Digging Deeper into Nonresponse Reduction and Adjustment Techniques: Frequently Asked Questions

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During the 2023 OPRE Methods Meeting, titled "Addressing Unit Missingness in Social Policy Survey Research," Dr. Raphael Nishimura gave a presentation titled "Nonresponse Reduction and Adjustment Techniques." In this session, Dr. Nishimura described weighting, imputation, and other analytic strategies researchers can use to minimize the impact of unit missingness—the failure to obtain survey information from an intended respondent—on survey data.

In his presentation, Dr. Nishimura described several strategies available to researchers interested in addressing unit missingness after data collection. Weighting approaches can be used to adjust for unequal selection probabilities, unknown eligibility, and nonsampling errors. Researchers can use calibration strategies such as poststratification, raking, and generalized regression to improve the efficiency of weighted estimates. Dr. Nishimura also discussed how imputation methods can be used to address item missingness, and leverage information about respondents and nonrespondents to predict responses. Imputation methods include mean value imputation, hot-deck imputation, regression imputation, and sequential regression imputation.

This document was developed from questions posed by 2023 Methods Meeting attendees to Dr. Nishimura and serves as a reference for researchers interested in learning more about nonresponse reduction and adjustment approaches.

OPRE encourages readers who did not attend the meeting to watch Dr. Nishimura's 2023 Methods Meeting presentation at this link (see session 6) before reviewing the document. Readers who attended the 2023 Methods Meeting can refresh their memories of Dr. Nishimura's presentation by watching the recording at this link, too (see session 6). Key terms appear in bold and italics throughout the document.

Please follow the links below to view questions by topic:

Selecting a strategy

Q1: When should researchers use nonresponse weighting adjustment, and when should they use data imputation?

A: ***Nonresponse weighting adjustment*** and data imputation serve different purposes in addressing missing data in surveys.

Researchers typically use nonresponse weighting adjustment when dealing with ***unit nonresponse***—that is, when we fail to obtain any survey measurement (through a questionnaire, for instance) on certain sample elements, whether because of noncontact or refusal. Nonresponse weighting aims to adjust the survey estimates by attributing larger weight to respondents who are underrepresented due to nonresponse.

Data imputation is suited for handling ***item nonresponse***, where respondents have completed most of the survey but left out answers to specific questions. Imputation methods fill in these missing items with plausible values based on the patterns found in the rest of the data.

Q2: Can any statistical tests show whether the missing mechanism in your survey is *Missing Completely at Random (MCAR)*, *Missing at Random (MAR)*, or *Missing Not at Random (MNAR)*?

A: The only formal statistical test to identify a specific missing mechanism pattern in the data is Little's MCAR test (Little, 1988). This test evaluates the null hypothesis that the missing pattern is ***MCAR***. If the test is significant, we can reject the hypothesis that the missing pattern is MCAR, but it does not help differentiate between ***MAR*** and ***MNAR***.

Although no formal statistical tests differentiate between MAR and MNAR, researchers can conduct sensitivity analyses using specific models to deal with MNAR, such as Pattern-Mixture Models, to evaluate the impact on the estimates under different scenarios (Andridge & Little, 2011).

Q3: Do we need to make any nonresponse adjustments if the missing mechanism is MCAR?

A: If the missing data mechanism is truly MCAR, nonresponse adjustments, such as ***weighting*** or imputation, are not strictly necessary to obtain unbiased survey estimates. Estimates based on the observed data are expected to be unbiased because the observed data can be considered a random subsample of the full sample. However, even if the missing mechanism is MCAR, a loss of precision can still occur because of a reduced sample size, which affects the variability and efficiency of the estimates. In the case of an item missing data, using imputation can remedy it.

Despite the lack of bias in the survey estimates under MCAR, in practice, it is often difficult to verify that data are indeed MCAR (see Q2). As a result, the recommendation is to conduct nonresponse adjustments, particularly with substantial amounts of missing data, to increase the precision of estimates because of either an increased sample size or a strong relationship between the auxiliary variables and the survey outcomes (Little & Vartivarian, 2005; see Q9). If the latter condition is true, even if the missing mechanism is MCAR, we expect to get gains in precision in the survey estimates due to the nonresponse adjustment because such correlation tends to further reduce the sampling variability of the estimates, in a similar fashion that proportionate allocated stratification or poststratification does.

Q4: Is using nonresponse adjustment methods still recommended if the response rate is high or the amount of item missing data is low?

A: Even if the ***response rate*** is high or the item missing rate is low, some substantial ***nonresponse bias*** may exist because of large differences between respondents and nonrespondents in survey outcomes. Therefore, nonresponse adjustment is still advised in those situations, unless further nonresponse bias analyses (such as comparing respondents and nonrespondents on important auxiliary variables; see Q9) present evidence that differences between respondents and nonrespondents may be small. Studies have found empirically that there is no strong association between response rates and nonresponse bias (Groves & Peytcheva 2008; Tourangeau et al., 2017).

Q5: In longitudinal surveys, if participants provided data at baseline and post program but did not participate at subsequent follow-ups, would they be considered nonrespondents? Would weighting or imputation be more appropriate in this case?

