Article

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Reducing Nonresponse and Data Linkage Consent Bias in Large-Scale Panel Surveys

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Abstract: Selection bias is an ongoing concern in large-scale panel surveys where the cumulative effects of unit nonresponse increase at each subsequent wave of data collection. A second source of selection bias in panel studies is the inability to link respondents to supplementary administrative records, either because respondents do not consent to link or the matching algorithm fails to locate their administrative records. Both sources of selection bias can affect the validity of conclusions drawn from these data sources. In this article, I discuss recently proposed methods of reducing both sources of selection bias in panel studies, with a special emphasis on reducing selection bias in the US Health and Retirement Study.

Keywords: health and retirement study, post-survey adjustments, questionnaire design, selection bias

1 Introduction

Nearly all surveys are faced with the problem of selection bias. The most well-known source of selection bias in surveys is unit nonresponse. Unit nonresponse occurs when a portion of the originally sampled units, who are otherwise deemed eligible, do not participate in the survey. Typical reasons for nonresponse include refusal and non-contact but may also include the inability to participate due to language barriers or physical or cognitive limitations. Numerous studies have shown that unit nonresponse is a non-random process and that respondents often differ systematically from nonrespondents on characteristics that are measured (and not measured) in the survey (Groves 2006; National Research Council 2013).

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Thus, survey data are at risk of nonresponse bias and inaccurate estimates if the selection mechanism is not sufficiently explained.

In panel surveys, the risk of nonresponse bias is accentuated by compounding nonresponse at each subsequent wave of data collection. The largest effects of nonresponse are typically seen at the initial recruitment wave and these effects become cumulative as initially-willing respondents drop out of the study (or attrit) in later waves. It is thought that the decision to attrit is related to characteristics that are often measured in panel surveys, such as changes in one's health status, changes in employment status, and other significant life events that affect one's likelihood of continued participation in the study. Thus, panel surveys may underestimate changes over the life-course as only those respondents whose life situations are stable enough to continuously participate in the survey are observed. Hence, it is critical that panel surveys explicitly address the problem of nonresponse and attrition to minimize the risk of drawing inaccurate inferences about the target population over time.

Another source of selection that is common in panel surveys is record non-linkage. Large-scale panel surveys often link respondents' survey records to external records, such as administrative records. The Health and Retirement Study, for example, links to multiple administrative data sources including Social Security and Medicare records. Linking survey data to administrative data opens-up innovative research opportunities and allows researchers to answer important research questions that would otherwise be infeasible using survey data alone. Many research committees and organizations have emphasized the importance of increasing administrative data linkages in longitudinal survey research (Davis-Kean et al. 2018; US Commission on Evidence-Based Policymaking 2017). However, not all respondents can be successfully linked to administrative records and this source of selection can potentially distort conclusions drawn from linked-data analyses (Sakshaug and Antoni 2017).

The inability to link respondent records can arise from at least two distinct causes. First, not all respondents consent to linkage. Ethical and legal considerations typically require surveys to obtain consent from respondents before attempting to link their survey data to administrative data. Consent is often requested through an opt-in process where respondents provide an explicit answer to the linkage consent question. Depending on the mode of data collection, respondents may express their answer in the form of a verbal response in a face-to-face or telephone survey, or by ticking a box in the case of an online or mail survey. A signature may also be required as further documentation of the respondent's decision to consent. Sometimes there is a further request for an ID number (e.g. Social Security number) or other personal identifier that facilitates locating the administrative record belonging to the survey respondent. Much has been written about linkage consent rates and the finding that linkage consenters often differ from non-consenters on characteristics observed in the survey and/or administrative data (Sakshaug et al. 2012; Sakshaug and Kreuter 2012; Sala, Burton, and Knies 2012; Jenkins et al. 2006). Thus, linkage non-consent can introduce selection bias in estimates derived from linked survey and administrative data, just as unit nonresponse has the potential to do the same for estimates derived from survey data.

