Evaluating Nonresponse Bias for a Hypernetwork Sample Generated from a Probability-Based Household Panel

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Abstract

Hypernetwork sampling aims to generate representative samples of populations for which a sample frame does not exist or is too costly to construct. This multi-level sampling method relies on nominations from one sample source (Stage 1 sample) to construct another sample (Stage 2 sample). However, nonresponse from the Stage 1 sample has the potential to produce bias in Stage 2 of the hypernetwork sample if Stage 1 respondents differ from nonrespondents. This paper examines nonresponse in a hypernetwork sample of religious congregations in the U.S. generated from a probability-based household panel that includes background information for all panelists including Stage 1 nonrespondents. This study also illustrates the benefits of constructing a hypernetwork sample by using a sample of already recruited panelists for whom information has already been collected. We find Stage 1 nonrespondents tend to be from rural areas and not from the Midwest, compared to Stage 1 respondents. Results also suggest that the impact of subsequent survey reminders on key Stage 1 estimates decreased after the third reminder during Stage 1 fielding. Additionally, we find that Stage 1 nonresponse impacts the Stage 2 estimates for congregational characteristics. Specifically, the congregations nominated by Stage 1 late respondents tend to have the following characteristics: located in the South, predominantly African American, more likely to be

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conservative/evangelical Protestant or black Protestant, younger, urban or suburban, helped people register to vote, less likely to have a school, and have fewer child participants. Post-survey weighting adjustment of the Stage 1 sample decreased the risk for nonresponse bias in the Stage 1 hypernetwork sample and in the Stage 2 sample of congregations.

Keywords: Hypernetwork sampling, multi-level sampling, online probability-based household panel, nonresponse bias, survey recruitment, post-survey weighting adjustment

JEL Classification Codes: C8, C83

Introduction

Generating representative samples of populations for which a sampling frame does not exist or is too costly to construct has been an enduring challenge for researchers (Fulton & King, 2022). Hypernetwork sampling methodology provides an efficient option for addressing this challenge (McPherson, 1982; Sirken, 2005). This sampling technique can generate representative samples of organizations, associations, and events (such as protests, flash mobs, etc.) by incorporating a multi-level sampling methodology that requires an initial sample of individuals, referred to as the Stage 1 sample, who are asked to nominate an organization, association, or event to which they are linked. The subsequent sample generated from the list of nominations is referred to as the Stage 2 sample. If the Stage 1 sample is not representative of the population being studied (for instance, limited to a geographical cluster or to a convenience sample), the Stage 2 sample will likely be similarly non-representative (Chaves et al., 1999). Thus, it is critical that the Stage 1 sample used to generate a hypernetwork sample be representative of the population being studied. This paper examines a hypernetwork sampling method that uses a probability-based panel for the Stage 1 sample. Specifically, the study assesses nonresponse bias during the creation of a national sample of religious congregations generated from a probability-based household panel (Fulton, 2020).

Online probability-based household panels have yet to be utilized by practitioners seeking to generate hypernetwork samples. Such panels start with a probability-based sample frame (e.g., an address-based sample) to assure representativeness of the target population, but rely heavily on web response modes, supplementing with telephone and other modes as needed (Callegaro et al., 2014; Yeager et al., 2011). Panelists are then interviewed to study targeted or general populations via cross-sectional surveys and to study change in those populations via longitudinal surveys. Online probability-based panels can offer a cost-effective method for generating hypernetwork samples. Panelists (the Stage 1 sample) can be asked to nominate an entity, such as a congregation or organization that will produce a Stage 2 sample. As with any study, however, nonresponse can impede accurate population estimates in probability-based online panels if nonrespondents differ significantly from respondents. Since generating a hypernetwork sample relies on surveying a representative sample of panelists, differential nonresponse among sampled panelists has the potential to undermine the representativeness of the hypernetwork sample they generate.

Few studies examine the impact of differential nonresponse and concomitant nonresponse bias that can arise when constructing samples through hypernetwork sampling (Fulton, 2018; Peytchev et al., 2022). Research analyzing the use of probability-based panels to generate hypernetwork samples is even scarcer. This paper addresses this research gap by estimating the degree of nonresponse bias in a hypernetwork sample of religious congregations in the United States generated from a probability-based household panel. To measure the nonresponse bias in the hypernetwork sample of congregations generated from this panel, we use the background information previously collected on all of the panelists in the Stage 1 sample. We examine differences between respondents and nonrespondents in the fielded Stage 1 sample with regard to characteristics often associated with nonresponse and characteristics correlated to congregational attributes (e.g., children in the household, region, urban-rural classification, etc.) (Adler et al., 2020). Additionally, we assess the extent to which Stage 1 and 2 survey estimates become more accurate as the field period progresses and as more refusal conversion efforts are implemented. This study examines characteristics of nonrespondents, the ability to reduce nonresponse bias in the Stage 1 sample, and the impact of reducing Stage 1 nonresponse bias on Stage 2 estimates. Specifically, our research questions (RQs) are as follows:

RQ1: Are there significant differences between responding and nonresponding panelists in the Stage 1 sample with regard to characteristics often associated with nonresponse and characteristics correlated with congregational attributes (e.g., number of children in the household, region, and community type)?

RQ2: At what point in the Stage 1 data collection process do estimates for the Stage 1 characteristics and Stage 2 estimates stabilize? That is, when do estimates based on the early respondents converge with those based on all of the respondents (i.e., when do the estimates become no longer significantly different)?

