Lecture 6 Notes: Natural Experiments, Difference-in-Differences, and Fixed Effects

Econ 4523: Economics of Education
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Last Time

- Regression and correlation
- Confounders and selection bias as "omitted variable bias"
- Ways to get causal effects from regression:
  - Include every possible variable
  - Assume unconfoundedness
  - Leverage natural/quasi experimental variation

Today's Big Questions

- What is a natural experiment?
- What is difference-in-differences and how is it like an experiment?
- What are fixed effects?

1 Natural Experiments

A *natural experiment* is a setting in which observational data is collected, but treatment is either randomly assigned, or "as if" randomly assigned. In particular, treatment is not assigned by the researcher (otherwise it would be a randomized experiment).

1. True natural experiment: Typically takes the form of a lottery (either to gain access to medicaid, gain access to a school, etc.). Treatment is truly random, so we can proceed just the same as in the randomized experiment case.

2. As if natural experiment: Typically leverages some kind of government policy change or administrative quirk. The primary argument is that treatment is unrelated to any other variables that determine the outcome.

1.1 Justifying as-if randomization

To make sure that the as-if randomization is convincingly randomized, follow these two steps:

1. Make a qualitative argument that randomization happened. (e.g. "The state decided to implement this policy for purely idiosyncratic reasons")
2. Perform a balance check (i.e. test that the treatment and control groups look similar on all of the observable measures in your data)
    - Note that you can't tell whether the groups are balanced on unobservable measures! (Example: Tennessee STAR experiment (Schanzenbach, 2006))

2 The difference-in-differences approach

We can use the difference-in-differences approach to analyze the effects of policy changes enacted by governments.

2.1 Example

Suppose that the state of Texas decides to start offering free community college to its residents in certain towns. We want to analyze how a reduction in tuition impacts aggregate enrollment at each institution. [1]

Q: What is the treatment variable here, what is the outcome variable, and what is the unit of analysis?

2.1.1 Changes in outcomes for the treated group

One way to approach this is to look at enrollment numbers at the colleges in the towns that were treated:

$$Treatment\ Trend = Enr_1 - Enr_0,$$

where Enr is the number of students attending and 1 indexes "after the policy" and 0 indexes "before the policy."

But what's the assumption here? The assumption is that Enr_0 acts as a counterfactual for Enr_1. But what if something was different about Enr_0 relative to Enr_1 (besides

[1] Denning (2017) examines this exact question. He uses a framework similar to the one described in 2.1 and finds that community college enrollment in the first year after high school increased by 5.1 percentage points for each $1,000 decrease in tuition

treatment status)? Then we would have an unobserved confounder. For example, maybe there was an economic shock that happened at the end of period 0 that would affect students' likelihood of attending community college. Or what if there was an upward trend in general in community college attendance over the period?

2.1.2 Changes in outcomes for the control

One way to correct for potential confounders in our treated group is to look at how the control group behaved over this same time.

$$Control\ Trend = Enr_1^c - Enr_0^c$$

where the superscript c indexes "control group."

2.1.3 The counterfactual

Here we can use the fact that we observe treatment and control over multiple periods to account for overall trends in behavior that affect both groups. The **parallel trends assumption** of the difference-in-differences method tells us that the trend in the control group between 0 and 1 is the counterfactual for the trend in the treatment group from 0 to 1.

We know from earlier that

$$\text{Treatment Effect} = \text{Observed Outcome} - \text{Counterfactual Outcome}$$

So here we have

$$\begin{aligned} ATE &= Treatment\ Trend - Control\ Trend \\ &= (Enr_1 - Enr_0) - (Enr_1^c - Enr_0^c) \end{aligned}$$

which is called the **difference in differences estimator**.

Another, equivalent, way to think about it is

$$\begin{aligned} ATE &= Treatment\ Effect_1 - Treatment\ Effect_0 \\ &= (Enr_1 - Enr_1^c) - (Enr_0 - Enr_0^c) \end{aligned}$$

in this case the "counterfactual" is the treatment effect that occured before the policy change in period 0.

Each of these approaches constitute one set of "difference" columns in Table 3.3 of Lovenheim and Turner, and you should feel free to think about either one. A similar table is reproduced here:

	Treatment towns	Control towns	Difference
Pre	Enr_0	$Enr_0^c\ (= \alpha)$	$Enr_0 - Enr_0^c\ (= \gamma)$
Post	Enr_1	Enr_1^c	$Enr_1 - Enr_1^c$
Difference	$Enr_1 - Enr_0$	$Enr_1^c - Enr_0^c\ (= \theta)$	$(Enr_1 - Enr_1^c) - (Enr_0 - Enr_0^c)\ (= \delta)$

The Greek symbols in the table on the previous page correspond to parameters of the following regression equation.

