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Dealing with nonresponse: Strategies to increase participation and methods for postsurvey adjustments

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Too much nonresponse may devaluate a survey. A survey error is defined as "the deviation of a survey response from its underlying true value" (Biemer, 2010: 817). The authors of this issue develop techniques to increase response rates and devise methods for postsurvey adjustments aimed at reducing biases due to nonresponse.

1. Various forms for nonresponse

Nonresponse takes various forms. A "nonresponse unit" comprises the sampled individuals not responding to a specific survey question. "Wave nonresponse" refers to units not participating in a particular wave of a panel. The presence of nonresponse units damages the representativeness of the panel. The damage is smaller in cross-sectional surveys because respondents are not the same across waves. Attrition results from panel members ceasing to participate in the multiple-wave survey, temporarily or definitely. "Item nonresponse" designates the units' refusal to respond to specific items. With item nonresponse, the unit is recorded in the data set but with at least one variable missing.

These types of nonresponse can affect the quality of the survey separately or jointly and increase the total number of survey errors. If some groups are misrepresented (in a way that is not corrected by applying sampling weights to adjust for unequal probability of selection), and if these groups behave differently with respect to the investigated question, then nonresponse is selective and results are biased.

Nonresponse can stem from the inability to contact potential respondents, from the unit's refusal or lack of cooperation, or from language or technical difficulties. In practice, indicators measuring the representativeness of the collected data help overcome possible nonresponse biases. Postsurvey adjustment techniques can then be implemented to help reduce nonresponse

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biases. Moreover, preventing nonresponse also passes through devising the questionnaire acceptable to the respondents.

2. Methods to increase response rates

Groves, Cialdini, and Couper (1992) modeled factors of survey participation, combining socio-demographic, survey design, and psychological considerations. Survey design includes guidelines for initial contact, persuasion, length and difficulty of the survey, layout, interviewer abilities and attributes in face-to-face and telephone surveys, topic of the survey, and incentives (Dillman, 2007). The best known strategies to increase response rates are incentives and mode of contact.

The use of incentives for increasing response rates is based on the principle of reciprocation. It implies that people are more willing to respond to a survey question when compliance works as a payment of a perceived gift, favor, or concession (Groves et al., 1992: 480). Church (1993) distinguished incentives into monetary and nonmonetary incentives and whether these incentives are granted when presenting the questionnaire or when respondents return the questionnaire. Nonmonetary incentives consist of lotteries, donations, charities, and gifts. Prepaid or unconditional incentives concern all individuals invited to take part in the survey, regardless of whether they complete the survey. Postpaid or conditional incentives are given only to respondents. Church (1993), Singer et al. (1999), and Göritz (2006), from experiments conducted to study the power of incentives to stimulate participation in a survey, showed that prepaid incentives work better than postpaid (hence conditional) incentives and that people are more motivated by money than by any nonmonetary incentive.

In addition to incentives, personal contact increases response rates. Dillman (2007) mentioned that the unit's decision to participate in the survey depends on the total number of contacts, the timing for the first contact, the time interval between successive contacts, the way each contact is done, the personalization of the contact, information on sponsorship, words used, and the visual design. The design should be survey specific.

Monitoring should help identify underrepresented people by adjusting the questionnaire designs during real-time investigation when response rates are too low (responsive design), or before fieldwork by a better knowledge of people's psychology (adaptive design). These so-called "para-data" may be taken from the sampling frame, registers, or during data collecting. Both designs can be group specific; for example, web surveys can be preferred for the young and face-to-face interviews for the older.

3. Methods for postsurvey adjustments

In addition to design, postsurvey adjustment techniques, including imputation and weighting, are devised to reduce nonresponse biases. Imputation methods rely on information available on individuals for other variables than those to impute. Missing values can be replaced by the mean of the variable to impute or by values forecast in a regression by other explanatory variables. Missing values due to attrition can be reduced by extrapolating from previous waves. Deterministic imputation methods tend to underestimate the variances. The introduction of a random component, which increases the variances, has the merit to counterbalance this effect. Different imputation techniques are commonly used to contain the biases introduced by a specific technique.