RQ3: To what extent can nonresponse bias be reduced in Stage 1 respondents' key characteristics and Stage 2 estimates by using data on nonrespondents when constructing the sample weights for the hypernetwork Stage 2 sample?

The rest of this paper is organized as follows: In Section 2, we review approaches to measuring and decreasing nonresponse bias and discuss the impact of nonresponse on hypernetwork samples. In Section 3, we present the details of constructing the hypernetwork sample used for this study, and the details of the analytical approach we used to answer our research questions. In Section 4, we present the results of our analyses for each research question. In Section 5, we discuss the results and offer concluding thoughts.

Background

Nonresponse Bias

Despite survey researchers' diligent recruitment efforts, survey response rates continue to decrease both nationally and globally (Dahlhamer et al., 2021; Luiten et al., 2020; Smith, 1995; Stoop, 2005). Accordingly, researchers seek ways to mitigate the negative impact of declining response rates. Although considered by some scholars to be a measure of survey quality (Biemer & Lyberg, 2003), response rates are not a direct measure nor a predictor of nonresponse bias or the quality of survey estimates (Groves & Peytcheva, 2008; Keeter et al., 2000; Krejci, 2010). Nonresponse bias occurs in studies when those who respond to a survey are significantly different than those who do not respond to the survey (Groves, 2004;

Rogelberg & Stanton, 2007), and is relevant when the reason(s) for nonresponse are dependent on the study objectives and variable(s) of interest (Gelman & Hill, 2007; Goyder, 1987). If the propensity to respond is correlated with the study's relevant variable(s), then the respondents are less likely to be representative of the sample (and hence the target population), which will then produce biased survey inferences related to the topic of interest. If nonresponse follow-up efforts used to increase response rates are able to capture difficult to reach or uncooperative individuals who are systematically different than the initially recruited respondents, this may decrease nonresponse bias and increase the accuracy of survey inferences.

Measuring the impact of nonresponse bias typically requires information from nonrespondents. However, there is often little or no available information on nonrespondents. As a result, researchers use several methods to measure and assess nonresponse bias in surveys. These methods include: 1A) using sample frame data/administrative records/auxiliary information/ paradata (Al Baghal et al., 2014; Kreuter et al., 2010; Sakshaug & Huber, 2016) comparing respondents who participated in the study during earlier (low effort) versus later (high effort) stages of the data collection period (Fulton, 2018; Studer et al., 2013) comparing respondents who are recruited via different types of data collection efforts and protocols (Bilgen et al., 2019; Keeter et al., 2006; Keeter et al., 2000) comparing survey estimates with other studies (Brick & Williams, 2013); and 5A) comparing multiple waves in panel studies (Mercer, 2012; Sakshaug & Huber, 2016).

Researchers also seek to reduce nonresponse bias by trying to decrease nonresponse in general; strategies here include: 1B) "tailoring" data collection design protocols during nonresponse follow-up (Dillman et al., 2014; Stern et al., 2014) mixing modes (De Leeuw, 2005; De Leeuw et al., 2012; Dillman et al., 2014) providing differing levels of incentives (Singer et al., 2000; Singer & Ye, 2013) to predict and prevent refusals (Keeter et al., 2000) employing responsive and adaptive design strategies that use prior data (Couper & Wagner, 2011; Groves & Heeringa, 2006; Tourangeau et al., 2017) using post-survey data collection statistical adjustment strategies (see Brick, 2013 for an overview). In this paper, while we mainly focus on using information from nonresponding panelists within a probability-based household panel consistent with Method 1A, we also use post-survey data collection adjustment strategies (Method 5B) and evaluate respondents who participate in the survey at different stages of the data collection period to assess stability in the variables of interest over the course of fielding period, relative to nonresponse bias reduction (Method 2A).

Nonresponse and Hypernetwork Samples

Hypernetwork samples produce probability samples of a target population, and nonresponse is likely related to characteristics of the individual respondents rather than characteristics of the target population (Tomaskovic-Devey et al., 1994). However, nonresponse among the individuals surveyed could introduce nonresponse bias into the hypernetwork sample. For example, if Hispanic respondents are less likely to participate in a hypernetwork survey of organizations, then organizations associated with Hispanic respondents may be underrepresented in the hypernetwork sample of organizations. To optimize the representativeness of a hypernetwork Stage 2 sample and improve Stage 2 estimates, it is important to know key characteristics of the survey nonrespondents in Stage 1 sample and to weight the resulting sample to account for the nonresponse bias associated with these characteristics. Nonresponse bias among hypernetwork survey respondents can be known and accounted for when respondents are drawn from a panel survey. Although individual-level nonresponse bias within hypernetwork samples is a critical concern, analyses rarely mention or address its potential presence. Using panel data, this study is among the first to assess the presence of individual-level nonresponse bias in a hypernetwork sample and to show how this bias can be addressed by increasing the fielding period during Stage 1 and constructing sample weights for the hypernetwork Stage 2 sample.

