Disentangling Longitudinal Treatment Effects by Regimes: A Comparison of Selection Bias Adjustment Approaches

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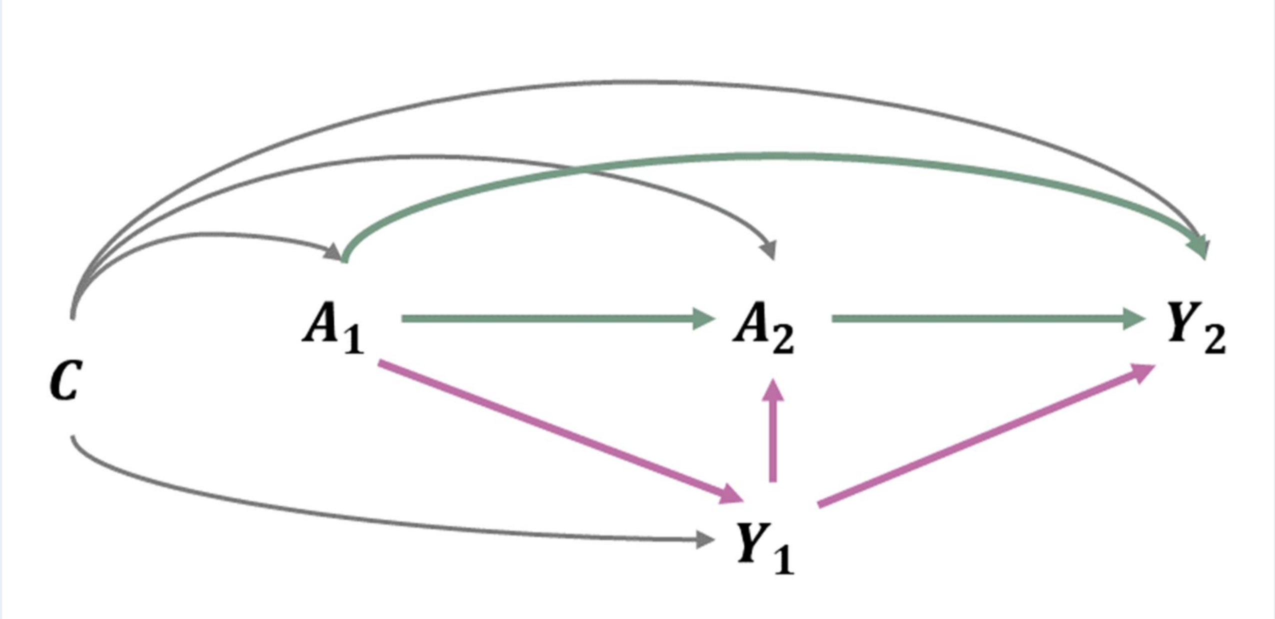
1. Study Design and Research Questions

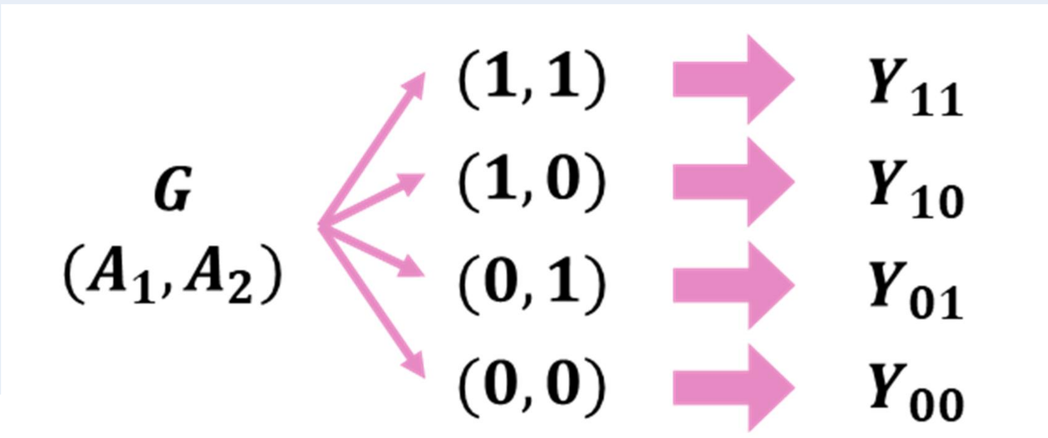
- Multiple treatment regimes occur from longitudinal treatments implemented at multiple time points.
- Contrasting specific regimes, we can determine the effectiveness of competing implementation strategies and explain treatment effect heterogeneity over time.



