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THE IMPACT OF NONRESPONSE RATES ON NONRESPONSE BIAS
A META-ANALYSIS

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Abstract Fifty-nine methodological studies were designed to estimate the magnitude of nonresponse bias in statistics of interest. These studies use a variety of designs: sampling frames with rich variables, data from administrative records matched to sample case, use of screening-interview data to describe nonrespondents to main interviews, followup of nonrespondents to initial phases of field effort, and measures of behavior intentions to respond to a survey. This permits exploration of which circumstances produce a relationship between nonresponse rates and nonresponse bias and which, do not. The predictors are design features of the surveys, characteristics of the sample, and attributes of the survey statistics computed in the surveys.

Introduction

Much survey research follows the inferential paradigm that assumes 100 percent response rates on a probability sample of a designated frame. That is, the unbiasedness of estimates and of their measured standard errors permits probability statements about population characteristics when all sample elements are measured. When only a subset is measured, none of the properties of the probability sampling inference pertains, unless some model of the impact of nonresponse is posited.

The survey profession is undergoing challenges to this basic paradigm of inference because of the falling response rates in sample surveys throughout the richer countries of the world (de Leeuw and de Heer 2002). The challenges are exacerbated by the fact that survey designs seeking high response rates are

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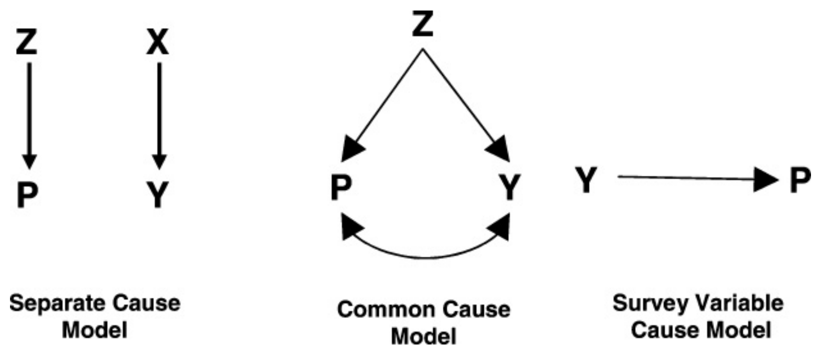

Figure 1. Three Relevant Causal Models Linking Response Propensity with Nonresponse Bias.

experiencing increasing costs, generated by repeated efforts to obtain access to sample units and to address any concerns of the sample persons.

Groves (2006) examined a set of 30 studies estimating nonresponse bias of descriptive statistics. He finds that the nonresponse rate, by itself, is a poor predictor of bias magnitudes on the 319 different estimates that can be computed from the studies. Nonresponse rates "explain" only about 11 percent of the variation in different estimates of the nonresponse bias. He notes that a meta-analytic study of a larger number of such studies might be able to examine characteristics of estimates that are related to bias. This paper presents such a meta-analysis.

Theories Linking Nonresponse Rates and Nonresponse Bias

Survey researchers have lamented the lack of theory involving nonresponse bias for some time (Goyder 1987; Brehm 1993). Part of this lack of theory may be due to an overconcern among social scientists with nonresponse rates versus nonresponse bias in their theorizing (Bradburn 1992; Martin 2004).

If one turns from response propensities to nonresponse bias, then a set of causal models becomes of paramount importance (Groves 2006). As graphically shown in figure 1, the "separate cause" model asserts that the vector of causes of the Y variable is independent of the causes of response propensity, P. In this case, expected values of Y among respondents would be unbiased estimates of those among all sample persons and it corresponds to the "missing completely at random" case (Rubin 1987). The "common cause" model asserts that there are shared causes (Z) of response propensity and the Y variable; this model corresponds to the "missing at random" case. The "survey variable cause" model asserts that Y itself is a cause of response propensity; this is the "nonignorable" condition of nonresponse.

All three of these concern possible causal structures underlying nonresponse bias, which, for a simple respondent mean, can be portrayed as $\sigma_{yp}/\bar{p}$, where

σ_{yp} is the covariance between a given survey variable, y, and the response propensity, p; and $\bar{p}$ is the expected propensity over the sample members to be measured (Bethlehem 2002). The separate cause model would produce a zero covariance; the common cause model would produce a nonzero covariance (but a zero covariance, controlling for Z); and the survey variable cause model would have a nonzero covariance.

The expression above reminds us that nonresponse bias varies over different estimates within a survey, as a function of whether the likelihood of survey participation is related to the variable underlying the estimate. The scientific question associated with this expression is "what causes a correlation between Y and P" or "what causes a survey variable to be correlated to the likelihood to respond?"