Data and Methods

Hypernetwork of Congregations Study

Stage 1: Survey Data Collection from Panelists and Construction of Hypernetwork Sample

We generated a hypernetwork sample of congregations in the U.S. using NORC's AmeriSpeak Panel as the sample source (see Appendix 1). The entire active panel (24,041 panelists) comprised the Stage 1 sample, and every panelist was invited to take the survey. As a screening question, panelists were asked to indicate how often they attend religious services. Panelists who indicated attending religious services at least once a year were considered eligible and were asked to provide the name and location of their congregation in order to generate the Stage 2 hypernetwork sample of congregations. Eligible panelists were offered points (the cash equivalent of $2) for completing the remainder of the survey and an additional $2 (in points) if they provided contact information for their congregation. The survey was offered both in English and Spanish and administered online and over the phone. On average, the survey took approximately 9 minutes to complete. Neither the survey topic nor length were mentioned in the invitation or in the reminder materials in order to eliminate self-selection bias during recruitment. The weighted response rate for the Stage 1 survey is 41%, with a sample size of 24,041 panelists and a total of 10,144 completed interviews.[2]

Stage 2: Survey Data Collection from Hypernetwork Sample of Congregations

Using the Stage 2 hypernetwork sample of congregations generated from the Stage 1 panelists, we conducted the National Study of Congregations' Economic Practices (NSCEP) (Fulton & King, 2018). The NSCEP included an online survey that was completed by a key informant (typically a leader in the congregation) who answered questions about the congregation's characteristics, its activities, and economic practices. The weighted response rate for the Stage 2 survey is 40%, with a sample size of 4,842 congregations and a total of 1,227 congregations completing the survey (King et al., 2019).

Nonresponse Bias Analysis Methodology

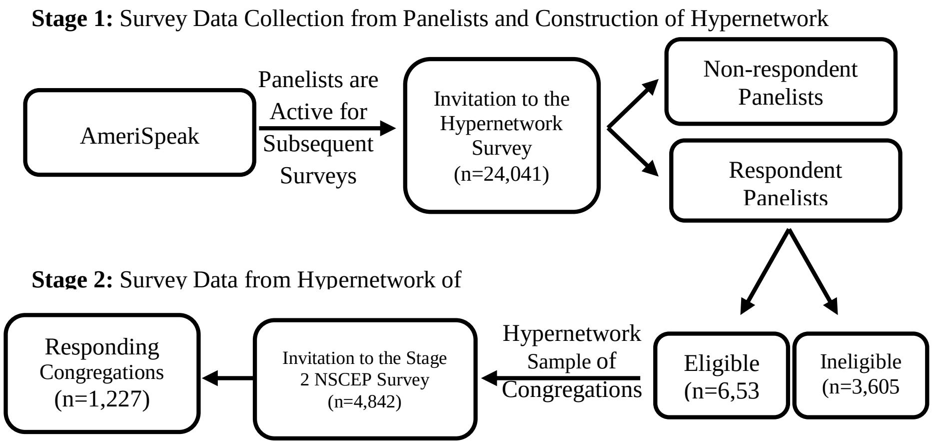
Our analysis uses panelists' profile data from both Stage 1 respondents and nonrespondents. To join the panel, recruited participants must complete the Panel Recruitment Survey. This recruitment survey collects data such

[2] The weighted cumulative response rate for this study is 10.4%. The weighted cumulative response rate takes into account all stages of nonresponse from panel recruitment, panel attrition, study-specific nonresponse, and eligibility for the Stage 1 survey.

as contact information, socio-demographic and household composition, party identification, voting behavior, language skill, and media usage. These data are used to compare survey nonrespondents to respondents from the Stage 1 sample fielding. In our analysis, we coded panelists who completed at least the screening question as respondents.[3] We coded panelists who did not complete the screening question as nonrespondents. Among the 24,041 panelists who were invited to participate in the survey, 10,144 were completes; the remaining 13,897 panelists were nonrespondents (see Figure 3.1). All of the respondents and nonrespondents completed the Panel Recruitment Survey.

Figure 3.1

Two-Stage Data Collection Process for the Hypernetwork of Congregations Study



We conducted logistic regression analyses to address RQ1 about whether there are differences between respondents and nonrespondents using PROC SURVEYLOGISTIC procedure in SAS 9.4 in order to account for the complex survey sample design of the panel, specifically taking into

[3] The screening question asks, "*How often do you attend religious services?*" Among the 10,144 panelists who responded to the survey, 3,605 panelists (35.5%) completed the screening question, but did not meet the screening criteria of attending religious services at least once a year.

account stratification, clustering, and unequal weighting (see Appendix 2 for more information on logistic regression procedures). The SURVEYLOGISTIC procedure employs the Maximum Likelihood Estimation method for discrete binary response survey data. Final panel base weights, which incorporate probabilities of selection and exclude any nonresponse weighting adjustments, are employed for these analyses (see Appendix 3 for more information on weighting procedures).

For RQ2 (At what point in the data collection process do the estimates for the respondents' key characteristics stabilize?), we conducted bivariate analyses comparing key variable proportions from all respondents (obtained after each contact/recruitment stage conducted throughout the study fielding period) to all of the cases in the sample calculated using the *svymean* procedure in R, in order to understand how early respondents differ from all respondents. Using the key variable proportions of all respondents as the baseline, we then calculated the proportion difference and its 95% confidence interval after each contact/recruitment effort using the *svycontrast* procedure. We visualized comparisons using the *ggplots* procedure in R software. We used the final panel base weights for these analyses. We then replicated these analyses for Stage 2 estimates to investigate the impact of the Stage 1 data collection process on the Stage 2 estimates for congregational characteristics.