2.2 Diff-in-diff in regression form

We can also think about difference in differences in regression form, since we can also express experimental treatment effects in regression form. For the Texas community college question, the model takes the form

$$Enr_{it} = \alpha + \gamma \text{Treated Counties}_{it} + \vartheta Post_t + \delta \text{Treated Counties}_{it} \times Post_t + \varepsilon_{it} \qquad (1)$$

where i indexes colleges and t indexes year.

This model contains a series of **dummy variables**, which are variables that only take on values of 0 or 1.[2] (Computer programmers call these logical variables or boolean variables. Econometricians also call them indicator variables.) The Treated Counties variable is equal to 1 for colleges located in counties where tuition decreased, and 0 for all other colleges. It controls for any fixed, unchanging attributes about the treated counties that would affect enrollment. The *Post* variable is equal to 1 in the post period and 0 in the pre period. It controls for any systematic differences across all colleges that might affect enrollment, but that have nothing to do with the policy (e.g. it accounts for common trends in enrollment at all institutions). *Post* does not vary across colleges. Finally, the **interaction term** (a multiplication of two dummy variables) gives us the difference-in-difference estimate by showing how enrollment was different in the treated counties after the policy, net of any characteristics unique to the treatment counties or any common trends in all counties.

Thus, δ is equivalent to the bottom-right element of the Table.

3 Fixed effects

Our use of difference in differences leveraged a unique feature of our data: that we can measure outcomes for the same units over time. Such data is called **panel data** or **longitudinal data**. In essence, using panel data can allow us to observe a counterfactual for each unit: the same unit in a previous time period. (Now, as discussed above, this counterfactual may be confounded by events that happen over time, which is why we need the difference in difference estimator.)

Going back to the Texas community college question, suppose that we obseved more than two periods of data. Instead, suppose we observed three periods of data before the policy change, and three after. Also, suppose that we think that, even among the treated counties, there are considerable differences in the landscape of the community that would

[2] Why are they called dummy variables? The name may sound funny, but the word "dummy" can mean "something designed to stand in for the real thing" in addition to meaning "someone who is unintelligent, or who makes silly mistakes on a routine basis." In some cases (but not in this case) the "dummy" is "standing in for" a larger list of categories. For example, a person's race or ethnicity could be categorized as {Caucasian, African American, Hispanic, Asian, Other}. A dummy variable for caucasian would be "standing in for" the caucasian category of the longer list.

result in different enrollment behavior. We can correct for these by generalizing the model in (1):

$$Enr_{it} = \alpha + \gamma_i + \vartheta_t + \delta \text{Treated Counties}_{it} \times Post_t + \varepsilon_{it} \tag{2}$$

here, γ_i is a long list of dummy variables for each county, ϑ_t is a long list of dummy variables for each year, and δ gives us the difference in differences estimate that corresponds to the causal effect we're interested in.

3.1 Fixed effects in other applications

We can also use fixed effects on student-level data, if we have longitudinal data on student outcomes. For example, the state of North Carolina maintains a large database on all public school students as they progress from kindergarten until 12th grade. Many researchers have used this data set to examine the effects of national economic policies like No Child Left Behind, or state-level changes to teacher compensation, or how the composition of one's classmates affects a student's educational outcomes. In each of these cases, the counterfactual of "today's student" is "that same student yesterday," while also controlling for potential confounders in a similar way as difference-in-differences does.

3.2 Other examples of difference in differences

Some other examples of how to use difference-in-differences to understand causal effects:

- Hurricane Harvey damages (i.e. compare changes in infrastructure, jobs, etc. in San Antonio and Austin vs. Houston)
- Minimum wage increase in Seattle (compare employment levels in Seattle before and after introduction of the minimum wage, relative to how employment changed in other places near Seattle before and after the minimum wage hike)
- Immigration (compare employment of US-born workers before and after an immigration wave in cities that were more or less exposed to immigrants)

Video links

- https://www.youtube.com/watch?v=xdRyjhGVj_Q
- https://www.youtube.com/watch?v=y9kRenmqIkg
- https://www.youtube.com/watch?v=K9DysSNxdx8
- https://www.youtube.com/watch?v=tO99T1GQ6SY
- https://www.youtube.com/watch?v=6d64Vy2-peY
- https://www.youtube.com/watch?v=jJoMEqVRk2I

References

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