Note on Confounders in Causal Inference

by P. Richard Hahn, 6/16/2025

Did you know that there are two distinct kinds of confounding in causal inference?  
   
Well, there may be more than two, but the two I have in mind are particularly useful: prognostic confounding and treatment effect confounding.   
   
Here’s how it works. Think about the potential outcomes in terms of each individual’s prognosis — their expected outcome without treatment — and each individuals treatment effect — the difference between their prognosis and their expected outcome under treatment.   
   
Now consider an observational study where individuals select into treatment. The usual worry in such cases is that people who seek out treatment differ systematically from people who do not, rendering any treated vs controls comparison \*confounded\* by the (self) selection.   
   
But notice that the systematic difference can be either on the prognosis or on the treatment effect (or both, or neither).   
   
 I like to think about this in terms of selection based on need (prognosis) or on efficacy (treatment effect).   
  
You can seek out treatment because you need it (you expect to have a bad outcome if you don’t get treated) or because you expect that it will improve your outcome (even if that outcome is not expected to be especially bad).   
  
Both of these kinds of selection lead to an upward bias of the treatment effect.  
   
 But if there is \*only\* treatment response confounding, you can still estimate the average treatment effect among the treated (ATT), which is the appropriate estimand in the event that your treatment would be deployed as an opt-in intervention anyway.  
  
 What’s especially cool is that you can ensure a lack of prognostic confounding by randomizing eligibility for treatment. Among people that select into treatment, randomize those who actually receive it and those who don’t. Then, among the presenting population, the average prognosis will be the same in the treated and control groups (due to randomization).   
  
Of course, that average prognosis is different than it is for the population at large, but that doesn’t matter for treatment effect estimation (we only need those terms to cancel out when we take a difference).

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# References

[1] [Estimand, Estimator, Estimate, P. Richard Hahn, 2025](https://github.com/dimitarpg13/generalized_synthetic_control_for_testops/blob/main/articles/Estimand_Estimator_Estimate.pdf)

[2] [Regression Adjustment for Causal Inference: A Primer with Examples, P. Richard Hahn, Andrew Herren, 2025](https://github.com/dimitarpg13/generalized_synthetic_control_for_testops/blob/main/articles/causal_inference/causal_primer_with_examples.pdf)

[3] [Introduction to Estimands, K. Baltrusaitis, 2022](https://github.com/dimitarpg13/generalized_synthetic_control_for_testops/blob/main/articles/IntroToEstimands_Baltrusaitis_2022.pdf)

[4] [An Applied Researcher’s Guide to Estimating Effects From Multisite Individually Randomized Trials: Estimands, Estimators, and Estimates, Luke Miratrix, 2020](https://github.com/dimitarpg13/generalized_synthetic_control_for_testops/blob/main/articles/JREE_Estimands-Intro_2020_09_11.pdf)

[5] [Causal Inference: What If, Miguel A Hernan, James M Robins, 2024](https://github.com/dimitarpg13/generalized_synthetic_control_for_testops/blob/main/books/Causal_Inference_What_If_Hernan_Robins_2jan24.pdf)