Assessing risk of nonresponse bias and dataset representativeness during survey data collection

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Introduction

• Focus has shifted from nonresponse rate to nonresponse bias

• Key question: How to monitor, assess and minimise (risk of) nonresponse bias?
  – Post or during data collection

• Questions from survey practice: when to stop calling?
Introduction

• Fully observed information on both respondents and nonrespondents necessary

• Sample frame information from
  – register / Census
  – administrative data
  – previous wave

• Datasets (face-to-face surveys):
  – ONS Census nonresponse link study
  – Understanding Society
How to assess the risk of nonresponse bias?

- **Main idea:** measure similarity between sample data obtained and frame data in terms of variation in response rates

- Use of a response propensity model to obtain estimated response propensities

- **Representativeness indicators:** estimate variation in these response propensities (SD = Standard deviation of the response propensities)

- Low variability in response propensities imply high representativeness
Representativeness Indicators

• **R indicator:**

\[
R = 1 - 2SD
\]

SD = standard deviation of response propensities
Ranges between 0 and 1
Close to 1 indicates high representativeness

• **CV (Coefficient of Variation):**

\[
CV = \frac{SD}{r}
\]

r = response rate
CV close to 0 indicates high representativeness

• Here computed at each call (visit to a household by interviewer)
Applying these Methods – Key Research Objectives

1. **Visualise** trends in dataset representativeness
2. Are trends in representativeness generalizable **across surveys** (of the same population)?
3. Can we derive **stopping points** for an adaptive data collection strategy – can these be generalised?
Data

- **ONS 2011 Census Non-Response Link Study (CNRLS)**
- Links response indicator from three UK social surveys to survey call record data and census household (HH) information on sample frames
- 3 (cross-sectional) face-to-face surveys:
  - Labour Force Survey (LFS) (wave 1)
  - Life Opportunities Survey (LOS) (wave 1)
  - Opinions Survey (OPN)
- Up to 20 calls to a household
Application and Results
final response rate: LFS = 65.7%
LOS = 70.1%
OPN = 64%.
In case of low response rates (as is the case early on in data collection) small response propensity variation, limited potential for response propensity divergence

- R indicators close to 1, falsely indicating high representativeness
- R-indicator can be misleading in this case
CV (Coefficient of Variation)

- CV standardises SD by $r$; overcomes the problem of the R indicator
- CV decreasing, close to 0 indicating high representativeness
(Unconditional) Partial Indicators

- Aim: estimate the extent to which response is representative with respect to a covariate or a particular category
- We found similarities across surveys, some variables improve across calls, some remain the same (but do not improve)
Phase Capacity or Stopping Points
Stopping or Phase Capacity Points

• When to change a survey data collection method?
  (Phase capacity point)

• When to stop calling?
  (Stopping point)
Stopping or Phase Capacity Points

• Adaptive Strategy: **stop when** indicator within 0.02 of minimum value (points later when threshold decreased)
• Responsive strategy: **stop when** indicator within 0.02 of previous value
Stopping or Phase Capacity (PC) Points

• Overall:

<table>
<thead>
<tr>
<th>Survey</th>
<th>PC point (adaptive)</th>
<th>% calls saved</th>
<th>PC point (responsive)</th>
<th>% calls saved</th>
</tr>
</thead>
<tbody>
<tr>
<td>LFS</td>
<td>6</td>
<td>8%</td>
<td>5</td>
<td>12%</td>
</tr>
<tr>
<td>LOS</td>
<td>8</td>
<td>15%</td>
<td>7</td>
<td>18%</td>
</tr>
<tr>
<td>OPN</td>
<td>6</td>
<td>13%</td>
<td>6</td>
<td>13%</td>
</tr>
</tbody>
</table>

• Also possible by variable
Further Evidence from Understanding Society
Understanding Society Data

- Longitudinal study
- Assess (risk of) nonresponse bias at each call for wave 2 for a range of survey variables as measured at wave 1
Further Data Quality Indicators

• Proposed approach
  – Dissimilarity indices (e.g. Delta index)
  – Basic idea: compare two distributions (those for respondents and those if everyone had responded)

• Comparison to
  – Coefficient of Variation (CV)
Dissimilarity Index: Categorical

- Delta index

\[ \Delta_z = \frac{1}{2} \sum_{k=1}^{K} |\hat{\pi}_{z,k} - \pi_{z,k}| \]

\(\hat{\pi}_{z,k}\) observed proportion in category k of survey variable z

\(\pi_{z,k}\) corresponding expected proportion

- ranges from 0 to 1
- the higher the delta index the more dissimilar is the estimated distribution to the true distribution
- values below 0.03 may indicate similarity (negligible nonresponse bias)
- no model required
Delta Index
Binary and Categorical Variables

![Graph showing the delta index for different variables over calls.](image-url)
Response Rate, R-indicator and CV
Summary

• Representativeness increases similarly in the surveys over call records
  – Sources of non-representativeness are under-representation of economically active HHs, HHs located in London / SE, and single adult HHs

• CV preferred over the R-indicator

• Data collection stopping points differ (slightly) between surveys

• Dissimilarity index:
  – Can monitor categorical variables with several categories
  – Allows monitoring of several variables in the same graph
  – Does not require the fit of a model at every call

• Results for CV very similar to Dissimilarity Indices – reassuring
Implications for Survey Practice

• Number of calls could be reduced (no more than 8 calls)
• Implications for cost savings without potentially much loss of data quality
Thank you.

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