Leverage-salience theory can be used to motivate hypotheses about when variation in nonresponse propensity tends to induce nonresponse bias (Groves, Singer, and Corning 2000). That theory asserts that the causes of the survey participation decision vary over persons and over the presentational content of the survey request. Some persons are stimulated to respond because of one feature of a survey request (e.g., the stated purpose of the survey), and others, because of some other feature (e.g., the fact the survey is quite short). The impact of each feature is determined by how salient the given feature is made in the introduction to the survey. When a factor that has great leverage on the survey participation decision for many sample persons is also an item of survey measurement, survey statistics based on it are likely to have large nonresponse bias.

It is noteworthy (especially for this meta-analysis) that leverage-salience theory suggests few main effects of single influences on nonresponse bias; the theory is inherently one of the statistical interaction effects. It notes that different leverages for a given aspect of the survey task exist for different people, and that they should affect the respondent distributions of only that subset of survey variables related to those aspects. If diverse factors influence participation, then bias depends on how those factors link to the survey variables. For example, Lahaut et al. (2002) show that both teetotalers and heavy alcohol users tend to be reluctant respondents to a survey on alcohol use. This empirical result is compatible with a lack of interest in alcohol among teetotalers influencing their nonresponse and a fear of embarrassment among the heavy consumers. In short, useful theories about nonresponse *bias* versus nonresponse *propensity* require conceptual linkage between individual survey measures and participatory influences. Unfortunately, meta-analyses are strong tools to find main effects of single influences on some phenomenon; they are weaker tools when the phenomenon has complicated, multivariate influences. The meta-analysis presented in this paper faces that burden.

This paper reports on a meta-analysis of correlates of nonresponse bias based on 59 studies designed to produce such estimates. We address three questions: (a) Are there characteristics of survey design that are systematically related to nonresponse bias? (b) Are the properties of target populations related to nonresponse bias? and (c) Are there characteristics of survey estimates that are systematically related to nonresponse bias?

Research Design

The articles in the meta-analysis result from a search of a wide variety of electronic databases for the literature on survey nonresponse published since 1978, including the Scholarly Journal Archive (JSTOR), Gale/Info Trac Expanded Academic ASAP, ABI/INFORM Global, LexisNexis, Proquest Research Library, SilverPlatter databases, OCLC Social Science Abstracts, ECO and ArticleFirst databases, SocioFile, ISI Web of Knowledge, Web of Science's Social Sciences Citation Index and ISI Proceedings, and ScienceDirect. Searches of journals with a specific focus on survey methodology, such as *Public Opinion Quarterly* and *Journal of Official Statistics*, and searches of survey methodology reference books, such as *Nonresponse in Household Interview Surveys*, were also performed. We reviewed proceedings of the American Statistical Association Survey Research Methods Section and papers presented at the 1999 International Conference on Survey Nonresponse. In addition, we conducted general Google Internet searches for the survey nonresponse literature and specific searches for nonresponse studies from the Survey of Consumer Finances and National Center for Education Statistics surveys. Then, we pursued references to other works cited in the retrieved articles. Much of the literature exists in journals in the biomedical field, possibly because of the availability of record bases, which are used as gold standards in the studies. The effort resulted in 47 articles that fit the criterion; in total, 59 separate studies were reported in the articles (see the appendix for a complete list of references).

To be eligible, the research needed to have produced estimates of nonresponse bias for a set of estimated population means or percentages. Acceptable techniques for producing these were:

1. sample frame data (i.e., where records were available both on respondents and nonrespondents), and means on the record variables were estimated;
2. supplemental data, for both respondents and nonrespondents, linked to the sample person's data;
3. screener interview data, used to compare respondents and nonrespondents to a later larger interview;
4. followup studies of sample persons who were nonrespondents to a survey, comparing the earlier respondent group to those former nonrespondents measured in the followup; and
5. reports of intentions to respond to a later survey, comparing those who report agreeing to respond with those who decline to respond.

The studies examined a wide variety of target populations, including the US national population, communities, health-service members, physicians, employees of an organization, company customers, low-income women, visitors to a recreational lake, disabled people, university students and alumni, special interest groups, voters, new parents, and others. The most prevalent topic was health (59 percent), followed by employment (11 percent). Most estimates arose from self-administered surveys (56 percent); 27 percent, from face-to-face surveys; and 17 percent, from telephone surveys. The vast majority of studies are documented in peer-reviewed journals (81 percent).

In addition to recording the nonresponse bias estimates, we attempted to record the following characteristics of the surveys: survey length, survey topic, likely topic interest among sample persons, survey sponsor, evidence for respondents' involvement with the survey sponsor, prenotification about the survey request, incentives, mode of data collection, and mode of the nonresponse followup. We coded population type, sample characteristics such as mean age, gender, and majority/minority distributions, and urbanicity of the sample. We coded each reported estimate by the type of statistic (percentage, mean, median), relevance of the statistic to the survey topic, and the type of measure (attitudinal, behavioral).