A second cause of non-linkage occurs when a respondent consents to link but the matching algorithm fails to locate a corresponding record in the administrative database. Such a failure can arise due to poor matching variables that are unable to identify a corresponding record pair with a high level of certainty, or because the respondent does not have a corresponding record in the target administrative database. For example, a respondent who recently moved to the US may not have a Social Security record yet. In this case, it is entirely plausible that the matching algorithm fails to identify a matching administrative record. Respondents that are unlikely to belong to the administrative population can sometimes be identified through their survey data, in which case they can be flagged and excluded from the linkage procedure in advance.

Both sources of selection bias – nonresponse and non-linkage – are typically addressed through post-survey weighting adjustments and/or imputations that attempt to compensate for the compositional imbalances caused by these forms of selection. The Health and Retirement Study, for example, produces separate weights adjusting for nonresponse and non-linkage which users are advised to incorporate into their analyses (HRS Staff 2019). Response propensity weighting adjustments are typically based on a selection of auxiliary variables collected during the current-wave and/or prior-waves. Panel surveys have an advantage over cross-sectional surveys in that they have rich background data collected over multiple time points that can be utilized in statistical adjustment procedures. However, such data come with challenges, such as missing data and the fact that once respondents have dropped out of the study their background data become increasingly outdated and less relevant for continually adjusting for their attrition. Thus, a key objective for panel surveys is to maximize the available background information used in selection adjustments, but also continuously search for new sources of auxiliary information that may enhance the effectiveness of their adjustment procedures.

In this article, I discuss a selection of recently proposed methods for reducing selection bias due to unit nonresponse and non-linkage in panel surveys. I conclude the article with a set of recommendations on how these methods could be applied to the Health and Retirement Study. However, the methods and recommendations I discuss are applicable to all panel surveys.

2 Adjusting for Selection Bias

2.1 Nonresponse and Attrition

As previously noted, unit nonresponse and attrition are among the most well-known sources of selection bias in panel surveys. The majority of nonresponse occurs at the initial recruitment wave and increases cumulatively over time as study participants attrit in later waves. The primary concern is that units who stay in the panel become systematically different on key survey variables compared to those who drop-out. Nonresponse is typically addressed through weighting procedures which re-balance the composition of the sample based on auxiliary information. Auxiliary information used in sample-based weighting adjustments (e.g. response propensity weighting) typically consists of prior-wave interview data and prior- or current-wave paradata used to model a unit's likelihood of participation in the current wave. The most effective auxiliary data for weighting adjustments are those which are correlated with the participation outcome as well as the substantive survey variables (Little and Vartivarian 2005).

Panel surveys have the advantage that the substantive survey variables collected in the previous wave are likely to be correlated with the same variables collected in the current wave and are therefore prime candidates to be used in weighting adjustments. However, a drawback is that these variables are only observed until the prior wave (or earlier waves) and do not include more recent information about the study member's situation that may have affected their likelihood of participation in the current wave. Moreover, as the panel continues to mature and respondents who dropped out of the study become further removed from the panel, their previously collected data become outdated and lose their effectiveness as weighting variables for subsequent attrition adjustments. Nevertheless, instead of relying solely on the most recent (i.e. prior-wave) survey data for weighting adjustments, it may be beneficial to consider the full range of variables collected from respondents over the entire life of the panel. The life-course patterns observed over all previous waves of the study may serve as informative auxiliary information for the unobserved patterns of nonrespondents in subsequent waves. However, including all survey variables from all prior waves into a single model that predicts one's likelihood of participation can be challenging, especially in a long-running panel survey such as the Health and Retirement Study.

