Administrative Data
Research Centre
England

An ESRC Data
Investment

Do representativeness indicators approximate non-response biases during survey data collection?

(Survey covariates with census analogues)

Gabriele Durrant,
Jamie Moore and Peter W.F. Smith
University of Southampton

Better Knowledge   Better Society

Motivation

- In many countries, survey response rates are declining.
- This is despite greater efforts to interview non-respondents. The trend leads to concerns about non-response biases and dataset quality.
- Nonresponse bias not easily estimated directly because only respondents answer
- Biases are weakly predicted by response rates.
- Hence, there has been a shift away from simply maximizing response rates to minimizing (risks of) biases.
- However, how to assess bias risks?
- In addition, given (increased) costs of data collection, when to stop calling?

Assessing non-response bias risks

- An indirect approach is to consider sample – respondent similarity given a fully observed auxiliary covariate set.

- We have previously proposed using the Coefficient of Variation of response propensities (CV):

$$CV = \frac{SD}{p}$$

where *SD* = Standard deviation of estimated propensities

p = average propensity (response rate)

- Low propensity variation implies low bias risk (high representativeness; CV close to 0).

See Moore et al. (in press) JRSSA

Monitoring data collection

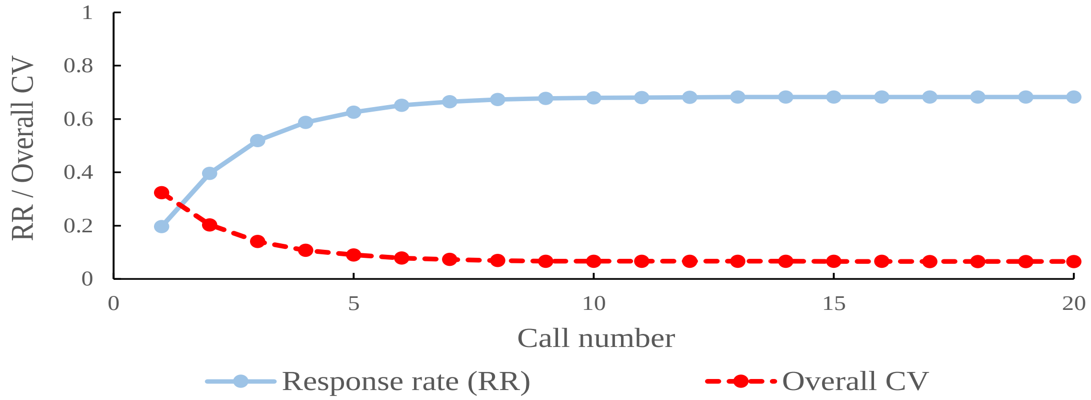
- Partial CVs also exist to quantify associations between auxiliary covariates and propensities.
- These enable under-represented sub-groups to be identified for targeting with collection method modifications.
- We use CVs to monitor UK social survey datasets during collection, computing them at each call (visit to a household by interviewer) in the call record (up to 20).
- In addition, we identify indicator based phase capacity (PC) points in records after which dataset quality increases minimally i.e. when to stop calling (calls 6 to 8).

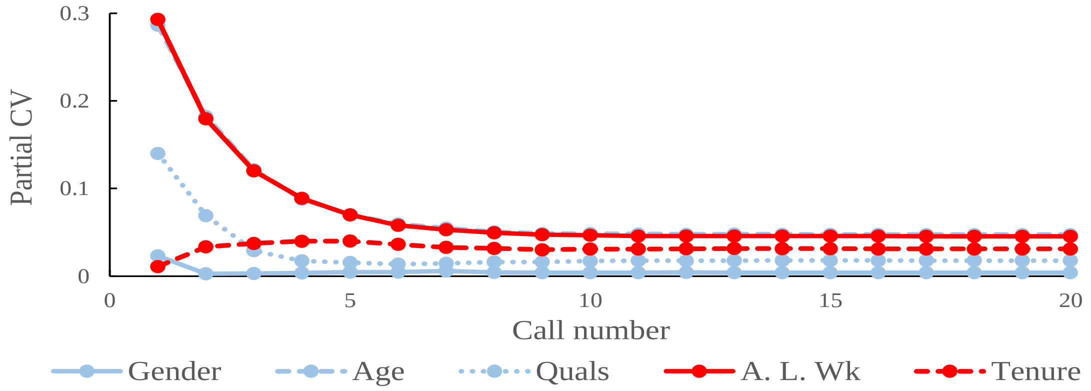
Data

- ONS 2011 Census Non-Response Link Study (CNRLS)
- Links UK social survey (here the Labour Force Survey (LFS)) sample frames and survey responses to individual level auxiliary information from the concurrent census.
- We also link call record data detailing interview attempts, enabling monitoring over data collection.
- Aim: We compute overall and partial CVs estimated given eight census sample information auxiliary covariates at each call in the record (max. 20 calls), and given indicators identify PC points.

