Bias Propensity to Inform Responsive and Adaptive Survey Design in a Longitudinal Study

CNSTAT Workshop on Improving Consent and Response in Longitudinal Studies of Aging

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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

- Responsive Design (Groves and Heeringa, 2006)
  - Multiple phases with alternative protocols
- Adaptive Survey Design (Wagner, 2008; Schouten, Peytchev, and Wagner, 2017)
  - 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
- Opportunity: Longitudinal studies offer data needed to inform this approach

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 probability-based sampling (recovering the original probabilities of selection)

- 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

High School Longitudinal Study of 2009 (HSLS:09) 2013 Update

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

$$logit(R_{Phase1}) = \alpha + \boldsymbol{x\beta} + \boldsymbol{y\gamma}$$

where

$\boldsymbol{x}$ is a vector of demographic covariates,

$\boldsymbol{y}$ is a vector of substantive variables (from the administrative records and prior rounds)

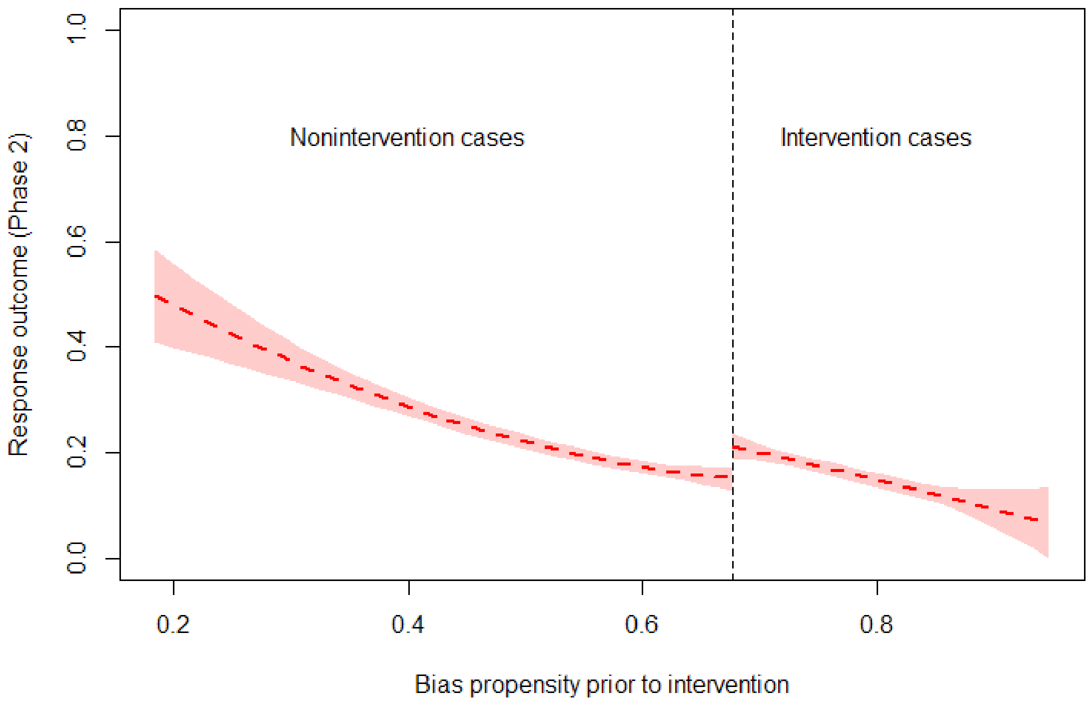
and

$$\hat{p}_{bias} = 1 - \hat{p}(R_{Phase1} = 1) = \frac{e^{logit(R_{Phase1})}}{1 + e^{logit(R_{Phase1})}}$$

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

Evaluation of Effectiveness of Intervention



At threshold for assigning cases, response rate was 16% for nonintervention cases and 20% for intervention cases

