Models of Causal Exposure and Identification Criteria for Conditioning Estimators

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January 30, 2017

In economics, our bread and butter is the potential outcomes framework. I was pleasantly surprised by the perspective taken from the causal graphs framework on "confounder variables." Rather than adjust for confounders, our goal should be to remove any noncausal association between our policy D and the outcome Y. As I was reading the chapter, I was thinking how easy it would be to use the back-door criterion. However, this is conditional on knowing the correct causal graph. But the more I thought about it, I realized that when economists use the potential outcomes framework, we usually "hand-wave" whenever a potential confounder is thrown our way. That is, although it is practically impossible to draw the correct causal graph, one is at least transparent about assumptions.

Another advantage of using a causal graph and the back-door criterion is that it allows one to differentiate between a conditioning strategy that seeks to balance determinants of the policy D (matching) and one that adjusts-for-other-causes of the outcome Y (regression). Moreover, one can then select the minimum covariates required to obtain a causal estimate. One point that was not mentioned in the chapter is the following. Suppose S is the full set of covariates that we could control for in order to get a causal effect. Suppose S' is the minimal set needed to achieve this same goal. One could then test adding the element in $(S')^c \cap S$ one-by-one into the regression to see whether point estimates are affected. If so, there might be a problem with the causal graph. In addition, adding covariates in $(S')^c \cap S$ could soak up variation and reduce standard errors, giving more precision to the point estimates of the regression.

In terms of my project, I think I need to be more careful about the assignment model I consider. As of now, I simply assume a selection mechanism where region-industry specific unions bargain with firms on choosing a probationary period regime for all employees. Firms then fill job vacancies by taking a random draw from the pool of applicants, which is characterized by a known distribution in quality. **Q1)** Are the region-industries that negotiate shorter probationary periods systematically different from those with longer periods in any other way that would affect firing decisions? **A1)** Shorter periods could indicate: stronger union, better recruitment, and tasks with less learning-by-doing. Stronger unions are unlikely to affect separations during probationary periods since these workers are unlikely to be a priority for the union due to their low tenure. Better recruitment may be something that varies across firms within an industry-region. Thus, checking for heterogeneity in separation histograms across firms may be important. Finally, the learning-by-doing component of a task is likely to vary by occupation. Hence, occupation should also be a covariate to consider for robustness checks. **Q2)** Does probationary period assignment o firms affect the pool of applicants from which a firms takes a random drawn? **A2)** Unless a worker is very high skilled, I find it hard to believe that individuals shop for jobs. It is also unlikely that one chooses their profession based on the length of the current probationary period of an industry—I'm pretty certain workers are not aware about the length of probationary periods before seeing the employment contract. Since the wage received is a signal of the supposed skill of the worker, this is another variable that I should use to test for heterogeneity in outcomes.