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R-indicators for Assessing Representativeness for Survey and Non-survey Data

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Topics Covered

- Introduction
- R-indicators and Partial R-indicators
- Population-based R-indicators
- Applications on assessing representativeness:
    - Adaptive Survey Design: Dutch Crime Victimization Survey
    - 2011 EU-SILC datasets
    - Nonprobability Sample
    - Administrative Data

Introduction

- Response rate insufficient quality indicator to measure impact of non-response
- EU 7th Framework Research Project: RISQ developed quality indicators (R-indicators) to measure survey representativeness
- R-indicators measure the contrast between respondents and non-respondents
- R-indicators used to compare surveys across time or topics, effectiveness of survey strategies and data collection modes
- Representativity defined as the variation of response propensities given a set of auxiliary variables (demographic, socio-economic information and paradata)

Introduction

- Response is representative if all response propensities in the sample are equal: $S^2(\rho)$ =0
- Auxiliary variables should be strong predictors of survey estimates that impact on nonresponse bias
- Decompose variance of response propensities to obtain partial R-indicators
- Partial R-indicators measure the impact of a single variable/category on deviations from representative response
- Allows building profiles (characteristics) where more (or less) attention is required in data collection to reduce the contrast

Introduction

- Monitoring and controlling data collection is known as an adaptive survey design
- Adaptive survey designs aim to differentiate field management and data collection with respect to known characteristics of the data units
- Efforts to increase response directed to those contributing most to non-response bias

Notation:

- Let U be set of units in population and s set of units in sample
- Let R_i =1 if unit responds, 0 otherwise

R-indicators

- Response propensity defined by x_i known for all sample units and may include interactions:

$$\rho_X(x_i) = E(R_i = 1 \mid X = x_i) = P(R_i = 1 \mid X = x_i)$$

- R-indicator: $R(\rho_X) = 1 - 2S(\rho_X)$
- Logistic regression model to estimate response propensities:

$$\log[\rho_X / (1 - \rho_X)] = x'\beta$$

- Estimated response propensity: $\hat{\rho}_X = \dfrac{\exp(x'\hat{\beta})}{\exp(x'\hat{\beta}) + 1}$

R-indicators

- Variance estimated by: $$\hat{S}^2(\hat{\rho}_X) = \frac{1}{N-1}\sum_s d_i(\hat{\rho}_X(x_i) - \hat{\bar{\rho}}_X)^2$$

  where $\hat{\bar{\rho}}_X = \frac{1}{N}\sum_s d_i \hat{\rho}_X(x_i)$ and $d_i = \pi_i^{-1}$

- Estimate by: $$\hat{R}(\hat{\rho}_X) = 1 - 2\hat{S}(\hat{\rho}_X)$$

  and equals 1 when response propensities are constant and close to zero for maximal variation ($\bar{\rho} = 0.5$)

- R-indicators adjusted for size-bias and variance estimates for confidence intervals and significance testing (Shlomo, et al. 2012)

Partial R-indicators

- Unconditional partial indicator: between variance given a stratification on variable Z having categories $h = 1,2, \ldots H$

  $R_U(Z, \rho_X) = S_B(\rho_X|\mathrm{Z})$ and estimated by:

$$\widehat{S_B^2}(\rho_X|\mathrm{Z}) = \frac{1}{N-1}\sum_{h=1}^{H} \widehat{N}_h \left(\hat{\bar{\rho}}_{X,h} - \hat{\bar{\rho}}_X\right)^2 \cong \sum_{h=1}^{H} \frac{\widehat{N}_h}{N}\left(\hat{\bar{\rho}}_{X,h} - \hat{\bar{\rho}}_X\right)^2$$

where $\hat{\bar{\rho}}_{X,h} = \frac{1}{\widehat{\widehat{N}_h}}\sum_{i \epsilon A_h} d_i \widehat{\rho_X}(x_i)$ and $\widehat{N_h} = \sum_{i \epsilon A_h} d_i$

At the category level, estimated by:

$$R_U(Z = h, \rho_X) = \widehat{S_B}(\rho_X|\mathrm{Z} = h) \cong \sqrt{\frac{\widehat{N}_h}{N}}\left(\hat{\bar{\rho}}_{X,h} - \hat{\bar{\rho}}_X\right)$$

Partial R-indicators

- Conditional partial R-Indicator measures remaining variance on variable Z within sub-groups formed by all other remaining variables, denoted X^{-} , *j=1,…,J*
- Let δ_h be the 0-1 indicator equal to 1 if Z=h and 0 otherwise
- Estimate conditional partial R-indicator by
  $R_C(Z, \rho_X) = S_W(\rho_X | X^{-})$ and estimated by:

$$\widehat{S_W^2}(\rho_X | X^{-}) = \frac{1}{N-1} \sum_{j=1}^{j} \sum_{i \epsilon A_h} d_i \left(\hat{\rho}_X(x_i) - \hat{\bar{\rho}}_{X,h}\right)^2$$

- At the category level:

$$R_C(Z = h, \rho_X) \cong \sqrt{\frac{1}{N-1} \sum_{j=1}^{j} \sum_{i \epsilon A_h} d_i \delta_{h,i} \left(\hat{\rho}_X(x_i) - \hat{\bar{\rho}}_{X,h}\right)^2}$$

R-Indicators

- Unconditional partial R- indicator high and conditional partial R-indicator high → contributing to lack of representativeness, otherwise, if conditional partial R-indicator low → representativeness explained by other variables
- X variables categorical then R-Indicators measure variability of subgroup response rates
- The more subgroup response rates change, the lower the R-indicator
- If a category has a much higher response rate than another, this may result in biased estimates, even after adjusting with survey weights

CVs and Partial CVs

- Other indicators: imbalance IMB(X) and distance dist(X) (Sarndal, 2011)
- More robust measures for data monitoring:

$CV(X) = \frac{S(\rho_X)}{\bar{\rho}}$ Similarly,

$CV_U(X_j) = \frac{R_U(X_j)}{\bar{\rho}}$ and $CV_C(X_j) = \frac{R_C(X_j)}{\bar{\rho}}$

$CV_U(X_j, h) = \frac{R_U(X_{j,h})}{\bar{\rho}}$ and $CV_C(X_j, h) = \frac{R_C(X_{j,h})}{\bar{\rho}}$

- Bias adjustments and confidence intervals have also been developed for these indicators
- Auxiliary variables and link function need to be fixed for a given survey to ensure comparability across time leading to consider parsimonious models
- Application on an Adaptive Survey Design shown in Schouten and Shlomo (2017)

Population–based R-indicators (Bianchi, et al. 2019)

- Response indicator r_i =1 for all units in dataset *A*
- Known information $\boldsymbol{x_i} = (x_{1,i}, x_{2,i}, \ldots, x_{K,i})^T$ of a vector of K auxiliary variables ***X***, for example, sex, age group, etc.
- $x_{k,i}$ binary indicator variable and $\boldsymbol{x_i}$ are observed for all individuals $i \epsilon A$
- Assume $\boldsymbol{x_i}$ at the aggregate level is known: the population total $\sum_U \boldsymbol{x_i}$ and population cross-products $\sum_U \boldsymbol{x_i}\, \boldsymbol{x_i}^{\boldsymbol{T}}$
- Estimate aggregates and cross-products using a census or large probability random sample, s, where each individual i has survey weight w_i adjusted and calibrated to population size *N*

Population–based R-indicators (Bianchi, et al. 2019)

