Econometrics
Chapter 13: Experiments and 'Natural' Experiments

Experiments

Experiments are very rare in economics/business. So why even bother talking about them?

They provide a 'benchmark' against which we can evaluate observational studies.

This is particularly important for 'program evaluation' - a field interested with assessing how effective programs/treatments are.

Potential Outcomes

Say we care about some effect of some treatment T on some outcome Y.

We can think that each person has a potential outcome given some potential treatment:

$Y_i(T = 1)$: potential outcome under case in which they received the treatment.
$Y_i(T = 0)$: potential outcome under case in which they did not receive the treatment.

Treatment Effect: $Y_i(T = 1) - Y_i(T = 0)$. The difference in the two potential outcomes.

Now we won't see both potential outcomes for any person.

But assume we run an experiment and randomly assign treatment, then we can still see the Average Treatment Effect (ATE):

$$E[Y_i(T = 1) - Y_i(T = 0)] = E[Y_i(T = 1)] - E[Y_i(T = 0)]$$

So we can compare the average outcome for people with treatment to average outcome of people without treatment. And we could do this with OLS:

$$Y_i = \beta_0 + \beta_1 T_i + u_i$$

Of course we still need out assumptions to hold. But if we randomly assigned treatment, then $E(u|T) = 0$.

This issue is what experiments avoid - because since treatment is randomly assigned there is no difference between who took and who didn't take treatment.

Now maybe we want to control for other variables that may affect the outcome but not the treatment. This is a good thing to do because it will in general reduce the SE of our estimates.

Now maybe treatment is based on some characteristic. So only people with specific Xs got treatment. Then we need to include those variables and our main assumption becomes: $E(u|T, X) = E(u|X)$, because once we control for those Xs the treatment is 'as if' randomly assigned.

Issues

Internal Validity Issues:
1. Not really randomized.
2. Some people don't comply with the treatment - like don't actually take the medicine. But in this case treatment assignment is a valid IV!
3. Attrition - people drop out of study. If random no problem, but may be related to the treatment itself.
4. Hawthorne effect - maybe people act different just because they are in a study.

External Validity Issues:
1. Is the sample representative of the population?
2. Is the experiment program really like what would be implemented in the population?
3. General Equilibrium Effects - say you help a few students get higher grades on a test and so they are more likely to get into college. But then you expand it to every student in the country. Well all you did was really 'raise the bar'. Or similarly think about giving skills to workers - when you give it to many you get big supply side shifts.

'Natural Experiments'

Difference-in-Difference

Say you have a 'treatment' and 'control' group (or non treated group).

But you can't control for all possible differences between groups that might have affected treatment and outcome.

The idea then, is instead of comparing differences between Y's for the groups is to compare differences in the change in the Y's.

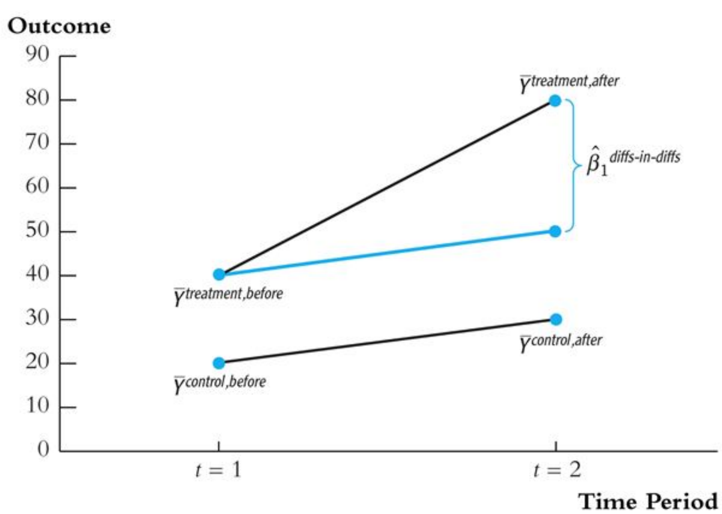

Figure 1: Idea of Diff-in-Diff

In this sense you control for the difference between the groups in their Y's in the initial observation of Y.

$\beta_1^{Diff-in-Diff} = (\overline{Y}^{T,after} - \overline{Y}^{T,before}) - (\overline{Y}^{C,after} - \overline{Y}^{C,before})$

More specifically we regress ΔY_i on treatment group assignment:

$\Delta Y_i = \beta_0 + \beta_1 D_i + u_i$

And we can always add needed X's if they are needed to ensure treatment is 'as if' random, or just to minimize SEs.

(Sharp) Regression Discontinuity Estimators

Say there is some rule/law that determines some treatment.

Further, say this rule is based on some continuous variable W.

Example: If a student has under 2.2 GPA they must go to summer school for 6 weeks.

How might we determine the effect of summer school on next years GPA? Well obviously looking at those who did and didn't go to summer school is a problem - only those with below a 2.2 went!

But what if we compare next years GPA to those just below and just above that 2.2 cut-off. If we see a big difference between these two groups then the effect is likely because of summer schools.

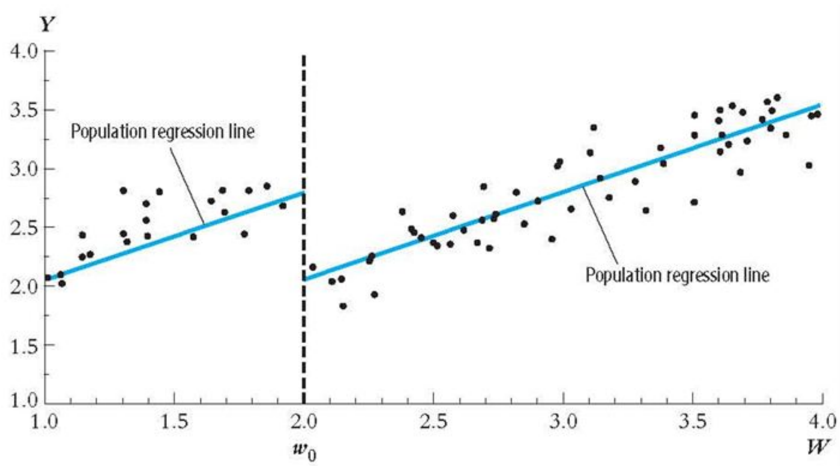

Figure 2: R-D Estimator

So what we do is regress our outcome Y on W and a dummy for whether the student is above the cut-off point X.

$Y_i = \beta_0 + \beta_1 X_i + \beta_2 W_i + u_i$

Then β_1 is an estimate of the effect of summer school (assuming that 2.2 cut-off did not have some other special significance).

Heterogenous Effects

Say people differ in their effect β_1.

So each has a different β_{1i}

If the OLS assumptions hold, then OLS still give the Average Treatment Effect (ATE) in the population.

But in general TSLS does not. TSLS measures the average effect for people influenced by the instrument. We call this the Local Average Treatment Effect (LATE).

And this is likely different since not everybody is influenced, or influenced the same by the instrument.