

¹ Nonresponse and Sample Weighting in Organizational Surveying

Abstract

Post-stratification weighting is a common procedure used in public opinion polling applications to correct demographic constituency differences between samples and populations. Although common practice in public opinion polling, this form of data remediation is only sparsely acknowledged as a procedural topic worthy of empirical investigation within the organizational surveying literature. The current paper induces survey nonresponse via data simulation across fictional constituent groups (aka organizational strata) and documents the impact of weighting on the accuracy of sample statistics. Our goal was to evaluate the effectiveness of weighting when confronted with *passive* versus *active* forms of nonresponse in an effort to: 1) interject this data-remediation procedure into the established organizational surveying literature focused on nonresponse, while also 2) exploring organizationally-relevant sampling scenarios that: a) benefit from, b) are “hurt” by, or c) are unaffected by post-stratification weighting. The results confirm that sampling contexts characterized by active nonresponse do benefit from application of sample weights, but only when accompanied by constituency differences in underlying population construct (e.g., surveyed *attitude*) standing. Alternatively, constituent member differences in population attitudes, when characterized by passive forms of nonresponse, exhibit no benefit from weighting (in fact these scenarios are somewhat *hurt* by weighting). The simulations reinforce that, moving forward, it would be prudent for surveyors of all disciplinary backgrounds to mutually attend to the traditional focus of both traditions: public opinion polling (e.g., multiple possible methodological sources of error as well as post-stratification adjustment) and organizational surveying (e.g., *form* of nonresponse).

Keywords: Survey methodology, sample weighting, nonresponse, response rate

25 Nonresponse and Sample Weighting in Organizational Surveying

26 Akin to differential variable weighting (for instance: a) construct indicators within
27 an assessment scale [aka factor loadings], or b) predictors within a selection system [aka
28 regression weights]; e.g., per data matrix “columns”), sample weighting alters the
29 proportional contributions of *individual respondents* within a data set (e.g., data matrix
30 rows). Some respondents’ responses are assigned greater relative contribution and others
31 are assigned less. This practice is commonplace in the summary of general population
32 polling data reflecting, for example, elections and politics (e.g., Rivers & Bailey, 2009),
33 prevalence rates of psychological disorders (e.g., Kessler et al., 2009), or feelings of physical
34 safety (e.g., Quine & Morrell, 2008). It is also seemingly in the periphery of awareness and
35 application within the published organizational surveying literature (see, for example,
36 Kulas et al., 2016; Landers & Behrend, 2015; Tett et al., 2014).

37 We speculate that this form of statistical remediation is gaining research interest in
38 the organizational surveying research domain, at least in part, because industrial
39 psychologists are keenly aware that response rates within organizational surveying
40 applications have been trending downward (see, for example, Anseel et al., 2010; Rogelberg
41 & Stanton, 2007). With lower response rates, surveyors are confronted with heightened
42 levels of scrutiny because, historically, a locally realized high response rate has been widely
43 interpreted as a positive indicator of data quality (e.g., Anseel et al., 2010; Cycyota &
44 Harrison, 2002, 2006; Frohlich, 2002). The orientation of this presentation, however, is that
45 although response rate is a commonly referenced proxy of survey quality, it is not response
46 rate but rather sample representativeness that should be the primary focus of concern for
47 survey specialists (see, for example, Cook et al., 2000; Krosnick, 1999). Representativeness
48 can of course be “hurt” by low response rates, but the relationship between these two
49 survey concepts is by no means exact (e.g., Curtin et al., 2000; Keeter et al., 2006; Kulas et
50 al., 2017). Stated differently, a high response rate is neither a sufficient nor necessary

51 condition for accurate population sampling.¹

52 In the context of any survey application, population misrepresentation ultimately
53 refers to a discrepancy between estimated sample statistics and actual population
54 parameters. Ideally, such discrepancies arise from completely random sources (in which
55 case resulting error is less likely to be reasonably characterized as bias). In reality, however,
56 discrepancies are driven not only by purely random causes. There are several broader
57 sampling methodology factors that may be systematically driving the relative under- or
58 over-selection of a population segment (see, for example, Kulas et al., 2016), but the most
59 commonly cited contributor within the organizational sciences is non-response (e.g., invited
60 individuals simply either forget [e.g., passive nonresponse] or consciously choose not to
61 participate in the survey process [e.g., active nonresponse], see, for example, Rogelberg et
62 al., 2000). Our presentation also focuses on this non-response contributor to sample
63 misrepresentation, but only because we aim to: 1) integrate the organizational
64 non-response and public-opinion post-stratification weighting literatures, while also 2)
65 highlighting the associations and dissociations between response rate and misrepresentation
66 (although we also note here that the current presentation and procedure address additional
67 sampling methodological sources of misrepresentation).²

¹ There are commonly mentioned benefits associated with higher response rates, such as greater statistical power. This benefit, however, should not be *attributed to* response rate, but rather its effect: larger n . Our presentation reflects the fact that greater power (and/or, relatedly, smaller confidence intervals) may in fact introduce a false sense of methodological confidence. Primarily for this reason, we stress that the methodological/statistical concepts of response rate, sample size, and power need to be fully disentangled from the principle of representativeness, and the importance of these dissociations drives the central theme of the current paper.

² Frequently presented as a separate consideration, *measurement error* is an additional contributor to population misrepresentation. The current focus is on deviations from a perfect sampling methodology as opposed to deviations from an ideal psychometric methodology. We do however note that future advancements within the broad domain of “survey error” would benefit from a unified perspective that

68 Nonresponse in Organizational Surveying

69 Within the organizational surveying domain, it is not uncommon for response rate
70 (RR) to be referenced as a proxy for survey data quality (see, for example, Baruch &
71 Holtom, 2008; Fan & Yan, 2010; Pedersen & Nielsen, 2016). Baruch (1999), for example,
72 states that, “...to have dependable, valid, and reliable results, we need a high RR from a
73 wide representation of the whole population under study” and that, “The level of RR is an
74 important, sometimes crucial, issue in relation to the validity of a paper’s results” (p. 422).
75 Fan and Yan (2010) similarly state that response rate is, “...the most widely used and
76 commonly computed statistic to indicate the quality of surveys” (p. 132). Pedersen and
77 Nielsen (2016) claim that a high survey response rate, “...diminishes sampling bias
78 concerns and promotes the validity of survey-based research findings” (p. 230). The general
79 consensus seems to be that there are three major (negative) consequences of low response
80 rates, including (a) yielding smaller sample size, which negatively impacts statistical power
81 and confidence intervals, (b) reducing the credibility of survey data, and (c) generating
82 biased samples that impair the generalizability of survey results (Biemer & Lyberg, 2003;
83 Luong & Rogelberg, 1998; Rogelberg et al., 2000).

84 To the likely frustration of those who associate response rate with survey data
85 quality, organizational survey response rates have, on average, been declining for decades.
86 Baruch (1999), for example, summarized response rates of 175 studies published in five
87 leading management and behavioral sciences journals in 1975, 1985, and 1995. His results
88 revealed an average response rate (across time periods) of 55.6% ($SD = 19.7\%$), but also a
89 trend within which response rates declined steadily from 64.4% to 55.7% to 48.4% over the
90 three time points. Nine years later, Baruch and Holtom (2008) conducted a follow-up
91 study of 1,607 studies published in 17 disciplinary-relevant journals in 2000 and 2005 but
92 found no substantial differences in response rates compared to those in 1995, suggesting

encompasses error arising from both methodological sources: measurement and sampling strategy.