- Response propensity: $E(r_i|\boldsymbol{x_i}) = \rho_X(\boldsymbol{x_i}) \equiv \rho_i$
- Model response propensities using identity link function:
  $\rho_i = \boldsymbol{x_i^T}\boldsymbol{\beta},\ i \in A$ and estimate propensities by:
  $\hat{\rho}_i^{OLS} = \boldsymbol{x_i^T}(\sum_{\boldsymbol{A}} d_i\, \boldsymbol{x_i}\boldsymbol{x_i^T})^{-\mathbf{1}} \sum_{\boldsymbol{A}} d_i\, \boldsymbol{x_i}\boldsymbol{r_i}\,,\ \ i \in A$
- $\hat{\rho}_i^{OLS}$ takes a similar approach to calibration-based method for estimating propensity scores for a non-probability sample (Chen, et al. 2022) when only population totals are known by solving the estimating equations $\sum_{NP} \frac{x_i}{\pi(x_i,\theta)} - \sum_U x_i = 0$
- Calibration-based vs maximum-likelihood estimators for parameters of the model are not equivalent in a mathematical sense, but both estimators are consistent assuming the parametric form for estimating propensity scores

Population–based R-indicators (Bianchi, et al. 2019)

- Use ‘plug-in’ estimators to approximate $\hat{\rho}_i^{OLS}$ by
  $\hat{\rho}_i^P = \boldsymbol{x}_i^T (\sum_U \boldsymbol{x}_i \boldsymbol{x}_i^T)^{-1} \sum_A d_i \boldsymbol{x}_i , i \in A$
- $\hat{\rho}_i^P$ is computed only on the set of individuals in data *A*
- In some applications, may need to approximate a pseudo- design weight d as the inverse of representativeness weight:
  $d = [M/N]^{-1}$ equal for all individuals $i \epsilon A$
- Note also similarity to the weight calibration approach and other linear-based survey quality indicators developed, for example, in Särndal and Lundström (2008).

Population–based R-indicators (Bianchi, et al. 2019)

Type 1: If we have access to census data or large probability-based random sample, estimate population-based auxiliary information: $\sum_U \boldsymbol{x_i} \approx \sum_s w_i \boldsymbol{x_i}$ and $\sum_U \boldsymbol{x_i}\, \boldsymbol{x_i}^{\boldsymbol{T}} \approx \sum_s w_i \boldsymbol{x_i} \boldsymbol{x_i^T}$

Type 2: If sample is small, rely on marginal information:

Step 1: Calculate an estimate for the mean from the sample:

$$\bar{X}_U = \frac{\sum_U \boldsymbol{x_i}}{N} \approx \frac{\sum_s w_i x_i}{N}$$

Step 2: Estimate cross-products by: $N\hat{S}_{XX} + N\bar{X}_U\bar{X}_U^T$ where $\hat{S}_{XX} = (\sum_{i=1}^{M} d_i)^{-1} \sum_{i=1}^{M} d_i(\boldsymbol{x_i} - \bar{X}_U)(\boldsymbol{x_i} - \bar{X}_U)^T$ estimated from data *A* of size *M*, and d_i is the design (or adjustment) weight, such that $\sum_{i=1}^{M} d_i = N$

Population–based R-indicators (Bianchi, et al. 2019)

- Estimate variance: $\hat{S}^2_{\hat{\rho}^P} = \frac{N}{N-1}\{\frac{1}{N}\sum_r d_i \hat{\rho}_i^P - [\frac{1}{N}\sum_r d_i]^2\}$ adjusted by $(\hat{\rho}_i^P)^{-1}$ (Bianchi, et al. 2019, formula 3.6)
- Under identity link function (Normal distribution): $\hat{R}_{\hat{\rho}^P} = 1 - \hat{S}_{\hat{\rho}^P}$
  - If response propensities all equal, STD under Normal Distribution is 0 and R-indicator is (close to) 1
  - If response propensities are completely random, STD under Normal Distribution is 1 and R-indicator is (close to) 0
- Bias adjustment added for sample size bias, similar to sample-based R-indicators
- Variance estimation implemented by bootstrapping

Population–based R-indicators (Bianchi, et al. 2019)

- Let $\boldsymbol{x_k} \subset \boldsymbol{X}$ categorical with H categories
- Let $N_h = \sum_{i \epsilon A} d\Delta_{h,i}$ where $\Delta_{h,i}$ is 0-1 indicator for unit i in h and $\sum_{h=1}^{H} N_h = N$
- Define $\hat{\bar{\rho}}_h$ average of propensities in category h and $\hat{\bar{\rho}}$ overall average propensity, based on $\hat{\rho}_i^P$
- Partial R-indicator (between variance) for variable $\boldsymbol{x_k}$ is:

$$R_U(\boldsymbol{x_k}) = \sqrt{\frac{1}{N} \sum_{h=1}^{H} N_h (\hat{\bar{\rho}}_h - \hat{\bar{\rho}})^2}$$

- Large value, stronger contribution of the variable to a lack of representativeness

Population–based R-indicators (Bianchi, et al. 2019)

- Category level h for variable $\boldsymbol{x_k}$, partial R-indicator is:

  $R_U(\boldsymbol{x_k^h}) = \sqrt{\frac{N_h}{N}}\,(\hat{\bar{\rho}}_h - \hat{\bar{\rho}})$, and can assume positive and negative values (plus sign over-representation and negative sign under-representation)

- To adjust estimates derived from the data, weight each individual i by its inverse response propensity: $(\hat{\rho}_i^P)^{-1}$

- Application on population-based R-indicators for survey data is in Shlomo, Luiten and Schouten (2022) where we assessed the representativeness of the 2011 EU-SILC datasets using Census 2011 benchmarks

- Applications for non-survey data: Shlomo, et al. (2023) and Shlomo and Kim (forthcoming)

Application 1

Adaptive Survey Designs using sample-based R-indicators

Schouten and Shlomo (2017)

Structured Trial & Error ASD

- Robust with mathematical rigor, objectivism and structure and allows for quality-cost trade-offs
- Assume survey with 2 phases: non-response follow-up

Repeated survey with strong prior knowledge with budgets invested in different treatments	One-off survey with weak prior knowledge that are run once and for a short period
Determine follow-up from previous survey (2 phases)	Determine follow-up after first phase only

Structured trial & error ASD

- Let n_R be size of nonresponse after phase 1 (or phase 1+phase 2) and *p* proportion to follow-up dependent on budget
- Inspect partial R-indicators and select variables where partials significantly different from zero
- Form a stratification by crossing all categories
- Compute category-level unconditional partial R-indicator on the new stratification variable and order the strata by their sign and *p*-value
- *Select* strata for follow-up based on their rank until pn_R cases selected

2011 Dutch Crime Victimisation Survey (CVS)

Strategy	Response rate	R-indicator	CV	Cost
Web	28.7% (1.0%)	0.806 (0.019)	0.368 (0.034)	1
Web → F2F	57.9% (1.1%)	0.829 (0.022)	0.168 (0.019)	22.3
Mail	49.0% (1.1%)	0.738 (0.020)	0.283 (0.020)	4.0
Mail → F2F	66.0% (1.0%)	0.812 (0.021)	0.157 (0.016)	19.2
F2F → F2F	67.9% (1.0%)	0.801 (0.021)	**0.160 (0.015)**	41.5

target

Investigate 2 strategies: Web to F2F and mail to F2F (continuous survey (both phases) and one-time survey (phase I only))

2011 Dutch Crime Victimisation Survey (CVS)

Partial variable level CVs: *(p-value: * = below 0.1%, † = below 1% , # = below 5%).*