For RQ3 (Can nonresponse bias be further reduced by employing data on nonrespondents during the construction of the weights?), we explored whether nonrespondent adjustment weighting procedures can reduce nonresponse bias. Employing the same R software procedures used for RQ2, we conducted bivariate analyses to compare key variable proportions from all respondents (obtained in different stages of the study) to all of the cases in the sample. We used nonresponse adjustment weights, calculated separately for each contact/recruitment stage for these analyses. We then replicated these analyses using Stage 2 estimates to investigate whether nonresponse bias can be further reduced by employing data on nonrespondents when constructing the Stage 1 weights.

Results of Nonresponse Bias Analyses

Key Individual Characteristics Associated with Nonresponse and Religious Affiliation and Practices

We conducted nonresponse model analyses using information gathered during the panel recruitment stage from both respondent and nonrespondent panelists (i.e., Method 1A described in the background section). We investigated the relationship between response propensity and salient survey variables related to generating the congregation hypernetwork sample. In the response models presented in Appendix 4, we assessed whether and to what extent there are significant differences between respondent and nonrespondent panelists in the Stage 1 sample with regard to characteristics often associated with nonresponse (e.g., socio-demographic information) and characteristics correlated to congregational attributes (e.g., number of children in the household, region, community type, etc.). Results from model 1, which includes the weighted panel recruitment data and controls for panelists' socio-demographics characteristics, indicate that respondents and nonrespondents significantly differ from each other based on several demographics characteristics often associated with nonresponse. Specifically, the panelists who are less likely to respond are those who are younger, male, racial minorities (Hispanic, non-Hispanic Asian, African American, and multi-race), not married, working, not from the Midwest, from a non-internet household, and politically conservative.

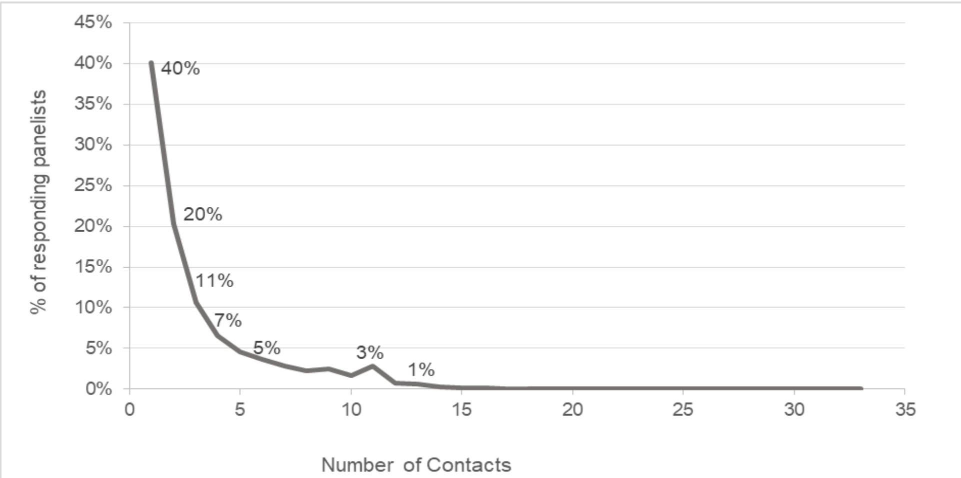
We also compared key variable proportions from all of the Stage 1 respondents to all sampled panelists using final panel base weights. The bivariate results are mainly consistent with the multivariate model results. Based on the bivariate analyses, the significant differences (base weighted variable proportion for all respondents minus base weighted variable proportion for all sample) range from -6.72 percentage points (Age: Millennial category) to 9.24 percentage points (Education: BA and above category). This large variation indicates that the significant differences we observe in Appendix 4 are not just a product of large sample sizes but are meaningful differences (see Appendices 5 and 6).

At What Point in the Data Collection Process Do Estimates of the Early and All Respondents' Key Characteristics Converge?

The second set of analyses that address RQ2 focus on respondents at different points in the data collection process. Specifically, we examined different points in the data collection fielding period to identify the point at which estimates for the respondent's and nonrespondent's characteristics converge. We inspected the differences among the respondents who responded at different contact points throughout the data collection process, with regard to their key characteristics correlated to congregational attributes (Mundey et al., 2019) (Fulton, 2016).

Figure 4.1

Percentage of Responding Panelists Who Completed the Survey by the Number of Recruitment Contacts



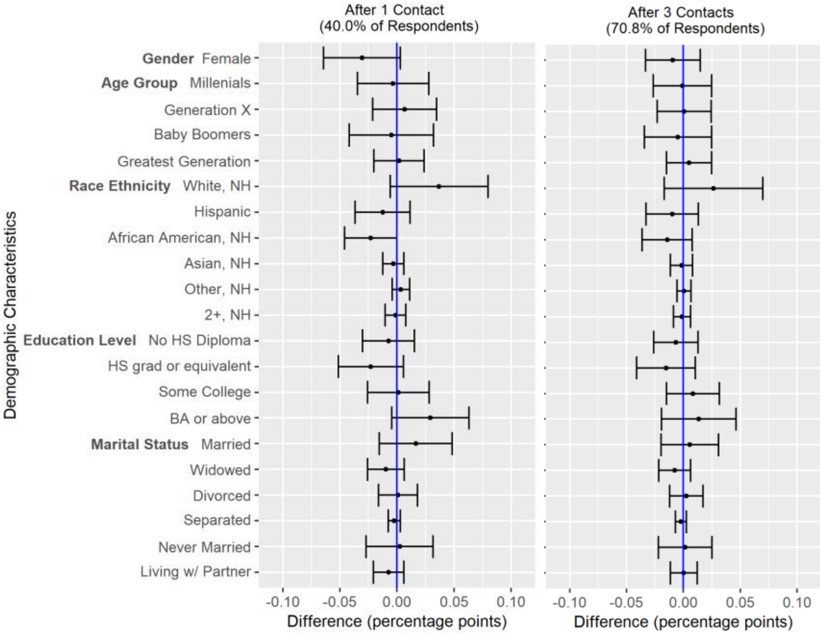
The distribution of completes by number of contacts provided in Figure 4.1 shows that 40.0% of the responding panelists completed the survey within the first contact/recruitment period, 70.9% of the respondents completed the survey after three contacts, 82.0% of the respondents completed the survey after five contacts, and 94.9% of the respondents completed the survey after ten contacts. Nearly all (99.6%) of the respondents completed the survey after the fifteenth contact. Overall, while nonrespondents received up to thirty-three contacts within a fifteen-week period of data collection, there was almost no increase in the response rate after the fifteenth contact and within ten weeks.