93 that the declining trend had perhaps reached a lower asymptote. However, a different
94 approach with similar goals (Anseel et al., 2010) analyzed 2,037 survey projects published
95 in 12 journals in Industrial and Organizational Psychology, Management, and Marketing
96 from 1995 to 2008 and did note a slight decline (overall $M = 52.3\%$) when controlling for
97 the use of response enhancing techniques.³

98 ***Form of Nonresponse***

99 Although high response rates are generally pursued as desirable within
100 organizational surveying applications, there has also been a broad acknowledgement that
101 not all forms of nonresponse should be considered equally worrisome. Rogelberg et al.
102 (2003), for example, propose a distinction between *active* and *passive* nonrespondents
103 based on intent and (in)action. According to Rogelberg et al. (2003), active
104 nonrespondents are those who intentionally refuse to participate in surveys, while passive
105 nonrespondents are those who fail to respond to surveys due to reasons such as forgetting
106 or misplacing invitations. Passive nonrespondents are thought to be similar to respondents
107 in both attitude (Rogelberg et al., 2003) as well as organizational citizenship behaviors
108 (OCBs, Spitzmüller et al., 2007), whereas active nonrespondents have been shown to
109 exhibit significantly lower organizational commitment and satisfaction, higher intention to
110 quit, lower conscientiousness, and lower OCBs than actual respondents (Rogelberg et al.,
111 2000, 2003; Spitzmüller et al., 2007).

112 The more commonly encountered form of organizational nonresponse appears to be
113 passive (Rogelberg et al., 2003; Rogelberg & Stanton, 2007), although subgroup rates may
114 evidence variability - men, for example, have a higher proclivity toward active nonresponse

³ It is also possible that the declination has stabilized with mean response rates hovering around 50% after roughly the turn of the millennium ($M = 52.5\%$ for HRM studies from 2009 to 2013, Mellahi & Harris, 2016; $M = 52.0\%$ for management studies from 2000 to 2004, Werner et al., 2007). This stability, if authentic, may again possibly be accounted for by an increased contemporary emphasis on response enhancing strategies (Anseel et al., 2010; Fulton, 2016).

than do women (Luong & Rogelberg, 1998; Rogelberg et al., 2000; Spitzmüller et al., 2007). Additionally, it has been noted that selection of an individual population element into a realized sample may in fact be predictable (because of, for example, an increased likelihood of not responding when dissatisfied or disgruntled, Taris & Schreurs, 2007). The organizational surveying baseline default expectation is that, *on average*, roughly 15% of nonrespondents should be expected to be accurately characterized as “active” (Rogelberg et al., 2003; Rogelberg & Stanton, 2007; Werner et al., 2007). It is this second, less frequently anticipated form of nonresponse that also carries the greater resulting threat of biased sample estimates (see, for example, Kulas et al., 2017; Rogelberg & Stanton, 2007). It is these biased estimates that are targeted when applying sample weights.

Sample Weighting - a Brief Overview

Within public opinion polling contexts, when realized sample constituencies (e.g., 44% male - by tradition from *carefully-constructed* and *randomly sampled* data frames)⁴ are compared against census estimates of population parameters (e.g., 49% male), weights are applied to the sample in an effort to remediate the relative proportional under- or over-sampling. This is because, if the broader populations from which the under- or over-represented groups are sampled differ along surveyed dimensions (e.g., males, within the population, are *less likely to vote for Candidate X* than are women), then unweighted aggregate statistics (of, for example, projected voting results) will misrepresent the true population parameter. This remedial application of sample weights should also be considered an option for researchers pursuing answers to analogous organizational pollings such as: “What is the mood of the employees?” This is because focused queries such as

⁴ These important sampling concepts are very carefully attended to within public opinion polling contexts. Conversely, within organizational surveying traditions, these considerations are not commonly acknowledged, at least explicitly within the published literature. The weighting procedure presented in the current manuscript remediates bias regardless of the methodological source, but is dependent on accurate “census” population constituency estimates.

137 this are (perhaps somewhat covertly) layered - implicit in the question is a focus not on
 138 survey results, but rather the broader employee population. Acknowledging this implicit
 139 target group is of course important, because the next step (after gauging the mood of the
 140 surveyed respondents) is *doing something* about it. Weighting should be considered a
 141 procedural option for organizational surveyors to potentially transition a bit closer from,
 142 “What do the survey results say”? to “What do the employees feel”?

143 **Procedural application**

144 *Proportional weights* are the form of weights most directly relevant to organizational
 145 surveying applications that traditionally focus on nonresponse as the primary contributor
 146 to sample misrepresentation. These weights are ratios of the proportion of a population
 147 within a given stratum to the proportion of the sample within that same stratum:

$$\text{proportional weight}(\pi_k) = \frac{(N_k/N)}{(n_k/n)} \quad (1)$$

148 Over-sampling of elements of a stratum (k) results in proportional weights less than
 149 one, while under-sampling (relative to the population) results in proportional weights
 150 greater than one. The common procedure for weight estimation *when more than one*
 151 *stratum is specified* is an iterative process that may be referred to by multiple substantively
 152 synonymous terms: *rim weighting*, *iterative proportional fitting*, or *raking* (see, for example,
 153 Deming & Stephan, 1940). Regardless of label, the procedure guides the surveyor to:

- 154 1) Determine proportional weights for all levels within one stratum, and then assign
 155 these weights to cases.
- 156 2) Determine proportional weights for a second group (ratio of population percent to
 157 *current* sample percent [the current sample percent will be affected by the step 1
 158 weighting procedure]). Multiply previous (step 1) weights by the proportional
 159 weights for this second stratum and assign these new weights to cases.

- 160 3) Determine proportional weights for a third stratum (which will once again require
161 re-inspection of the *current* sample percent). Multiply the previous step 2 weights by
162 the third stratum proportional weights and assign to cases.
- 163 4) Iterate through steps 1, 2, and 3 (or more if more than three strata are considered)
164 until the weighted sample characteristics match the population characteristics to your
165 desired level of precision.

166 Possible strata relevant for organizational survey weighting include: branch, full-,
167 part-, or flex-time status, functional area, gender, geographic location, hierarchy,
168 remote-working categorization, salaried status, subsidiary, tenure, work shift, or any other
169 groupings especially suspected to plausibly possess a relatively disporportionate number of
170 active nonrespondents (through application of forecasting strategies such as those
171 advocated by, for example, Rogelberg and Stanton, 2007). Each of these strata may of
172 course also be the targeted focus of survey results feedback, but when *aggregating* results
173 across (or even within) strata, a consideration of the impact of nonresponse *has the*
174 *potential* to yield more accurate survey estimates. The explicit goal is therefore a closer
175 approximation of sample descriptive statistics to population parameters via statistical
176 remediation, and drives the current paper's focus on the interplay of four survey concepts
177 (distribution of attitude within the larger population, response rate, nonresponse form, and
178 remedial weighting).

179 *Research question 1:* What role does overall response rate play in population
180 misrepresentation?

181 *Research question 2:* What role does nonresponse form (passive versus active) play
182 in population misrepresentation?

183 *Research question 3:* What impact does the application of weights have on both
184 biased (e.g., misrepresentative) and unbiased sample estimates?

185 We view these questions as being analogous to similar questions asked and answered

186 with differential variable weighting within the broader applied psychological disciplines.

187 Just as, for example, there has been debate regarding the merits of differential versus unit

188 variable weighting in a selection context (e.g., Wainer, 1976) or simple aggregate scale score

189 definition (Bobko et al., 2007), we propose that a similar consideration is appropriate with

190 persons, and therefore compare and contrast unit- versus variable-sample element

191 weighting.