		Unconditional		Conditional	
		Phase 1	Phase 1 and 2	Phase 1	Phase 1 and 2
Gender	Mail	0.024 #	0.014	0.040 *	0.024 #
	Web	0.020 #	0.003	0.001	0.007
Ethnicity	Mail	0.077 *	0.058 *	0.043 *	0.033 *
	Web	0.039 *	0.047 *	0.022 †	0.021 #
Income	Mail	0.067 *	0.056 *	0.056 *	0.047 *
	Web	0.077 *	0.046 *	0.053 *	0.032 †
Urbanization	Mail	0.026 #	0.026 #	0.014	0.015
	Web	0.015	0.053 *	0.014	0.034 *
Age	Mail	0.087 *	0.051 *	0.064 *	0.037 *
	Web	0.061 *	0.036 *	0.041 *	0.022 #
Phone	Mail	0.038 *	0.027 †	0.016	0.011
	Web	0.029 *	0.046 *	0.016	0.026 †

2011 Dutch Crime Victimisation Survey (CVS)

- One-time survey:

  Web (income groups 10-15K and 15-20K, age group >75 years and non-western non-natives)

  Mail (males, age groups 15-25 years and 25-35 years and non-western non-natives)

- Continuous survey:

  Web (income group >30K, natives, persons with a registered phone and persons living in little or non- urbanized areas)

  Mail (income group >30K, natives, persons with a registered phone and age groups 55-65 years and 65-75 years)

- Stratifications formed and strata with significant unconditional values selected:

  One-time survey: 594 cases for Web and 329 for mail

  Continuous survey: 896 cases for Web and 601 cases for mail

2011 Dutch Crime Victimisation Survey (CVS)

Strategy	Response rate	R-indicator	CV	Cost
Web	28.7%	0.806 (0.019)	0.368 (0.034)	1
Web → F2F	57.9%	0.829 (0.022)	0.168 (0.019)	22.3
Web→ F2F one-off	39.7%	0.808 (0.021)	0.267 (0.026)	9.1
Web → F2F continuous	43.6%	0.846 (0.021)	0.206 (0.025)	13.2
Mail	49.0%	0.738 (0.020)	0.283 (0.020)	4.0
Mail → F2F	66.0%	0.812 (0.021)	0.157 (0.016)	19.2
Mail→ F2F one-off	54.1%	0.855 (0.022)	0.159 (0.020)	8.5
Mail→ F2F continuous	59.5%	0.878 (0.022)	0.129 (0.019)	12.2
F2F → F2F	67.9%	0.801 (0.021)	0.160 (0.015)	41.5

Application 2

Population-based R-indicators for EU-SILC survey data

Shlomo, Luiten and Schouten 2022

Representativeness of 2011 EU-SILC

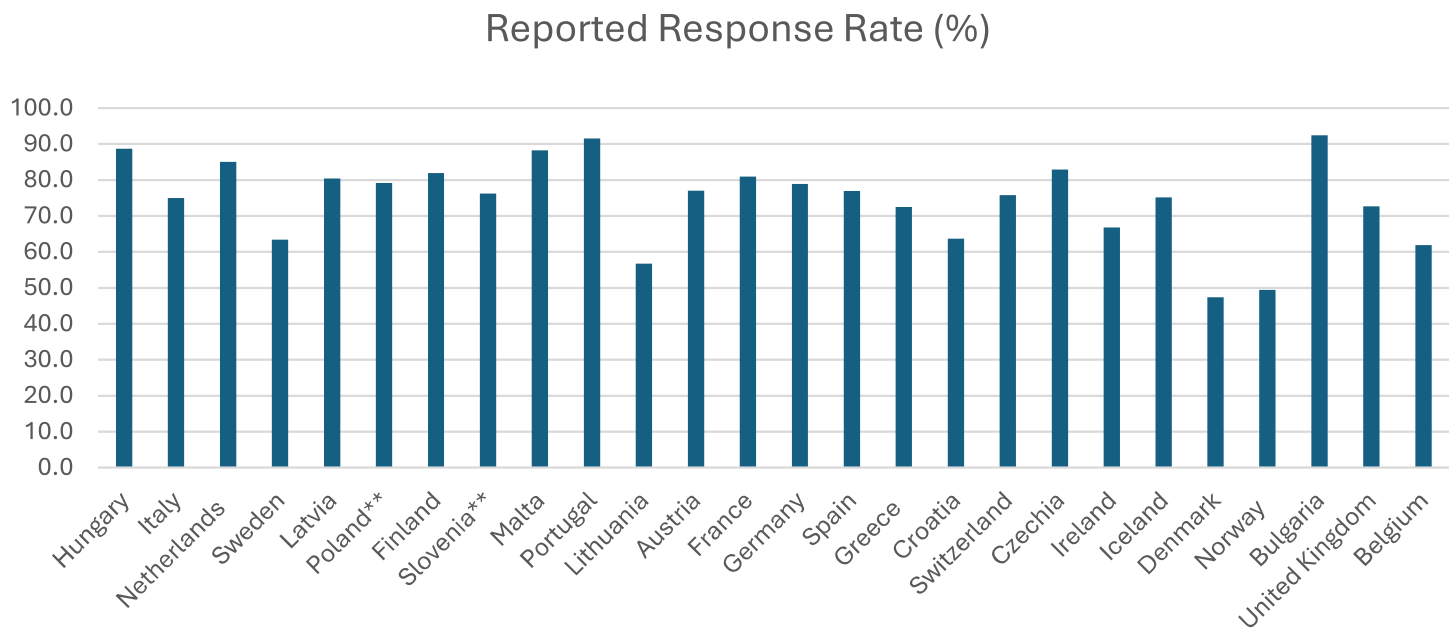
- Representativeness of 2011 EU-SILC responding samples across European countries, compared to population benchmarks obtained from the 2011 census for variables: age, sex, economic activity, education level and citizenship (Poland and Slovenia did not include citizenship)
- Census distributions from Eurostat Census hub
- Bias adjustment: ‘plugging in’ estimated response propensities in sample variances, using sample means and adjusting with inverse propensity scores leads to a small sample bias