Results

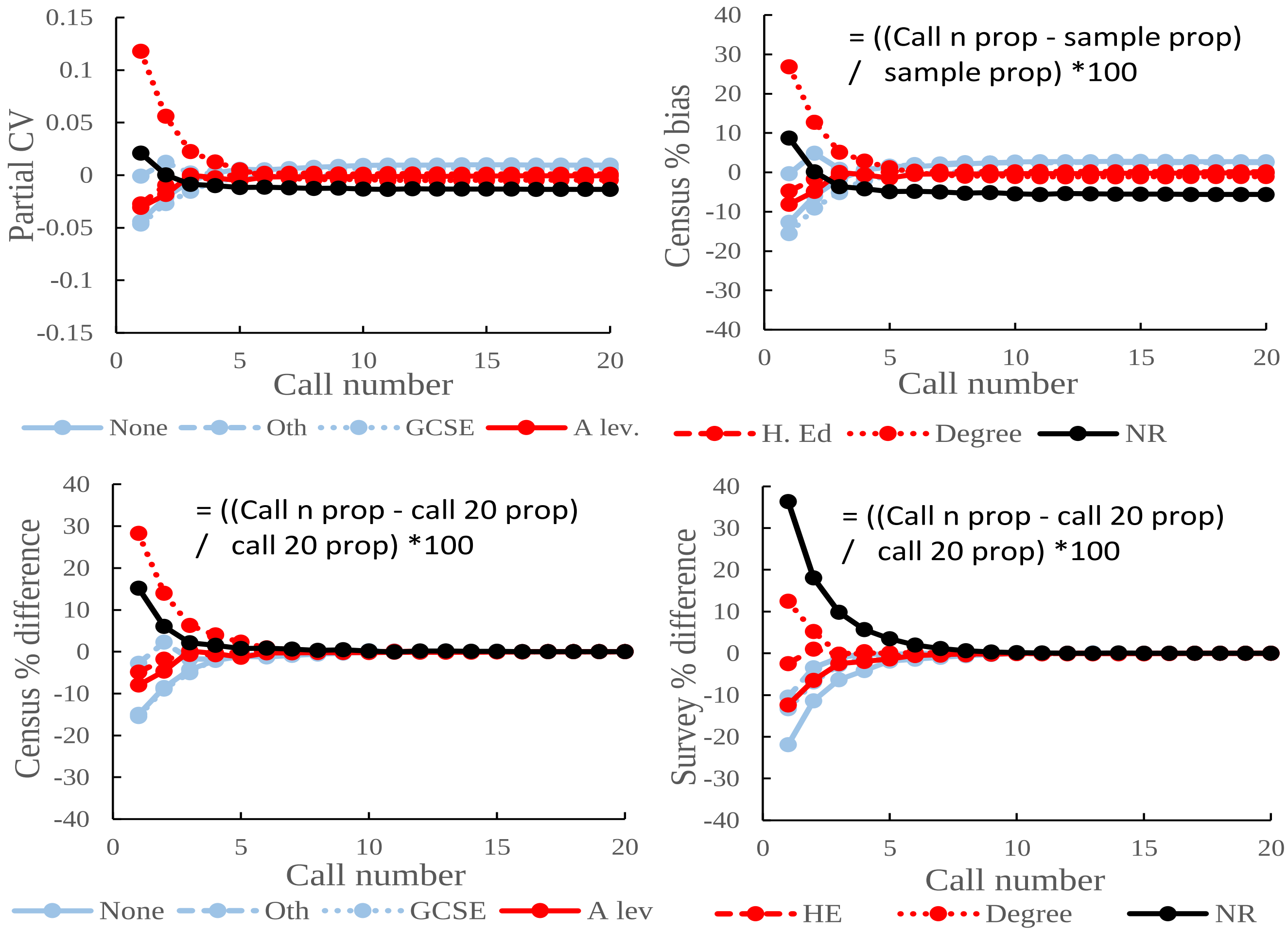
Overall and Partial CVs





- N = 33840, Final RR = 68.2%
- y~ gender + age + qualifications + activity last week + tenure
- Age, qualifications, activity last week & tenure impact

Qualification: category partial CVs, census ‘NR biases’, and census & survey differences to final values



Stopping and Phase Capacity Points

- When to stop calling?

  (Stopping point)

- When to change a survey data collection method?

  (Phase capacity point)

Stopping and Phase Capacity Points

- Defined as 0.02 of previous value (during data collection) or 0.02 of final value (after data collection)
- Overall phase capacity point (within 0.02 of minima) = call 6

PC points (Qualification)

- Defined as within 0.02 of previous value or 0.02 of final value

Category	CV diff.	C. ‘bias’ diff.	C. % diff.	S. % diff.
None	2	3	5	5
GCSEs	3	4	4	4

Further Research Questions

- However, such predictions from CVs have yet to be evaluated – this is our focus now.
- **How well do the proposed risk indicators approximate observed respondent dataset non-response biases?**
- Aim: we want to compare CVs to biases in survey covariates
- Survey covariates are partially observed, so methods depend on whether sample auxiliary information analogues (e.g. from external datasources such as Census) exist.
- In this talk, we consider covariates with such analogues (those without such analogous can also be investigated and we are doing this as a separate paper currently).

Evaluating CVs: covariates with auxiliary information analogues

- Schouten et al. (2009 Surv. Meth.) show that the overall CV quantifies survey covariate mean maximal absolute standardised non-response bias.

- Partial CV relations to (sample information) auxiliary covariate category biases are yet to be described; hence show: partial CVs make predictions about similar biases in auxiliary covariates.

See Moore et al. (submitted) JRSSA

Evaluating CVs: covariates with auxiliary information analogues

- show: partial CVs make predictions about biases in auxiliary covariates.
- To show this:
  - Note: Survey non-response biases are not quantifiable because only respondents answer, so we estimate logistic regression based census covariate standardised ‘non-response biases’ for comparison.
  - from sample information covariates (census) we can compute logistic regression based estimates of such biases **at each call** and identify PC points to compare to inference from CVs.
- Then, to test whether survey and sample information covariates are similar, we can compare respondent dataset category proportions over calls given each data source.

See Moore et al. (submitted) JRSSA

Fitting regression models

- We fit two statistical models. Model A estimates overall differences:

$$\log\left(\frac{\pi_i}{(1-\pi_i)}\right) = \beta_0 + \beta_1 r_i$$

- β_0 is log-odds of membership if a non-respondent, and β_1 the difference between β_0 and the log-odds if a respondent.
- With model A, β_1 quantifies the deviation from MCAR, similar to a CV_u.

