The Anchoring Method: Estimation of Interviewer Effects in the Absence of Interpenetrated Sample Assignment

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Interviewer Effects

- Despite efforts to train interviewers in standardized interviewing methods, numerous researchers have shown that estimates of key population parameters tend to vary between interviewers (Rice, 1929; Hanson and Marks 1958; Groves and Magilavy 1986; Mangione et al. 1992).
- Interviewers affect survey responses for both telephone and face-to-face surveys.
  - Verbal or nonverbal signals from the interviewer (West and Blom 2017).
  - Demographic features of the interviewer –> interviewer preferences and expectations.
  - Interviewer behavior and skills.
- Effect can be quite strong on sensitive or attitudinal questions (Kish 1962; Schnell and Kreuter 2005).

Interviewer Effects: History of Research

- Assuming random assignment of interviewers to respondents (interpenetration), $deff \approx 1 + (\overline{m} - 1)\rho$, where $\overline{m}$ is the mean number of interviewers conducted by an interviewer and ρ is the within-interviewer correlation for a given question.
  - Effect can be important: $\overline{m} = 35$ and $\rho = .03$ can double the variance of the estimate of a mean.
- Interviewer assignments are rarely randomized, and thus interpenetration can rarely be assumed.
- Von Sanden and Steel (2008) assume interpenetration for a random subset of PSUs, and a single interviewer in each of the remaining PSUs.
- Not relevant for our more general setting of interest
  - Interviewers cross PSUs
  - Interviewers do not work random subsamples of the full sample (no interpenetration).

Interviewer Effects: History of Research

- Alternative approach to approximate interpenetrated design: adjustment for the effects of area-level covariates in multilevel models (Hox, 1994; Schaeffer et al., 2010; West, Kreuter, and Jaenichen, 2013).
  - Assumes area-level covariates adequately account for all sources of variance in measurement that arise from the areas and would be attributed to the interviewers if the covariates were not accounted for.
  - Such covariates might not be available.
  - Conditions on these area-level covariates; these conditional estimators are typically not of interest.
  - Conditional/adjustment variables of interest might not be related to key sources of spurious additional coverage.

Lack of Interpenetration

- If cases with correlated values on a variable of interest are assigned to interviewers in a non-random fashion, we are just re-ordering the random sample given agents of the data collection process.
  - Two telephone interviewers work shifts such that one only interviewed 50 persons 65 or older and one interviewed 150 persons under 65 purely based on scheduling issues. Treating the interviewers as clusters would suggest that an indicator for 65-plus years of age would have an effective sample size of two, in contrast to the correct sample size of 200, assuming a simple random sample.
- Treating interviewer assignment as random in this setting will overestimate the interviewer variance and lead to overly conservative inference.
- Cannot correctly estimate which components of variance are due to sampling variability, true measurement error introduced by the interviewers, or differential non-response among the interviewers.

Anchoring Method

- Identify an ancillary variable ("anchor") that
  1. is unlikely to be subject to interviewer effects in measurement; and
  2. is correlated with a key survey variable of interest that may be subject to interviewer effects.
- Fit a model allowing the two variables to have correlated residuals, and include random interviewer effects <u>only</u> for the survey variable believed to be subject to them.
  - Removes the within-interviewer correlation due to non-random assignment, leaving a "clean" estimate of the between-interviewer variance

Anchoring Method: Model

- Consider a simple bivariate case, Y_1 assumed to be without measurement error, Y_2 possibly having measurement error.

$$y_{ijk} = \mu_k + I(k = 2)b_i + \varepsilon_{ijk}$$

$$b_i \sim N(0, \sigma_b^2),\ \varepsilon_{ijk} \sim N(0, \sigma_k^2),\ cov(\varepsilon_{ij1}, \varepsilon_{ij2}) = \sigma_{12}$$

  where $i = \{1, ..., I\}$ indexes interviewers, $j = \{1, ..., J_i\}$ indexes respondents within interviewers, $k = \{1, 2\}$ indexes the variable.

- Standard linear mixed model software can be used to obtain a REML point estimate of μ_2, along with an estimated variance component.
- High correlation between the residuals will lead to a more accurate estimate of the variance component.

Anchoring Method: Estimation

- Can fit using restricted maximum likelihood with standard mixed model software.
- Alternatively can fit using Bayesian prior, either weakly informative without prior data to inform their construction, or informative priors if previous data collection is available (West et al. 2020).
  - Helpful when variance components are small, since posterior draws of variance components are constrained to be positive, while frequentist model-fitting procedures generally fix such variance components to be zero (West and Elliott 2014).
- Key assumption is that selected variables are free from interviewer-induced error.
  - Like the “missing at random” assumption in the missing data literature, may need to rely on close approximations such as simple demographic measures or other factual questions with simple response options (e.g., age, current employment) with little room for the introduction of interviewer error.

