

Detecting and Mitigating Nonresponse Bias: Insights from Calibration Weighting*

Mehrnoush Mohammadi

March 1, 2024

Nonresponse bias, the systematic difference between respondents and nonrespondents, is a serious threat to the credibility of survey results. The Special Virtual Issue on Nonresponse Rates and Nonresponse Adjustments of the Journal of Survey Statistics and Methodology (JSSAM) sheds light on various aspects of this challenge. In this article, the focus is on calibration weighting, i.e., a method for adjusting the sample weights (at the sampling stage) to counteract possible nonresponse bias.

1 Introduction

Despite its crucial role in informing diverse fields like social science research and marketing campaigns, survey data can suffer from nonresponse bias when a significant portion of the sampled population fails to participate (Groves and Peytcheva 2008). Utilizing tools like R (R Core Team 2023) and Quarto, this paper explores methods for mitigating this bias and improving the accuracy of survey data.

2 Calibration Weighting: Addressing Nonresponse Bias

The JSSAM special issue emphasizes the importance of understanding and addressing nonresponse bias. One of the discussed approaches involves calibration weighting. This method leverages auxiliary variables, characteristics available for both respondents and nonrespondents, to adjust the weights assigned to individual respondents. The goal is to create a sample that, in terms of the auxiliary variables, closely resembles the target population. This, in turn, helps mitigate potential bias in the estimates of key survey outcomes.

*Code and data are available at: <https://github.com/mehrnoush68/Insights-from-Calibration-Weighting.git>

3 Strengths and Considerations of Calibration Weighting

Särndal and Lundquist (2014) in the JSSAM special issue discuss the advantages and considerations associated with calibration weighting. One key advantage is its effectiveness in improving the representativeness of the survey sample, especially when the response propensities (likelihood of participating) vary across different subgroups. Additionally, calibration weighting can be implemented even with incomplete information about nonrespondents, as it relies solely on auxiliary variables available for the entire sample.

However, the effectiveness of calibration weighting hinges on the quality and relevance of the chosen auxiliary variables. The variables must be highly predictive of both the survey outcomes and the response propensity (Peytcheva and Groves 2009). If the chosen variables are not sufficiently informative, the adjustments may be ineffective or even exacerbate the bias.

4 Alternative Approaches and Future Directions

While calibration weighting offers a valuable tool for mitigating nonresponse bias, it is important to acknowledge the existence of alternative approaches. Han and Valliant (2021) in the same special issue evaluate the performance of various adjustment methods, including post-stratification and general regression estimation, alongside calibration weighting. Their findings highlight the importance of both the predictive power of the auxiliary variables and the interaction effects between them in determining the most suitable adjustment method for a given survey situation.

Further research is needed to explore the effectiveness of calibration weighting in different survey designs and contexts. Additionally, investigating methods for identifying and incorporating the most informative auxiliary variables remains an ongoing challenge.

5 Conclusion

Nonresponse bias poses a significant challenge to the accuracy and reliability of survey data. Calibration weighting, as discussed in the JSSAM special issue, offers a promising approach to address this issue by adjusting survey weights based on auxiliary variables. However, its effectiveness relies on several factors, including the quality and relevance of the chosen auxiliary variables. By acknowledging the strengths and limitations of calibration weighting and exploring alternative approaches, researchers can work towards obtaining more accurate and reliable survey estimates.

References

- Groves, Robert M, and Emilia Peytcheva. 2008. “The Impact of Nonresponse Rates on Nonresponse Bias: A Meta-Analysis.” *Public Opinion Quarterly* 72 (2): 167–89.
- Han, Zheming, and Richard Valliant. 2021. “On General Calibration Models for Nonresponse Adjustments.” *Journal of Survey Statistics and Methodology* 9 (4): 704–32.
- Peytcheva, Emilia, and Robert M Groves. 2009. “Influence of Survey Design Elements on Nonresponse Bias in a Social Capital Survey.” *Sociological Methods & Research* 37 (4): 448–81.
- R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.
- Särndal, Carl Erik, and Per Lundquist. 2014. “Balancing and Calibration in Survey Sampling.” *Journal of Survey Statistics and Methodology* 2 (2): 119–43.
- Survey Statistics, Journal of, and Methodology. “Special Virtual Issue on Nonresponse Rates and Nonresponse Adjustments.” *Journal of Survey Statistics and Methodology*. <https://academic.oup.com/jssam/pages/special-virtual-issue-on-nonresponse-rates-and-nonresponse-adjustments?login=false>.