Bias Propensity to Inform Responsive and Adaptive Survey Design

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Acknowledgments

- Work with Dan Pratt and Michael Duprey

- U.S. Department of Education’s National Center for Education Statistics (NCES)
Outline

- Responsive and adaptive survey design
- Response propensity
- Concept of bias propensity
- Empirical example
  - Bias propensity in a longitudinal study design
  - Additional challenges and solutions
Responsive and Adaptive Survey Design
Responsive and Adaptive Survey Design – Oversimplified

- Responsive Design (Groves and Heeringa, 2006)
  - Multiple phases with alternative protocols
  - Varying protocols across sample members

- Nonresponse: With high rates of nonresponse, reducing the risk of nonresponse bias under cost constraints is a common objective
- Need for statistical models: Targeted use of more costly protocols
Bias Propensity
Response Propensity – Development

- Propensity score (Rosenbaum and Rubin, 1983)
  - “…the conditional probability of assignment to a particular treatment given a vector of observed covariates.”

- Response propensity for weighting (Little, 1986)
  - Development and implementation on probability-based surveys (e.g., Iannacchione, Milne, and Folsom, 1991; Lepkowski, Kalton, and Kasprzyk, 1989)
  - Applied to nonprobability settings (e.g., Schonlau et al., 2004; Lee, 2006)
Response Propensity – Primary Objective

- Reduce bias due to departure from randomization (nonresponse is a special case)

- Predict the probability of being a member of a group

- Include all available information, as long as it improves the model
  - Consistent with the underlying logic of

- Machine learning methods fit well with this statistical perspective (as opposed to social science)
Response Propensity – Flawed Implementation

- (Blind pursuit of) maximizing the prediction of group membership
  - Covariates selected based on association with R

- Theoretical perspective (Little and Vartivarian, 2005)
  - Association with R but not with Y can increase variance without commensurate reduction in nonresponse bias

- Empirical argument (Wagner et al., 2014)
  - Paradata predictive only of nonresponse
Response Propensity in Responsive and Adaptive Survey Design

- Propensity models used *during* data collection

- Models used to identify nonrespondents for alternative treatment regimens to reduce the risk of nonresponse bias
  - Lowest response propensities
  - Highest response propensities
  - Distance measures and other alternative models
  - Multiple criteria
  - ...

Bias Propensity: An Alternative Definition of Response Propensity, to Reduce Nonresponse Bias

- No longer maximizing prediction
  - INCLUDE variables associated with Ys
    - Proxy Ys
    - Demographic characteristics
  - EXCLUDE variables associated with R but not Y
    - Paradata, particularly variables endogenous to nonresponse (e.g., prior refusal)

- Defined as one minus this response propensity based on variables of interest
Challenges and Limitations in Prior Research

- Substantive data on respondents and nonrespondents are seldom available.
- Responsive and adaptive designs are often implemented with the goal of improving the survey outcome rather than to study the effectiveness of the approach.
  - Nonexperimental designs
- Often in well-funded surveys that use intensive data collection efforts, limiting the effectiveness of interim interventions when evaluated at the end of all data collection.
HSLS:09 2013 Update

- National probability-based sample of approximately 25,000 fall 2009 ninth-graders from 944 schools (21,441 eligible for this intervention)

- Baseline data collection in the 2009-2010 school year (86% RR)
- First follow-up in spring 2012 (82% RR)

- The 2013 Update survey was conducted in summer and fall 2013
  - Responsive and adaptive survey design used data from:
    - Baseline
    - First follow-up
    - Administrative data from schools
How Limitations Were Addressed for this Evaluation

- Measure nonresponse bias using three sources of information
- Create simulated control condition with propensity scoring, identifying response outcome of sample cases without experimental treatment
- Survey outcomes evaluated before and after intervention phase, rather than after multiple additional follow-up phases
Bias Propensity Model

\[ \text{logit}(R_{\text{Phase1}}) = \alpha + x\beta + y\gamma \]

where

\( x \) is a vector of demographic covariates,
\( y \) is a vector of substantive variables (from the administrative records and prior rounds)

and

\[ \hat{p}_{\text{bias}} = 1 - \hat{p}(R_{\text{Phase1}} = 1) = \frac{e^{\text{logit}(R_{\text{Phase1}})}}{1 + e^{\text{logit}(R_{\text{Phase1}})}} \]
Bias Propensity Variables Used in Model

- Only substantive variables and key demographic characteristics
  - Prior round student enrollment status
  - Student’s race/ethnicity
  - Grade when algebra I taken
  - Final grade in algebra I
  - How far in school student thinks he/she will get
  - How far in school parent thinks student will get
  - Grade in school as of spring 2012
Variables Used to Measure Nonresponse Bias

