The Estimation of Counterfactual Causal Effects with Longitudinal Data

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In this presentation I examine how longitudinal data can be used to estimate counterfactual causal effects. The focus is on how longitudinal data may be used to impute or predict the missing value under the counterfactual data. I examine two common methods – change scores and the analysis of covariance – and show why neither provides a satisfactory approach to longitudinal data. I argue that in general one needs more time periods than time parameters in order to test the fit of one's model. As such, standard pretest-posttest data is only good for testing the fit of cross-sectional models. I then discuss the strengths and weaknesses of a pure prediction versus a structural modeling approach. I illustrate my methods by examining the effect of additional yeas of schooling on measure mental ability.