What is the Value Added by using Causal Machine Learning Methods in a Welfare Experiment Evaluation?

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Abstract

Recent studies propose causal machine learning (CML) methods to estimate conditional average treatment effects (CATEs). In this study, I investigate whether CML methods add value compared to traditional CATE estimators by re-evaluating Connecticut's Jobs First welfare experiment. This experiment entails a mix of positive and negative work incentives. Previous studies show that it is hard to tackle the effect heterogeneity of Jobs First by means of CATEs. I report evidence that CML methods can provide support for the theoretical labor supply predictions. Furthermore, I document reasons why some traditional CATE estimators fail and discuss limitations of CML methods.

Keywords: Labour supply, individualized treatment e˙ects, conditional average treatment e˙ects, random forest.
JEL classi˙cation: H75, I38, J22, J31, C21.

The Manpower Demonstration Research Corporation (MDRC) provided me with the experimental data used in this article. I remain solely responsible for how the data have been used and interpreted. The study is part of the Swiss National Science Foundation (SNSF) project "Causal Analysis with Big Data", grant number SNSF 407540 166999, and is included in the Swiss National Research Programme "Big Data" (NRP 75).
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