Given that completion rates are not comprehensive indicators of nonresponse bias, we also examined differences among respondents who completed the survey at each contact attempt during the data fielding period and compared them with all respondents in order to address RQ2. Accordingly, we conducted a nonresponse assessment akin to Method 2A using information from respondents.[4] Figure 4.2 plots the key variable differences in proportions among socio-demographic and religion variables between respondents who completed the survey by the number of contact attempts and all respondents (e.g., % Difference = % Female among respondents who were reached after the first contact – % Female from all respondents). In Figure 4.2, if the 95% confidence interval for the estimated difference includes 0 (which is the estimated value for all respondents), then the difference is not statistically significant for that particular variable between respondents at different contact stages and all respondents. The results displayed in Figure 4.2 indicate significant differences of income and internet status between panelists who responded at first contact and all respondents. Specifically, late respondents tend to be from low-income (less than $30K/household) and non-internet households. Socio-demographic and religion variables converge after the third contact. Differences of income and internet status become minimal after the third contact between panelists who responded at the third contact or later and all respondents. Results suggest that *phase capacity*—the point during the data collection period at which additional responses do not significantly impact key statistics unless a new design phase is implemented (Groves & Heeringa, 2006)—was reached after the third contact and the impact of subsequent contact attempts on key estimates were increasingly smaller in size after the third contact. Additional *design phases*—the period during the study fielding in which data collection and recruitment protocols remain constant (Groves & Heeringa, 2006) e.g., nonresponse follow-up effort for the web mode panelists—did not significantly impact key variables (see Figure 4.2).

[4] Method 2A refers to the comparison of respondents who participated in the study during earlier (low effort) versus later (high effort) stages of the data collection period.

Figure 4.2

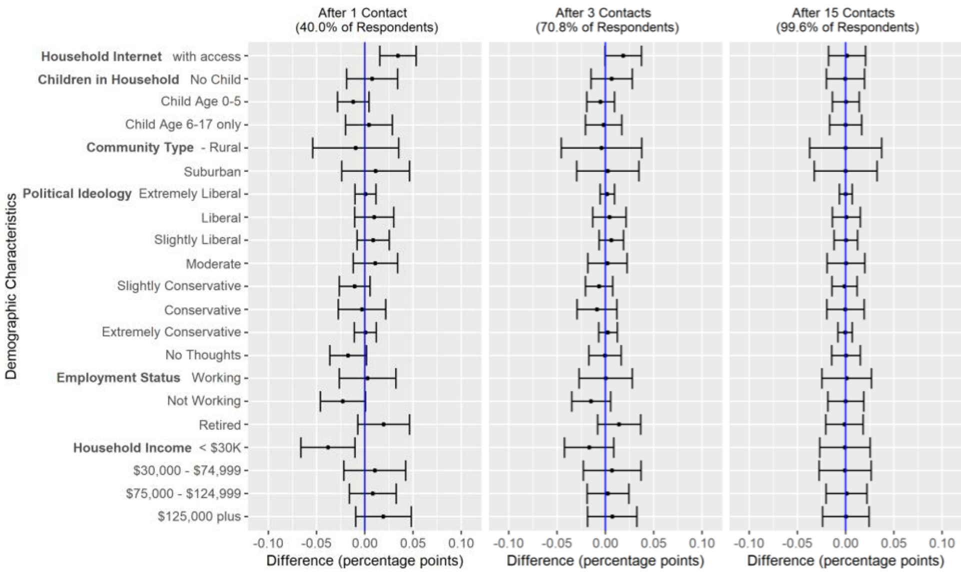
*Stage 1 Survey Outcome Differences between the Subset of Panelists Who Responded by the Number of Contact Attempts Made during the Stage 1 Fielding Period and All of the Responding Panelists**



Note: The horizontal bars for each variable in Figures 4.2, 4.3, 4.4, and 4.5 represent the 95% confidence interval. Accordingly, when the 95% confidence interval for the estimated difference includes 0, then the difference between the estimated value for that particular variable for the respondents at different contact stages and all of the respondents is not statistically significant.

Figure 4.2 (cont.)

*Stage 1 Survey Outcome Differences between the Subset of Panelists Who Responded by the Number of Contact Attempts Made during the Stage 1 Fielding Period and All of the Responding Panelists**



Note: Difference (percentage points) = 0.05 indicates 5% points difference between the estimates from Stage 1 study respondents at each contact in comparison to the estimates from all of the responding panelists (sample for the study).