Fitting regression models

- Model B estimates differences conditional on an auxiliary covariate vector $\boldsymbol{x}_i$:

$$\log\left(\frac{\pi_i}{(1-\pi_i)}\right) = \beta_0 + \beta_1 r_i + \boldsymbol{\beta}^T \boldsymbol{x}_i$$

- a β_1 of zero implies response with regard to a category is MAR given the auxiliary covariates, and non-zero values quantify the extent to which it is NMAR. This is similar to a CV_c

Nonresponse bias

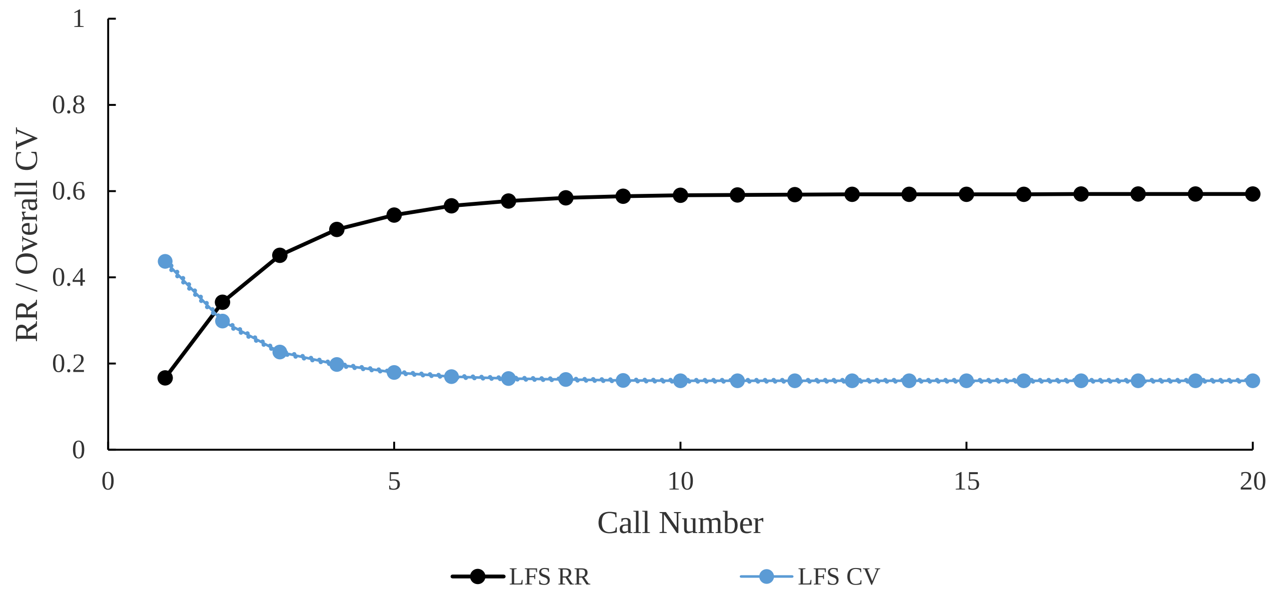
- Then, from parameter estimates, we compute standardised 'non-response biases' as, for category *c*:

$$\mathrm{Bias}(\hat{\hat{c}}_r) = \frac{\left(\left(\frac{m}{n}\right)(\bar{\pi}_r - \bar{\pi}_{nr})\right)}{S_{\bar{\pi}_s}}$$

- Concerning predictions, for two category covariates, covariate CVs should approximate bias absolute values

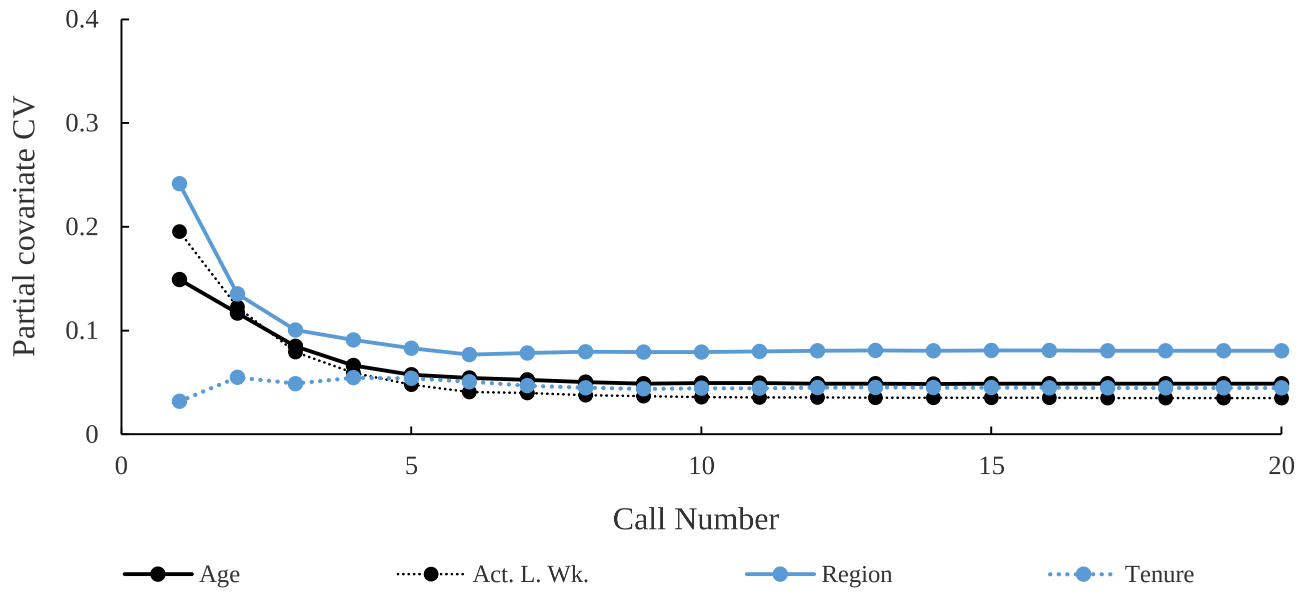
Results

Response rate & overall CVs



- N = 21150, Final response rate = 58.7%
- CV response propensity model = y~ gender + age + qualifications + activity last week + tenure + HH structure + ethnicity + region
- PC point (within 0.02 of call record best value) at call 5.