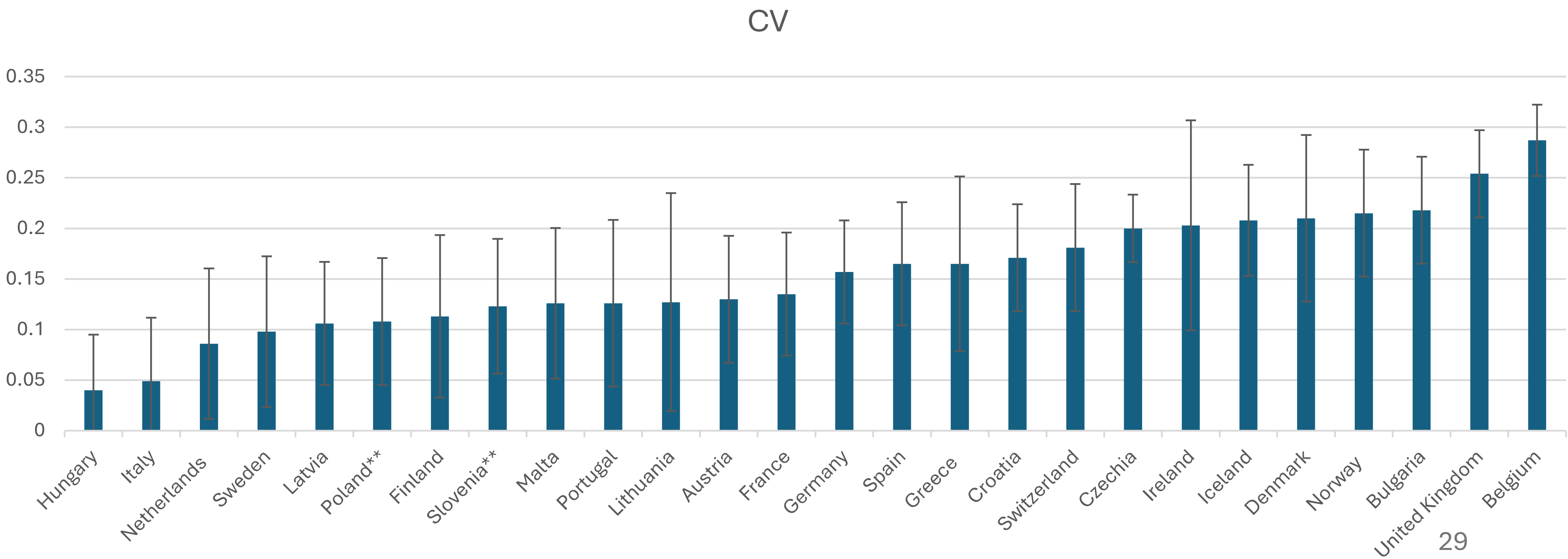
Representativeness of 2011 EU-SILC

- R-indicator: $\hat{R}^{Adj}_{\hat{\rho}^P} = 1 - 2[\hat{S}^2_{\hat{\rho}^P} - \hat{B}_{\hat{\rho}^P}\left(\hat{S}^2_{\hat{\rho}^P}\right)]^{1/2}$ and similarly for the CV
- Expressions for $\hat{B}_{\hat{\rho}^P}\left(\hat{S}^2_{\hat{\rho}^P}\right)$ under a complex survey design appear in Bianchi, et al. 2019
- To estimate $V\left(\hat{R}^{Adj}_{\hat{\rho}^P}\right)$, we use the bootstrap method
- Design weights approximated: $d_i^* = w_i^*(\frac{M^*}{N^*})$ where $w_i^* = N^*/\sum_r w_i$ and $M^* = \mathrm{R}_p \times N^*$

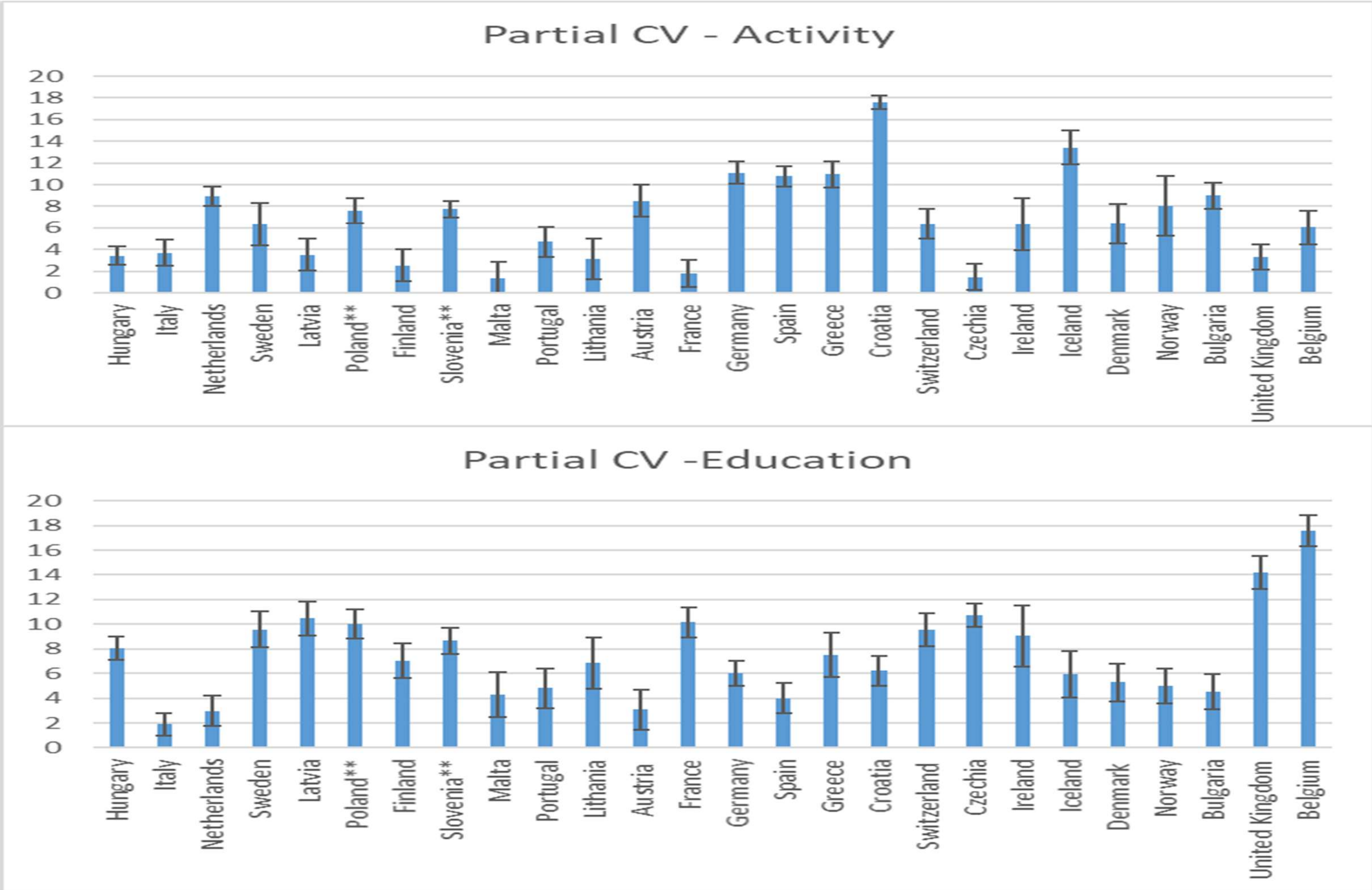
Representativeness of 2011 EU-SILC

Response rates for 2011 EU-SILC datasets and their CVs (with confidence intervals) the order is according to magnitude of the CV. Standard errors calculated using a bootstrap with 300 repetitions.





Representativeness of 2011 EU-SILC



Application 3

Population-based R-indicators for Non-probability sample: EVENS

Shlomo, et al. 2023

The Evidence for Equality National Survey (EVENS)

- EVENS conducted February to October 2021 (with a month break) developed by Centre on the Dynamics of Ethnicity (CoDE) and implemented by Ipsos (funded by the Economic and Social Research Council of the UK)
- Aim: collect information on extent and drivers of ethnic and religious inequalities during and post COVID-19 including experiences of racial discrimination
- Daily monitoring of responses for nonprobability online survey: all univariate and bivariate cross-tabs examined and population-based R-indicators (Bianchi, et al. 2019)
- Target under-represented groups by directing resources for recruitment, boosting samples collected from panel members and face-to-face interviewing

R-Indicators on Final Sample and Final Sample Size

Component	Sample Size		
	Ethnic minority (with Jewish)	White British	Total*
Main Survey	3292	114	3406
Panels	3554	4114	7668
Prolific	2856	285	3141
Total	9702	4513	14215