192 Methods

193 We address our research questions within a simulated context of organizational

194 surveying (wherein it is common to assess estimates of employee attitude or perception; for

195 example, commitment, culture/climate, engagement, satisfaction). We began the

196 simulations by establishing “populations”, each consisting of 10,000 respondents

197 characterized by demographic categorizations across gender (male and female) and

198 department (A and B). We therefore had four demographic groups (male-A, male-B,

199 female-A, and female-B). For these population respondents, we generated scaled continuous

200 responses (real numbers) ranging from values of 1 to 5, reflecting averaged aggregate scale

201 scores from a fictional multi-item survey with a typical $1 \rightarrow 5$ Likert-type rating scale.

202 In order to represent different proportions of relative constituency (for example,

203 more females than males or more department A workers than department B), we iterated

204 population characteristics at marginal levels (gender and department) starting at 20% (and

205 80%) with increments and corresponding decrements of 20%. For example, if males

206 accounted for 20% of the simulated population, then females were 80%; also if respondents

207 in Department A represented 60% of a population, then 40% were in Department B.

208 Marginal constituencies were therefore specified at all combinations (across the two

209 variables) of 20% and 80%, 40% and 60%, 60% and 40%, and 80% and 20%. This resulted

210 in population *cell* constituencies (e.g., men in department A) as low as 400 and as high as

211 6,400.

212 Additionally, each of these cell populations was characterized by an attitudinal
213 distribution in one of three different possible forms: normal, positively skewed, or
214 negatively skewed. These distributional forms were specified in an attempt to model
215 similarities and discrepancies in construct standing (e.g., commitment, satisfaction, or
216 engagement) across respondent groupings. The normal distribution exhibited, on average,
217 a mean of 3.0 whereas the skewed distributions were characterized by average means of 2.0
218 and 4.0, respectively. In total, eight crossings of distributional type across employee
219 categorization were specified (Table 1 presents the combinations of these distributions).
220 Note that these eight conditions are not exhaustive of all possible combinations of
221 constituent groups and attitudinal distribution - we specified scenarios that we expected to
222 be most efficiently informative.

223 Individual attitudes were randomly sampled from population distributions at the
224 cell level (e.g., Department A Males) without replacement. Response rates
225 (methodologically these could also be conceptualized as *sampling* rates) were controlled at
226 the marginal level using 10% increments ranging from 60% to 90%, and these were fully
227 iterated. Our cell-level response rates therefore ranged from 36% to 81% - a range of rates
228 chosen because they are, according to the organizational surveying literature, reasonable
229 expectations (e.g., Mellahi & Harris, 2016; Werner et al., 2007). We therefore investigated
230 error within the aggregate mean (e.g., grand mean or total sample mean) attributable to
231 different likelihoods of sample inclusion from constituent groups of different relative size
232 and representing populations of different attitudinal distribution, but at response rates
233 reasonably expected to exist in real-world organizational surveying contexts.

234 It should be noted here that there are several collective patterns of response that
235 are intended to represent sampling scenarios reflecting effectively *passive* nonresponse
236 across groups, regardless of response rate. These are the scenarios in which all subgroups

exhibit the same response rate (e.g., 36%, 36%, 36%, and 36%). All other combinations of response rate are intended operationalizations of active forms of nonresponse (e.g., not *as reasonably* characterized as missing at random), although the degree to which a sampling scenario should be reasonably considered to be reflecting active nonresponse is intended to increase incrementally across response rate conditions.

In an attempt to capture this “degree of active nonresponse”, we calculated a simple index of response rate discrepancy (SD; presented in Table 2). The “least” active nonresponse scenarios are characterized by two subgroups with identical response rates and two having a slightly different response rate (e.g., Dept A Males = 36%, Dept A Females = 36%, Dept B Males = 42%, and Dept B Females = 42%; see the second row of Table 2, the SD index = .034)⁵. Also here note that three of our eight Table 1 conditions represent scenarios where the presence of active nonrespondents is not expected to result in bias (e.g., regardless of patterns of nonresponse, the unweighted sample mean is expected to yield an unbiased estimate of the population mean). These are Table 1 conditions one through three, where attitudinal distributions are of *the same form* across groups, regardless of any individual group response rate discrepancy from others’.

These operationalizations of passive and active forms of nonresponse differ from other investigations with similar goals. Kulas et al. (2017), for example, directly tie probabilities of sample inclusion to an individual’s held attitude (the likelihood of sample inclusion is fully dependent on the population member’s attitude). Conversely, the

⁵ This method of simplifying the presentation of our response rate conditions is fully independent of consideration of population constituency and distributional form. That is, the amount of bias present in a sample estimate is expected to be quite different for Condition 7 with response rates of 48%, 48%, 72%, 72% versus 48%, 72%, 48%, 72%, even though the crude response rate index ($SD = 0.139$) is the same for both scenarios. There is additional information within these simulations (the effect of a *combination* of response rate and population form on degree of bias) that is therefore not captured via this simple SD index.

257 probability of sample inclusion in the current investigation is dependent only on *group*
258 membership (with some of these groups occasionally being characterized by unique
259 attitude distributional forms). Essentially, Kulas et al. (2017) operationalize active
260 nonresponse at the person-level whereas the current paper does so at the group level. This
261 may be a more appropriate procedural specification with regard to the implications of
262 these simulations, as organizational surveyors are more likely to have an inclination of a
263 group's collective attitude or likelihood to respond (e.g., night shift workers, machine
264 operators) than they are of any one individual employee.

265 Results

266 In total, we generated 327.68 million samples (4,096 unique combinations of
267 response rate and population constituency across gender and department, simulated 10,000
268 times each across our eight Table 1 conditions). Each of these samples was comprised of,
269 on average, $n = 5,625$, collectively representing an experiment-wide simulated n of 1.8432
270 trillion. For each individual simulation, weights were applied iteratively to the data at the
271 two marginal (variable) levels via raking, and were estimated via the *anesrake* package
272 (Pasek, 2018) in R version 4.2.2 (2022-10-31 ucrt).

273 We were most interested in comparing the extent to which unweighted (aggregated
274 responses without raking) and weighted (aggregated weighted responses) sample means
275 approximated the known population means across our controlled specifications of response
276 rate, nonresponse form, and attitudinal distribution. Population means were extracted
277 from each iteration, as the simulations specified a new population at each iteration. The
278 “misrepresentation” between sample and population was operationalized by calculating: 1)
279 the discrepancies between the population and both weighted and unweighted sample
280 means, as well as, 2) the averaged deviations of these discrepancies from the population
281 mean (discrepancy in the “mean” of the means is bias, dispersion about the “mean” of the
282 means is error). If the average weighted sample mean was closer to the true population

283 mean, relative to the unweighted one, then the weighting was deemed beneficial.

284 The plurality of our findings are presented visually, and they focus on the overall
285 mean (e.g., the average rating across all sample members).

286 Role of overall response rate

287 Research question 1 asked what role overall response rate plays in population
288 misrepresentation. This is presented most directly in Figure 1, with *moderate* response
289 rates exhibiting the greatest degrees of misrepresentation across our simulated conditions.

290 Note here again that conditions 1 through 3, which represent populations with similar
291 distributions of attitude, do not exhibit misrepresentation regardless of response rate.