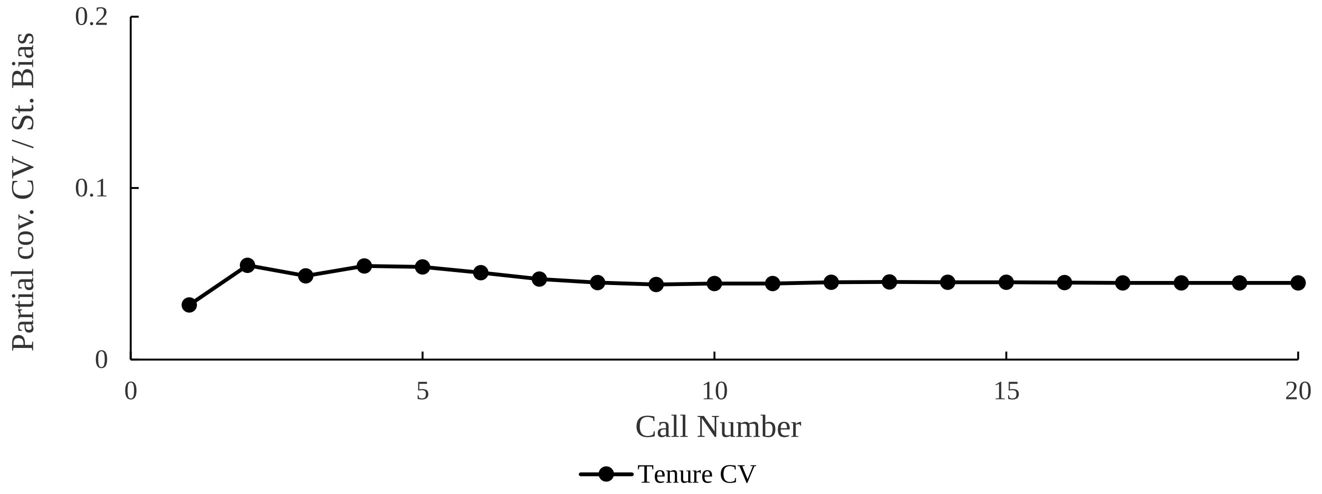
Partial covariate CVs



- Impacts of all covariates: a selection reported here.
- Under-represented categories include: under 40s, ‘Employed’, ‘in Ldn / SE’, not owned households.

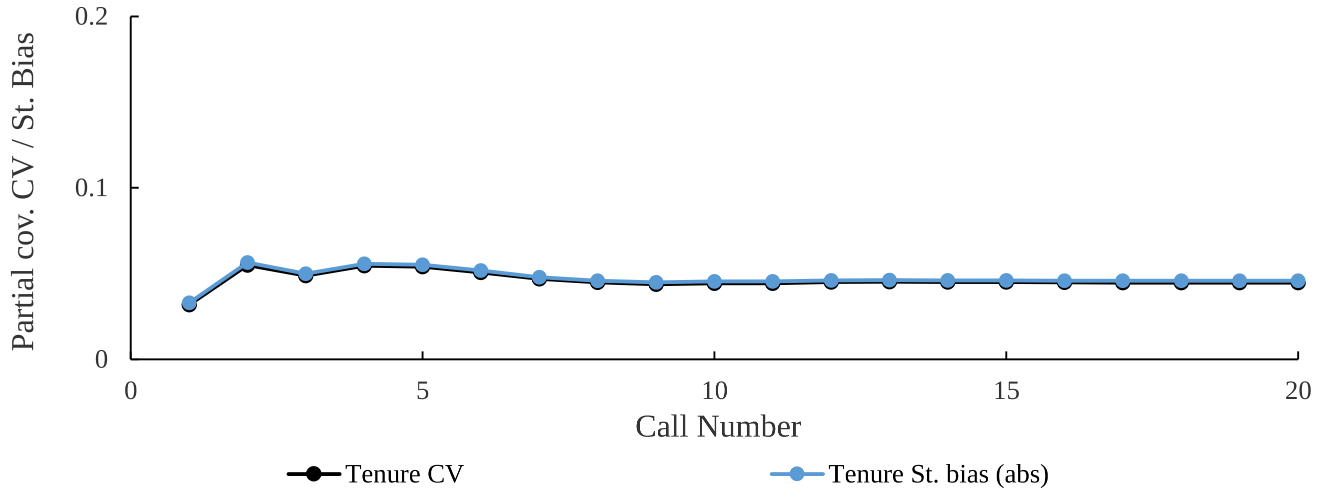
Evaluating CVs: Two category covariates

- For two category covariates, covariate CVs should approximate category mean absolute standardised non-response bias.
- For Tenure: partial CV