Analytic Plan

Each article provides estimates of the unadjusted respondent mean, $\bar{y}_r$; the nonrespondent mean, $\bar{y}_m$; and the full sample mean, $\bar{y}_n$. The number of cases for each mean is usually cited or could be computed from other reports in the article. Sample designs are reported. However, the element variances of the y variables are not generally reported, nor are standard errors of the estimated means.

We will view the meta-analytic data set as observations from 59 clusters (studies) of 959 observed nonresponse biases on estimates of sample means. These observed estimates are heteroskedastic because they are subject to different element variances in the studied populations and to different sampling variances because of the sample design and size.

In figure 2, we present all 959 estimates and their nonresponse bias, to give the reader a notion of the basic finding for the relationship between response rates and nonresponse bias. However, on many of these estimates we do not have sufficient information for classical statistical tests. We note that the respondent mean, $\bar{y}_r$, and the nonrespondent mean, $\bar{y}_m$, can be viewed as independent observations. When y is a binary variable, its element variance is a function of its mean value, and we can properly estimate the standard error of each of the observations. For count and continuous variables, we cannot do that. Hence, this paper limits the statistical analysis to 566 estimates of transformed y variables, using standardized variables that have equal element variances. These 566 estimates come from 44 of the 59 studies. We present estimated absolute values of differences between respondent and nonrespondent standardized means,

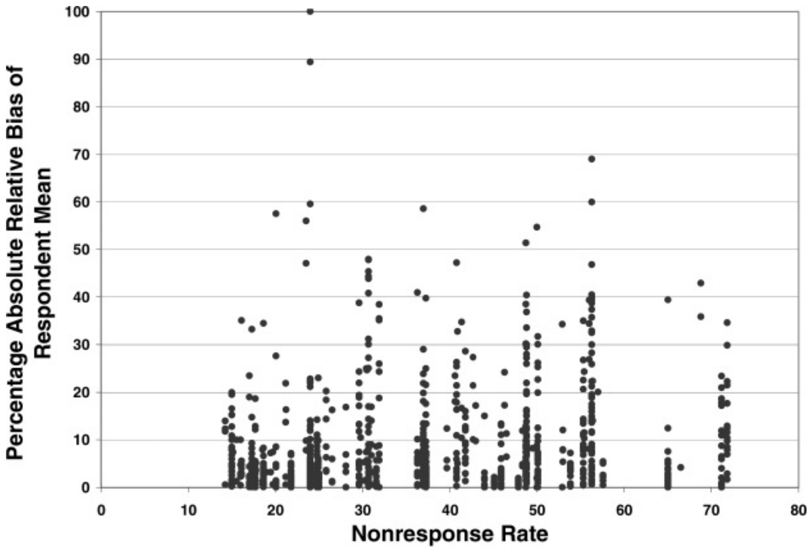

Figure 2. Percentage Absolute Relative Nonresponse Bias of 959 Respondent Means by Nonresponse Rate of the 59 Surveys in Which They Were Estimated.

$|\bar{y}_r - \bar{y}_m|$, weighting each observation by its sample size, to reflect unequal sampling variances. This statistic is a direct measure of how the attributes of respondents and nonrespondent differ. The differences can be interpreted in units of standard deviations of the standardized variables.

Despite repeated efforts to contact those responsible for the research studies to learn about undocumented attributes of the studies or their estimates, we failed in many cases. Faced with item-missing data, we preferred to avoid the complete-case analysis option. Instead, we built imputation models for the item-missing data. The use of sequential regression techniques in imputation permits the construction of a complete-case data set with all of the covariance properties of the original data set (Raghunathan et al. 2001). By using this technique in the context of a multiple imputation design, we can also estimate the impact of the imputation variance on estimates computed on the imputed data. We used IVEware (Raghunathan, Solenberger, and VanHoewyk 2002) within a SAS format, with 20 replicate imputed data sets with studies as a clustering factor, to estimate the standard errors of the estimated coefficients.

Of the predictor variables discussed in this paper, the variables indicating survey sponsorship and whether the sample had prior involvement with the sponsor of the survey had imputed values for 2 of 59 studies. Values for urbanicity of the sample were imputed for 15 of the 59 studies, while values for subcultural mix of the sample were imputed for 41 of the 59 studies.

The reader should note that prior conceptual work in nonresponse suggests that the mechanisms inducing nonresponse bias are inherently multivariate (e.g., Groves, Presser, and Dipko 2004). For example, incentives are seen to reduce nonresponse bias when the survey topic is made highly salient in the survey request (Groves et al. 2006). We have fitted multivariate models to the meta-analytic observations, but have found that many of the coefficients are rather unstable, given the sparseness of the data set for various contrasts. In this paper, we present bivariate relationships with nonresponse differences and comment on properties of the data set that evoke some cautions to the conclusions. We hope that the addition of other studies, with characteristics now underrepresented in the literature, will permit future multivariate modeling of the data.

The questions we posed to this meta-analytic data set are related to three possible linkages between nonresponse rates and nonresponse bias: (a) attributes of the survey design, (b) attributes of the sample population, and (c) characteristics of the individual statistic estimated in the survey.