292 These can be contrasted with conditions 6 through 8, which evidence considerable
293 misrepresentation, particularly so at moderate response rates (the greatest degree of
294 misrepresentation occurs with response rates ranging from roughly 40% to 70%).⁶

295 Role of nonresponse form

296 Research question 2 asked what role the *form* of nonresponse (passive versus active)
297 plays in population misrepresentation. In terms of explaining the error that did emerge
298 within unweighted means sampled from conditions 4 though 8, this error was largely
299 attributable to form of nonresponse (See Figure 2). The nature of the exact relationship
300 was slightly nonlinear, being fit with quadratic functions within each condition (collapsing
301 across conditions did exhibit slight within-array differences [which would affect the
302 statistically perfect relationship]).⁷

303 The “heteroskedasticity” of the Figure 2 scatterplots should also be acknowledged.

304 There are *active nonresponse* scenarios in which no error is present (see, for example, the

⁶ NEEDS FURTHER THOUGHT/EXPLANATION Middle range more cases - for the lowest case, there's only 256 cases (all with the same response rate of 36%). That explains the “upward slope” on the left of the graphing spaces.

⁷ Need to find these analyses if retain - Figure 2 looks linear with heteroskedasticity (6/16/23)

305 lower right-hand portions of conditions 4 through 8 in Figure 2 where discrepancy
 306 estimates of “0” appear all along the passive-active x-axis). These circumstances are
 307 simulated conditions within which the response rates “parallel” the distributional form. For
 308 example, in Condition Eight, the distributional forms were: *PositiveSkew_{Male(A)}*,
 309 *PositiveSkew_{Male(B)}*, *NegativeSkew_{Female(A)}*, *NegativeSkew_{Female(B)}*. In the most
 310 extreme cases of active nonresponse, marginal response rates that fully parallel
 311 distributional patterns (e.g., 20%_{Male(A)}, 20%_{Male(B)}, 80%_{Female(A)}, 80%_{Female(B)}) result in no
 312 error in the population mean approximation (average discrepancy = .0003, *SD* = .0002).
 313 Alternatively, when the response rates are inverted, (e.g., 20%_{Male_A}, 80%_{Male_B},
 314 20%_{Female_A}, 80%_{Female_B}), there is substantial error in approximation (average discrepancy
 315 = .51, *SD* = .14).⁸ Again, it is not merely response rate or form that is associated with
 316 biased sample estimates, but rather the nature of response rate relative to existing
 317 attitudinal differences.

318 To partially address this limitation, the discrepancies between population
 319 constituency and sampling proportions were additionally estimated via Cattell’s profile
 320 similarity index [r_p ; Cattell (1949); Cattell et al. (1966)]. r_p is sensitive to discrepancies in
 321 profile shape (pattern across profile components), elevation (average component score), and
 322 scatter (sum of individual components’ deviation from the elevation estimate. Figure 3
 323 demonstrates the pattern of unweighted sample mean deviation (from the population
 324 parameter) when this index is taken into consideration. Specifically, Figure 3 demonstrates
 325 a more pronounced *form of* nonresponse association when underlying attitudinal
 326 distributions evidence group differences, and in these scenarios, active nonresponse is
 327 shown to have a fairly large effect on error within the sample estimate (as well as
 328 systematically increasing degrees of heteroskedasticity paralleling the Cattell index,
 329 Breusch-Pagan = 3177.2, *p* < .001).

⁸ Need to redo this - .51 doesn’t appear on graph, highest should be .2

330 **Impact of weighting**

331 Research question 3 was focused on the impact of weights on both biased (e.g.,
332 misrepresentative) and unbiased sample estimates. Figure 4 provides a broad summary of
333 the results across the eight different attitudinal distribution conditions, presenting the
334 average absolute discrepancy from the population mean for the weighted and unweighted
335 sample estimates. Conditions one through three demonstrate that, on average, the
336 unweighted sample mean provides a good (unbiased) estimate of the population mean when
337 the distributional form does not differ across constituent groups (e.g., the distributions of
338 attitudes are of similar functional forms and locations for all constituent groups). This is
339 regardless of form or extent of nonresponse. Additionally, weighting remediates deviations
340 about the true mean in all five attitudinally discrepant conditions, even when substantive
341 relative error exists in the unweighted estimate (e.g., the rightmost bars in Figure 4).

342 To further elaborate this point, consider, for example, Condition 4 as presented in
343 Table 1. Here, three groups are characterized by similar distributions of attitudes (normally
344 distributed) and one, Females from Department B, is characterized by negatively skewed
345 attitudes. The greatest unweighted error here arises from sampling scenarios in which there
346 are many Department B females (e.g., in our specifications, 6,400) and fewer males and
347 Department A females⁹, but the Department B females exhibit a much lower response rate
348 (e.g., 20%) than do other groups, who respond at a high rate (e.g., 80%). That is, it is not
349 merely response rate, but response rate within these identifiable groups, and whether or
350 not those response rate differences parallel underlying attitudinal differences.

351 Although the *patterns* of unweighted sample mean discrepancies differed across
352 conditions, all eight conditions exhibited similar omnibus effect (weighting ameliorating

⁹ Because of the “marginal” versus “cell” specifications of population constituencies, our most extreme example here is necessarily 400 Department A males, 1,600 Department B males, and 1,600 Department A females. This was a decision based on keeping the population N’s at 10,000 and certainly more extreme population constituency combinations could be examined in future like-minded explorations.

353 error wherever it arose [in the unweighted statistic]).

354 ***Weighting and Sampling Error***

355 Mean square error is our second index for sample quality. It is a well-known
356 mathematical theorem that the application of weights increases (random) errors of
357 precision, which was also empirically true in the current study. For each condition in our
358 simulations, we calculated the standard deviations of 40.96 million unweighted and 40.96
359 million weighted samples means (4,096 possible population-sample combinations by 10,000
360 iterations), which yielded eight empirically-estimated standard errors of unweighted and
361 weighted sample means. Figure 4 visually presents these standard errors in eight pairs of
362 bars, demonstrating that the standard error of weighted sample means (red bar) tended to
363 be 16% to 18% larger than that of unweighted sample means (grey bar) regardless of
364 condition. These errors highlight the caveat that weighting should only be applied in the
365 active nonresponse case (e.g., although the aggregate effect of weighting with passive
366 nonresponse is error-minimizing, any one sampling condition is *more likely* to result in
367 greater deviation from the population parameter when weighting is applied the passive
368 nonresponse data).

369 **Collective roles of response rate, form, and attitudinal distribution**

370 As an aggregate across sampling events, weighting always corrects sample bias,
371 when it is present in the unweighted estimate. However, the standard errors suggest that
372 for any *one* sampling event in the absence of bias, the likelihood that the sample mean
373 approximates the *mean* of sample means is (slightly) greater for the unweighted estimate.
374 When bias is present, however, (in the unweighted estimate) there is obviously no
375 advantage to “being closer” to this biased mean of means. That is, under some
376 circumstances, the mean of unweighted sample means does not center on the population
377 mean. The implications of this seem quite obvious: Weighting should only be applied if
378 bias is anticipated in the sample estimate. This may seem to be a picayune

379 recommendation, but we note here that this advocacy is not heeded in public opinion
380 polling applications, where the computation and application of weights are default
381 procedures (CITES? - perhaps AAPOR standards or personal communication with polling
382 agencies such as Gallop).

