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Comments on "Exploring the assumption that commercial online nonprobability survey respondents are answering in good faith"

J. Michael Brick[1]

Abstract

Nonprobability samples are quick and low-cost and have become popular for some types of survey research. Kennedy, Mercer and Lau examine data quality issues associated with opt-in nonprobability samples frequently used in the United States. They show that the estimates from these samples have serious problems that go beyond representativeness. A total survey error perspective is important for evaluating all types of surveys.

Key Words: Total survey error; Fit-for-use; Fabrication.

Kennedy, Mercer and Lau (KML) make a valuable contribution to our understanding of the quality of estimates from opt-in panels. The clarity of the article is noteworthy since much of the literature associated with opt-in panels is related to selection bias and is so technically sophisticated that it may hinder practitioners from fully appreciating the key assumptions and their implications.

KML's research was intended to examine the accuracy of opt-in estimates for producing domain estimates. The ability to produce estimates for rare domains is a potentially significant benefit of opt-in panels because costs are so much lower for these samples. Most earlier studies had not looked closely at domain estimates. KML's findings reveal disturbing features of opt-in panels that are consistent with existing literature but may not be well-known to many users of opt-in panels. In essence, large fractions of opt-in interviews are of such poor quality that some researchers suggest dropping 15 to 50 percent of all interviews. I can only imagine what Dr. Deming would have thought of this solution to the problem where the supplier hides the "defects" and it is the customer's job to inspect and remove them. The typical Deming approach of working on the process or system to avoid the defects in the first place is not feasible for opt-in panels because the process is a black box that is unavailable to the customer.

Their initial study led KML to develop hypotheses about bogus respondents that could be tested in a smaller follow-up study. The follow-up survey clearly shows that a substantial portion of the respondents in opt-in panels are not credible respondents. Here again, they provide the evidence that users of opt-in panels should not ignore.

Before discussing some of the details, a subtext of KML is that the "assumption" that respondents in opt-in panels behave like respondents in probability samples is just an assumption – and a faulty assumption. For decades, surveys conducted with probability samples have been examined for multiple sources of error using the Total Survey Error (TSE) framework. Does it make sense to ignore this framework just because

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the source of the sample is different? Traditional criteria like coverage and response rates in TSE may not directly apply to opt-in surveys, but many other error sources do.

The most recent American Association of Public Opinion Research report (AAPOR, 2022) on quality metrics reveals the struggle to identify quality online samples is ongoing although progress is limited. Users have little reason to be comfortable with the quality of any opt-in panel. KML only briefly discuss the relative merits of their different opt-in panels. The search for a high-quality opt-in panel is something that many pursued for over a decade, but the evidence thus far suggests this is a chimera.

KML do not attempt a comprehensive review of all sources of error for opt-in surveys, but they clearly show that traditional survey assumptions may not apply to opt-in panels. Speed and low-cost data collection – the main advantages of opt-in panels – should not be the only criteria when deciding on how to conduct a survey. Accuracy of the estimates matters, or at least it should matter! Two important messages in KML are that (1) opt-in panels perform poorly compared to ABS probability-based panels in terms of the accuracy of estimates for domains, and (2) one of the reasons for the poor quality of opt-ins panels is the presence of bogus respondents. Every potential customer of an opt-in panel should understand these facts before deciding whether an opt-in panel is an appropriate source of data.

An opt-in panel could be fit-for-use if all that is needed is a general idea about the size of an estimate ("is it bigger than a breadbox?"). But customers should be very aware that increasing the sample size of the opt-in panel will not improve the accuracy of the estimates because bias does not decrease with sample size. Furthermore, KML show that increasing sample sizes to produce accurate domain estimates is not effective. The presence of bogus respondents adds noise that distorts estimates for domains.

Assumptions

KML show that sampling and selection biases are not the only differences between probability sample surveys and opt-in panel surveys. Let's begin by considering respondents. Two active lines of research on the quality of respondents in opt-in panels focus on concerns regarding professional respondents, or more generally panel conditioning (are opt-in panel respondents conditioned by responding to other surveys?), and validity (are respondents who they say they are?). Hillygus, Jackson and Young (2014) and Baker, Miller, Kachhi, Lange, Wilding-Brown and Tucker (2014) are examples of this work. However, many users act as if opt-in panel respondents are like probability sample respondents. KML show this assumption is unjustified.

