**Difference-in-differences with covariates**

**Directions:** In this exercise, we will implement DR, TWFE, CS and SA on two separate datasets.

**Doubly robust (Sant’anna and Zhao 2020)**

In his 1986 AER, LaLonde took a randomized controlled trial in which volunteers were randomly assigned to a job trainings program or nothing. The treatment was the program. The ATE was around $1800 using the experimental treatment and control.

But to illustrate the problem with program evaluation at the time, LaLonde then dropped the experimental control group and replaced it with the CPS which was a random sample of US workers. Regressing real earnings 1978 onto the treatment group yielded a biased ATE of -$8500.

In this exercise you will repeat this analysis using the doubly robust method by Sant’Anna and Zhao using the -did- package in either Stata or R. The NSW data with covariates and CPS controls can be found here under the code for nsw\_pscore.do, nsw\_pscore.R, nsw\_pscore.py at the Mixtape “matching and subclassification” chapter.

<https://mixtape.scunning.com/matching-and-subclassification.html>

1. Before we implement DR, let’s look at the issue of common support. Calculate a propensity score using the same covariates as used in the mixtape with logit maximum likelihood. Create a histogram showing the distribution of the propensity score for the treatment and control group. What share of the data satisfies common support?
2. Rearrange the data as a panel from 1974 to 1978 (you will need to reshape in Stata).
   1. Compare your results if using DR, OR or IPW.
   2. Estimate your model using TWFE and all covariates contained in the data. Can you estimate the coefficients on covariates? Why not?
   3. Estimate the ATT using the DR method by Sant’Anna and Zhao (2020). The package can be found here:

<https://asjadnaqvi.github.io/DiD/docs/01_stata/>

Do this using OR, IPW and DR. Compare your results to what you found using TWFE. Why are you able to condition on covariates using DR but not using TWFE in this example?

**Callaway and Sant’Anna (2020)**

The castle doctrine paper by Cheng and Hoekstra (2013) is about the impact that a self-defense in the US had on murder. The US historically followed English common law with regards to lethal self defense in that it was only justified against someone in one’s home (called “castle doctrine” because of the language “the home is one’s castle”). We will estimate the impact that this law had on the five *groups* of states that passed this law. This paper and code are described in the Mixtape here:

<https://mixtape.scunning.com/difference-in-differences.html#castle-doctrine-statutes-and-homicides>

1. You can find the data in programs castle\_1.do, castle\_1.R and castle\_1.py. How many states are treated and when? How many states are “never treated”?
2. Recreate figure 9.21 from the Mixtape comparing Florida to all “never treated” states. What appears to happen in Florida with respect to homicide rates relative to the rest of the US?
3. If you wanted to create a version of 9.12 using *all treated states* with respect to homicide rates compared to the never treated states and only the raw data (i.e., showing t-1, t-2, t+1, t+2), could you? Why not?
4. Estimate the effect of castle doctrine reform using CS.
   1. Specify the model using OR, IPW and DR and compare your results
   2. Specify the model using the never-treated states as controls and then separately the not-yet-treated. Compare the ATT under both. Show both the overall-ATT for both as well as the dynamic event study model. Discuss who is the controls under not-yet-treated.
   3. Using the never-treated, what is the *group* ATT by treatment date?