A: This is a typical case of *survey attrition,* when respondents of a longitudinal survey who answer the baseline and sometimes the initial waves do not participate in follow-up waves of data collection. This survey attrition is a type of unit nonresponse and, therefore, is typically addressed by using nonresponse weighting adjustments. The main difference, from a weighting adjustment perspective, between attrition and nonresponse in cross-sectional studies is that in the former, data from the baseline and previous waves in which the cases participated can be a rich source of auxiliary variables that can enhance the effectiveness of the weighting adjustments (see Q7 and Q9).

Weighting approaches and considerations

Q6: What is a best practice recommendation for how many classes to use in nonresponse class-based weighting adjustments?

A: ***Nonresponse class-based weighting adjustments*** group respondents and nonrespondents into classes according to observed auxiliary variables, such as geographical region or sociodemographic characteristics, to ensure the respondents can compensate the nonrespondents in each class.

There is no rule of thumb for the “best” number of classes to use in nonresponse class-based weighting adjustments. Ideally, we want to form as many classes as possible to ensure they are very homogenous in response propensities and survey outcomes (especially the latter, as discussed in Q9).

However, we also want to avoid having too few sample elements (respondents and nonrespondents) per class. This can result in some classes having zero respondents, which would not allow us to compute a weighting adjustment, or zero nonrespondents, leading to meaningless nonresponse adjustments. Sparse cells also tend to create unstable weighting adjustments. Such cases may require class collapsing—that is, combining sample cases from two or more classes to form a single class with a larger number of cases. Kim and colleagues (2007) provide some guidance on how to conduct such a collapsing procedure in the case of poststratification adjustment, but it can be applied to class-based weighting adjustment.

Q7: Are some nonresponse weighting adjustments better or more effective than others?

A: Empirical studies suggest that the choice of the auxiliary variables to be used in the nonresponse weighting adjustments (see Q9) is more important than the selection of the method itself (Kalton & Flores-Cervantes, 2003; Mercer et al., 2018). Some methods, such as ***classification and regression trees (CARTs) or random forests***, might provide some marginal advantages compared with other methods in certain situations, especially when dealing with the interactions between the auxiliary variables. However, the effectiveness of a nonresponse weighting adjustment is typically dictated by the selection of auxiliary variables and their functional forms used in the adjustment (Caughey et al., 2020).

Q8: When you compute nonresponse weights, does the item missing data count as nonresponse?

A: Some surveys establish a minimum number of questions that need to be answered for the sample case to be considered a respondent. If a case does not meet this criterion, it is counted as a nonrespondent. Otherwise, such case is considered a respondent for the purpose of nonresponse weighting adjustment, and the item missing data is dealt with using imputation. It is also important to note that if any of the auxiliary variables used for nonresponse adjustment have missing data, they need to first be imputed (typically through single imputation) to be used in the adjustment.

Imputation and other techniques

Q9: How can researchers use auxiliary variables to address unit missingness? Is there a best practice recommendation for what types of auxiliary variables to use in nonresponse adjustments?

A: Generally speaking, ***auxiliary variables*** are used in nonresponse adjustment, whether weighting or imputation, to identify respondents who are similar to nonrespondents (or exchangeable, in a more technical term). Such cases are used to “stand in” for the nonrespondents with those particular characteristics, to the extent that such auxiliary variables are correlated to the study outcomes.

First and foremost, the auxiliary variables used for nonresponse adjustments should be fully observed for both respondents and nonrespondents in the sample. One exception is if the auxiliary variables are used for a ***calibration adjustment***. Calibration (Deville & Särndal, 1992) is a weighting adjustment in which the sample distribution is matched to the population distribution on some auxiliary variables. This type of adjustment can, under certain conditions, increase survey estimates' precision and reduce bias from nonsampling error sources, such as nonresponse. In this case, the auxiliary variables only need to be observed for the respondents, although the population distribution on such variables should also be known or estimated.

Ideally, we would like to use auxiliary variables that are highly correlated with both nonresponse and survey outcomes. That is the only condition in which we can obtain both nonresponse bias reductions and gains in precision in the survey estimates (Little & Vartivarian, 2005). Under any other condition, we do not get nonresponse bias reductions, and if the auxiliary variables are not correlated with the survey outcomes but are highly correlated with nonresponse, we can have losses of precision in the survey estimates. For this reason, the recommendation is to use auxiliary variables strongly associated with the survey outcomes whenever possible.

Q10: For sequential regression imputation, is five cycles the standard? If not, how do you determine the number of cycles?

A: Sequential regression imputation (Raghunathan et al., 2001), also known as ***multiple imputation by chained equations***, is an imputation technique in which researchers impute missing values from multiple variables by performing a series of regression models. Each variable with missing values is modeled conditionally upon the other variables in a sequential manner, typically using chained equations. The process iterates until the imputed values converge and the missing data are replaced by plausible estimates based on the observed data.

The number of cycles required in a sequential regression imputation often depends on the convergence criteria of the imputation models: You want the distribution of the imputed values to stabilize. In practical terms, we would monitor the changes in imputed values across iterations and judge convergence by whether these changes diminish over successive cycles. Larger datasets with more complex imputation models may require more iterations to achieve convergence.

The recommendation is to use more than the minimum of cycles to ensure stability. As van Buuren (2007) notes, it may be safe to use a small number of iterations—such as five—in many situations. However, other researchers have recommended using more iterations (for instance, 10 or more) to ensure stability.

To determine the appropriate number of imputation cycles, it might be necessary to perform diagnostic analyses, such as trace plots or other convergence diagnostics. These can show whether the imputation process has stabilized or whether more cycles are needed.

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