383 **Question for David - Can we look at the “crossing point?” (e.g., when**
384 **MSE becomes excessive)**

385 [perhaps David can derive/find a proof to parallel our results?] (Table 1
386 + ResponseRate1 + SDForm2 + Figure 4) Maybe try to combine Figures 2
387 and 3 (put SD on Figure 3 - color code)

388 Added population attitudes (1/20/23) - not sure if this clutters but more
389 consistent with flow of introduction

390

Discussion

391 We view nonresponse as a serious problem that should be addressed via repeated
392 attempts to survey particularly reluctant or hard-to-reach respondents particularly because
393 nonresponse may be reasonably expected to be greatest in groups that are most unsatisfied
394 [e.g., it may be typical for individuals representing these groups to have their responses
395 diluted; see, for example, Taris and Schreurs (2007)]. However, several researchers have
396 noted potentially misplaced relative emphasis on survey response rates, with Cook et al.
397 (2000), Krosnick (1999), and Visser et al. (1996) articulating the point that
398 representativeness of the sample is more important than response rate. We also believe
399 that the goal in organizational surveying should be representativeness not exhaustiveness.
400 Krosnick (1999) specifically comments that, even when probability sampling is employed,
401 response rate does not necessarily implicate either good or poor sample representativeness.
402 One aim of this paper is to reinforce this primary ‘representativeness’ orientation to those
403 who may be otherwise inclined to focus on response rate as a sufficient index of quality

404 (and propose sample weighting as a practice that can potentially remediate
405 *misrepresentativeness*).

406 With the above in mind, we endeavored to answer three fairly straightforward
407 questions: What roles do 1) response rate and 2) form of nonresponse have on population
408 misrepresentation, and 3) what impact does the application of weights have on the quality
409 of sample estimates? The simulations demonstrate that: 1) response rate impact *depends*
410 on relationship between response rate and the underlying distribution of attitudes.
411 conditions 1 through 3 as well as all other conditions are occasionally immune to response
412 rate influence, depending on whether the pattern of nonresponse parallels the pattern of
413 attitudinal distribution differences or not). Active forms of nonresponse can harm the
414 unweighted sample estimate, but only when the pattern of active nonresponse is
415 accompanied by differing distributions of attitudes within the active nonrespondent
416 “populations” [this would appear to be a reasonable expectation based on the literature;
417 e.g., Rogelberg et al. (2000); Rogelberg et al. (2003); Spitzmüller et al. (2007)]. Weighting
418 “always” helps, as long as you capture the proper strata (which of course we were able to
419 do via controlled simulation), but also... Although the weighted mean proved an unbiased
420 estimate of the population mean across all simulations, in circumstances where no bias
421 existed in the unweighted estimate, the trade-off between bias-correction and random error
422 of precision (e.g., standard error) also needs to be acknowledged.

423 It may be noted here that the organizational surveying categorization of passive
424 versus active somewhat parallels the broader statistical focus on data that is missing at
425 random or completely at random (MAR or MCAR, see for example, Heitjan & Basu, 1996)
426 versus data not missing at random (MNAR, see for example, Enders, 2011). Imputation is
427 a common remediation technique for data MAR or MCAR whereas MNAR solutions may
428 involve strategies such as latent variable estimation procedures (Muthén et al., 1987). In
429 the context of organizational surveying, the current findings lead to a similar bifurcation of
430 remediation methods - post-stratification weighting is recommended only in the

431 circumstance of active nonresponse.

432 Previous presentations have noted that bias is sometimes associated with
433 nonresponse and othertimes it is not - this research has not been explicit in the specific
434 conditions that moderate this association, however. The current paper does make this
435 association explicit. It is not merely the form of nonresponse that determines whether or
436 not bias occurs, but also the underlying distributions that the response probabilities are
437 applied to. Some distributional patterns are immune to the biasing effects of active
438 nonresponse (see, for example, Conditions 1 through 3). Some patterns of active
439 nonresponse also result in no bias even when distributional patterns deviate substantially
440 (see, for example, Condition 8 where a 20%, 20%, 80%, 80% response rate pattern exhibits
441 no error). The target therefore should not be merely form of nonresponse but also
442 underlying attitudes. Regardless, however, weighting always remediates the error when it
443 occurs (and does not add error where it is absent).

444 The current findings are of course qualified by the uniqueness of our simulations,
445 most notably our ability to fully capture the correct population parameters (e.g., because
446 these were “created” by us, we were also able to identify these strata as the nonresponse
447 contributors). Even in the extreme conditions (e.g., a small “population” with a
448 correspondingly low response rate; see, for example, the lower-left hand corner of Figure 2),
449 the weighting algorithm was able to provide a bias correction. This is undoubtedly
450 attributable to our random sampling procedure (instead of, for example, sampling
451 conditionally from the population distributions), but here we do note that the raking
452 procedure is applied at the “margins” (e.g., variable level, not interaction level), although
453 our introduction of a biasing element is at the cell (interaction) level.

454 It has been stated that active nonresponse is relatively harmless unless the actively
455 nonrespondent group is relatively large [cites below]. The current study, however, suggests
456 that post-data-collection remediation. There may also be some important implications here

457 regarding sample (and population) size. Because organizational surveyors likely interface
458 with organizations of varying sizes (perhaps some of which are small- or medium-sized), the
459 implications of our simulations particularly in the small population conditions, were
460 highlighted. Findings specific to these conditions were: XXX, XXX, XXX.

461 There is of course no need to restrict weighting protocols to demographic groups -
462 organizational surveyors have a rich tradition of attending to drivers of nonresponse (see,
463 for example, Rogelberg & Stanton, 2007). Groupings of any sort can be the basis of
464 weighting (for example, pre-survey probing might assign probabilities of nonresponse, and
465 these probabilities can be retained post-administration as weighting guides.

466 It should also be pointed out that although the active nonrespondent group seems
467 to be a great concern, it will not seriously bias the results unless the proportion of active
468 nonrespondents is higher than 15% (Rogelberg et al., 2003; Rogelberg & Stanton, 2007;
469 Werner et al., 2007). "In this study we found that the active nonrespondent group was
470 relatively small (approximately 15%), but consistent in size with research conducted by."
471 (Rogelberg et al., 2003, pp. 1110–1111). "Furthermore, consistent with Roth (1994) who
472 stated that when missingness is not random (as we found for active nonrespondents),
473 meaningful bias will only be introduced if the group is relatively large (which was not the
474 case in this study)." (Rogelberg et al., 2003, p. 1112).

475 "If the results show that the active nonrespondent group comprises a low proportion
476 of the population, fewer concerns for bias arise. If the proportion of active respondents is
477 greater than 15% of the group of individuals included in the interviews or focus groups
478 (this has been the average rate in other studies), generalizability may be compromised."
479 (Rogelberg & Stanton, 2007, p. 201) * I believe there is an error here. The author want to
480 say that if the proportion of active nonrespondents is greater than 15% of the group .

481 "It has been suggested that it takes a response rate of 85% to conclude that
482 nonresponse error is not a threat (Dooeyl & Lindner, 2003). We agree that researchers

483 should provide both empirical and theoretical evidence refuting nonresponse bias whenever
484 the response rate is less than 85%." (Werner et al., 2007, p. 293).

485 Note here however, the seeming disconnect between the reports of 15% active
486 nonresponse and declining response rates (trending toward 50%). Certainly with
487 decreasing overall response rates, the likely reasons would appear to be more active than
488 passive (e.g., it is difficult to entertain the idea that potential respondents are more likely
489 to forget to respond today than they were 40 years ago).

490 Integration of IT/IS systems within HR functions hopefully assists the
491 (un)likelihood that organizational population frames are either deficient or
492 contaminated, although we note that this possibility (frame misspecification) is
493 much more plausible within organizations that do not have updated or
494 integrated HR IT/IS systems (perhaps, ironically, *smaller* organizations).

