The Effect of Serious Offending on Health: A Marginal Structural Model

Supplementary File

In non-experimental studies, to rule out alternative explanations, researchers need to suggest a plausible causal pathway between the treatment and the outcome informed by the subject-specific knowledge that is then carefully translated into empirical models (Greenland et al. 1999; Greenland and Brumback 2002; Hernán et al. 2002a). With longitudinal data, researchers have access to additional information and can choose from a variety of methods to isolate the treatment effect. For longitudinal studies, typical approaches adjust for potential confounders by including them on the right-hand side of a regression equation. But even when all the confounders are observed (i.e., there are no omitted variables), this approach runs the risk of inducing selection bias and underestimating the treatment effect (Daniel et al. 2013; Barber et al. 2004). First, selection bias results from the presence of so-called “collider” variables—time-varying characteristics that are a common effect of endogenous confounders and prior treatment status (Greenland 2003; Hernán et al. 2004). Second, the standard approaches may produce an underestimated effect of the treatment by over-adjusting for the indirect causal pathways to the outcome (Hernán et al. 2002b; Sampson et al. 2002; Anema et al. 2015). These issues, known as simultaneous time-dependent confounding and mediation, are described below.

The graph in Figure 1 highlights the role of victimization as a simultaneous time-varying confounder and mediator on the route from offending to health.

[Figure 1 here]

Variables that act as time-varying confounders and mediators have three characteristics (Robins et al. 2000; Hernán et al. 2000). First, they are independently associated with the outcome—see the arrow from L_1 to Y in Figure 1. As discussed earlier, there is a great deal of evidence for the association between victimization and health. Second, these variables are associated with the assignment of subsequent treatment. More specifically, in line with the "cycle of violence" thesis, victimization L_1 leads to offending A_1. And finally, they are affected by prior exposure status. In this case, victimization in one wave is affected by offending in the past wave—as illustrated by arrows from A_0 to L_1. The first two characteristics make victimization a confounder of the effect of subsequent offending on health, which means we need to adjust for victimization to produce an unbiased estimate of the effect of offending at that wave. But characteristics 1 and 3 make victimization an intermediate variable (or mediator) on the causal pathway from earlier offending to health. This implies we should not adjust for victimization—a variable affected by prior exposure—to avoid post-treatment bias (Rosenbaum 1984).

References

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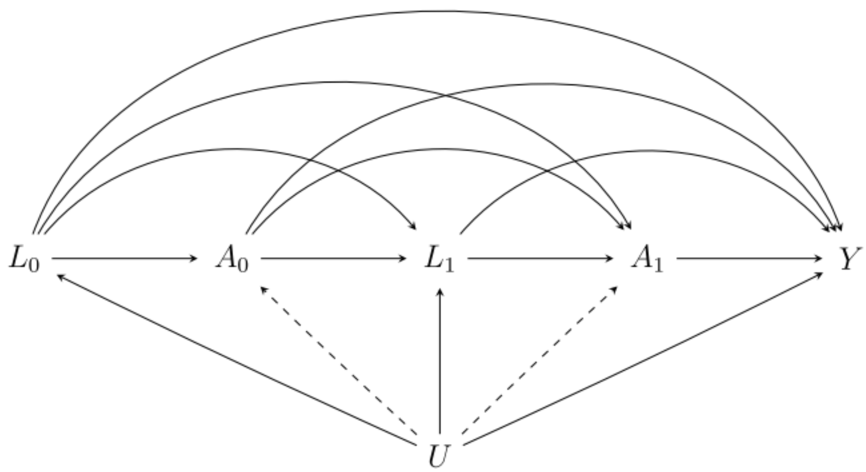
Figure 1: An illustration of simultaneous time-dependent confounding and mediation using a directed acyclic graph for a two-stage panel study (adapted from Bacak and Kennedy (2015))



where:

L_0 is a set of covariates at time 0 (e.g., victimization, education, etc.).

A_0 is offending status at time 0.

Y is the study outcome.

U are unobserved causes of the treatment, the outcome, and the covariates.