- *e.g.*, Children's vocabulary skills (Y_2) after staying in the Head Start program ($(A_1, A_2) = (1,1)$), combining Head Start with other childcare services ($(A_1, A_2) = (1,0)$ or $(0,1)$), or never attending Head Start ($(A_1, A_2) = (0,0)$) for two years
- For valid comparison, we need to adjust for baseline covariates (C) and intermediate vocabulary skills (Y_1)

2. Adjusting for Selection Bias in Multiple Treatments

- First, we conceptualize all possible patterns of treatment participation as categories of a multiple treatment (Imbens, 2000).
- *e.g.*, Head Start as a four-category treatment



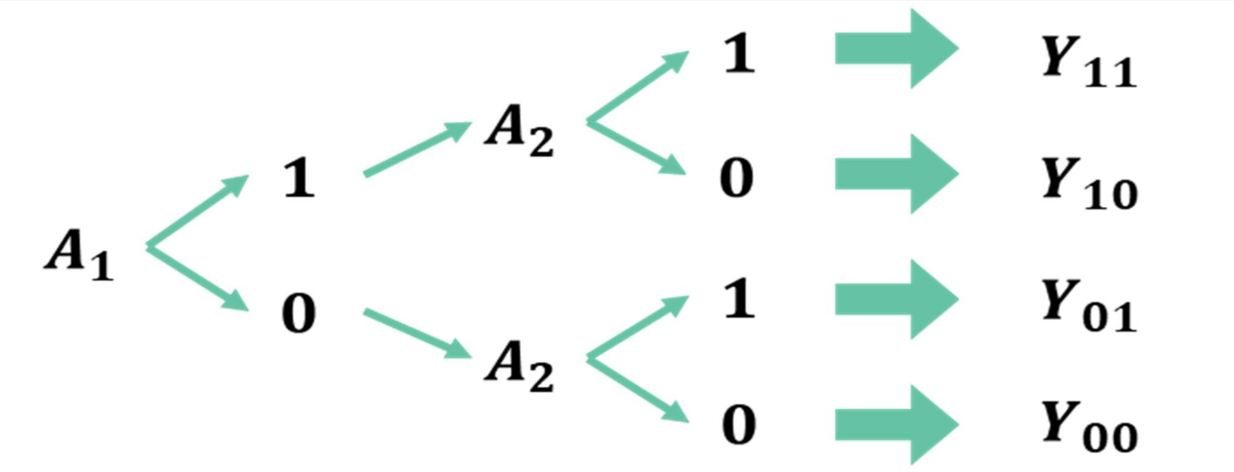
- Generalized propensity scores (GPS)

$$P(G_i = g|C) = \frac{\exp(\beta_{0g} + \beta_{1g}X')}{1 + \sum_{g=1}^{G-1} \exp(\beta_{0g} + \beta_{1g}X')}$$

- Weights computed by entropy balancing (Hainmueller, 2012)
- $E[Y_2|G = g, C = c] = \theta_0 + \theta_1 g + \theta_2 c' + \theta_3 g * c'$
- $\hat{\delta}_{ATE}^{WLS}(g_T - g_C) = \frac{1}{N}\sum_{i=1}^{N}\{\hat{E}_w[Y_2|g_T, c] - \hat{E}_w[Y_2|g_C, c]\}$
- HC3 standard errors computed for the contrasts

3. Adjusting for Selection Bias in Sequential Treatment Regimes

- On the other hand, we consider a sequence of treatments at successive time points.



- *e.g.*, Head Start as a sequence of binary treatments
- Multiplicative inverse probability of treatment weights are produced, and potential outcomes are estimated for different sequences of treatment participation.

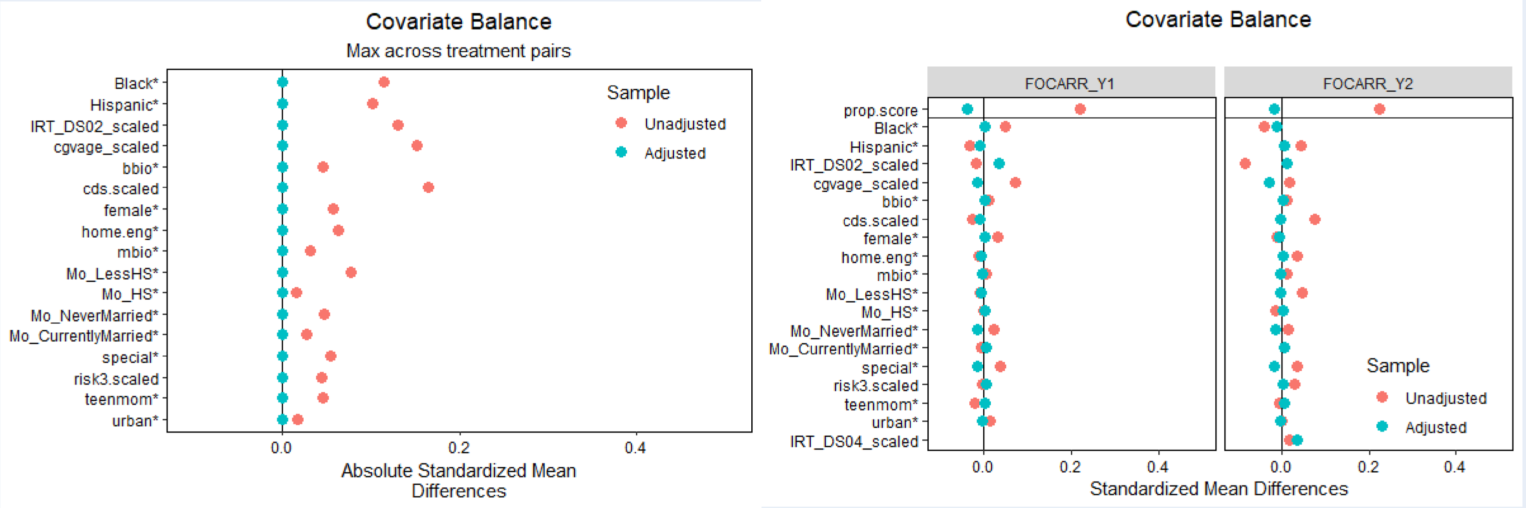
$$logit[P(A_1 = 1|C = c)] = \beta_0 + \beta_1 c'$$