R-indicator	0.706							
Variables and Categorical Level R-indicator:							Population Counts	Quotas
Region	**0.046**	**Sex**	**0.04**	**Age group**	**0.107**	**Ethnic group**	**0.125**	**0.132**
East Midlands	-0.004	Males	-0.030	18-24	0.060	Bangladeshi	0.000	-0.045
East of England	0.015	Females	0.026	25-34	0.037	Black African	0.004	0.021
London	-0.009			35-44	-0.024	Black Caribbean	0.006	-0.012
North East	-0.001			45-54	-0.059	Chinese	0.038	0.012
North West	0.009			55 over	-0.051	Indian	-0.021	0.033
Scotland	0.016					White and Black Caribbean	0.010	0.015
South East	-0.013					White and Black African	0.014	-0.031
South West	0.000					White and Asian	0.037	0.038
Wales	0.027					Other Asian	-0.005	0.026
West Midlands	-0.003					Other Black	0.007	-0.026
Yorkshire and Humber	-0.022					Arab	-0.017	-0.024
						Pakistani	-0.033	0.018
						White Roma	-0.009	-0.042
						White Eastern Europe	-0.067	-0.043
						White Irish	-0.059	-0.067
						White Gypsy/traveller	0.026	-0.022
						Jewish	0.042	-0.001

Application 4

Population-based R-indicators for Assessing the Quality of Administrative Data

Shlomo and Kim (forthcoming in SMJ)

Introduction

- NSIs developing quality frameworks for ingesting administrative (and other) data into national statistical systems that are qualitative and descriptive
- **Aim:** develop quantitative quality indicators to assess representativeness of the administrative data to target population and identify sub-groups that may be under-represented
- Use timely census data or high-quality probability-based (weighted) surveys to compare distributions between reference data and administrative data.

Introduction

- NSIs should utilize survey data collections, eg. Labour Force Survey
- Surveys suffer from high non-response, but are generally good quality with respect to steps taken to mitigate nonresponse bias (during and post- data collection adjustments, survey weights including calibration to known population benchmarks)
- High-quality survey data should be collected for the purpose of assessing quality and correcting for coverage errors in administrative data, censuses
- These surveys should be mandatory (similar to a census)

Introduction

- R-indicators avoids the need for record-level linkage, i.e. quality measures indicate representativeness on groups rather than record-level data
- Quantitative quality measures provides a more direct assessment of representativeness rather than use of check lists and score cards in Quality Frameworks.
- Estimated propensity scores in administrative data allows for adjusting estimates by weighting with the inverse of propensity score (IPW)

Simulation Set Up

- Census microdata from 2001 UK Census: 1,163,659 individuals, with variables: Geography (Local Authority) (6 categories), Sex (2 categories), Age Group (14 categories), Ethnic Group (16 categories), Marital Status (6 categories), Economic Status (10 categories)
- 2 steps:

  (1) simulate administrative data

  (2) draw 40 random sample without replacement to use as the probability reference sample (1:50 sample assuming full response, i.e. each individual in the sample has a weight of 50)

Simulation Set Up

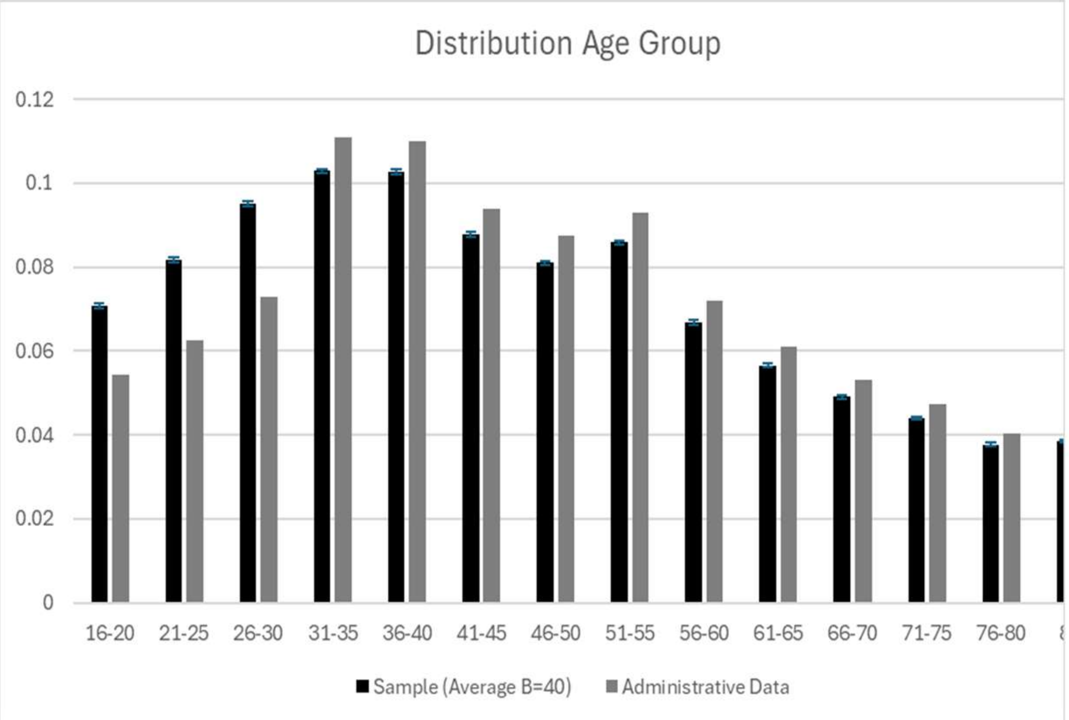
- From ONS experiences, 4 types of groups:
  - Group 1: Individual not represented in administrative data (deleted)
  - Group 2: Individual has moved to another location (geography changed)
  - Group 3: Individual recorded in correct location (no change)
  - Group 4: Individual has a duplicate record in another location (duplicate created).
- For each group, define a probability that varies across strata defined by: sex, ethnic group (White, Non-White) and age group (below 30, 31-44, 45 and over)