Evaluating CVs: Two category covariates

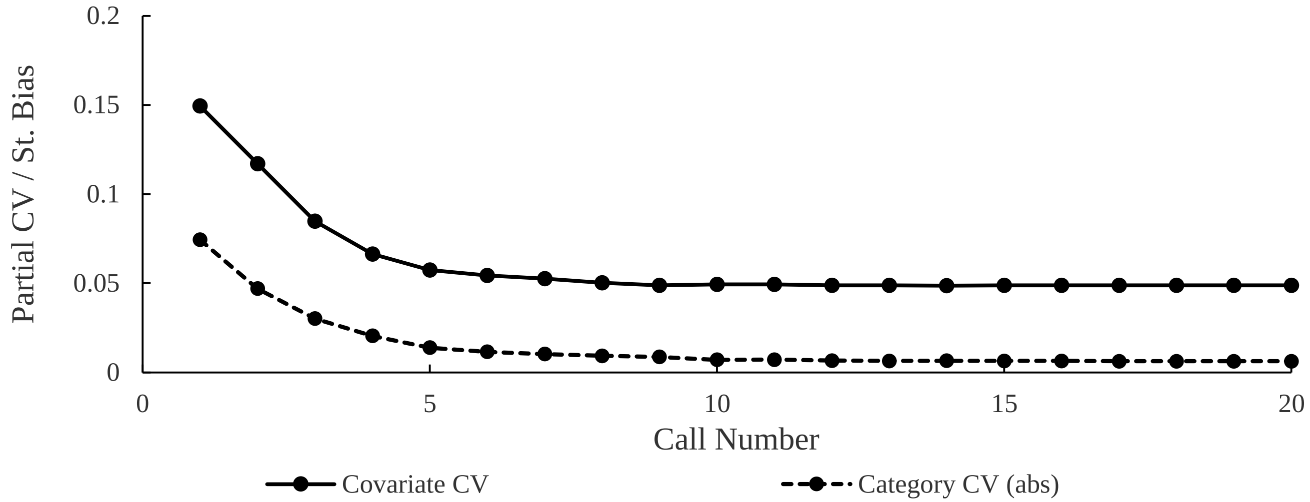
- For two category covariates, covariate CVs should approximate category mean absolute standardised non-response bias.
- For Tenure: partial CV and standardised bias



- PC points also the same: both at call 1.

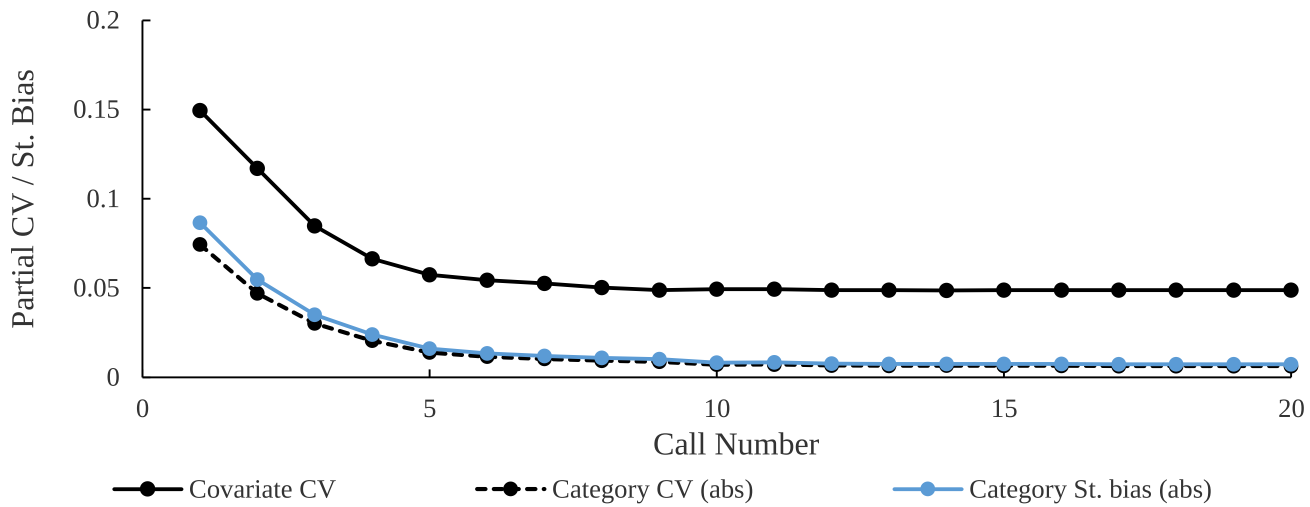
Evaluating CVs: Multi-category covariates

- For multi-category covariates, partial covariate CVs should quantify category mean absolute standardised bias maxima.
- (Absolute) category CVs should slightly under-estimate such biases if contribution to covariate level inequality substantial.
- For Age '27 to 39': partial CVs



Evaluating CVs: Multi-category covariates

- For multi-category covariates, partial covariate CVs should quantify category mean absolute standardised bias maxima.
- (Absolute) category CVs should slightly under-estimate such biases if contribution to covariate level inequality substantial.
- For Age ‘27 to 39’: partial CVs and category standardised bias