495 **Limitations**

496 The results are presented with at least three limitations: 1) our simulations are
497 comprehensive, iterating through all possible combinations of response rates - those
498 paralleling population distributions, those inversely mirroring population distributions, and
499 those "orthogonal to" population distributions, 2) the "SD" operationalization of passive to
500 active forms of nonresponse is a bit crude and insensitive to specific combinations of
501 response rates expected to manifest or not manifest in bias, and 3) substantial bias may be
502 present in the unweighted estimate even with only small proportions of active non-response
503 (e.g., only one or two groups exhibiting slightly different response rates, with the resulting
504 discrepancy [population versus sample mean] being quite large).

505 **Future Directions**

506 A very practical implication of this study is that future organizational researchers
507 may find more success implementing strategic sampling strategies as opposed to (or in

508 addition to) pursuing response enhancement. That is, as a field, organizational researchers
509 have been focused on response-enhancing strategies that minimize the presence of
510 nonresponse. The current findings suggest that more careful adherence to random sampling
511 from carefully constructed population frames may provide a different route to the same
512 end-goal of sample representativeness.

513 Experimental methods within the psychological discipline have long been criticized
514 for heavy reliance on samples of convenience (for instance, student samples). Very little
515 progress has been made regarding the application of appropriate population sampling
516 procedures in experimentation. Certain non-experimental procedures (most notably
517 organizational surveying) hold paradoxical advantage over experimental procedures
518 primarily in this arena of sampling - particularly in consideration of population coverage,
519 which refers to the percent of a population that is reachable by the sampling procedure
520 (e.g., postal, intra-office, or internet invitation) and likelihood of having access to
521 population parameter estimates (e.g., strata constituencies). There is a rich tradition and
522 literature of public opinion polling procedures and techniques from which to draw. These
523 procedures, however, only hold advantage if the non-experimental methodologist
524 acknowledges the criticality of sample representativeness. The current paper provides one
525 corrective technique (post-stratification weighting) as an important focus for the
526 organizational surveyor who shares this primary interest in maximizing sample
527 representativeness.

528 We note the above “advantage” held by organizational surveyors because extensions
529 of the current protocol include investigating how inaccurate census estimates (and/or
530 grabbing the “wrong” group) affects the quality of sample estimates. That is, in our
531 controlled simulations, we were able to know population constituencies, because they were
532 set by us! In real-world applications, there is likely more error between the population
533 estimate and actual population constituency. Similarly, if the association between attitude
534 and group membership were to be controlled, there may be conditions identified whereby

535 weighting loses its efficacy (e.g., low “correlations” between attitude and group
536 membership). Future simulations should test boundary conditions for this type of error,
537 identifying at what point inaccuracy in the population constituency estimate appreciably
538 degrades the weighting procedure. Furthermore, it was demonstrated here that, when bias
539 exists, weighting corrects it. Weighting also, however, results in a larger mean square error
540 (MSE; expected spread of sample estimates around the population parameter). Feasibly
541 then, there is a point at which the decreased bias is accompanied by an unacceptably
542 inflated MSE. At which point does this occur? This is another fertile area for future
543 exploration.

544 Most potential issues with weighting are addressed through careful consideration of
545 the appropriate strata to take under consideration as well as ultimate level of aggregation
546 (what group constitutes the population of interest or focus of feedback; e.g., regional,
547 functional, or organizational?). We recommend the surveyor especially considers groups
548 that might have issues of active forms of nonresponse and collect those demographics so
549 weighting is an option. It is particularly in these contexts of ‘unsatisfied’ employees being
550 less likely to respond to surveys that pre-stratification consideration becomes critical (for
551 instance, if there is an inclination that attitudes may differ across, for example, night
552 versus day shift workers, it is important that shift be measured and incorporated as a
553 stratum prior to survey administration).

554 For Condition 5 (for example, low/high response rates with minority/majority
555 population constituencies). The lower-right to upper-left diagonal reflects response rates
556 that parallel population constituencies. The patterns across these stressors were consistent,
557 with the weighted sample means (red dots) providing unbiased estimates of the population
558 parameter, whereas the unweighted sample means (grey dots) tended to yield unbiased
559 estimates when the population constituencies were roughly equal (e.g., close to 50%/50%).

560 Figure 3 drills down this information further by extracting unweighted and weighted

561 estimates in one specific marginal population parameter combination (here, 60% males and
562 40% females; 40% in department A and 60% in department B). In doing so, the population
563 parameters were in control and sample parameters were set free (see dotted red rectangle
564 in Figure 2). Therefore, Figure 3 was then arranged in a fashion that allowed further
565 investigation into the interactive effect of marginal sample parameters (gender on the
566 x-axis and department on the y-axis) on the effectiveness of post-stratification weighting
567 reflected by the pattern of grey and red dots. **Huh? - find old version or delete**

568 PRIOR TO RQs: after chatting with Yang (10/31/19) these need to be
569 clarified a bit - reading 11/3 they make sense but need to be read very carefully.
570 Check with Yang on 1/26 Skype. 2/1 revisions seem ok to Kulas. Three moving
571 parts: underlying attitudinal distributions, response rate, and form of
572 nonresponse <- perhaps we should make these variables more explicit prior to
573 the procedure/results...

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Table 1*Attitudinal Distribution Conditions Specified in Current Paper*

Condition	Distributional Shape	mu	Male		Female		Bias Susceptibility
			Dept A	Dept B	Dept A	Dept B	
1	Normal	3	X	X	X	X	Low
	Positive Skew	2					
	Negative Skew	4					
2	Normal	3					Low
	Positive Skew	2	X	X	X	X	
	Negative Skew	4					
3	Normal	3					Low
	Positive Skew	2					
	Negative Skew	4	X	X	X	X	
4	Normal	3	X	X	X		Moderate
	Positive Skew	2					
	Negative Skew	4				X	
5	Normal	3	X	X			Moderate/High
	Positive Skew	2			X	X	
	Negative Skew	4					
6	Normal	3		X	X		Moderate/High
	Positive Skew	2	X				
	Negative Skew	4				X	
7	Normal	3					High
	Positive Skew	2	X		X		
	Negative Skew	4		X		X	
8	Normal	3					High
	Positive Skew	2	X	X			
	Negative Skew	4			X	X	

Table 2

Example Summarized Response Rate Conditions Represented in Figures 2 through 5

Example Response Rates (Any Combination)							Form (and degree) of Nonresponse
Male Dept A	Male Dept B	Female Dept A	Female Dept B	SD Index	Number of Conditions	Form (and degree) of Nonresponse	Passive
36%	36%	36%	36%	.000	256		
36%	36%	42%	42%	.034	128		
48%	48%	54%	54%	.035	64		
42%	42%	49%	49%	.040	192		
48%	48%	56%	56%	.046	128		
56%	56%	64%	64%	.047	64		
54%	54%	63%	63%	.051	128		
63%	63%	72%	72%	.052	64		
36%	42%	42%	49%	.053	64		
42%	48%	49%	56%	.057	128		
49%	56%	56%	64%	.061	64		
48%	54%	56%	63%	.062	128		
56%	63%	64%	72%	.066	128		
36%	36%	48%	48%	.069	128		
64%	72%	72%	81%	.069	64		
42%	42%	56%	56%	.081	128		

Table 2 continued

Example Response Rates (Any Combination)