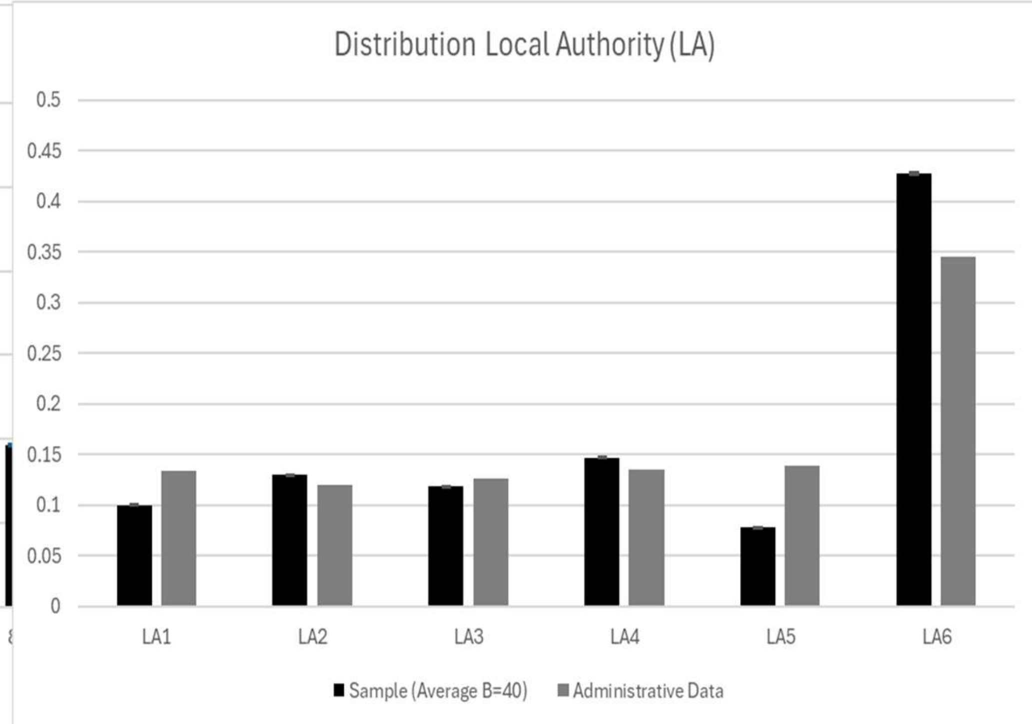
Simulation Set Up

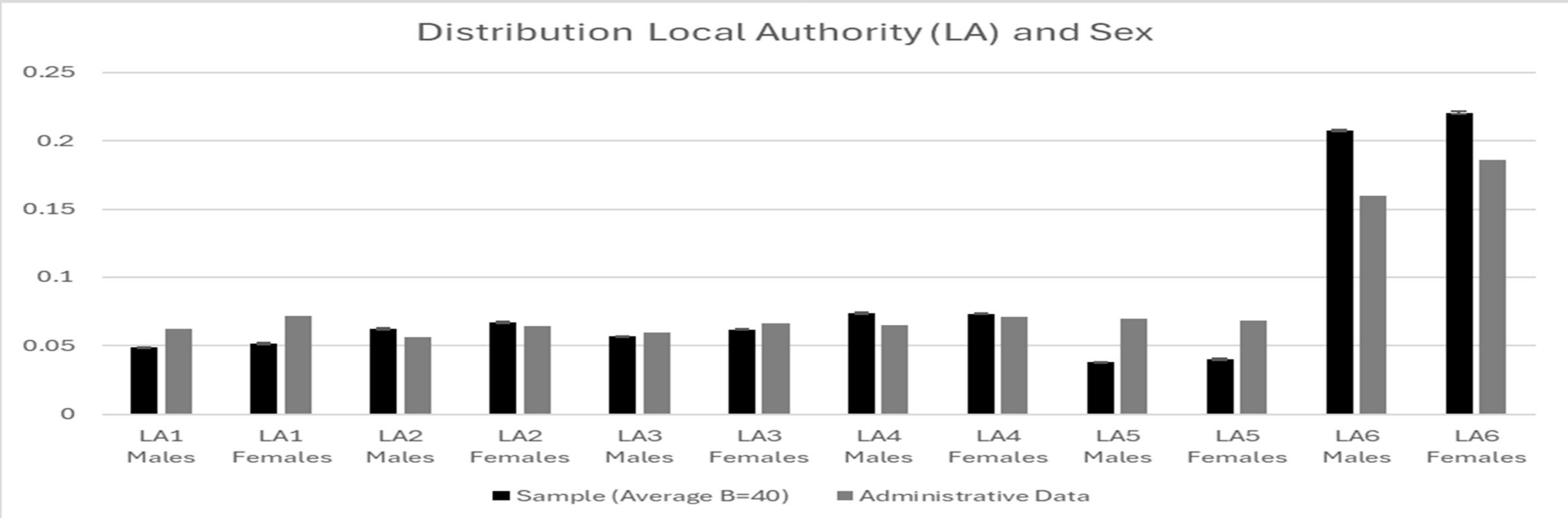
Age Group	Ethnic Group	Sex	p1	p2	p3	p4
below 30	White	Male	0.45	0.15	0.3	0.1
31-44	White	Male	0.2	0.2	0.5	0.1
45 and over	White	Male	0.1	0.15	0.7	0.05
below 30	White	Female	0.4	0.15	0.35	0.1
31-44	White	Female	0.15	0.15	0.55	0.15
45 and over	White	Female	0.1	0.1	0.75	0.05
below 30	Non-White	Male	0.37	0.15	0.43	0.05
31-44	Non-White	Male	0.15	0.2	0.6	0.05
45 and over	Non-White	Male	0.05	0.13	0.8	0.02
below 30	Non-White	Female	0.33	0.15	0.47	0.05
31-44	Non-White	Female	0.1	0.18	0.67	0.05
45 and over	Non-White	Female	0.05	0.1	0.83	0.02

Final simulated administrative data set with N=1,026,969

Comparing Survey and Admin Data







R-indicators

R-indicator:

Type 1 (population covariance): **R=0.7228 (0.0013)**

Type 2 (mixture) **R=0.7413 (0.0010)**

Variable level R-indicators: Geography and Age Group variables have larger partial R-indicators and are contributing the most to lack of representativeness

Variable	Partial R-Indicator: Type 1	Partial R-Indicator: Type 2
Geography (6)	0.2869 (0.00218)	0.2106 (0.00093)
Sex (2)	0.0145 (0.00094)	0.0234 (0.00087)
Age Group (14)	0.1005 (0.00081)	0.1312 (0.00105)
Ethnic Group (16)	0.0288 (0.00069)	0.0230 (0.00064)
Marital Status (6)	0.0617 (0.00088)	0.0794 (0.00096)
Economic Status (10)	0.0534 (0.00068)	0.0674 (0.00086)

R-indicators

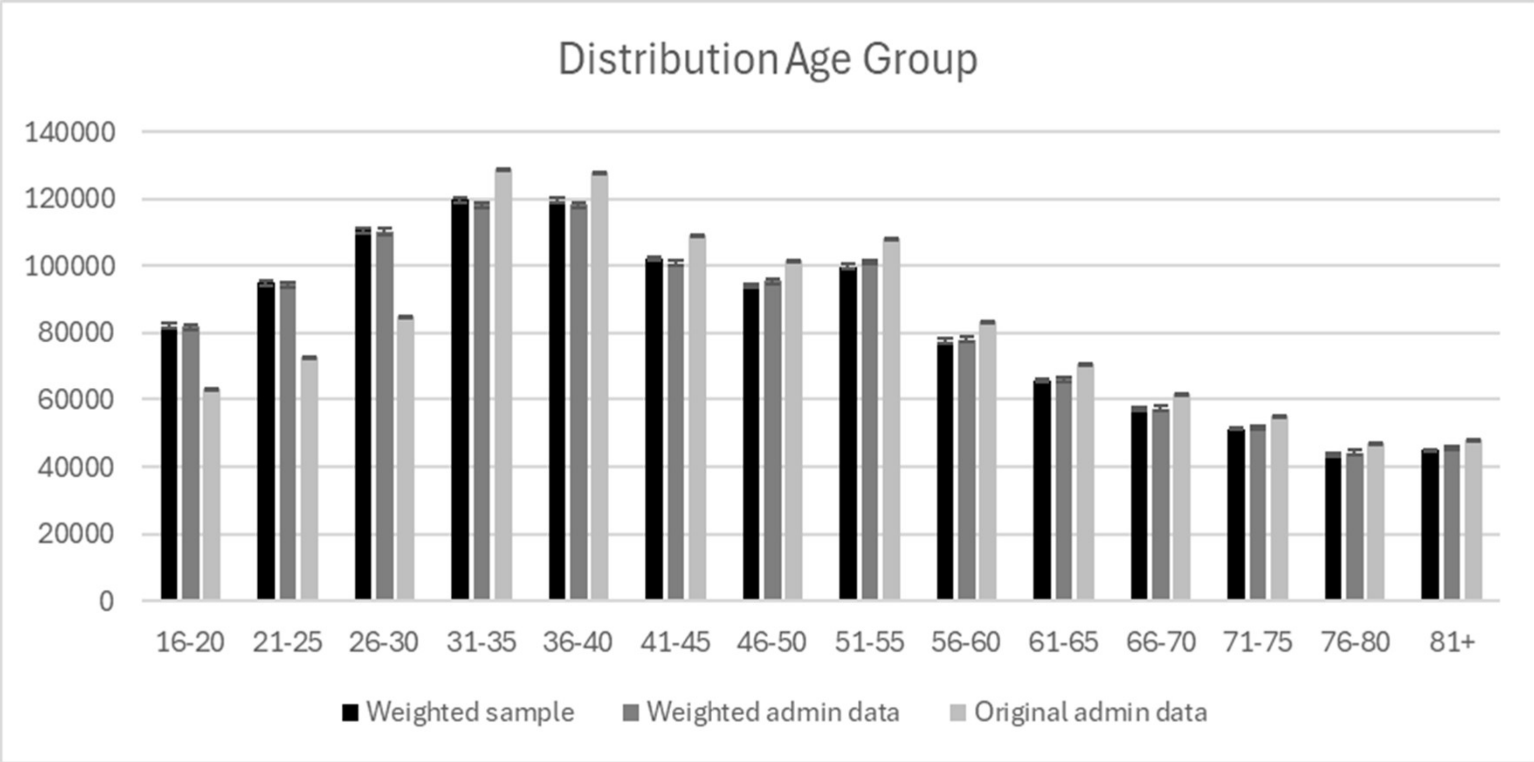
Categorical-level R-indicators for Geography and Age Groups