CHARACTERISTICS OF THE META-ANALYSIS OBSERVATIONS

There is now a well-established empirical literature to show that the various types of nonresponse (e.g., noncontact, refusal) are differentially productive of bias in statistics of different types (e.g., Groves and Couper 1998; Campanelli, Sturgis, and Purdon 1997). Unfortunately, the articles used in the meta-analysis combine all the types of nonresponse into one category and present differences between respondents and the total set of nonrespondents.

We note that across all the estimates, the nonresponse rates of the studies range from 14 to 72 percent, with a mean nonresponse rate of 36 percent. Most of the estimates come from studies using nonsurvey records (24 percent from the sampling frame, 32 percent from a supplementary data set); 28 percent come from studies using followup of nonrespondents with some extraordinary effort. The remainder is mostly studies using screener interview data (14 percent). A very small percentage (2 percent) use reports of intentions to be a respondent or nonrespondent.

Figure 2 presents a scatterplot of 959 estimates of the absolute value of the relative nonresponse bias:

$$\left| \frac{100^{*}(\bar{y}_r - \bar{y}_n)}{\bar{y}_n} \right|$$

where the numerator contains the difference between respondent and full sample means, and the denominator is the full sample mean.

This figure contains a point for each of the means reported in the 59 studies, with complementary percentages for binary variables.[1] The plot displays

1. For each binary variable, two percentages can be computed. The smaller of the two tends to generate higher relative nonresponse bias. Hence, the figure presents the nonresponse bias of both complementary percentages.

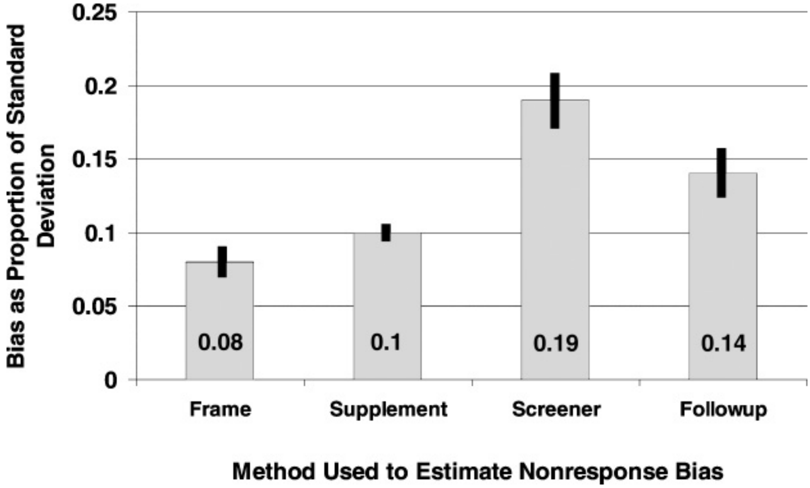

Figure 3. Average Nonresponse Differences, $|(\bar{y}_r - \bar{y}_m)|$, for 566 Standardized Estimates from 44 Studies Grouped by Methods Used to Estimate Nonresponse Bias.
NOTE.—Black lines reflect one standard error above and below the group mean, with standard errors reflecting the clustering of observations into studies.

vertical sequences of points, representing different estimates computed from the same survey. The figure clearly shows that (a) large relative nonresponse biases exist in the studies, (b) most of the variation in nonresponse lies across estimates within the same survey, and, as implied by that observation, (c) the nonresponse rate of a survey, by itself, is a poor predictor of the absolute relative nonresponse bias.[2] In short, insight into the linkage between nonresponse rates and nonresponse bias needs more information about the circumstances of each survey measurement.

Upon first examination of nonresponse differences we noticed an unexpected pattern related to the method used in the nonresponse study (see figure 3, based on the 566 of 959 estimates that were percentages). Nonresponse bias studies using sampling frame and supplementary data produce lower average bias (nonresponse differences[3] of 0.08 and 0.10, respectively) than other studies. Studies using a screening-interview technique produce a larger average nonresponse difference, 0.19. Similarly, if the nonresponse bias study compared early to later respondents during the course of the followup, the average nonresponse difference is 0.14. In short, the "screener" and "followup" methods tend to produce larger estimated nonresponse biases than other methods.

2. If a naïve OLS regression line were fit to the scatterplot, the R^2 would be 0.04.
3. For economy of language, we will use the more compact phrase, "nonresponse differences" instead of "differences between respondent and nonrespondent means."

Some of these differences may reflect different kinds of variables measured in the studies (e.g., items relevant to the topic of the survey versus others). Some may reflect different modes of data collection in the secondary phase of data collection for the "screener" and "followup" techniques. They, thereby, may confound nonresponse and measurement errors.