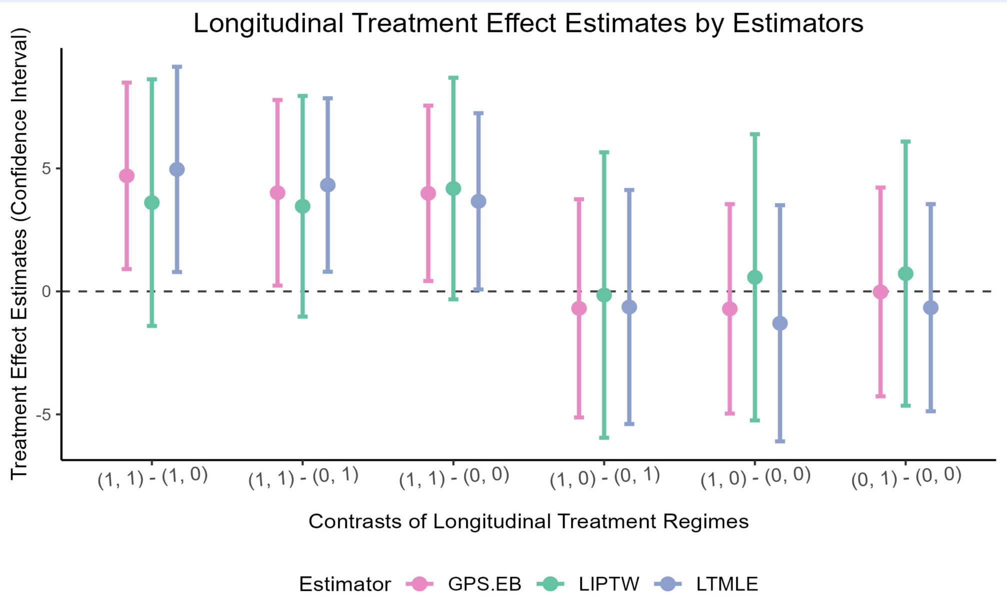
$$logit[P(A_2 = 1|C = c, A_1 = a, Y_1 = y)] = \beta_2 + \beta_3 c' + \beta_4 a + \beta_5 y$$

- Longitudinal IPTW estimation
- $w(A_1 = a_1, A_2 = a_2) = \frac{P(A_1 = a_1)}{P(A_1 = a_1|C)} \times \frac{P(A_2 = a_2|A_1 = a_1)}{P(A_2 = a_2|A_1 = a_1, C, Y_1)}$
- $\hat{\delta}_{ATE}^{LIPTW}(g_T - g_C) = \frac{\sum_{i=1}^{N} w(A_1 = a_{1T}, A_2 = a_{2T}) \times Y_i}{\sum_{i=1}^{N} w(A_1 = a_{1T}, A_2 = a_{2T})} - \frac{\sum_{i=1}^{N} w(A_1 = a_{1C}, A_2 = a_{2C}) \times Y_i}{\sum_{i=1}^{N} w(A_1 = a_{1C}, A_2 = a_{2C})}$
- Longitudinal TMLE presented for comparison

4. Real Data Analysis Results

- Head Start Impact Study (HSIS) data analysis
- Both GPS entropy balancing and longitudinal IPTW achieved covariate balance.





5. Discussion

- This study proposed two distinct ways of inverse probability weighting based on different conceptualization of longitudinal treatment regimes.
- Considering longitudinal Head Start as a multiple treatment produced smaller standard errors compared to the sequential treatment approach.
- However, time-varying covariates (e.g., Y_1) cannot be appropriately incorporated within the multiple treatment approach.
- Alternative estimators such as the LTMLE can help gain precision and double robustness.
- Further extensions may address partially or fully clustered data and evaluate the performances of multiple estimation methods with simulation studies.

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