Methods

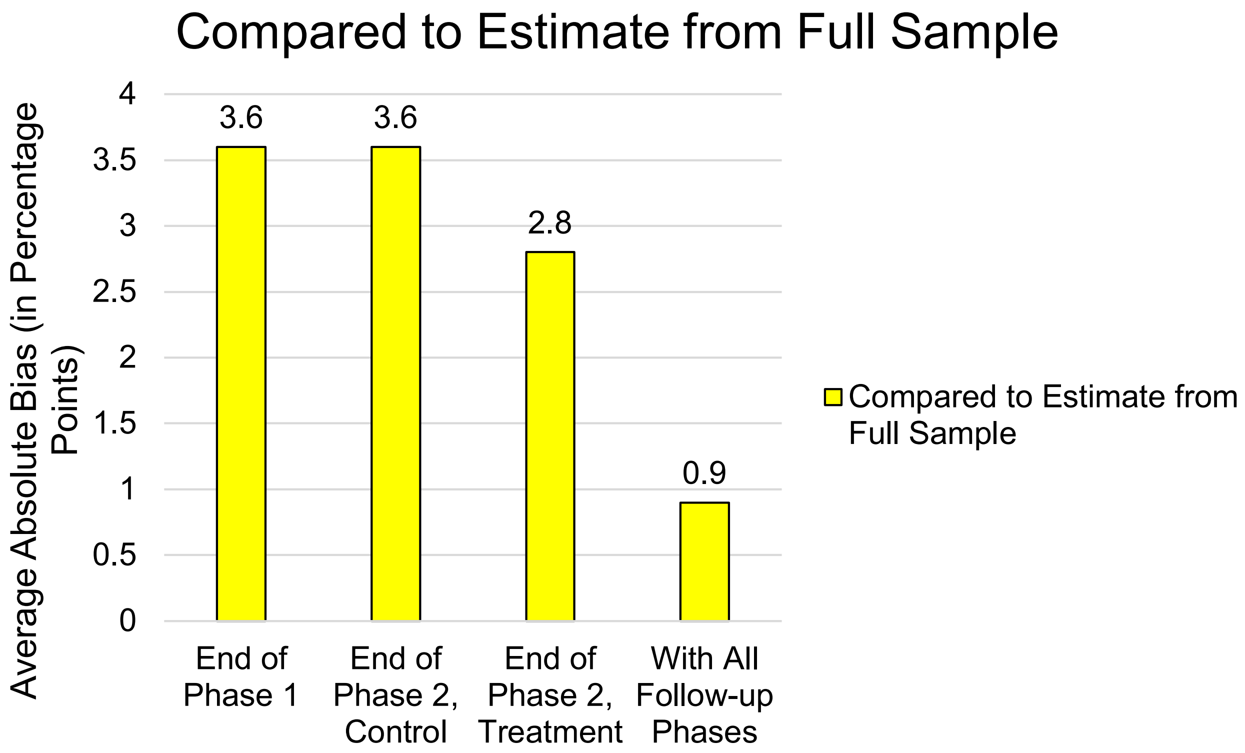
- Simulation of control condition: “If we did not implement the $5 prepaid incentive intervention for the high bias propensity cases, which cases would remain nonrespondents?”
- Estimated logistic regression model, *including paradata*
- Fit model using data from cases not targeted in Phase 2
- Estimated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