From a different perspective, the higher nonresponse differences for screener and followup studies may be real and ubiquitous. *Survey* variables (versus frame or supplemental data variables) sometimes act as influencers for the participatory decision. If the knowledge of what is to be measured influences cooperation, then larger nonresponse biases on such estimates could result. Persons with different values on the variables could vary in their response propensities, producing biased respondent estimates.

Indeed, the apparent sensitivity of bias estimates to the method used to estimate them displayed in figure 3 may be an important finding of the meta-analysis, and one that deserves further exploration. For later analyses of the data set presented below, we have decided to pool across the four methods. For each, however, we have replicated the analysis on the combined "frame" and "supplemental data" studies only. We will note below when discrepancies arose between the full data set and those two methods.

Attributes of the Survey Design

NONRESPONSE DIFFERENCES AS FUNCTIONS OF NONRESPONSE RATES

Some survey researchers have speculated that the differences between respondents and nonrespondents are themselves functions of the response rate (Keeter et al. 2000). This is implied by the hypothesis of the "continuum of resistance," a notion largely unsupported in empirical studies (e.g., Lin and Schaeffer 1995). Sometimes the argument is made that in surveys with higher nonresponse rates, there is a more heterogeneous mix of nonrespondents. With very low nonresponse rates, the argument goes, nonrespondents are quite different from the bulk of the sample. However, if the 44 studies were grouped into tertiles by their nonresponse rates, it is clear that nonresponse differences are largely similar across the range of nonresponse rates found. A separate analysis (not presented) shows that the nonresponse *bias* estimates themselves do not reliably vary across these three groups (again, merely reflecting large variation across estimates in surveys with similar nonresponse rates).

INFLUENCES ON RESPONSE RATES

The survey methodological literature is replete with techniques to increase response rates, for example, prenotification (de Leeuw et al. 2006) and incentives

(Singer 2002). From a conceptual point of view, few, if any, of these techniques should have general value of reducing nonresponse differences on *all* types of survey estimates. However, there is some indication of tendencies for poorer persons to be more sensitive to incentive effects (and hence, measures of socioeconomic status might have larger nonresponse bias with versus without incentives).

Table 1 shows the average difference between respondents and nonrespondents, using the 566 standardized percentage estimates in the 44 studies. The estimates from studies using prenotification have a mean nonresponse difference of 0.11 standard deviations, and those not using prenotification, 0.13. The standard error of the difference of 0.019 is 0.028. Thus, although we know that prenotification acts to increase response rates, it appears not to be associated, in general, with the magnitude of differences between respondents and nonrespondents on the survey variables.

Note that it would be erroneous to infer that prenotification *never* changes the nonresponse bias of any survey estimate. For example, we can imagine prenotification emphasizing specific purposes of the survey leading to more biases on items most closely related to those purposes.

Similar results apply to incentives—use of an incentive is not reliably related to the magnitude of nonresponse differences. (We note that few studies offered incentives and hence, the standard errors of the contrast are large.)

SPONSORSHIP OF THE SURVEY

Sponsors of the survey are often policy-makers or advocates for the topics of the surveys they sponsor (e.g., companies conduct customer satisfaction surveys and manage the service delivery with customers). When the sample persons judge that the sponsor has an identifiable "point of view" on the survey topic, that viewpoint can influence the person's decision. Sample persons who have prior connections with the sponsor are most likely to experience these influences. For survey variables that are related to that point of view, nonresponse bias can result.

We rated the surveys relative to whether the sample had prior involvement with the sponsor. Examples in the data set of surveys with prior involvement include a satisfaction and general health survey by the Hospital of the University of Pennsylvania mailed to patients who had undergone total knee arthroplasty (Kim et al. 2004) and a survey sent via e-mail to subscribers to a computer network managed by the survey sponsor (Walsh et al. 1992). In the table 1 analysis, when the full sample had prior involvement with the survey sponsor, on average there were lower nonresponse biases (difference of 0.05 of a standard deviation, $p = .05$).

A similar sponsorship influence may be related to the tendency for government surveys to achieve higher response rates than those of other sponsors (de Leeuw and de Heer 2002). In the meta-analysis, some examples of government

Table 1. Weighted Absolute Nonresponse Differences, $|\bar{y}_r - \bar{y}_m|$, by Subgroup for Standardized Percentage Estimates

		Average absolute differences between standardized respondent and nonrespondent mean		
		$\lvert\bar{y}_r - \bar{y}_m\rvert$	Standard error	N
Prenotification				
Yes		0.11	0.010	229
No		0.13	0.026	337
	Difference	−0.019	0.028	566
Incentives				
Yes		0.16	0.069	48
No		0.11	0.011	518
	Difference	0.050	0.070	566
Respondent's involvement with the sponsor				
Yes		0.093	0.0051	200
No		0.14	0.021	366
	Difference	−0.052**	0.022	566
Sponsorship				
Government		0.15	0.026	203
Other		0.10	0.0010	363
	Difference	0.048*	0.028	566
Mode				
Self-administered		0.10	0.010	275
Interviewer-administered		0.14	0.021	291
	Difference	−0.040*	0.024	566
Topic				
Health		0.11	0.017	358
Other		0.13	0.013	208
	Difference	−0.018	0.023	566
Population type				
General		0.17	0.032	159
Specific		0.10	0.0059	407
	Difference	0.075**	0.033	566
Urbanicity				
Urban		0.11	0.014	224
Mixed		0.12	0.021	342
	Difference	−0.013	0.027	566
Subculture				
Majority		0.11	0.018	236
Other		0.14	0.052	330
	Difference	−0.030	0.061	566

Continued.

