportions) $\pi_t = P\{C = t\}$
- Classification probabilities $p_{tb} = P\{C^* = b \mid C = t\}$



Applying the equation in experiment

- Plug in true values of probabilities and $\mu_2 \mu_4$
 - upper bound 0.549
 - observed absolute bias 0.537



Approximations in practice

- Preliminary approximations
 - Subjective estimate of misclassification probability (like 0.01)
 - Plug in class proportions
 - Plug in maximum difference of class means of Y
- Later
 - upper bound for $max_i |\mu_i \mu_b|$ that holds with probability 0.99



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Thank You!

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