Why wouldn't respondents to opt-in panels behave like respondents to probability samples? Perhaps the better question is why would we ever believe they are similar? Opt-in panel respondents choose to join a panel or respond without being asked to respond to a specific survey. The motivations of probability sample respondents and opt-in panel respondents are likely to be very different (Keusch, Batinic and Mayerhofer, 2014). Those who argue that choosing to respond to a panel is like choosing to respond to direct survey request in a probability sample are making a large and unsubstantiated assumption. My unverified assumption is that the act of reaching out and actively requesting a household to join is perhaps the major

quality advantage that probability-based panels have over opt-in panels. Similarly, the literature of panel conditioning from probability samples may not have much relevance to opt-in panels (or probability-based panels) because that literature examines the effects on responses over time to the same general set of questions rather than every survey request being different.

In Table 3.3 KML provide striking evidence of much greater bias in the opt-in panels than the probability-based panels. Suppose we assume a simple measurement error model where the survey response is subject to error but the benchmark is error-free. This model is

$$y_{s,i} = \mu_i + \varepsilon_{s,i},$$

where $y_{s,i}$ is the 0-1 response to having the government benefit for survey s and respondent i, μ_i is the true value for respondent i, and $\varepsilon_{s,i}$ is the error in survey s for respondent i. In this simple case, the measurement error bias is

$$\text{bias}_{\text{me}} = (1-\mu)\gamma_{\text{FP}} - \mu\gamma_{\text{FN}},$$

where μ is the finite population mean of the μ_i, γ_{FP} is the false positive probability, and γ_{FN} is the false negative probability. Table 3.3 shows the opt-in panel absolute biases for the 4 different government benefits range from 1.3 to 5.1 times higher than those for the ABS samples suggesting poor quality for the opt-in panels.

If we assumed $\gamma_{\text{FP}} = \gamma_{\text{FN}}$, we might think these findings are reasonable, but there is a substantial literature on these rates from probability samples that show γ_{FP} is *negligible* compared to γ_{FN}. As a result, Table 3.3 in KML also raises serious questions about the overestimation of benefits for the probability-based samples. Celhay, Meyer, and Mittag (2022) report the SNAP estimates from the Survey of Income and Program Participation (a longitudinal probability sample) has $\gamma_{\text{FN}} = 0.180$ and $\gamma_{\text{FP}} = 0.013$ resulting in an underestimation of SNAP participation. This finding suggests that the assumption that a probability-based panel behaves like a probability sample may not hold. Survey conditions do matter, and we should be wary of importing an assumption from one setting into another without evidence. The data alone do not allow us to assess whether the unexpected overestimation of benefits in the ABS samples is due to a particular cause or some aggregation of causes. More careful studies of probability-based panels are needed.

Bogus respondents

In the follow-up study, KML confirm their hypothesis that Hispanics and young respondents are much more likely to be bogus respondents. They also rightly question whether these respondents are even Hispanic or young since their responses to these items might also be fabricated.

They suggest that the high rate of fabrication in these subgroups might be related to the motivation to opt into the sample since young and Hispanic respondents are needed for many surveys. Bogus respondents might be motivated to state they are members of these subgroups to obtain incentives or other rewards. This

idea seems plausible given the high probability of bogus responses to other "test" items for members of these subgroups.

KML do not discuss bogus respondents in opt-in panels for those who are not members of these subgroups in any depth. But isn't that the implication from the findings that 3.5 percent of those 35 and older are licensed to operate a nuclear submarine? At the least, the user should be aware of the possibility that a high fraction of *all* responses are bogus.

Is the solution to try to find a way to drop these bogus cases? KML do not endorse that solution and show that even if we wanted to do this, there is no simple way to do it effectively. I completely agree with them. If there is adequate motivation, people will find ways to defeat inspection tools. If opt-in panels wish to be accepted as producing high quality results, then they have considerable work to do. KML have done us a service by clarifying what choices in sample sources really entail.

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