Data-driven approaches used to identify predictors of nonresponse may lend themselves to the problem of selecting a subset of relevant predictors from all-possible variables collected in a long-running panel survey. One such approach was implemented in the National Child Development Study and the Next Steps cohort study (Mostafa et al. 2021; Silverwood et al. 2020). The basic idea was to identify the most important predictors of nonresponse for a given wave using a multi-stage analytic strategy. In the first stage, univariable regression models of nonresponse were fitted to each predictor variable at wave t. All statistically significant predictors ("stage 1 predictors") were then retained for the second stage. In the second stage, multivariable regression models of nonresponse in the target wave were fitted to all wave t predictor variables. All remaining statistically significant predictors were then retained ("stage 2 predictors"). In the third stage, multiple imputation was applied to all stage 2 predictors to "fill in" the incomplete records for respondents who did not respond in any of the previous waves. After imputation, a series of multivariable regression models of nonresponse in the target wave were fitted to the stage 2 predictors. The stage 2 predictors were cumulatively added into the model, starting with wave 1, followed by wave 2, and so on, to preserve the temporal sequence of the longitudinal information available in the panel. The remaining statistically significant predictors ("stage 3 predictors") can then be used to impute the nonrespondents in the target wave or used as weighting variables to adjust for nonresponse in the target wave. These empirical studies showed that the method reduced nonresponse bias and improved sample representativeness for several respondent characteristics. The method has also been applied to adjust for mode effects in the Next Steps cohort study (Peycheva, Sakshaug, and Calderwood 2021; Sakshaug et al. 2022).

A disadvantage of the approach is that it relies heavily on available survey data collected from wave 1 onward with very limited information available for wave 1 nonrespondents, and no information about between-wave events that may be predictive of nonresponse in the target wave. Further, after a panelist drops out of the study their survey data are likely to become less relevant for attrition adjustment over time.

Another source of auxiliary data that often contains information about between-wave events, and events that occurred after the respondent has left the panel, is administrative data. Administrative data may contain substantive longitudinal information that is correlated with key survey variables. For example, Social Security records may contain information about earnings, periods of employment and unemployment, benefit receipt, among other substantive information that are commonly collected in panel surveys or correlated with panel measures. In principle, this information is collected continuously and can point to between-wave events that may affect one's likelihood of participation in the subsequent wave of a panel study. Moreover, administrative data may be useful for continuously adjusting for attrition long after the study participant has dropped out of the panel.

While administrative data is promising for nonresponse bias adjustment in panel surveys, these data also have drawbacks. For instance, it is not always possible to directly link survey units to administrative data, especially if the units were not sampled from a population register or cannot be linked using a unique identifier. Population registers are commonly used for sample selection in some countries (e.g. the Netherlands), but other countries, such as the United States, do not have high quality registers that cover the general population. In addition, there are ethical issues regarding whether individual-level administrative data should be used for nonresponse adjustment without the consent of the nonresponding units. Lastly, without a unique identifier the linkage would have to be performed indirectly using non-unique and error-prone identifiers (e.g. postal address), which can introduce linkage errors. Some studies have indirectly linked administrative records to survey respondents and nonrespondents for methodological research and report on the quality of these linkages (e.g. Bee, Gathright, and Meyer 2015; Sakshaug, Antoni, and Sauckel 2017). Sakshaug and Antoni (2019) showed that linked administrative data can be used to measure and, in some cases, reduce nonresponse bias in the initial wave of a panel survey. As the administrative data were linked only to paradata of the sampled units and not to their interview data, consent was not required.

Büttner, Sakshaug, and Vicari (2021) proposed an alternative approach to using administrative data for nonresponse bias evaluation and adjustment in panel surveys that makes use of existing linkages for survey respondents. Since many panel surveys link their respondents to administrative records, conditional on consent, there is an opportunity to exploit these linkages and use the linked information as an auxiliary data source to address future nonresponse and attrition. The authors demonstrated the method using the National Educational Panel Study (NEPS) in Germany, which is a piggyback panel survey based on respondents who participated in a previous cross-sectional survey – the “Working and Learning in a Changing World” (ALWA) study. In the cross-sectional survey, respondents were asked for their consent to link their interview data to federal administrative records. Among those who consented and were successfully linked, their administrative data were then carried forward for methodological purposes and used to evaluate and adjust for nonresponse bias in the initial and subsequent waves of the NEPS panel survey. Additional adjustments were applied to address other sources of selection in the cross-sectional survey and linked-data (e.g. unit nonresponse, non-linkage, panel willingness, etc.) that carried over to the NEPS. Thus, the linked sample were only a subset of the eligible NEPS sample, and only representative of the NEPS sample to the extent that all sources of selection leading up to the initial NEPS wave were accounted for.

