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## Accounting for non-response bias using participation incentives and survey design: An application using gift vouchers



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#### HIGHLIGHTS

- Standard missing data approaches like imputation assume that data are missing at random (MAR).
- There are many contexts in which this MAR assumption is implausible.
- Heckman-type selection models can be used to test for MAR.
- Robustness to alternative selection variables and dependence structures strengthens the credibility of results.
- Randomized incentives or survey interventions provide ideal selection variables.

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#### ABSTRACT

Standard corrections for missing data rely on the strong and generally untestable assumption of missing at random. Heckman-type selection models relax this assumption, but have been criticized because they typically require a selection variable which predicts non-response but not the outcome of interest, and can impose bivariate normality. In this paper we illustrate an application using a copula methodology which does not rely on bivariate normality. We implement this approach in data on HIV testing at a demographic surveillance site in rural South Africa which are affected by non-response. Randomized incentives are the ideal selection variable, particularly when implemented ex ante to deal with potential missing data. However, elements of survey design may also provide a credible method of correcting for nonresponse bias ex post. For example, although not explicitly randomized, allocation of food gift youchers during our survey was plausibly exogenous and substantially raised participation, as did effective survey interviewers. Based on models with receipt of a voucher and interviewer identity as selection variables, our results imply that 37% of women in the population under study are HIV positive, compared to imputation-based estimates of 28%. For men, confidence intervals are too wide to reject the absence of non-response bias. Consistent results obtained when comparing different selection variables and error structures strengthen these conclusions. Our application illustrates the feasibility of the selection model approach when combined with survey metadata.

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#### 1. Introduction

Because of the implications for estimation, adjusting for missing data is an important component of program evaluation. Missingness can arise in various contexts including attrition in panel surveys (Thomas et al., 2001), mortality (Attanasio and Hoynes, 2000), and declining to answer particular survey questions or participate in auxiliary health or biomarker modules (Lillard et al., 1986).

\* Correspondence to: Queen's Management School, Riddel Hall, 185 Stranmillis Road, Belfast BT95EE, Northern Ireland, United Kingdom. Adjustments are especially problematic because by definition we do not observe outcomes for non-respondents, so missing data mechanisms are generally not directly testable (Nicoletti, 2006). This has contributed to a reliance on methods which assume missing at random (MAR), often conditional on observables. These approaches include imputation (Conniffe and O'Neill, 2011), and inverse-probability weighting (Wooldridge, 2007). However, there are many contexts in which MAR may not be realistic.

Alternative selection model approaches (Heckman, 1979), simultaneously specify participation alongside the outcome without requiring MAR. However, Heckman-type selection models

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have been criticized because alternative assumptions are necessary (Vytlacil, 2002). First, in practice an exclusion restriction is required, a variable which predicts participation but not the outcome. Plausible selection variables can be elusive (Madden, 2008), but model performance depends on their validity (Leung and Yu, 1996). Second, they can require parametric assumptions. The original formulation specified the joint distribution of the error terms in participation and outcome equations as bivariate normal. Extensions incorporate binary outcomes (Van de Ven and Van Praag, 1981) and semiparametric and nonparametric variants (Ahn and Powell, 1993; Das et al., 2003; Gallant and Nychka, 1987; Newey et al., 1990). The latter have larger data requirements and are less efficient than their parametric counterparts. Moreover, the intercept is often the quantity of interest (Heckman, 1990), and estimating the intercept in semiparametric or nonparametric selection models generally focuses on continuous outcomes and requires additional identification at infinity assumptions (Andrews and Schafgans, 1998; Schafgans and Zinde-Walsh, 2002). Reduced information inherent in binary (relative to continuous) data precludes estimation of the intercept without parametric restrictions (Klein et al., 2015).

Therefore, there is a trade-off between two sets of assumptions when attempting corrections for non-response. Lacking viable selection variables, it is understandable that researchers would proceed on the basis of MAR, even if objectively implausible. Alternative bounding approaches can be useful for avoiding this trade-off (Behaghel et al., 2015; Lee, 2009; Manski, 1990), but may not be informative when rates of non-response are high, resulting in too wide a range of possible estimates. Improving the methodology for implementing selection models therefore provides opportunities to avoid having to assume MAR.