Table 1. Continued

		Average absolute differences between standardized respondent and nonrespondent mean		
		$\lvert \bar{y}_r - \bar{y}_m \rvert$	Standard error	N
Question type				
1. Behavioral		0.11	0.019	304
2. Attitudinal		0.24	0.012	25
3. Demographic		0.11	0.010	237
	1–2 difference	−0.14***	0.022	329
	1–3 difference	−0.0081	0.019	541
	2–3 difference	0.13***	0.014	262
Topic saliency				
1. Yes		0.10	0.017	270
2. No		0.17	0.061	53
3. Undetermined		0.11	0.013	243
	1–2 difference	−0.075	0.064	323
	1–3 difference	−0.012	0.021	513
	2–3 difference	0.063	0.063	296
Statistic's relevance to the topic				
Yes		0.12	0.023	315
No		0.11	0.0089	251
	Difference	0.06	0.023	566

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

surveys include the Fundus Photography component of the US National Health and Nutrition Examination Survey (Khare et al. 1994) and a study on nutrition and health conducted in Roskilde, Denmark (Osler and Schroll 1992). The meta-analytic finding is that government-sponsored surveys tend to generate larger nonresponse differences (mean 0.15) than do those of other sponsors (mean 0.10). The difference is beyond traditional ($p < .05$) levels of statistical significance; however, when only the studies using frame or supplemental data are examined, the difference disappears.

MODE OF DATA COLLECTION

In contrast to interviewer-administered surveys, some self-administered modes (e.g., a mailed paper questionnaire survey) permit the sample person to examine the questions prior to making the participatory decision. This can influence response propensities. Mechanisms facilitating that influence may include negative emotions connected to the topic (e.g., fear of revelation of socially undesirable traits) or assessment of high burden of the questions (e.g., complicated reports of past behaviors, lookup of household records). If persons with such reactions tend to have different distributions on the y variables, then nonresponse bias should be induced by the decision-making circumstances.

With interviewer-administered surveys, interviewers are commonly trained to emphasize the purpose of the survey. Further, when interviewers tailor their remarks to the concerns of the sample person, they often try to relate the topic of the survey to the concerns of the respondent. In short, there are reasons to expect differences in either direction.

Table 1 shows that interviewer-administered surveys tend to produce larger nonresponse differences than do self-administered surveys (0.14 standard deviation difference versus a 0.10 difference, $p < .10$).

TOPIC OF THE SURVEY

Health surveys often attain higher response rates than surveys on other topics; electoral behavior surveys commonly have lower response rates (e.g., Voogt and Van Kempen 2002, in the appendix). We coded the surveys as either health-related topics or something else. In table 1, there was no reliable difference between the two types of surveys in the nonresponse differences their variables displayed.(When the frame and supplemental data methods are examined, health surveys display lower average nonresponse differences than surveys on other topics.)

Attributes of the Sample Population

TYPE OF SAMPLE POPULATION

Some of the surveys use general population sampling frames; others are specific to members of an organization, students of a school, patients of a hospital, etc. It is very common for surveys of such specific populations to generate higher response rates, *ceteris paribus*. Further, it is common to note that respondents to membership surveys tend to be more attached to the organization than the nonrespondents (Rogelberg et al. 2000). Because general population surveys usually do not have rich frames to study such nonresponse tendencies, the literature tends not to contain such findings. Hence, the impression that membership surveys tend to suffer from unusually large nonresponse biases may be fallacious.

Table 1 shows that surveys of the general population tend to generate larger average nonresponse differences (mean = 0.17) than surveys of specific populations (mean = 0.10). The difference of 0.075 has a standard error of 0.033 ($p < .05$).

URBANICITY OF TARGET POPULATION

One of the most common correlates of response rates in household surveys is the urbanicity of the population sampled (e.g., House and Wolf 1979; Steeh 1981). First, many of the other attributes related to low response rates tend to cluster in cities (e.g., single-person households, households without children). Second, social psychologists have observed that the pace of urban life, filled with fleeting, superficial interactions with strangers, sharply contrasts with the deeper, multidimensional relationships among residents of nonurban settings.

We coded the studies by whether they sampled only urban populations or mixed populations (we had no examples of purely rural samples). Table 1 shows no differences between the two groups in the nonresponse differences on survey variables. We remind the reader, however, that this finding is subject to rather high imputation variance of the urbanicity variable.

