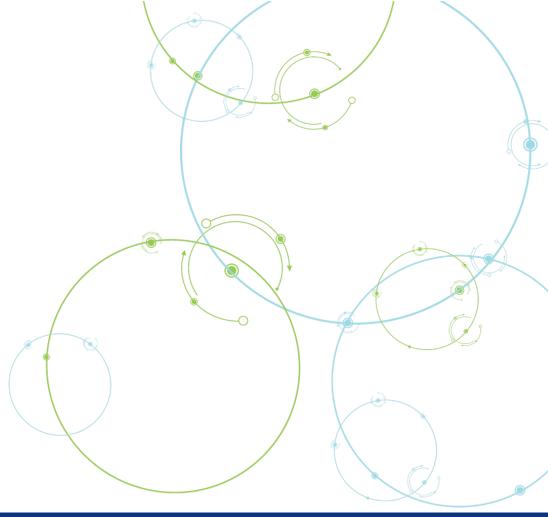
Bias Propensity to Inform Responsive and Adaptive Survey Design

Andy Peytchev
JPSM/MPSDS Seminar Series
February 3, 2021





Acknowledgments

- Work with Dan Pratt and Michael Duprey
- U.S. Department of Education's National Center for Education Statistics (NCES)

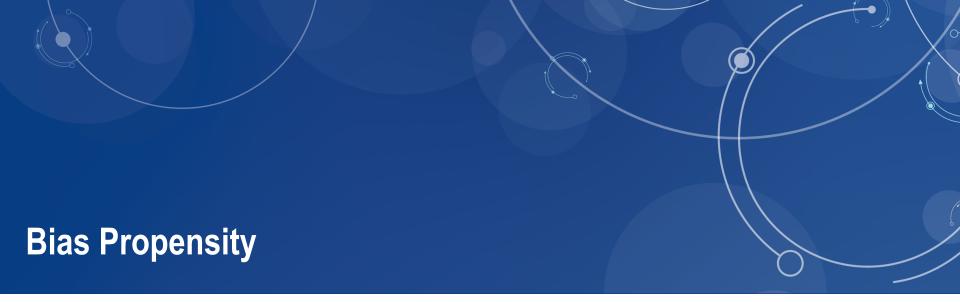
Outline

- 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 – Oversimplified

- 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



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., lannacchione, 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 ninthgraders 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

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

where

x is a vector of demographic covariates,

y is a vector of substantive variables (from the administrative records and prior rounds)

and

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

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

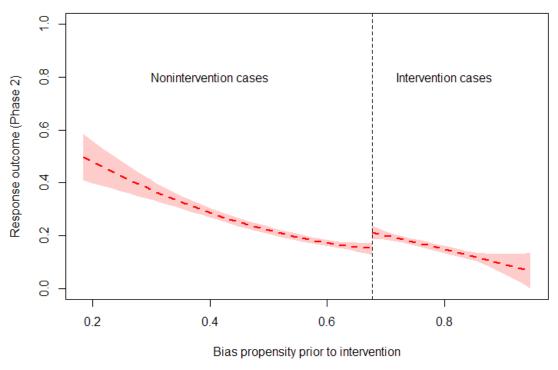
Variables Used to Measure Nonresponse Bias

- 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

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

Sample Size and Sample Counts by Phase, Treatment Group, and Response Outcome

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

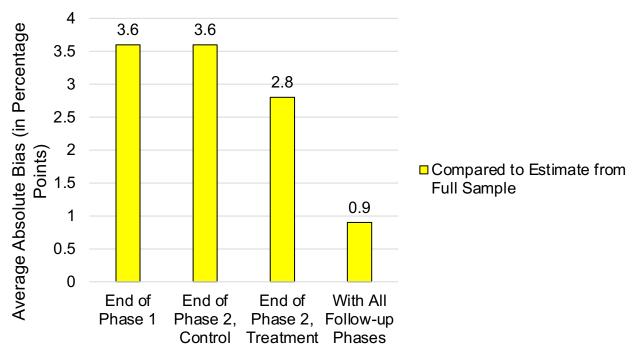
Evaluation

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

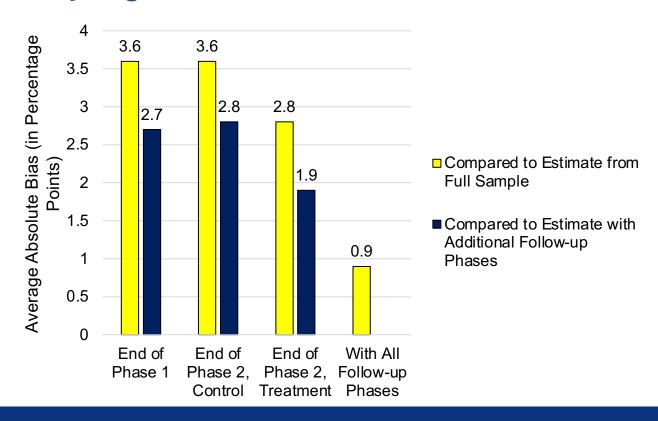
- Phase 1 main data collection;
- Phases 1&2, without change in protocol in Phase 2;
- Phases 1&2, with treatment protocol in Phase 2;
- Estimates based on additional phases to collect data from nonrespondents as of the end of Phase 2; and
- Benchmark estimates based on administrative data and prior round data.

Average Absolute Bias for Variables from a Past Round and from the Sampling Frame

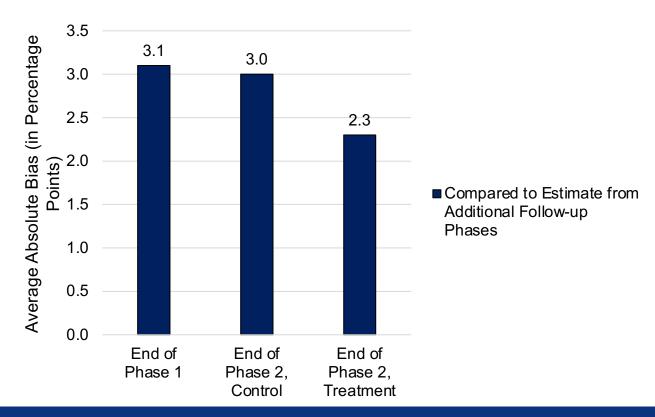
Compared to Estimate from Full Sample



Average Absolute Bias for Variables from a Past Round and from the Sampling Frame



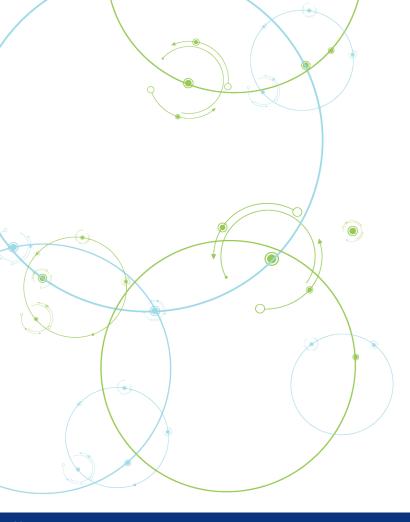
Average Absolute Bias for Variables Available Only in the Survey



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



Thank you

Andy Peytchev apeytchev@rti.org

Full paper:

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

Andy Peytchev ™, Daniel Pratt, Michael Duprey

Journal of Survey Statistics and Methodology, smaa013,

https://doi.org/10.1093/jssam/smaa013

Published: 21 December 2020