The linked administrative data were used as a means of estimating nonresponse bias and as weighting variables to adjust for nonresponse bias across the first seven waves of the NEPS survey. The results revealed that several of the linked-administrative variables were correlated with the NEPS survey variables and wave-specific participation. In particular, administrative measures of current- and between-wave events were correlated with wave-specific nonresponse and attrition. The weighting models also achieved a modestly better fit when the linked administrative variables were included, as several administrative covariates were significant predictors of response in multiple waves. There was evidence of reduction in nonresponse bias for some descriptive estimates, indicating some utility of using the linked-administrative data in weighting adjustments.

2.2 Record Non-Linkage

Methods of adjusting for non-linkage bias have received comparatively less attention than adjustment methods for nonresponse bias. In principle, any sample-based nonresponse adjustment method can be used to adjust for non-linkage bias, including the methods outlined above. The most common adjustment method is weighting (Sakshaug 2021; Yang, Fricker, and Eltinge 2019). Weighting adjustments are typically constructed using available survey data and/or paradata, which are fully observed for the linked and non-linked units. All variables collected during the interview may be considered as weighting variables, although in practice only a relatively small subset of variables is selected. Weighting tends to be the simplest adjustment method as it does not require access to the administrative data. Other adjustment approaches apply imputation (or statistical matching) procedures to predict the values of administrative records for non-linked respondents (Gessendorfer et al. 2018; Zhang, Parker, and Schenker 2016). Such approaches require access to the linked administrative data as these data are used as covariate information in the imputation models. Other challenges include constructing an imputation model for administrative variables that do not have standard parametric forms or are highly skewed, as well as the aforementioned issue that some respondents do not have a corresponding administrative record, in which case it may not be useful to impute administrative data for these units.

3 Optimizing Linkage Consent Rates

In addition to post-survey adjustments, the risk of selection bias can be reduced by optimizing the response rate or data linkage rate at the design stage. While much has been written about methods of optimizing response rates in panel surveys, less has been written about methods of optimizing data linkage rates. In this section, I review some methods and design features that have been shown to improve linkage rates. These methods mainly focus on features of the linkage consent question – a key source of non-linkage – which are largely under the control of the survey researcher, including the question's placement, framing, and repeated administration in panel surveys.

3.1 Placement

Where to place the linkage consent question in the questionnaire is a decision that is usually under the control of the researcher. Surveys have traditionally administered the linkage consent question at (or near) the end of the questionnaire. However, experiments have consistently shown that asking for linkage consent earlier in the questionnaire yields higher consent rates in face-to-face, telephone, and online surveys compared to asking at the end, with a corresponding reduction in linkage consent bias (Sakshaug and Vicari 2018; Sakshaug et al. 2019a; Sakshaug, Tutz, and Kreuter 2013; Sala, Knies, and Burton 2014). The optimal placement, in terms of consent rates, tends to be at (or near) the beginning of the questionnaire followed by the middle, with both placements outperforming placement at the end of the questionnaire. Though, placement effects tend to be modest with increases in consent rates ranging between 7 and 16%.

3.2 Framing

The framing or phrasing of the linkage consent question is partially under the control of the researcher. Although the consent question should contain required elements, including the purpose of linkage, potential risks (if any) to the respondent, and data confidentiality assurances, the researcher has some freedom in how they frame the linkage request to respondents. A common framing strategy is to emphasize the benefits of linkage (gain framing), for example, by highlighting the enhanced research opportunities, cost savings, and a shorter, and less burdensome questionnaire that avoids asking explicit questions that can be answered using the linked administrative data. However, gain framing has yielded mixed results in experimental studies. For example, emphasizing the time savings benefit of linkage yielded no overall effect in two telephone surveys (Sakshaug et al. 2019b; Sakshaug, Tutz, and Kreuter 2013), with the exception of "busy" respondents (those who work longer hours and have children) who consented at a higher rate when exposed to the time savings argument (Sakshaug et al. 2019b). In a web survey, Sakshaug and Kreuter (2014) found that the time savings argument led to a higher consent rate compared to a neutral argument. When present, framing effects tend to be modest with increases in consent rates between 4 and 10%.