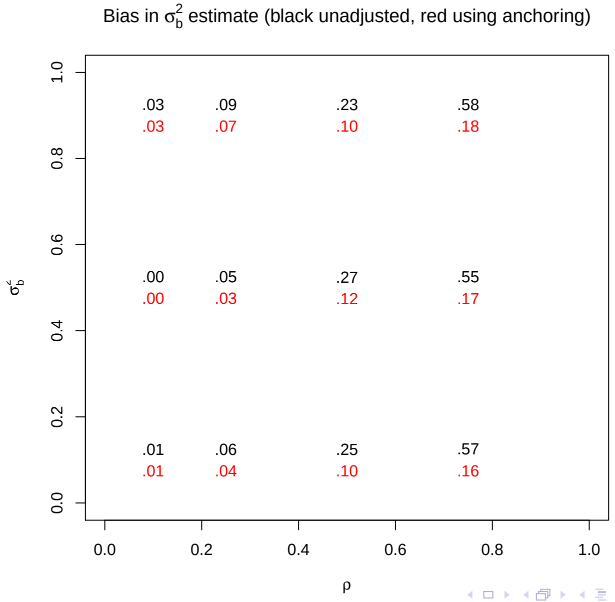
Simulation Study

- Generate data from a trivariate distribution

$$\left(\begin{array}{ccc} Y^*_{1ij} & Y^*_{2ij} & Z_{ij} \end{array} \right)^T \sim N_3\left(\mu, \Sigma\right)$$

  where $j = 1, ..., J = 30$ indexes hypothetical respondents nested within $i = 1, ..., I = 30$ interviewers.
- $Y_{kij(z)} = Y^*_{kij(z)} + I(k = 2)b_i$, $b_i \sim N(0, \sigma^2_b)$ where $Y^*_{kij(z)}$ is ordered by the values of Z_{ij}.
- Y_1=age (anchoring variable), Y_2=self-reported overall health measure (prone to interviewer effects), Z=amount of time spent at home (associated with interviewer scheduling).
- Higher correlation of Z with the other variables introduces “counterfit” interviewer variance before interviewer effects on Y_2 are taken into account.
- Assume for simplicity $\mu_{Y_1} = \mu_{Y_2} = \mu_Z = \mu$, $\sigma^2_{Y_1} = \sigma^2_{Y_2} = \sigma^2_Z = 1$, and $\rho_{Y_1 Y_2} = \rho_{Y_1 Z} = \rho_{Y_2 Z} = \rho$.

Simulation Study



Simulation Study

- Correlation between the no measurement error variable Y_1 and the interviewer measurement error variable Y_2 can be used to reduce bias in estimation of measurement error and thus intra-class correlation coefficient.
- The stronger this correlation and the less measurement error, the more effective the proposed methods are.

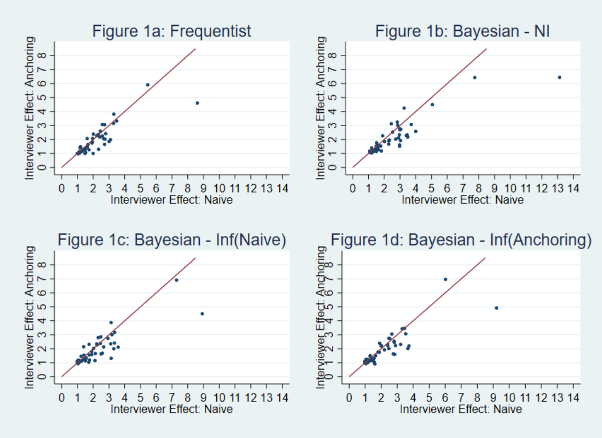
Anchoring Illustration

- Use data from the 2012 BRFSS (473K telephone interviews in all 50 US states).
- Variable of interest is perceived health status (1 = poor,...,5 = excellent).
- Assume that the measurement error free variable is age
  - More likely to be reported without differential measurement error (?)
  - Associated with interviewer assignment: interviewers tend to work shifts at different times of the day, and interview time of day is associated with age.
  - Associated with health status.

Anchoring Illustration

- We compute the interviewer effect for mean health status in each of the 50 states and District of Columbia assuming
  - Interpenetration ("naive").
  - Anchoring using REML mixed effect model ("frequentist").
  - Anchoring using Bayesian model
    - using non-informative priors
    - using half$-t$ with 3 df (Gelman 2006) and SD defined by estimated SD of 2011 interviewer random effect using naive estimator.
    - using half$-t$ with 3 df and SD defined by estimated SD of 2011 interviewer random effect using anchoring estimator.

Anchoring Illustration



- Anchoring tends to reduce estimates of the interviewer effects: 63% to 78% of states reduced in the estimated interviewer effects depending on the estimation approach used.
- In some cases anchoring increased estimated interviewer effects: predominantly cases where effects were very small.

Discussion

- We have developed and evaluated a new method – “anchoring” – for estimating interviewer effects in the absence of interpenetrated assignment of sampled units to interviewers.
- Via simulation and application we have demonstrated the ability of the proposed method to improve estimates of interviewer effects in the absence of interpenetrated
- Can also easily be applied in a Bayesian framework, leveraging prior information to improve the quality odf inferences related to interviewer components of variance.
- In interviewer-administered survey data collections, interviewer effects should generally be monitored to prevent excessive problems with interviewer variance
  - Survey managers responsible for this type of monitoring will likely benefit from the easy-to-use anchoring method, improving any real-time intervention decisions made for individual interviewers.

Alternatives and Extensions

- Extend to $K \geq 2$ "anchoring" variables.
  - Now only require high correlation with linear combination of $Y_1, .., Y_K$ and Y_{K+1}.
- Extend to estimate of regression model parameters.
- Extend to dichotomous outcomes by use of probit random effect models or arbitrary distributions by use a Gaussian random effects copula model (Wu and de Leon, 2014).
- Factual and self-administered items have been found to show variation across interviewers as well (O'Muircheartaigh and Campanelli 1998). How can we verify this key assumption?