

# Nonresponse Bias Analysis Methods: A Taxonomy and Summary

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#### Overview

- Background
- Five approaches
  - Response rate comparisons
  - Subgroup response rate variation
  - Comparisons to external estimates
  - Changes due to level of effort
  - Contrasting alternative adjustment strategies
- Conclusion



## Background

- Nonresponse bias concerns have grown
- Nonresponse bias evaluation has been a burgeoning area of research
  - Groves (2006) provides useful taxonomy
- OMB requires nonresponse bias analysis for surveys with response rates lower than 80%
- FCSM Nonresponse Bias Subcommittee report: "Best Practices for Nonresponse Bias Reporting"



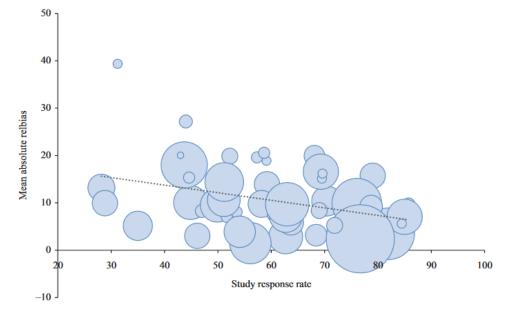
# Background

- Nonresponse bias analysis is driven by the available data:
  - Sampling frame/auxiliary data
  - Paradata
  - Survey data
  - Administrative data
- Want data that are "closer to the target"



## 1. Response Rates

- Response rates are a valuable indicator
  - Not the only, and maybe not the best
- Groves and Peytcheva (2008)
  - "NR rate by itself is a poor predictor of...NR bias"
- Brick and Tourangeau (2017) reanalysis





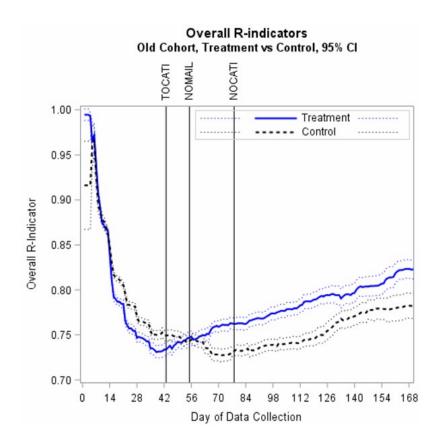
#### 2. Subgroup Response Rate Variation

- We can also think of as comparisons -responders vs nonresponders
- Using sampling frame, auxiliary, and paradata
  - Ideally, proxy-Y variables
- Controlling variation seems helpful
  - Assume balanced response is better
  - Assume better than simply adjusting



#### 2. Subgroup Response Rate Variation

- Example indicator: R-Indicator (Schouten, et al., 2009)
  - Variation of estimated response probabilities
  - $-1-2SD(\hat{\rho}_i) --> 1$  is perfect balance
  - Schouten et al. (2016)
    - Simulation study: increases in sample balance are associated with reductions in bias



Coffey, et al., 2019



#### 2. Sugroup Response Rate Variation

- Comparison of responders and sample
- Based on administrative data:

Survey variable	Sample	Respondent
Cumulative GPA	3.18	3.26
Avg. weekly Campus Rec Facility visits	0.78	1.02***
Avg. PE classes skipped	2.98	2.95
Greek life participant	0.2	0.18*
Residential village participant	0.49	0.54

<sup>\*</sup>p < 0.05, \*\*p < 0.01, \*\*\*p < 0.001

Standish and Umbach (2019) 8



#### 3. Comparisons to External Estimates

- Poststratification factors
- Comparison so other surveys

HINTS 4 Cycle 1 compared to NHIS/MEPS (abridged from Maitland, et al., 2017)

Characteristic	Final calibrated estimate	Bench-mark estimate	Bench-mark source
Access to Internet	78.1	70.9*	
Excellent, very good, or good health	84.9	86.9	
Never visited doctor	21.2	19.0*	NHIS
Looked for health information on the Internet (Internet users only)	78	57.9*	
Health professionals always explain things in a way you understand	61	61.4	
In past 12 months, health professionals always spend enough time with you	44.6	52.4*	MEPS
*n<0.05			0

\*p<0.05



# 4. Variation within survey

- Comparison of estimates by level-of-effort
  - Special nonresponse follow-up studies

#### • Example:

- Early vs Lateresponders inCanadian AddictionSurvey
- CATI → Completion
   within 1-6 (Early) vs 7+
   (Late) attempts
- Zhao, et al., (2009)

Substance	Early	Late	
Alcohol			
12 months*	77.57	83.24	
Chronic risky use*	6.25	8.23	
Heavy weekly use	4.69	5.55	
Cannabis			
Lifetime*	42.94	47.88	
12 months*	13.21	16.35	
Any illicit drug			
Lifetime*	43.66	48.47	
12 months*	13.64	16.69	

<sup>\*</sup>p<0.05



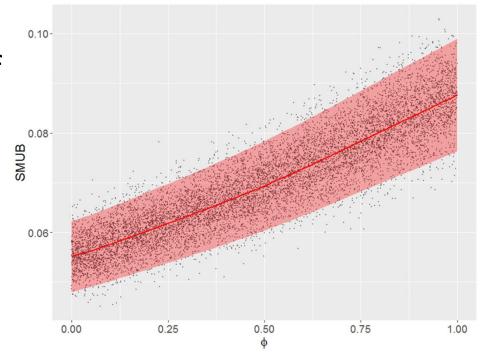
## 4. Variation within survey

- Which design features reduce the risk of nonresponse bias?
  - Groves and Heeringa (2006): Change design when current design no longer leads to changes in estimates – "phase capacity"
  - Peytchev et al. (2009)
    - More of the same (e.g. additional call attempts) does not lead to changes in estimates
    - Changing the protocol in a way that addresses the mechanism leads to changes in estimates
      - Example: Reduced length questionnaire



#### 5. Contrasting post-survey adjustments

- "Sensitivity" to nonresponse and poststratification adjustment model selection
  - Little, et al. (2020)
     Standardized Measure of Unadjusted Bias (SMUB)
    - Using Pattern-Mixture
       Models to estimate bias
       under different
       assumptions about
       nonrespondents,
       including NMAR





#### **Lessons Learned**

- Choose design features that minimize risk of nonresponse bias
  - Reduce the impact of multiple mechanisms:
    - Topic not interesting, Too little time, etc.
- Multiple approaches to evaluation is a best practice
- Check sensitivity to model assumptions
- Allow users to evaluate risks relative to their analyses



#### Thank You!

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