- Same set of variables from administrative data and prior rounds of data collection
- Set of key survey variables in 2013 Update
  - Whether has high school credential
  - Working for pay
  - Starting family, taking care of children
  - Serving in military
  - Attending college full-time or part-time
  - Taking postsecondary classes
  - Completed student financial aid application
Phased Design and Phase to be Evaluated

- Phase 1: Email, postal invitations for self-administered web survey followed by telephone interviewers calling sample members
- Phase 2: $5 prepaid incentive to cases with highest bias propensity that had not participated by end of phase 1
- Subsequent phases: $15 and $25 promised incentives, abbreviated interviews
At threshold for assigning cases, response rate was 16% for nonintervention cases and 20% for intervention cases.
Methods

- Simulation of control condition: “If we did not implement the $5 prepaid incentive intervention for the high bias propensity cases, which cases would remain nonrespondents?”
- Estimated logistic regression model, including paradata
- Fit model using data from cases not targeted in Phase 2
- Estimated Phase 2 response propensity without prepaid incentive for each case
- Determined response propensity cut point, setting those below the cut point to simulated nonrespondents
Sample Size and Sample Counts by Phase, Treatment Group, and Response Outcome

<table>
<thead>
<tr>
<th>Sample</th>
<th>Total (n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total sample</td>
<td>21,441</td>
</tr>
<tr>
<td>Responded to Phase 1</td>
<td>8,920</td>
</tr>
<tr>
<td>Phase 2 total sample</td>
<td>12,521</td>
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<tr>
<td>Phase 2 non treated cases</td>
<td>6,183</td>
</tr>
<tr>
<td>Responded to Phase 2</td>
<td>1,267</td>
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<tr>
<td>Did not respond to Phase 2</td>
<td>4,916</td>
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<tr>
<td>Phase 2 treated cases</td>
<td>6,338</td>
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<tr>
<td>Under treatment condition</td>
<td></td>
</tr>
<tr>
<td>Responded to Phase 2</td>
<td>1,038</td>
</tr>
<tr>
<td>Did not respond to Phase 2</td>
<td>5,300</td>
</tr>
<tr>
<td>Counterfactual simulation of response outcomes</td>
<td></td>
</tr>
<tr>
<td>Under no treatment condition (control condition)</td>
<td></td>
</tr>
<tr>
<td>Responded to Phase 2</td>
<td>605</td>
</tr>
<tr>
<td>Did not respond to Phase 2</td>
<td>5,733</td>
</tr>
</tbody>
</table>
Evaluation

Comparison of weighted estimates (and average absolute bias) based on:

- Phase 1 main data collection;
- Phases 1&2, without change in protocol in Phase 2;
- Phases 1&2, with treatment protocol in Phase 2;
- Estimates based on additional phases to collect data from nonrespondents as of the end of Phase 2; and
- Benchmark estimates based on administrative data and prior round data.
Average Absolute Bias for Variables from a Past Round and from the Sampling Frame

Compared to Estimate from Full Sample

<table>
<thead>
<tr>
<th></th>
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</tr>
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<tbody>
<tr>
<td>End of Phase 1</td>
<td>3.6</td>
</tr>
<tr>
<td>End of Phase 2, Control</td>
<td>3.6</td>
</tr>
<tr>
<td>End of Phase 2, Treatment</td>
<td>2.8</td>
</tr>
<tr>
<td>With All Follow-up Phases</td>
<td>0.9</td>
</tr>
</tbody>
</table>
Average Absolute Bias for Variables from a Past Round and from the Sampling Frame

<table>
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<th>Phase</th>
<th>Compared to Estimate from Full Sample</th>
<th>Compared to Estimate with Additional Follow-up Phases</th>
</tr>
</thead>
<tbody>
<tr>
<td>End of Phase 1</td>
<td>3.6</td>
<td>2.7</td>
</tr>
<tr>
<td>End of Phase 2, Control</td>
<td>3.6</td>
<td>2.8</td>
</tr>
<tr>
<td>End of Phase 2, Treatment</td>
<td>2.8</td>
<td>2.8</td>
</tr>
<tr>
<td>With All Follow-up Phases</td>
<td>1.9</td>
<td>0.9</td>
</tr>
</tbody>
</table>
Average Absolute Bias for Variables Available Only in the Survey

- End of Phase 1: 3.1
- End of Phase 2, Control: 3.0
- End of Phase 2, Treatment: 2.3

Compared to Estimate from Additional Follow-up Phases
Summary

- Treatment condition was more effective in reducing nonresponse bias compared to control condition for most estimates, bringing estimates closer to benchmark estimates.

- Treatment condition reduced average absolute bias by approximately 1 percentage point, reducing estimated nonresponse bias by roughly one quarter.

- Estimated average absolute bias reduction achieved as measured by certain 2013 Update survey variables as well as prior round variables and sampling frame data.
Thank you

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Full paper:

Responsive and Adaptive Survey Design: Use of Bias Propensity During Data Collection to Reduce Nonresponse Bias

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