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Nonresponse Bias Analysis Methods: A Taxonomy and Summary

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FCSM Conference
November 4, 2021

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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

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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"*

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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"

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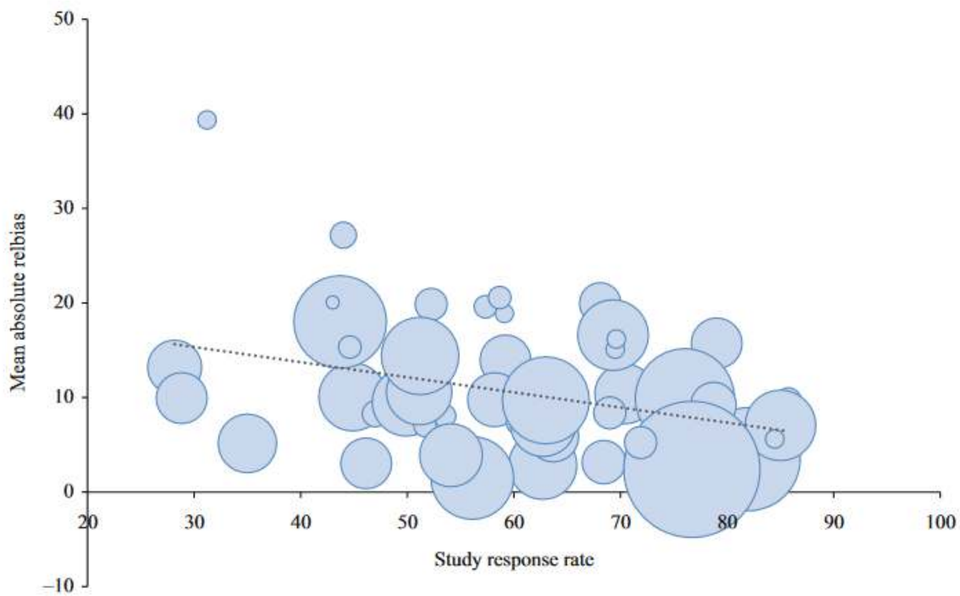
1. Response Rates

- 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



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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

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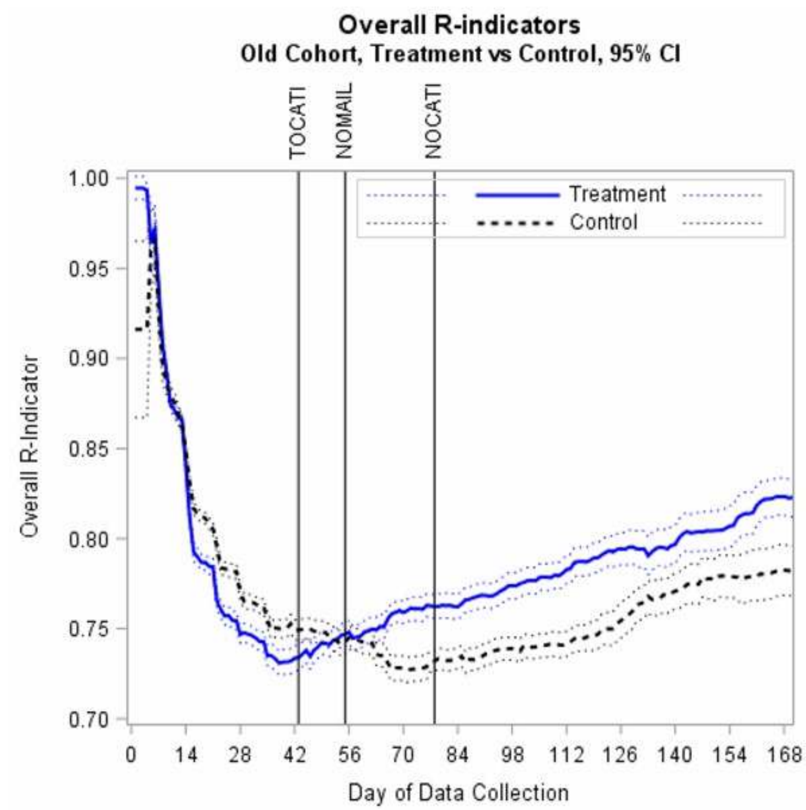
2. Subgroup Response Rate Variation

- 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

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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

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Standish and Umbach (2019)

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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*	NHIS
Excellent, very good, or good health	84.9	86.9	NHIS
Never visited doctor	21.2	19.0*	NHIS
Looked for health information on the Internet (Internet users only)	78	57.9*	NHIS
Health professionals always explain things in a way you understand	61	61.4	MEPS
In past 12 months, health professionals always spend enough time with you	44.6	52.4*	MEPS

*p<0.05

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4. Variation within survey

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

- Example:
  - Early vs Late responders in Canadian Addiction Survey
  - 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

*p<0.05

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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

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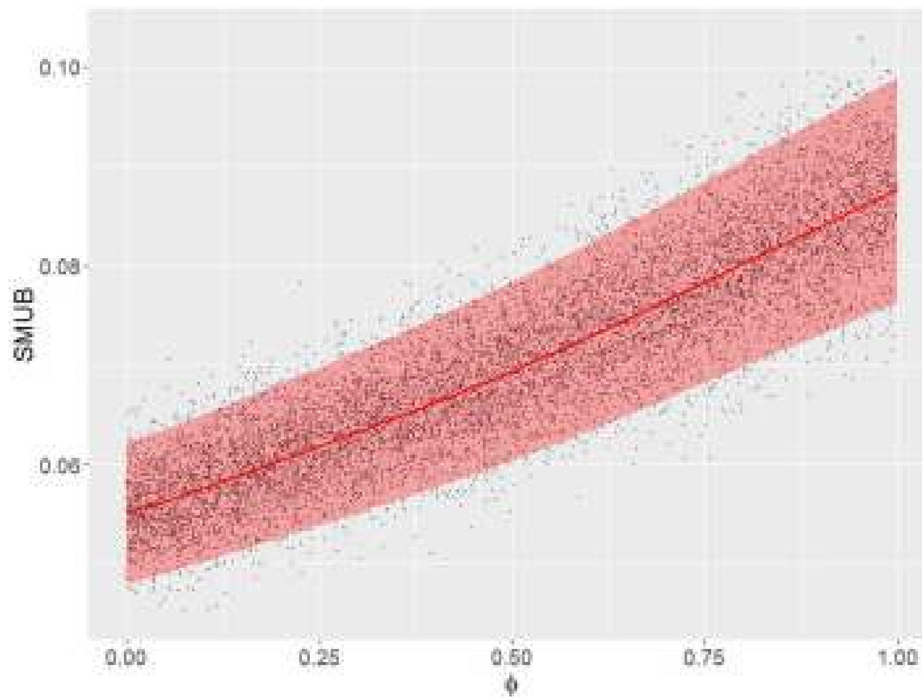
5. Contrasting post-survey adjustments

- "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



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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

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Thank You!

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