Note: LA6 under-represented as well as lower ages)

Geography	Category-level Partial R-indicator: Type 1	Category-level Partial R-indicator: Type 2
LA1	0.0858 (0.00122)	0.0821 (0.00072)
LA2	-0.0441 (0.00080)	-0.0241 (0.00081)
LA3	-0.0065 (0.00096)	0.0200 (0.00079)
LA4	-0.0464 (0.00076)	-0.0272 (0.00078)
LA5	0.2270 (0.00231)	0.1437 (0.00081)
LA6	-0.1382 (0.00089)	-0.1229 (0.00076)

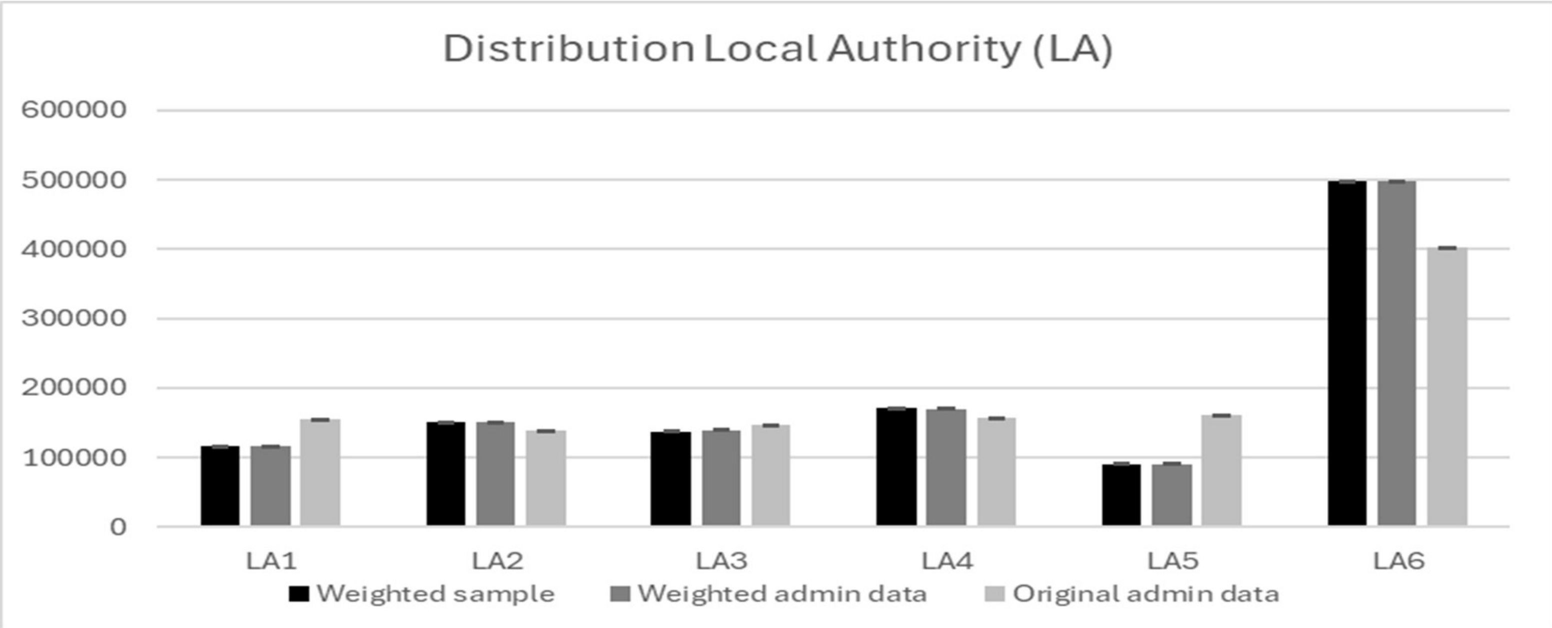
Age Group	Category-level Partial R-indicator: Type 1	Category-level Partial R-indicator: Type 2
16-20	-0.0455 (0.00070)	-0.0619 (0.00110)
21-25	-0.0520 (0.00073)	-0.0675 (0.00106)
26-30	-0.0545 (0.00073)	-0.0723 (0.00107)
31-35	0.0211 (0.00093)	0.0216 (0.00078)
36-40	0.0187 (0.00099)	0.0194 (0.00081)
41-45	0.0180 (0.00092)	0.0173 (0.00078)
46-50	0.0105 (0.00100)	0.0190 (0.00086)
51-55	0.0127 (0.00085)	0.0207 (0.00075)
56-60	0.0114 (0.00113)	0.0170 (0.00092)
61-65	0.0113 (0.00116)	0.0158 (0.00097)
66-70	0.0108 (0.00102)	0.0157 (0.00087)
71-75	0.0089 (0.00074)	0.0139 (0.00059)
76-80	0.0068 (0.00122)	0.0124 (0.00102)
81+	0.0044 (0.00084)	0.0116 (0.00066)

IPW for Administrative Data Estimates



(1-HD) weighted sample, weighted admin data=0.9956 (0.00010)