Nonresponse units are usually too little documented to allow serene adjustment. Poststratification consists of distributing the population into groups using auxiliary common variables such as sex, age, and education so that the auxiliary variables are distributed as in the whole population. This is achieved by dividing the population percentage of a poststratification cell by the sample percentage in that cell and using the ratio as a weight. Kalton and Flores-Cervantes (2003) argue that poststratification weighting is often used when little is known about nonrespondents and auxiliary information is limited. Deming and Stephan (1940) devised estimation by raking, a variant of poststratification. Poststratification relies on the joint distributions of the auxiliary variables, raking on their marginal distributions. Linear regression involves neither joint nor marginal distributions but helps adjust sample estimates to population parameters (Deville and Sarndal, 1992). The estimate from the sample is equated to the population total output. The weights are chosen to fit the population totals and can be viewed as regression coefficients. Adjustment by propensity score (Rosenbaum and Rubin, 1983) is devised to modify the mean values of the auxiliary variables in the sample closer to those estimated from a higher-quality sample of reference. The common procedure is to regress the indicator variable of the sample versus the sample of reference on attitudinal or web-related variables. Inverse propensity scores can be used as weights. The quality of the adjustment depends on the relevance of auxiliary variables to the question under study and to their correlations with the nonresponse biases.

4. In this special issue "Dealing with nonresponse"

Angelo Mazza and Antonio Punzo address omitted answers in a survey on social integration of immigrants in Italy. Social integration can be measured only indirectly. Item response theory is helpful to handle survey data. When omitted responses depend on the latent trait of interest, estimates of the parameters of the variables of interest are biased. A technique for dealing with omitted responses is to model the latent trait as a linear function of the propensity to respond to innocuous questions. The authors have considered the questions related to social integration in the 2008 *Initiatives and Studies on Multi-Ethnicity Foundation* survey. Missing answers are correlated with country of citizenship, religion, level of education, age at the time of migration, duration of stay, intention to migrate, employment status, and to a score measuring social integration. These correlations show that missing data cannot be ignored. The authors then model social integration with a latent regression partial credit model, including the propensity to respond as a covariate.

The purpose of nonresponse adjustment is to reduce nonresponse biases while preserving the precision of the estimate. It must then be built on relevant auxiliary variables. Caroline Vandenplas, Michèle Ernst Stähli, Dominique Joye, and Alexandre Pollien compare two sets of variables for nonresponse adjustment in the *European Social Survey* conducted in Switzerland in 2012. The first set comprises variables from the population register and is commonly used in nonresponse adjustment because respondents and nonrespondents are documented. The correlation with response propensities and survey variables may, however, be low. The second set of variables, coming from a nonresponse survey, should lead to a better correction of nonresponse bias because the variables are designed to be correlated with response propensities. However, this survey among the nonrespondents to questions in the initial survey has itself its nonrespondents, and we must deal with that fact. The authors compare these two sets of variables in the nonresponse adjustment and show that one set of variables is slightly better than the other, in terms of both bias reduction and precision. The authors conclude that variables such as education, political interest, and trust in institution are better auxiliary variables to include in a nonresponse adjustment than socio-demographic variables, especially in the presence of a strong correlation between target and auxiliary variables. However, such data are seldom accessible for nonrespondents.

Annamaria Bianchi and Silvia Biffignandi investigate representativeness in panel surveys. They use indicators together with comparing the distributions of specific variables to those having known distributions in the whole population. They assess the representativeness of the panel after recruitment and after attrition. An auxiliary analysis clarifies the functioning of the panel and the behaviors of panel members. A cumulative analysis clarifies the joint effect of nonresponse due to recruitment and attrition. The authors apply their method to *Understanding Society*, a U.K. household longitudinal study. They demonstrate that representativeness changes mostly in the first waves of the panel and that all variables retained contribute statistically significantly to the lack of representativeness. At each wave, they identify under- or overrepresented groups. They use their techniques to improve survey designs and procedures in reducing nonresponse biases. For example, they recommend contacting young people through their favorite communication channels rather than through the usual ones, and to follow up more closely.

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