Nonresponsive Rates and Nonresponse Adjustments in Survey Methodology*

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The editorial presents the virtual issue of Nonresponse Rates and Nonresponse Adjustments in the Journal of Survey Statistics and Methodology. It presents a summary of significant articles published in the journal that explore the issues of response rate loss over varying survey modes and methodological solutions for correcting nonresponse bias. A significant problem that is brought out is the requirement for robust auxiliary variables that one can use to simulate nonresponse propensity and perform post-survey corrections. The topic of building better nonresponse propensity models using theory-driven auxiliary variables will be my focus of discussion.

The editorial stresses that high response rates do not mean the absence of nonresponse bias; however, low response rates remain a problem as they may indicate systematic differences between respondents and non-respondents (Groves & Peytcheva2008). Even though modifications in data collection measures can positively influence response rates, but still need to eliminate possible bias. In this context, models capable of predicting a person's likelihood to respond, utilizing accessible supplementary data, can serve multiple functions. They permit assessment of the degree of nonresponse bias, targeting of non-respondents during data collection, and post-survey nonresponse weighting adjustments (Kalton & Flores-Cervantes2003; Wagner et al2014). Nevertheless, it is still challenging to uniquely identify auxiliary variables that strongly predict both the propensity to respond and the critical survey variables.

The papers by Wagner et al. (2014) and Amaya and Harring (2017) show some difficulties in constructing good nonresponse propensity models in practice. Wagner et al. (2014) studied the explanatory capacity of data variables concerning survey effort, for instance, the number of contact attempts or interviewer observations. Although the data variables are highly predictive

*Code and data are available at: https://github.com/yetaoguo/miniessay5.git of the propensity to respond, modeling based on these variables alone does not reduce the non-response bias shown by important survey results. This implies that the variables were poorly correlated with the survey variables. However, Amaya and Harring (2017) looked at social integration measures, assuming that individuals with more socially integrated lives would have higher response rates. Their research confirmed that several factors like religious service attendance and voting behaviour, reflected response propensities. However, models using only these variables can only reduce the bias in volunteering estimates to a limited extent.

In their work, Ytchev, Presser, and Zhang (2018) offer a more practical approach to using theoretical variables in their performance analysis. In particular, their study focused on the relationship between volunteering and voting behavior, as well as other social indicators of both propensities to respond and various attitudinal and behavioral variables routinely measured in surveys. Research revealed that volunteering and voting are among the best auxiliary predictors of survey participation. More importantly, these variables also form a bond with various survey outcomes. This implies their possibility for nonresponse bias evaluation and correction. The authors further demonstrate that response propensity models with volunteering and voting variables produce more effective post-survey weighting corrections to reduce non-response bias than standard weighting methods.

These investigations emphasize the role of auxiliary variables that predict propensity to respond and relevant survey variables of interest. It satisfies both parts and permits more accurate diagnostics concerning potential nonresponse bias and modifications related to weighting adjustments (Little & Vartivarian, 2005). Similarly, establishing and verifying such auxiliary variables is a challenging task in this kind of research; this task mostly requires theorization of the survey topic, the targeted population, and the response process.

Peytchev et al. (2018) offer a practical illustration of using social science theory applications to choose auxiliary variables that may comply with the dual criteria. In their strategy, it was critical to find attitudes and behavioral patterns tied to civic participation and topics often addressed in surveys. Blending theory about the response mechanism and survey outcomes delivered auxiliary variables suitable for nonresponse diagnostics and adjustment.

As Peytchev et al. (2018) note, the fact that the researchers ask questions about past voting and volunteering behavior within surveys, to facilitate the production of auxiliary variables with valuable data. As they point out, such behaviors are over-reported in surveys. The propensity would not reduce the usefulness of the nonresponse model because associated measurement errors would work the same across respondents. This is because such theory-guided supplementary variable collection could boost the process of assessing and adjusting for nonresponses in major social surveys.

In conclusion, it is both important and difficult to develop models for diagnosing and changing nonresponse bias, which requires keeping auxiliary variables that strongly predict survey propensities and critical outcomes. The articles demonstrate the potential gains offered by using such social science theory to steer the selection and measurement of auxiliary variables if it is used for such dual ends. In practice across a wide range of surveys, this theory-orientated approach can significantly enhance non-response tendency modeling and calibration.

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