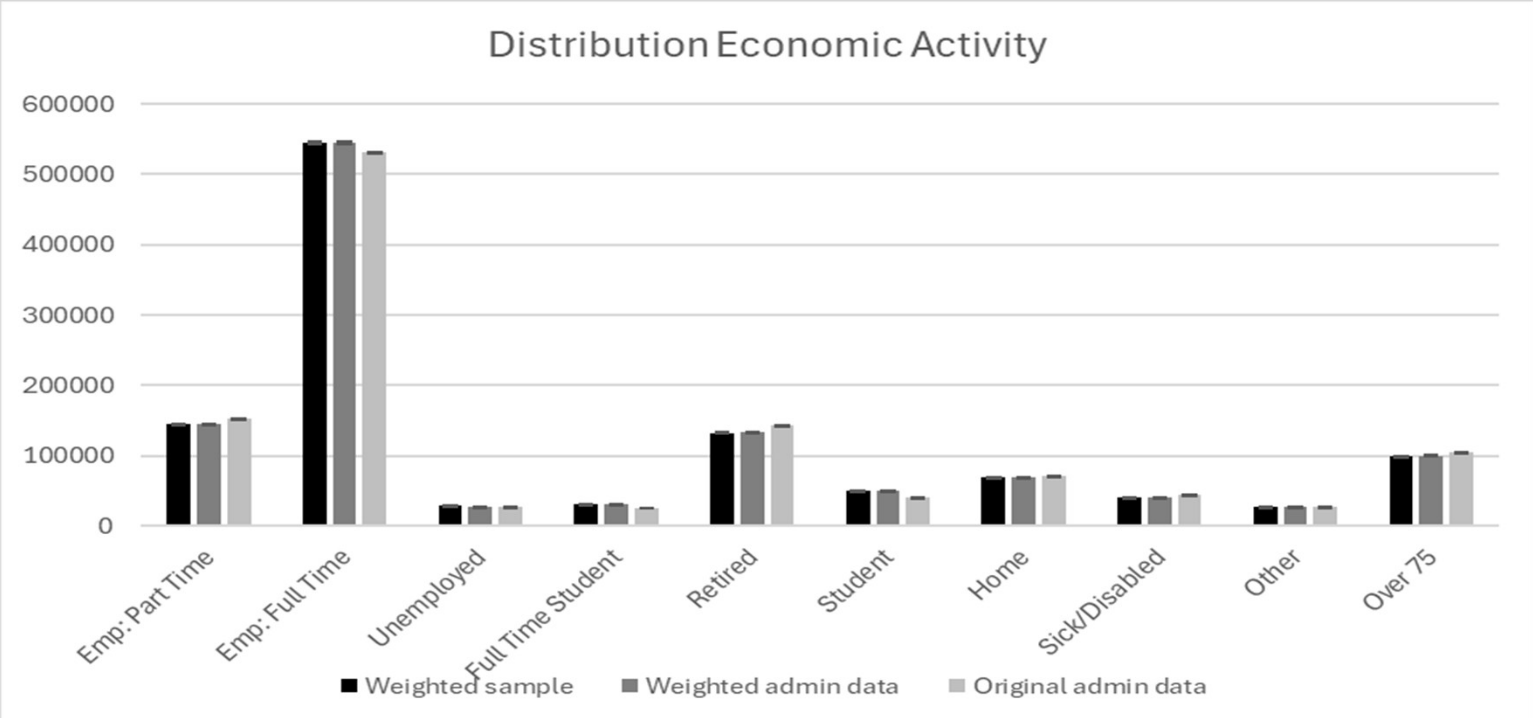
(1-HD) weighted sample, original admin data =0.9500 (0.00038)



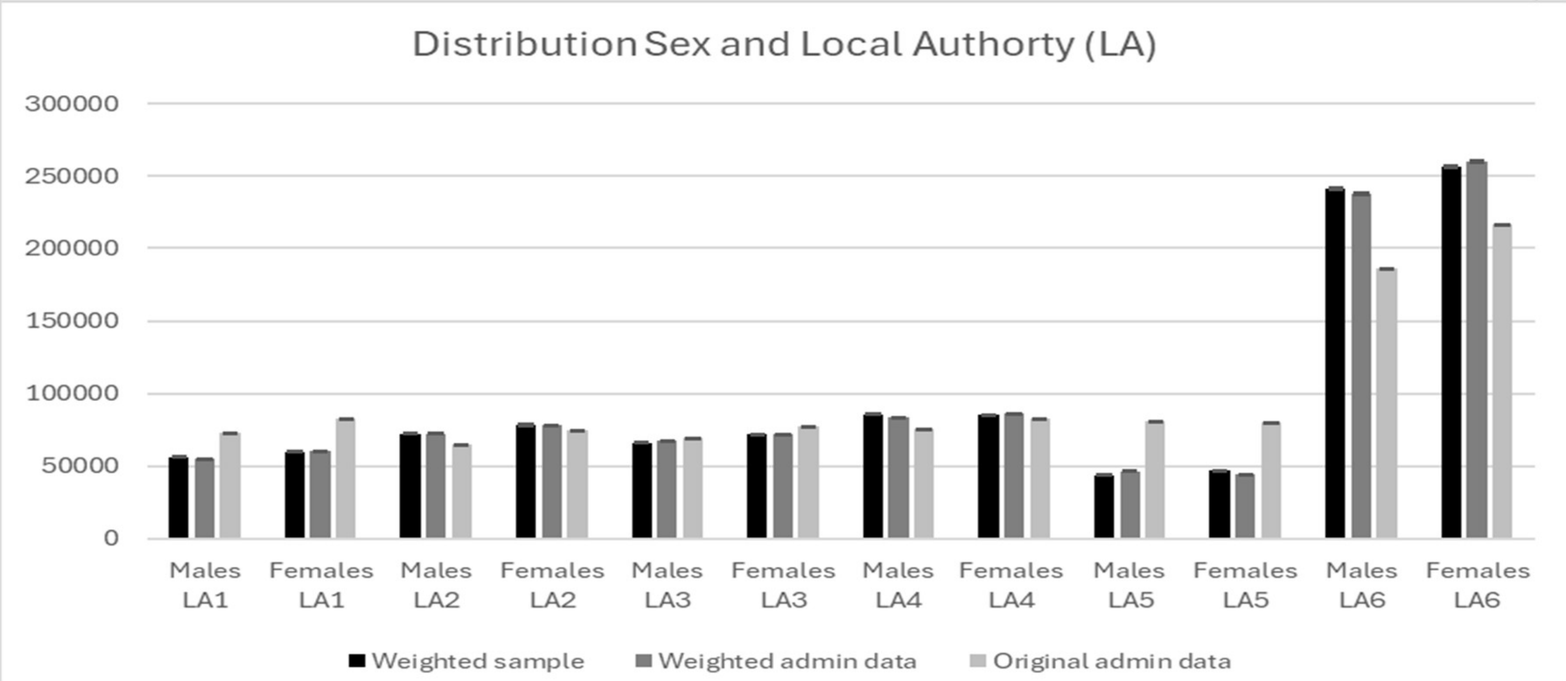
(1-HD) weighted sample, weighted admin data=0.9981 (0.00005)

(1-HD) weighted sample, original admin data =0.9103 (0.00043)

IPW for Administrative Data Estimates



(1-HD) weighted sample, weighted admin data=0.9962 (0.00010)
(1-HD) weighted sample, original admin data =0.9738 (0.00032)



(1-HD) weighted sample, weighted admin data=0.9911 (0.00034)
(1-HD) weighted sample, original admin data =0.9091 (0.00043)

Final Points

- GitHub https://github.com/sook-tusk/qualadmin
- ONS assessed representativeness in Ethnicity Dataset (ABHED) derived by combining three admin-based composite data sources: Admin-based ethnicity dataset version 3.0 (ABED), admin-based household estimates version 3.0 and Admin-based housing stock version 1.0 (ABHS)
- Census 2021 used as comparative population data on four variables: sex, age group, accommodation type and ethnicity, in one LA
- See report here: https://www.ons.gov.uk/methodology/methodologicalpublications/generalmethodology/onsworkingpaperseries/qualityindicatorsforrepresentativenessinadministrativedatarindicatorsanddistancemetrics#:~:text=R%2Dindicators%20and%20distance%20metrics%20use%20variables%20from%20the%20census,auxiliary%20data%20in%20this%20paper
- Code now includes deriving R-indicators from frequency tables for very large datasets

Thank you for your attention

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