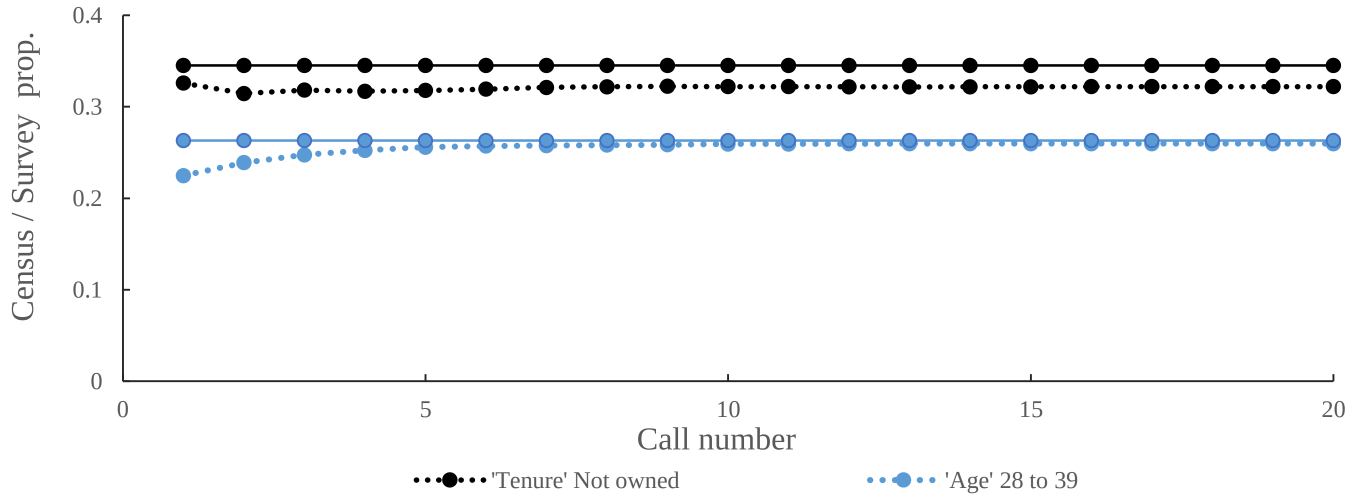
- PC points also the same: both at call 4.

Evaluating CVs: Multi-category covariates

- census covariate category standardised ‘non-response biases’ are consistent with predictions from CVs
- two category covariate covariate CVus and CVcs are quantitatively similar to overall (model A) and conditional (model B) bias absolute values respectively

Are census and survey covariates similar?

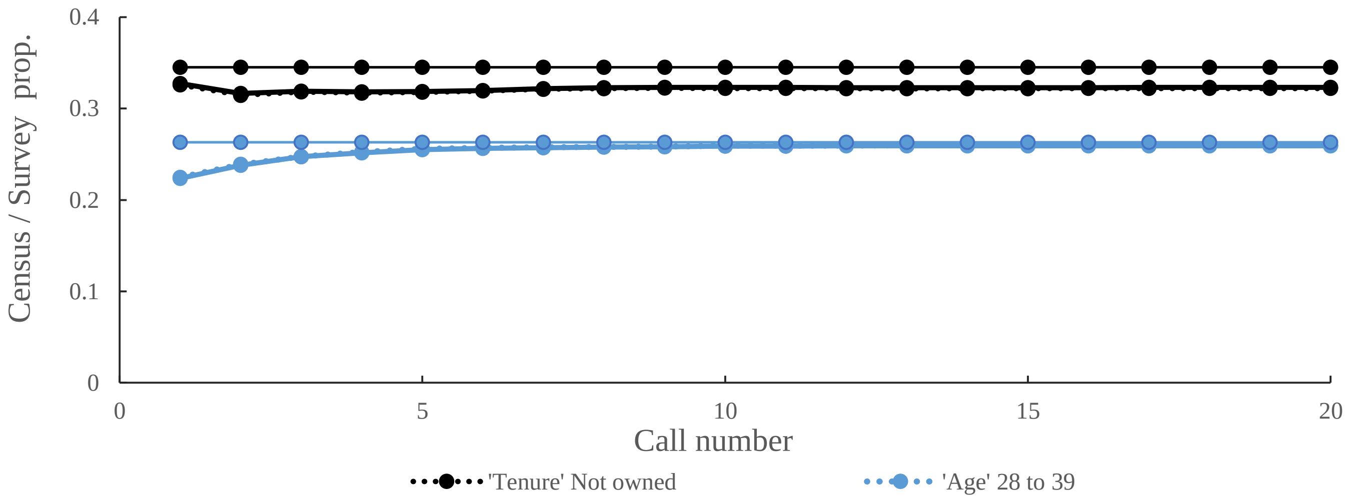
- Census covariate category respondent proportions over calls.



- Census covariates:
  - solid line: sample dataset proportion (census covariate for both respondents and nonrespondents);
  - Dotted line: respondents dataset proportion only (census covariate for respondents only)

Are census and survey covariates similar?

- Census covariate category respondent proportions over calls.



- Census covariates:
  - solid line: sample dataset proportion (census covariate for both respondents and nonrespondents); dotted line: respondents dataset proportion only (census covariate for respondents only)
- Additional dotted line: survey respondent proportion
- There is close correspondence with census and survey covariates!!

Summary and implications for survey practice

- LFS individual dataset quality as quantified by CVs increases over call record.
- Partial CVs identify a number of census auxiliary covariate associated dataset non-representativeness.
- In certain conditions, partial CVs also closely approximate (survey) covariate non-response biases: for best results, code as a binary covariate and use covariate CVs.
- Such correspondence with biases is consistent with CVs being of utility when monitoring survey data collection.
- The overall CV PC point is at call 5: a substantial call saving (18%)!!

Acknowledgements

This work was funded by the ESRC National Centre for Research Methods, Workpackage1 (grant reference number ES/L008351/1) and the ESRC Administrative Research Centre for England (ADRCE) (grant reference number ES/L007517/1).