There is also some evidence that framing the linkage consent question in terms of negative consequences of not linking the respondent's data (loss framing) increases consent rates relative to other framing approaches. In a telephone survey of US registered voters, Kreuter, Sakshaug, and Tourangeau (2016) showed that loss framing (emphasizing that the respondent's interview data will be less useful if they cannot be linked) yielded a 10% higher consent rate than gain framing (emphasizing that the respondent's interview data will be more useful if they can be linked), which is consistent with findings from Prospect Theory which states that people are risk-seeking when faced with choices leading to losses and risk-averse when faced with choices leading to gains (Kahneman and Tversky 1979, 1984).

3.3 Interaction between Placement and Framing

Sakshaug et al. (2019a) examined the interaction between placement and framing on linkage consent in two separate telephone and web surveys. They found that placement was the most influential design feature – administering the linkage consent question at the beginning of the survey yielded between 12 and 16% higher consent rates than at the end of the survey, irrespective of gain/loss framing. Overall, framing had very little effect on the consent rate with one exception. Loss framing yielded a 10% higher consent rate in the web survey, but only when the consent question was administered at the end of the survey. This finding suggested that respondents were more risk-seeking when the consent question mentioned that the answers that they already provided in the survey would be less valuable if they could not be linked, as opposed to at the beginning of the survey when they had not yet provided any answers and had nothing to lose. The fact that this result was found only in the web survey may indicate that the framing treatment was more salient to respondents when presented visually, which is consistent with the other framing studies mentioned above.

3.4 Dependent Linkage Consent

Some panel surveys, including the Health and Retirement Study, periodically repeat the linkage consent request to the same respondents over multiple timepoints. This is carried out to fulfill requirements set forth by the study's ethics review board and/or the administrative data custodian. Linkage consent may need to be requested anew at each subsequent wave of data collection, or only in select waves after a certain period of time has elapsed (e.g. 6 years). Sala, Knies, and Burton (2014) analyzed the impact of reminding respondents of their prior-wave consent decision in the current wave of the UK Household Longitudinal Study's Innovation Panel. They found that this dependent consent strategy produced higher consent rates among those who previously consented to linkage, but lower consent rates among those who did not previously consent to linkage, relative to the standard practice of independently administering the consent question without reminder. Thus, there may be a benefit to reminding respondents of their previous consent decision, but only if they had provided consent.

4 Conclusions and Recommendations

I conclude this article with a list of specific recommendations for the Health and Retirement Study, which can also be applied more generally to other panel surveys.

4.1 Implement Data-Driven Adjustment Approaches to Reduce Selection Bias

The Health and Retirement Study has collected an immense amount of interview data from multiple cohorts over several waves of data collection. These data contain rich information about social, behavioral, and economic patterns that may serve as useful predictors of survey participation and adjustment variables for reducing nonresponse and attrition bias. Data-driven procedures, such as the method by Mostafa et al. (2021) and Silverwood et al. (2020), could be used to identify the most relevant nonresponse adjustment variables from the full HRS database for each cohort in each subsequent wave of data collection. Moreover, the method could be applied retrospectively to all previous waves to update and enhance older adjustments that did not make use of the full range of HRS data. The updated weights could be disseminated as a separate data product to allow researchers to apply a consistent set of weights across all waves of data collection in longitudinal data analyses. Multiply imputed survey data products could also be disseminated as an alternative to weights. Different machine learning approaches should also be considered for addressing nonresponse, as they have shown promise over traditional nonresponse modeling and variable selection methods (Kern, Klausch, and Kreuter 2019; Kern, Weiß, and Kolb in press). I also recommend that these data-driven tools be used in the context of adjusting for non-linkage bias by utilizing the full range of predictor information in the HRS data to compensate for compositional imbalances between the linked and non-linked cases.