SUBCULTURES REPRESENTED IN THE SURVEY

A common speculation in surveys is that racial and ethnic minorities tend to have lower response rates than majority groups (Brehm 1993). There is some evidence that this results from unusually high noncontact rates and specific types of survey content (Groves and Couper 1998). If survey variables tend to be correlated with minority status, then we might hypothesize that surveys studying majority populations would have higher nonresponse differences than those focusing on minority subcultures.

Table 1 shows that the two types of surveys yield similar average nonresponse differences on survey variables. We note, however, that imputation variance on this predictor variable is quite high.

Attributes of the Survey Estimates

Figure 2 shows that most of the variation in nonresponse bias of survey estimates lies within surveys, across estimates. It seems clear that attributes of individual estimates must play a part in the explanation of nonresponse bias.

MEASUREMENT OF SUBJECTIVE VERSUS OBJECTIVE PHENOMENA

There are speculations that statistics based on attitudinal measures might be more subject to nonresponse bias than those based on objective phenomena (Stinchcombe, Jones, and Sheatsley 1981). This might arise if attitudinal states dominantly influence the survey participation decision, such that, when attitudes are measured in the survey, they tend to be correlated with those attitudes driving participation. If behaviors are measured, the reasoning continues, they would be less correlated with the attitudes influencing participation.

We find that behavioral measures have lower average biases than measures of nonobservable attributes (by 0.12 standard deviation, $p = .10$). The attitudinal variables tend to come from studies using screener variables or followup studies comparing early and late responders. We remind the reader that those methods generated higher nonresponse differences, and the finding merits some caution.

TOPIC INTEREST OR SELF-INTEREST RELATED TO PARTICIPATION

Some persons, when the topic of the survey is made salient in the request for participation, become positively disposed because the topic itself is of interest to them (Groves, Presser, and Dipko 2004). They have learned through experience that cognitive engagement in the topic brings them some satisfaction. Because this reaction of self-interest in the topic is influential for these persons' decision to participate, the respondent pool tends to be disproportionately "interested" persons.

When interest is correlated with different distributions on survey variables, nonresponse bias can be induced on their estimates. For the variables concerning the stated topic in the questionnaire, the respondent distribution is likely to be different from the nonrespondent distribution.

We created two ratings relevant to these hypotheses: (a) is the topic of general interest to the population studied (e.g., health symptoms among a sample of patients as in Macera et al. 1990); and (b) is the estimate measured on a variable that is key to the topic of the survey (e.g., percent drinking less than once a week in a survey on alcohol use as in Wild, Cunningham, and Adlaf 2001). Neither the study-level test nor the estimate-level test supported this hypothesis.

STATISTICAL ATTRIBUTES OF ESTIMATES

It is common to hope that biases "cancel out" when measures of relationships or differences over time in a statistic are examined (Cochran 1977, pp. 379–80; Martin 2004; Goudy 1976). For example, when the mean of subclass 1, $\bar{y}_{r1}$, is biased and the mean of subclass 2, $\bar{y}_{r2}$, is biased, it is hoped that the difference of the two subclass means, $\bar{y}_{r1} - \bar{y}_{r2}$, enjoys some canceling of biases. This hope taken to the extreme leads some practitioners to believe that if their survey statistics are comparisons of subgroups (or measures of relationships between variables), their analysis is immune to nonresponse bias.

Some of the studies assembled have nonresponse bias estimates for subclasses and include the appropriate documentation for computation of the bias of the difference of subclass means. There are 234 subclass means that are reported that also have estimated nonresponse biases. Figure 4 is a scatterplot of 117 estimates—each comparison of two subclass means (of, say, $\bar{y}_{r1} - \bar{y}_{r2}$)

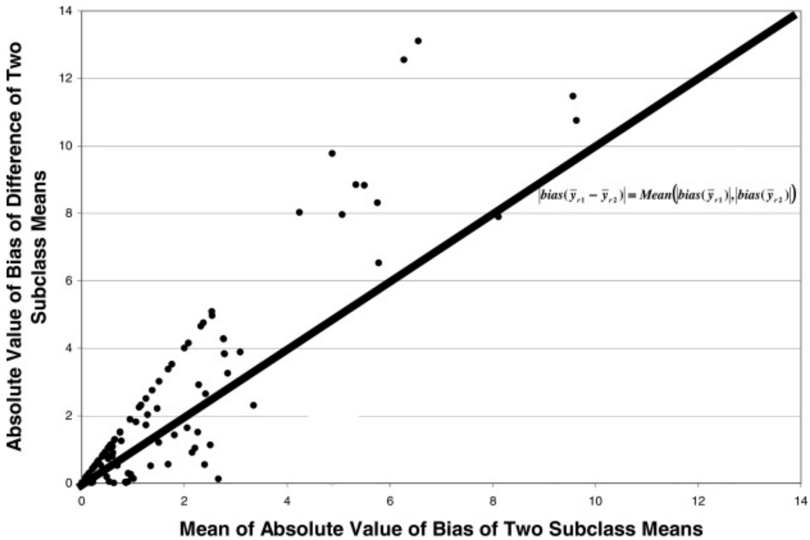

Figure 4. Absolute Value of Bias of 117 Differences of Two Subclass Means, $|Bias(\bar{y}_{r1} - \bar{y}_{r2})|$, by Mean of Absolute Value of the Biases of the Two Contrasted Subclass Means, $Mean\{|Bias(\bar{y}_{r1})|, |Bias(\bar{y}_{r2})|\}$.