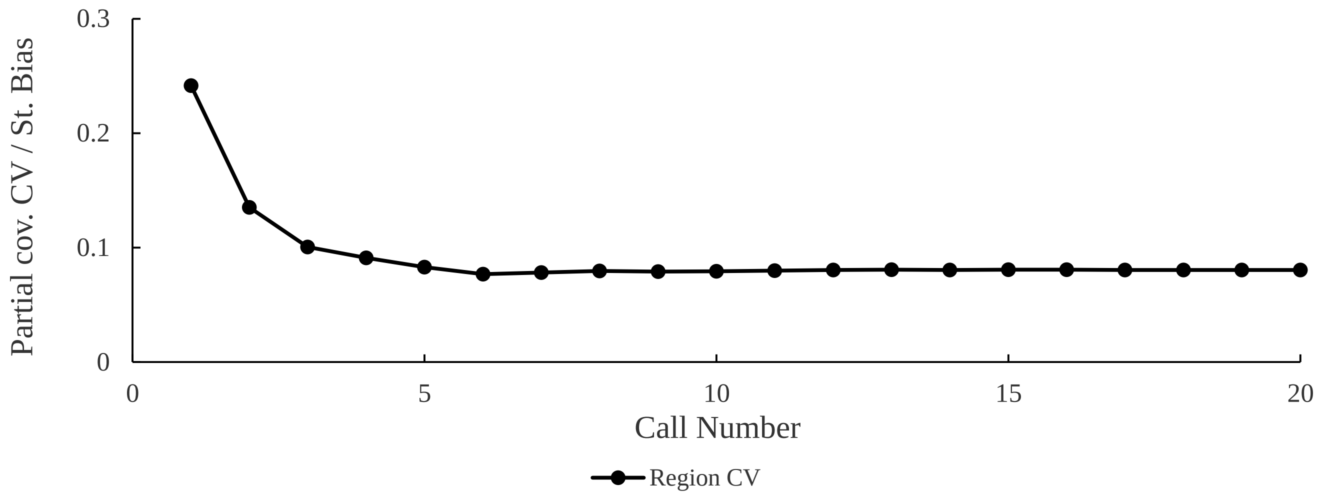
This work contains statistical data from ONS which is Crown Copyright. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

Thank you

g.durrant@southampton.ac.uk

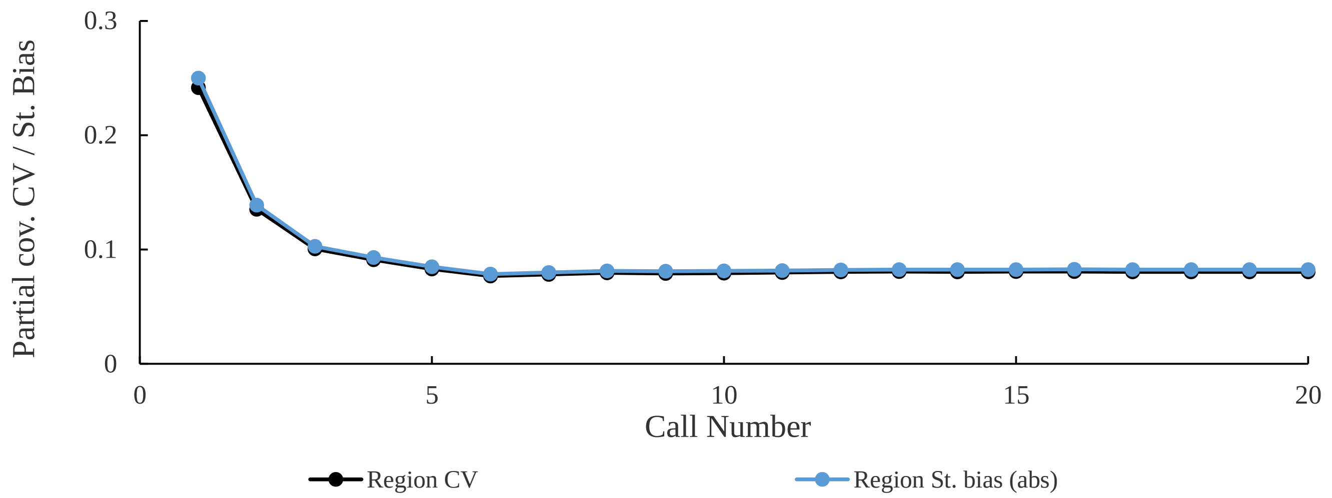
Evaluating CVs: Two category covariates

- For two category covariates, covariate CVs should approximate category mean absolute standardised non-response bias.
- For Region:



Evaluating CVs: Two category covariates

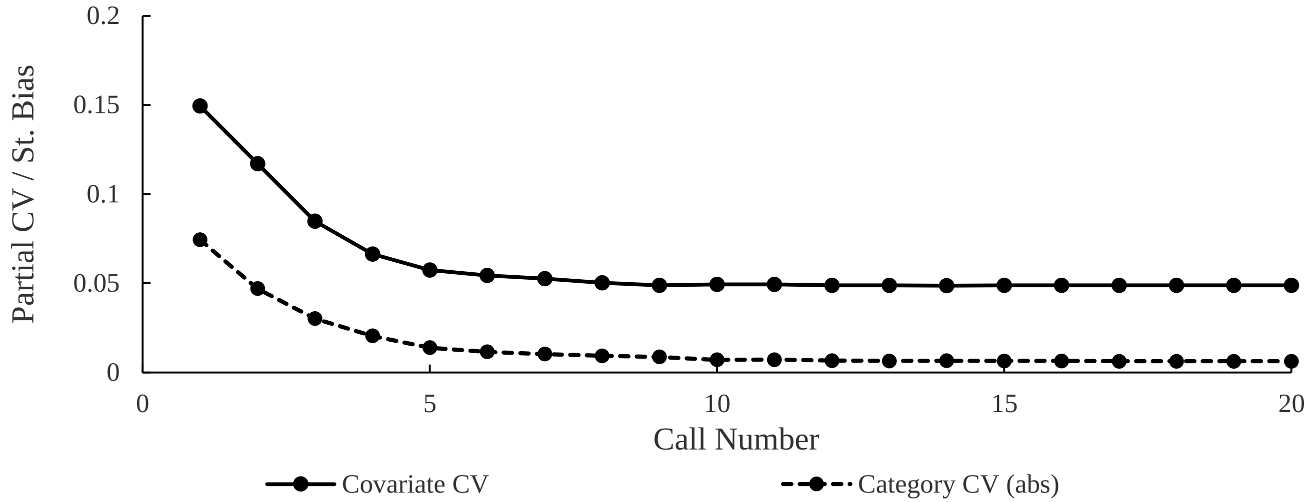
- For two category covariates, covariate CVs should approximate category mean absolute standardised non-response bias.
- For Region:



- PC points also the same: both at call 4.