4.2 Use Existing Administrative Linkages as a Source of Auxiliary Data for Nonresponse and Attrition Bias Evaluation and Adjustment

The Health and Retirement Study has already conducted many linkages between respondents and their administrative records. Although the primary purpose of these linkages has been to enhance substantive research, they may also be considered for methodological purposes – namely, as a source of auxiliary information for nonresponse and attrition bias evaluation and adjustment. The administrative longitudinal data may contain useful predictors of survey participation, including between-wave events that correlate well with the substantive survey variables. This situation lends itself to the use of these administrative data to correct for wave-specific nonresponse and attrition bias. These data could also be incorporated into the data-driven nonresponse adjustment approach recommended above to enhance the effectiveness of the adjustment.

4.3 Produce Multiply Imputed Administrative Data for the Non-Linked Cases

Related to the first recommendation, I recommend that HRS produce multiply-imputed administrative data for the non-linked units that can be analyzed jointly with the actual administrative data of the linked units. These synthetic data could be released as a separate data product. This would allow researchers to analyze a complete, rectangular dataset with all respondents and a larger sample size than the standard HRS linked-data products. No linkage weights would be needed as the non-linkage adjustments would be built into the imputation procedure. Some attention may be needed to ensure that units which are unlikely to have an eligible record in the target administrative database are excluded from the imputation procedure.

4.4 Ask for Linkage Consent at (or Near) the Beginning of the Interview

One of the most consistent findings in the linkage consent literature is that placing the linkage consent question at (or near) the beginning of the questionnaire produces higher consent rates than asking for consent later in the questionnaire (and especially at the end of the questionnaire). This finding seems to be consistent across self- and interviewer-administered modes. Therefore, I recommend that linkage consent be requested as early as possible in the HRS interview. If linkage consent is sought before the interview takes place (e.g. via advance letter), then linkage consent can be requested at the beginning of the interview only for those respondents who did not previously consent prior to the interview.

4.5 Ask for Linkage Consent again at the End of the Interview for Those Respondents Who Didn't Consent at the Beginning

There is evidence that asking respondents for linkage consent again if they previously denied the request has a positive effect on the consent rate in subsequent waves of data collection as some respondents tend to change their mind as they acquire more experience in the panel survey (Sakshaug and Huber 2016). The same effect may also occur within a single interview if respondents who did not grant the linkage request earlier in the interview reconsider their decision later in the interview. Therefore, I recommend that HRS ask for linkage consent once again towards the end of the interview if the respondent denied the earlier request to confirm whether the respondent is firm with their previous decision or is willing to reconsider after having completed the interview and become more familiar with the study.

4.6 Experiment with Framing the Linkage Consent Question

Although framing effects tend to be modest and mixed across studies, there is evidence that they can improve linkage consent rates, especially in web surveys where the framing treatment is visually salient to respondents. The sparse evidence suggests that gain framing may be more effective when the linkage consent question is administered at (or near) the beginning of the questionnaire and that loss framing may be more effective when the consent question is posed at the end of the questionnaire. Following my previous recommendation of administering the linkage consent question a second time among respondents who denied the first request, my suggested implementation would be to use gain framing when administering the linkage consent question at the beginning of the interview and use loss framing in the final request administered at the end of the interview.

4.7 Implement a Dependent Linkage Consent Strategy for Respondents Who Previously Gave Consent

Experimental research suggests that reminding respondents that they previously consented to linkage in a prior wave of data collection has a positive effect on obtaining consent in the current wave versus not reminding them at all, but reminding respondents who previously denied the linkage request of their decision negatively affects the consent decision. Therefore, I recommend implementing this dependent linkage consent strategy among respondents who previously gave linkage consent and continue administering the standard independent linkage consent question (without reminder) for those respondents who did not give linkage consent previously.

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