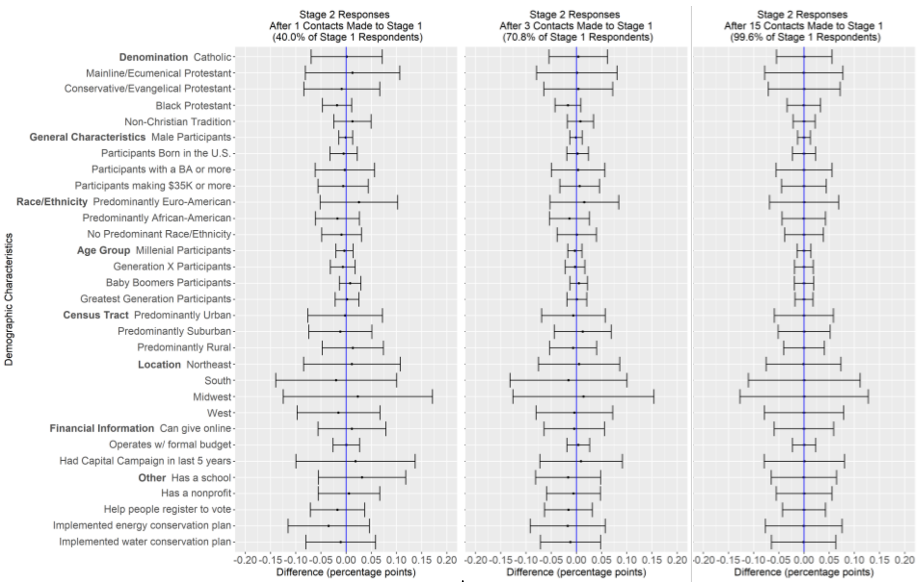
* Final panel base weights are applied in these analyses.

Figure 4.3 plots the key Stage 2 estimate differences in congregational characteristic proportions between Stage 1 respondents who completed the survey by the number of contact attempts and all respondents (e.g., % Difference = % of Stage 2 congregations located in the South that are nominated by Stage 1 respondents after the first contact - % of Stage 2 congregations located in the South from all Stage 1 respondents). The results displayed in Figure 4.3 indicate slightly larger differences of congregation denomination, predominant race/ethnicity, location of the congregation, number of adult and child participants in the congregation, whether the congregation has a school, and whether the congregation helped their participants registered to vote among congregations nominated by panelists who responded at first contact compared to all respondents in Stage 1

(Fulton, 2016). Specifically, the congregations that are nominated by late respondents tend to be located in the South, predominantly African American, more likely to be conservative/ evangelical protestant or black protestant, younger, urban or suburban, helped people register to vote, less likely to have a school, and have fewer child participants (Fulton, 2011). Having said that, similar to Stage 1 estimates, Stage 2 estimates mainly converge after the third contact. Differences among congregational characteristics are significantly mitigated between panelists who responded at the fifteenth contact or later and all respondents.

Figure 4.3

Stage 2 Survey Outcome Differences between Respondents at Each Contact during the Stage 1 Fielding Period and All Stage 2 Respondents (Final panel base weights are applied in these analyses)



Note: Difference (percentage points) = 0.05 indicates 5% points difference between the estimates from Stage 2 study respondents at each contact in comparison to the estimates from all of the Stage 2 respondents.

Because almost the entire panel was invited to participate in the survey, the number of congregations needed for robust Stage 2 estimates was reached from respondents interviewed in earlier stages of the Stage 1 fielding period due to the large sample size. Based on these results, the responsive design approach suggests re-evaluating the sample design and nonrespondent follow-up at an earlier point, taking into account the sample size needed to address key research questions. Higher response rates do not guarantee zero/reduced nonresponse bias; however, lower response rates increase the risk of nonresponse bias in important survey outcomes. This is also the case when constructing a hypernetwork sample. There is always a trade-off between survey time and cost and the risk of bias in hypernetwork sample estimates in determining a study's optimal nonresponse follow-up efforts. When available, it is advisable to use information from nonrespondents to examine if error due to nonresponse within key variables is minimized at earlier stages of the data collection period.

To What Extent Can Nonresponse Bias be Further Reduced by Employing Data on Nonrespondents during Construction of Weights for the Hypernetwork Sample?