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



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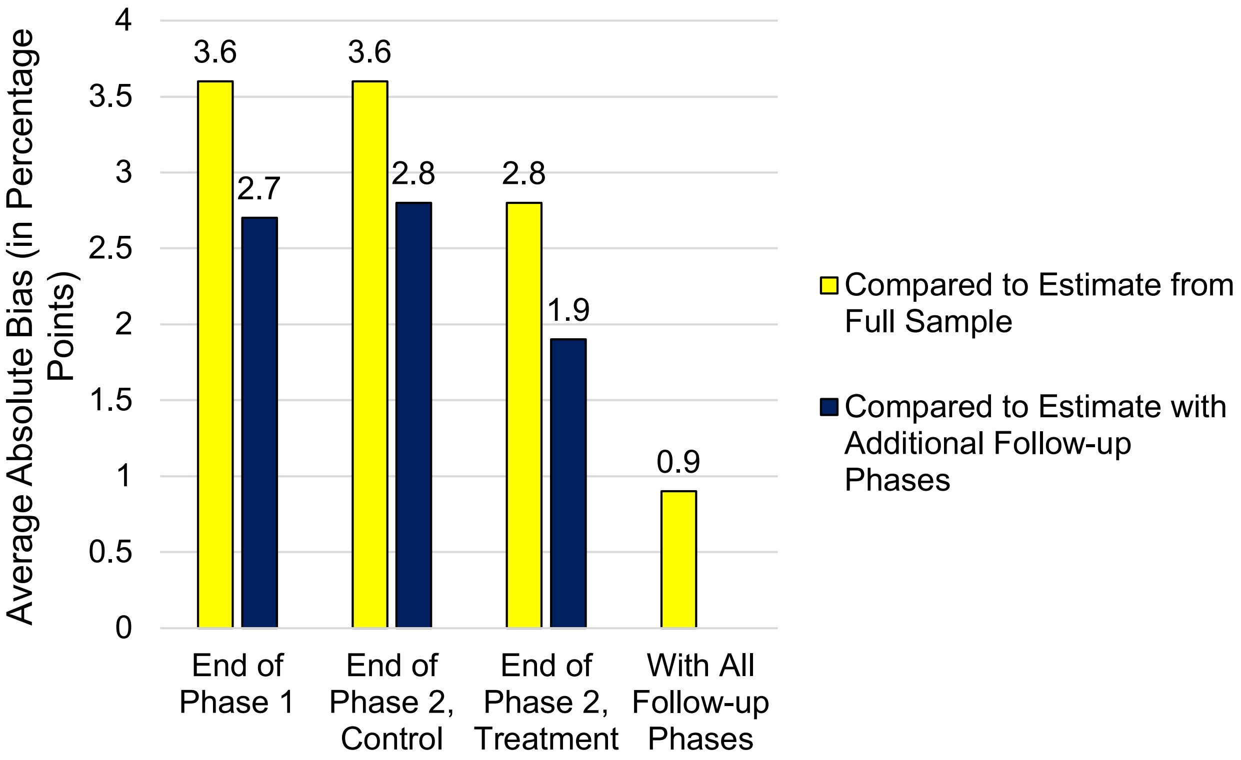
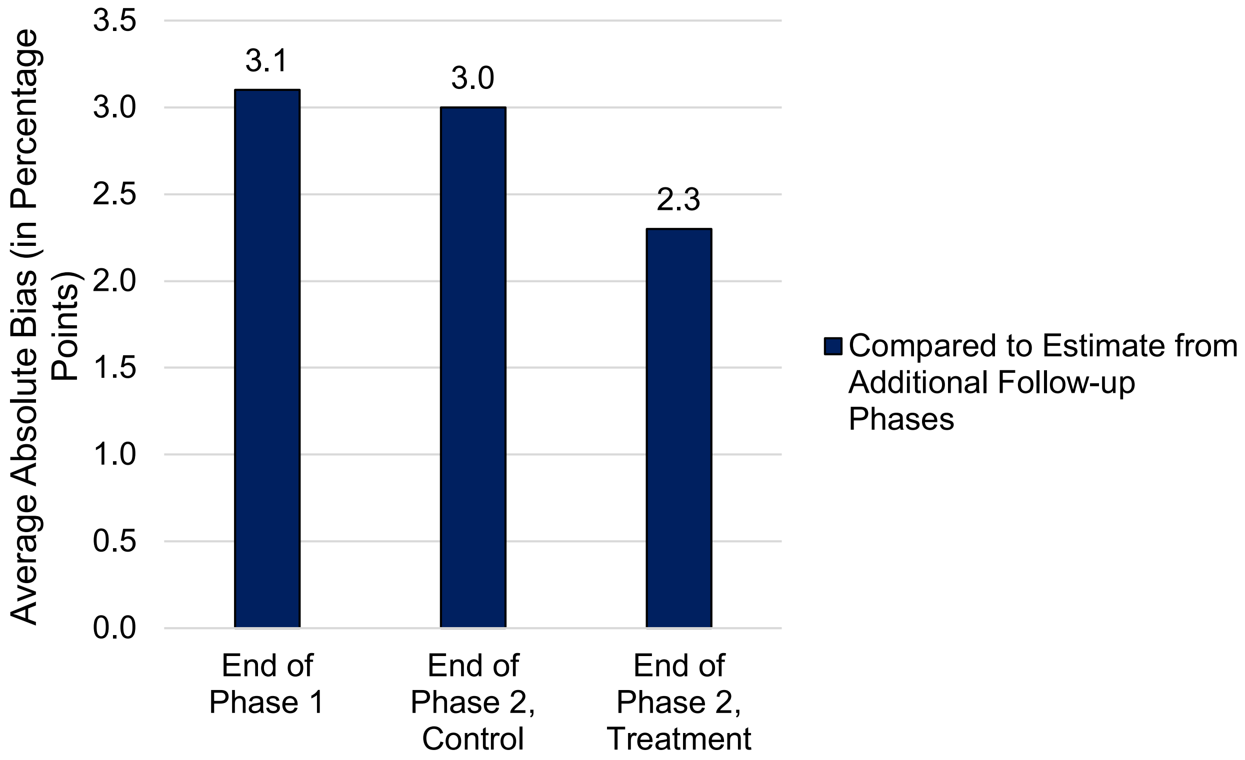


Average Absolute Bias for Variables Available Only in the Survey



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

Full paper in Advance Access:

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

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