Male Dept A	Male Dept B	Female Dept A	Female Dept B	SD Index	Number of Conditions	Form (and degree) of Nonresponse
36%	42%	48%	56%	.085	128	
42%	49%	54%	63%	.089	128	
48%	48%	64%	64%	.092	128	
42%	48%	56%	64%	.096	128	
49%	56%	63%	72%	.098	128	
36%	36%	54%	54%	.104	192	
48%	54%	64%	72%	.106	128	
56%	63%	72%	81%	.109	128	
36%	48%	48%	64%	.115	64	
36%	42%	54%	63%	.120	128	
42%	42%	63%	63%	.121	64	
42%	54%	56%	72%	.123	128	
49%	63%	63%	81%	.131	64	
42%	48%	63%	72%	.137	128	
48%	48%	72%	72%	.139	64	
36%	48%	54%	72%	.150	128	

Table 2 continued

Example Response Rates (Any Combination)						
Male Dept A	Male Dept B	Female Dept A	Female Dept B	SD Index	Number of Conditions	Form (and degree) of Nonresponse
48%	54%	72%	81%	.154	128	
54%	54%	81%	81%	.156	64	
42%	54%	63%	81%	.164	128	
36%	54%	54%	81%	.186	64	Active

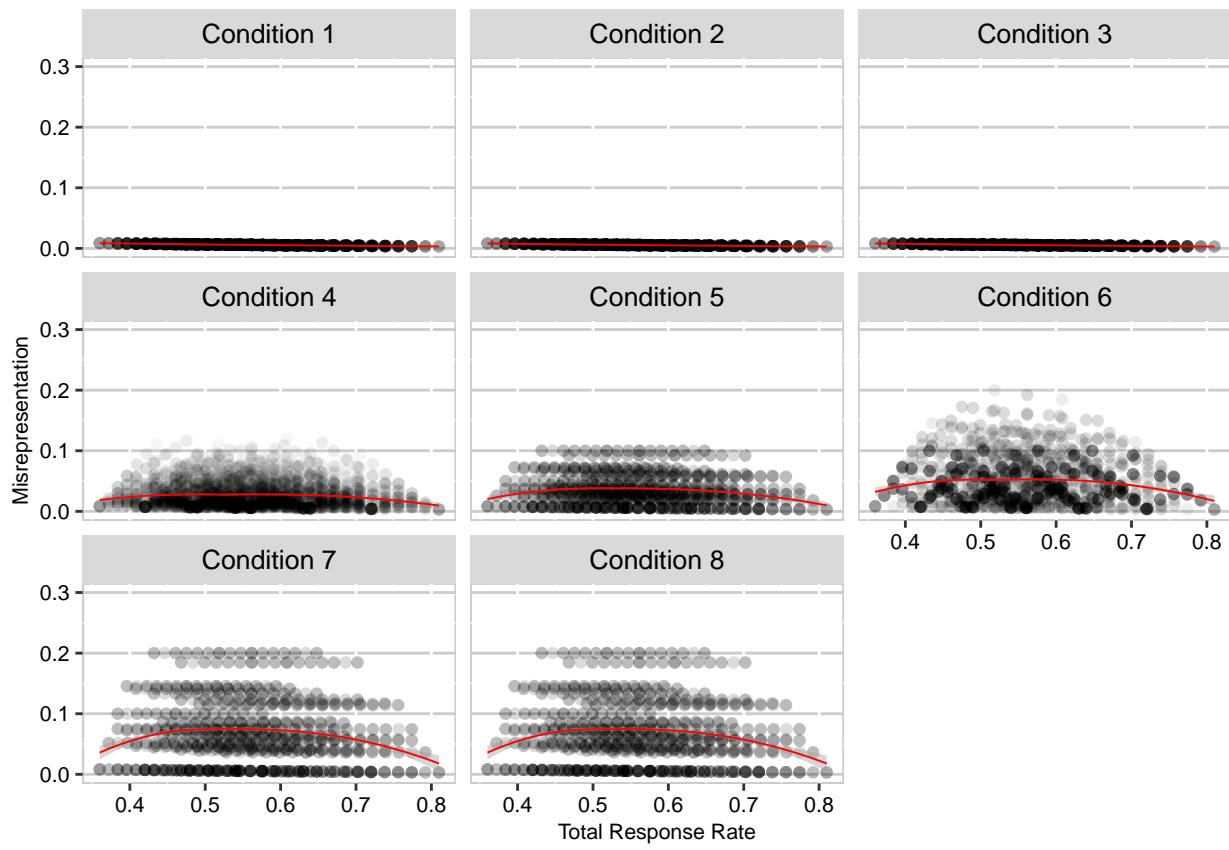


Figure 1

Relationship between total response rate and misrepresentation.

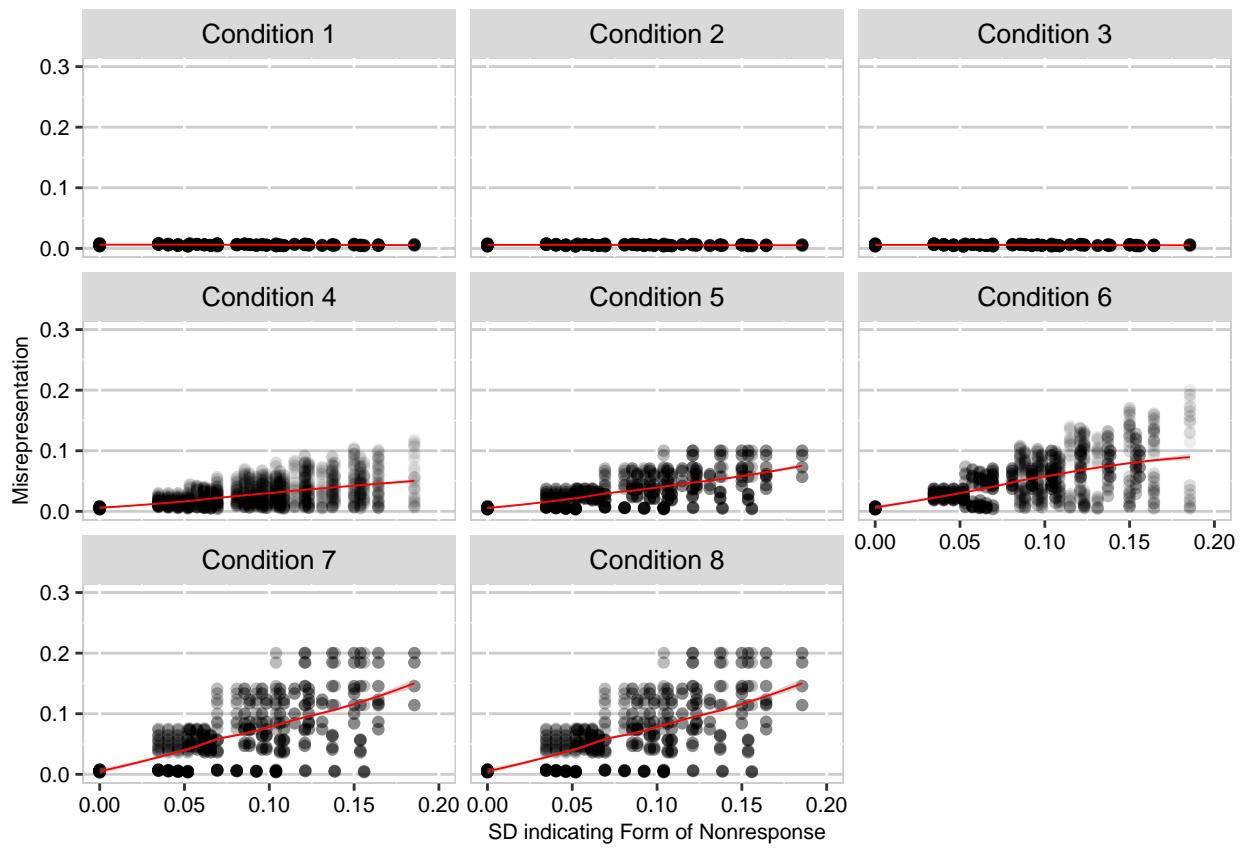


Figure 2

Relationship between nonresponse form and misrepresentation.