contributes one point to the scatterplot. The x-axis is the mean of the absolute value of the biases of the two subclass means (the average bias of the subclass means). The y-axis value is the nonresponse bias of the difference of the two subclass means. To ease the reading of the plot, the line representing $y = x$ is placed into the plot, corresponding to the case when the bias of the contrast between the two subclass means equals the average bias of the two subclass means themselves. Points below the diagonal line are those where the differences of subclass means have lower nonresponse bias than the subclass means, on average. This is a desired state for all researchers doing analytic comparisons.

Of the 117 differences of subclass means in figure 4, only 41 have lower nonresponse biases than those of the contrasted subclass means. (The ridge of values on the y dimensions arises when the subclass means have opposite signs.) In short, there is little evidence that biases tend to cancel when comparing two subclasses.

Conclusions and Discussion

As with all meta-analyses, conclusions must be made with considerable caution. Meta-analyses may be good tools when single variables influence a phenomenon, but rarely do they have complete representation of possible patterns of predictor variables to support complex multivariate analysis. We are very concerned about undetected confounds in the set of published articles we were able to assemble. Thus, we order our conclusions by the strength of our belief that they will withstand replication attempts.

1. Large nonresponse biases can happen in surveys.
   High response rates can reduce the risks of bias. They do this less when the causes of participation are highly correlated with the survey variables. Indeed, in the studies we assembled, some surveys with low nonresponse rates have estimates with high relative nonresponse bias.
2. The search for mechanisms that link nonresponse rates and nonresponse bias should focus on the level of individual measures and not on the level of the survey.
   The meta-analysis shows much variability in nonresponse bias within surveys, across estimates. We know from statistical expressions that when influences on survey participation are themselves measured in the survey, they will show the largest nonresponse bias. To predict what survey estimates are most susceptible to nonresponse bias, we need to understand how each survey variable relates to causes of survey participation.
3. Differences of subclass means do not, in general, enjoy lower nonresponse biases than their constituent subclass means.
   We cannot rely on full or partial canceling of nonresponse biases when we subtract one subclass mean from another. The bias of the difference is a function of differences of response rates and covariances between response propensities of the subgroups and the survey variable.
4. How we estimate nonresponse bias may make a difference.
   We found that nonresponse differences in the literature tend to be higher when screener data and data from followup efforts are used (relative to using frame or supplemental data sources). These techniques try to estimate bias on the survey variables as actually measured in the data collection. Thus, they are informative about bias in the key survey estimates themselves. Further, when knowledge of the survey items influences the decision to participate, our theory predicts larger nonresponse biases on those items. On the other hand, the screener and followup methods often employ different modes of data collection or other changes in measurement conditions. Given the documentation of studies in the literature, we cannot easily separate the measurement errors from the nonresponse errors.

Given the uniqueness of this meta-analytic data set, we offer the reader some further cautions and suggestions. First, we observed high correlations among a set of attributes of the assembled studies (a) using screener or followup technique to estimate bias, (b) studying general populations, (c) having government sponsorship, and (d) not having prior involvement of the target population with the sponsor. All of these attributes relate to higher nonresponse differences and therefore nonresponse biases. Unfortunately, the meta-analytic data set has too few cases with variation on those four attributes. We need more studies with different mixes of these attributes to have more confidence in the statistical findings of table 1.

Second, our theoretical framework suggests one linkage between nonresponse rates and bias that should lie at the estimate level. When the estimate is based on survey items highly relevant to the topic of the survey as presented at the time of recruitment *and* the topic is a very salient attribute of the survey request, then the conditions for nonresponse bias should exist. Unfortunately, the documentation about recruitment protocols is almost nonexistent in the printed literature we found. Hence, we remain cautious about the findings involving our coding of estimates on relevance to the topic. Gathering more documentation on the nature of the survey introduction to the sample could be of benefit.

Third, even though the nonresponse differences between interviewer-administered surveys versus self-administered surveys were only marginally significant, we find this result very intriguing. We believe this finding may itself be a function of the nature of how interviewers recruit the respondents and what information guides compliance with self-administered survey requests. That is, we suspect different mechanisms may produce the covariance between response propensities and survey variables in the two modes. This is a rich area for study, given our field's movement to mixed-mode surveys.

Appendix A

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