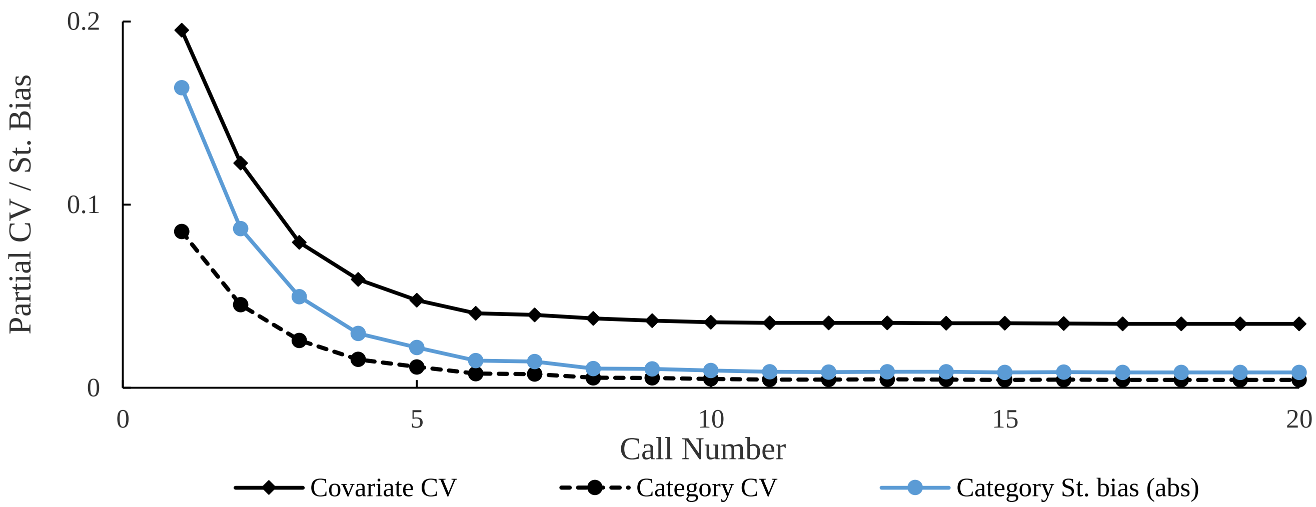
Evaluating CVs: Multi-category covariates

- For multi-category covariates, partial covariate CVs should quantify category mean absolute standardised bias maxima.
- (Absolute) category CVs should slightly under-estimate such biases if contribution to covariate level inequality substantial.
- For Activity Last Week ’Employed’:



Evaluating CVs: Multi-category covariates

- For multi-category covariates, partial covariate CVs should quantify category mean absolute standardised bias maxima.
- (Absolute) category CVs should slightly under-estimate such biases if contribution to covariate level inequality substantial.
- For Activity Last Week ’Employed’:



- Category CV PC point at call 4, Bias PC point at call 5.

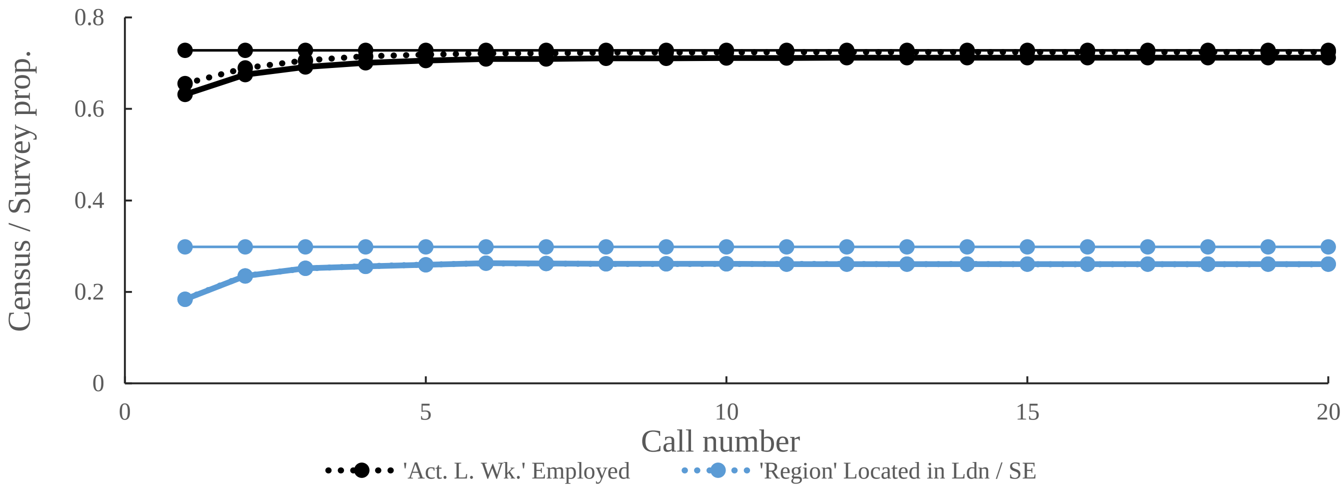
Are census and survey covariates similar?

- Census covariate category respondent proportions over calls.

- Implied biases as expected.

Are census and survey covariates similar?

- Census covariate category respondent proportions over calls.



- Plus close correspondence with survey covariates!!