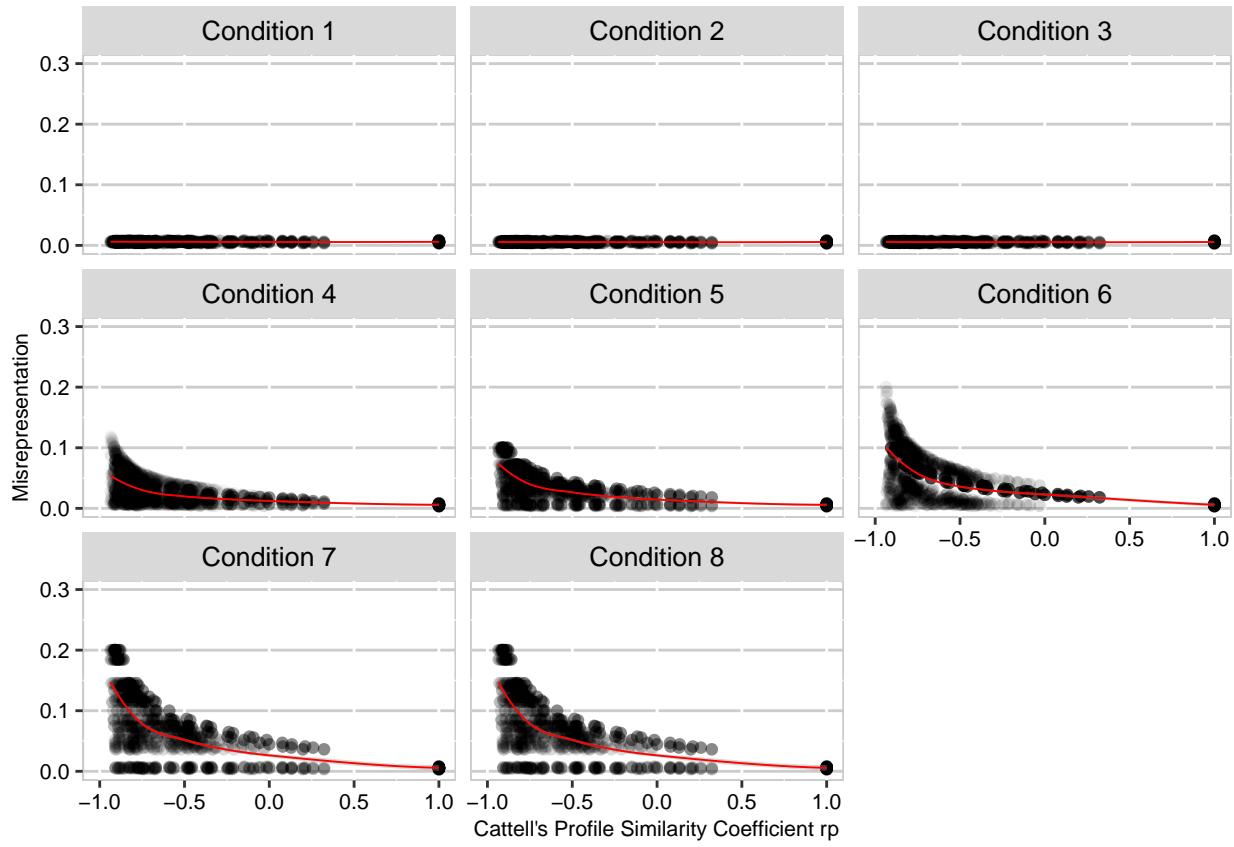


Figure 3

Relationship between sample representativeness and misrepresentation.

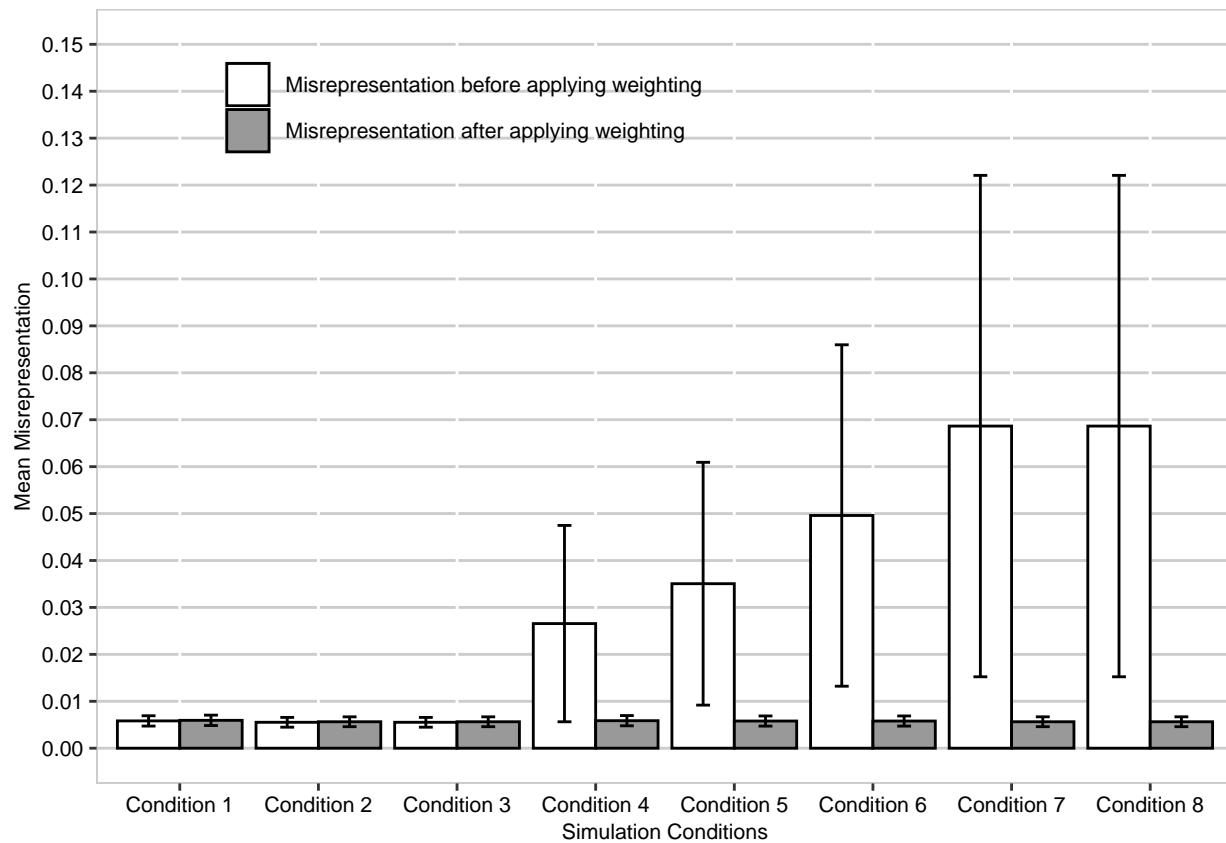


Figure 4

Average absolute discrepancy (unweighted in white and weighted in grey) across the eight attitudinal conditions.