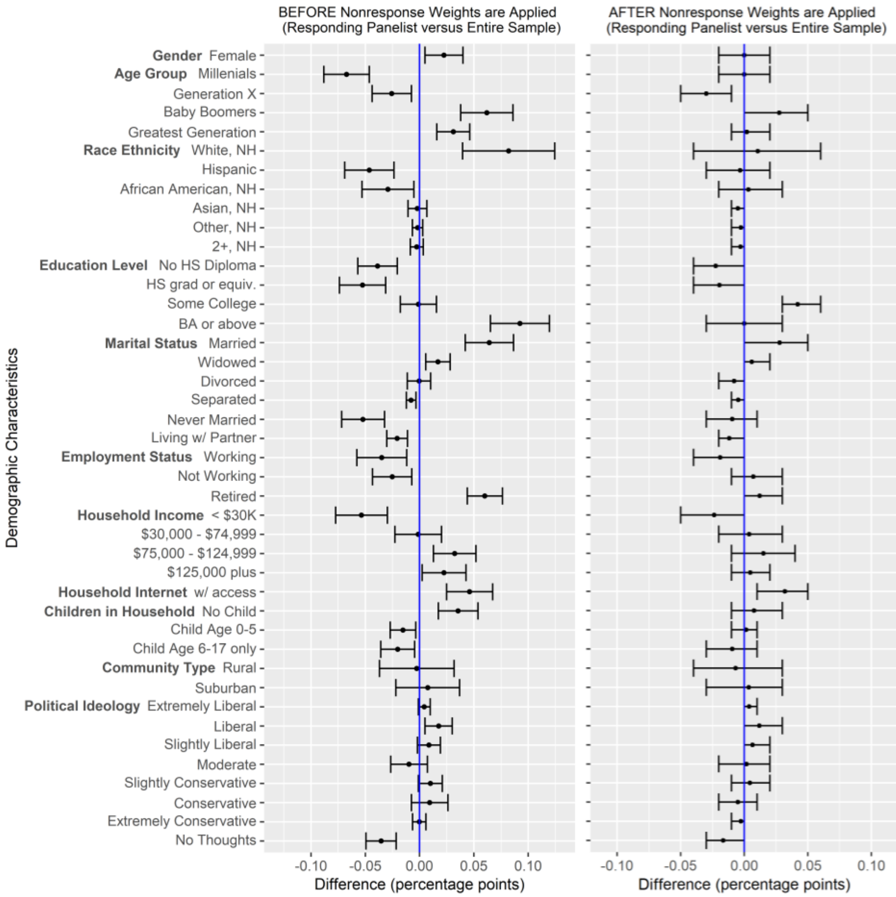
We conducted additional analyses using information from nonresponding panelists in order to investigate whether post-data collection nonresponse adjustment to sample weights reduced the nonresponse error identified in the Stage 2 sample, and to assess differences between panelists who completed the survey at different contact points and all sampled panelists. In these analyses, we examined the potential impact of post-survey weighting adjustment by illustrating the amount of nonresponse bias eliminated through Method 5B (i.e., post-survey nonresponse bias weights). Additionally, we assessed differences among the key characteristics between responders during different stages of the study (with post-survey nonresponse weights) and all panelists in order to further investigate whether, in fact, the error within key variables was minimized at earlier stages of the data collection period. In Figure 4.4, we assessed nonresponse error and impact of post-survey data collection nonresponse adjustment by measuring the deviation of the group proportions of key variables between responding panelists and all sampled panelists before and after the nonresponse weights are applied (e.g., % Difference = % Female among the respondents - % Female among the entire sample). Based on the bivariate nonresponse bias analyses illustrated in Figure 4.4, the nonresponse weighting adjustment substantially improved Stage 1 survey estimates overall. Prior to nonresponse weighting adjustments, respondents tend to be significantly older, white, have higher education, be married (or widowed), be retired, have higher incomes, be internet users, not have children in the household, and report having liberal views. Given that age, gender, education, and race/ethnicity variables are employed during nonresponse weighting construction, it is expected that the majority of respondent proportions are similar (or the same) as sample proportions for these variables. Once the nonresponse weighting adjustment is applied, we observe a significant decrease in differences of the examined proportions for almost all variables except for a slight underrepresentation of younger (Generation X) panelists and an overrepresentation of internet households. The adjustment overcorrected for education by over-representing people with some college. We see a significant decrease in error among variables correlated with religiosity and religious congregation attendance. The weighting adjustment corrected for overrepresentation of white, older, highly educated, married, retired, and liberal respondents. The weighting adjustment also corrected for overrepresentation in the responding sample of higher income households, as well as households with no children.

In order to further investigate the impact of Stage 1 nonresponse error on the Stage 2 hypernetwork sample, we also examined the variables associated with congregations collected during Stage 2 of the study. In Figure 4.5, we assessed nonresponse error and the impact of post-data collection nonresponse adjustment in Stage 1 by measuring differences in the group proportions of key Stage 2 estimates of congregational characteristics before and after Stage 1 nonresponse weights are applied (e.g., % Difference = % of Stage 2 congregations located in the South nominated by Stage 1 respondents *before* Stage 1 nonresponse weighting - % of Stage 2 congregations located in the South nominated by Stage 1 respondents *after* Stage 1 weighting).

Based on the bivariate nonresponse bias analyses illustrated in Figure 4.5, the nonresponse weighting adjustment slightly improved the Stage 2 estimates overall for congregations' denomination type and number of adult participants. Nonresponse weighting adjustments in Stage 1 resulted in a higher share of black Protestant congregations and increased the share of predominantly African American congregations.

Figure 4.4:

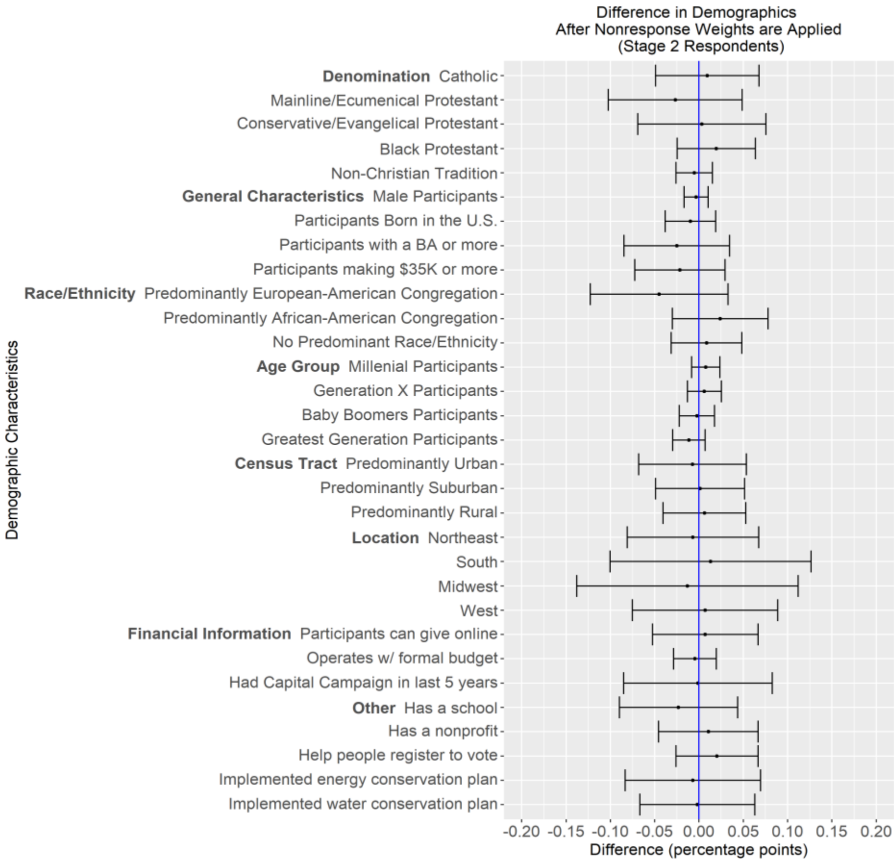
Stage 1 Survey Outcome Differences between the Entire Sample of Panelists and All of the Panelists Who Responded to the Stage 1 Hypernetwork Survey (With and Without Nonresponse Weights Applied)



Note: Difference (percentage points) = 0.05 indicates 5% points difference between the estimates from all Stage 1 study respondents (with and without nonresponse weights) and the estimates from all of the responding panelists (sample for the study).

Figure 4.5

Stage 2 Survey Outcome Differences from All of the Panelists Who Responded to the Stage 2 Survey (Comparing With and Without Nonresponse Weights Applied)



Note: Difference (percentage points) = 0.05 indicates 5% points difference between the unweighted and weighted estimates from all of the Stage 2 study respondents.

Discussion and Conclusion

Understanding how individual characteristics are related to survey response patterns can help researchers generate representative hypernetwork samples. This study is among the first to use a probability-based panel to assess nonresponse bias when generating a hypernetwork sample. Because this study used an online probability-based household panel to generate a hypernetwork sample, we were able to assesses nonresponse bias during the creation of the sample (i.e. during Stage 1). This feature allowed us to analyze differences between responding and nonresponding panelists in the Stage 1 sample and identify the point in the Stage 1 data collection process that the Stage 2 estimates stabilized. Finally, this approach allowed us to assess the extent to which the nonresponse bias can be reduced in Stage 2 estimates by using data on nonrespondents when constructing the sample weights for the hypernetwork (i.e. Stage 2) sample.

The individual characteristics associated with nonresponse bias in this study are related to those often associated with nonresponse (age, gender, race/ethnicity, education level, marital status, employment status, region, internet access, and political ideology). Specifically, we find nonrespondents in the Stage 1 hypernetwork sample are younger, male, minority (Hispanic, non-Hispanic Asian, African American, and multi-race), less likely to be married, working, not from the Midwest, from a non-internet household, and politically conservative.

The results also indicate that nonresponse in the Stage 1 data collection process slightly impacts the composition of the Stage 2 hypernetwork sample and congregational estimates from that sample. In our study, we found that the congregations nominated by late respondents tend to be located in the South, predominantly African American, more likely to be conservative/ evangelical Protestant or black Protestant, younger, urban or suburban, helped people register to vote, less likely to have a school, and have fewer child participants.

Given these constraints, future research could provide special attention to panelists with these characteristics in order to increase their likelihood of participating—e.g., tailoring contact materials to them, offering different incentives or other survey modes. Knowing that hypernetwork sampling efforts aim to generate a sampling frame for target populations that otherwise lack one, it is important for future studies to address issues that threaten the representativeness of samples. In light of declining response rates and the limited empirical attention given to assessing nonresponse bias, this article seeks to help researchers improve the quality of hypernetwork sampling by identifying individual characteristics associated with nonresponse bias.

We found that post-survey weighting adjustment can decrease the risk of nonresponse bias for a hypernetwork sample of congregations. Our results indicate that post-survey weighting not only reduced differential nonresponse for socio-demographic characteristics within Stage 1 results, but also corrected for bias in Stage 2 estimates for congregational characteristics. Relying on a hypernetwork sample to generate a sampling frame for a target population requires that respondents who nominate cases are a representative sample of the population. Our results indicate that low response rates can undermine the external validity of the data because when a large proportion of sampled respondents do not nominate a case, the risk of nonresponse bias increases.

These analyses also highlight the importance of determining an adequate threshold for the acceptable amount of nonresponse bias a study can risk without threatening the accuracy and validity of its conclusions. Although nonresponse bias can be reduced by increasing response rates, this goal needs to be weighed against the additional cost required to increase response rates and reduce differential nonresponse. Researchers must identify which variables are critical for their analysis and critically assess—with the data at hand or via collection of additional data—whether the response rate is sufficient to help ensure those variables do not contain significant nonresponse bias. This process can be made more efficient and cost-effective when the Stage 1 sample is comprised of panelists for whom information has already been collected.

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