Although well known that (quasi) experimental manipulation can solve for endogenous sorting into treatment groups, (quasi) experiments can also be used for dealing with non-response. Survey design affects participation (Hirano et al., 2001; Hill and Willis, 2001), and these findings have informed methods to reduce measurement error (Gibson et al., 2015). The resulting impact on participation has also been used to adjust for non-response bias, as these features of survey design can be used as selection variables in a Heckman-type framework. For example, Bhattacharya and Isen (2008) use a \$5 gift certificate randomized to a subset of student respondents to adjust for non-response in a survey on willingness to pay for health care. Bailey (2017) examines sample selection in political surveys by randomly allocating some participants to a condition in which the political questions are asked after those on another topic. Interviewer identity is another selection variable which has been used to adjust for panel attrition (Van den Berg et al., 2007) and missing data in biomarker data (Reniers et al., 2009; Tchetgen and Wirth, 2017).

The ideal selection variable in this context is a randomized incentive or survey intervention because it is guaranteed to be unrelated to the outcome (in expectation) other than through any effect on participation. Because this approach is relatively rare, there are not many opportunities to leverage randomization to correct for missing data. However, there may be elements of survey design which are as good as random in some survey contexts ad therefore provide credible selection variables enabling this approach to be adopted more widely.

The contribution of this paper is to apply this methodology to data on HIV testing from demographic surveillance in South Africa, comparing standard approaches which assume MAR to selection model estimates. We adopt the copula-based framework developed in Marra et al. (2017) which allows flexible specification of unobserved dependence using various distributional forms. We build on this analysis by illustrating an application using two selection variables based on survey design; a food gift voucher

and interviewer identity, which although not randomized, are plausibly exogenous in this survey context. We argue that showing results are robust to alternative exclusion restrictions and different distributional assumptions, as this framework allows, strengthens the conclusions from selection models.

#### 2. Non-response in HIV research

Non-response is particularly concerning when there is an incentive not to participate. For example, people who are HIV positive may systematically opt out of testing because they fear disclosure of their status (Obare, 2010). However, accurate estimates of HIV prevalence are important because they provide information about the spread of the epidemic (Beyrer et al., 1999) and facilitate intervention evaluation (Baird et al., 2010).

Nationally representative household surveys and surveillance sites routinely include blood tests, and resulting prevalence estimates are considered the gold standard (Boerma et al., 2003). However, in some contexts less than half of eligible respondents participate (Larmarange et al., 2015). Trials are also affected; of 57 RCTs conducted before 2012 with HIV status outcomes, missing data ranged from 3% to 97% (mean 26%), with no study reporting their assumptions for managing non-response (Harel et al., 2012). Given the potential for HIV positive individuals to be systematically less likely to participate (Arpino et al., 2014), imposing an incorrect MAR assumption could result in substantial bias.

## 3. Participation incentives and survey design as selection variables

The Africa Health Research Institute (AHRI) cohort is a continuous survey of residents of a rural area in KwaZulu-Natal, South Africa. The main survey and HIV surveillance have provided valuable information on the epidemic for over a decade. Table 1 demonstrates that 45% of women participated in testing in 2010; compared to 33% of men. HIV prevalence among these participants was found to be 27% (women) and 16% (men). Potential implications of non-response are clear from nonparametric bounds, which, in this case, are too wide to be informative. In this paper we use the terms participation and consent to test interchangeably as relatively few individuals decline to participate in the survey (before consent to test for HIV is sought), but in other contexts they may need to be considered separately. Further information about the survey and cohort are presented in the supplementary material.

To increase participation, a gift voucher intervention was conducted in 2010. During the last 10 weeks of the surveillance, interviewers presented potential respondents with a food voucher worth 50 South African Rand to the first person they met in each household. 7% of those contacted in 2010 received a voucher, which was not conditional on consent. While not randomized, the intervention reflected concern among management about low participation in the first half of the surveillance, and apart from the timing, was not otherwise targeted. Previous evaluation found the gift voucher successfully raised participation by 25 percentage points (PP) (McGovern et al., 2016). Almost all those who received the voucher were living in households that were contacted in October or November. Once month of interview is controlled for, there is little evidence that the characteristics of those who received the voucher differ from those who did not receive the voucher (as shown Table A3 in the supplementary material). A joint test of covariates other than month yields an F statistic of 0.80, p = 0.88. Although this does not conclusively rule out a role for unobserved factors, and results should be interpreted with this in mind, it does provide some support for the hypothesis that the gift voucher was as good as randomly distributed (conditional on the timing of the interview). Given this, we use gift voucher receipt as a Download English Version:

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