Homework for Chapter 18: Difference-in-Differences

*How Does It Work?*

1. In the Event Studies chapter we estimated the effect of something that occurs at a specific time by just comparing before-event to after-event, without really using a control group. What assumption is made by no-control-group event studies that we *don’t* have to make with difference-in-differences?

Answer： The assumption made by no control-group event studies is that we assume that we could use before treatment information to construct a counterfactual after-treatment untreated prediction.

1. Which of the following potential back doors is controlled for by comparing the treated group to a control group? Answer: b
   1. The treated group may be following a trend, unique to the group, that would make the outcome change from before-treatment to after-treatment anyway
   2. There may be events affecting everyone that would change the outcome from before-treatment to after-treatment anyway
   3. There may be differences in typical outcome levels between the treated group and the untreated group
   4. The decision to treat the treated group, rather than some other group, may be based on factors that are related to the outcome (regression to mean)
2. Consider a treatment and control group. Looking only at the pre-treatment period, they have exactly the same outcomes (zero gap between them in each period).
   1. Despite having exactly the same outcomes pre-treatment, it happens to be the case that parallel trends is violated for these two groups. How is this possible? Explain what it means for parallel trends to be violated in this case, or give an example of how it could be violated.

Answer: These two groups might violate the parallel trends in the case the control (untreated) group will change suddenly around the time of treatment. If these two groups violate the parallel trends in this case, the effects of treatment calculated by DID will be mixed up with the effects that makes the control group suddenly changed around the time of treatment. For example, if we have a strong evidence that the control group will change suddenly around the time of treatment, then effect calculated by DID will be mixed up with the effects that lead to the sudden change.

* 1. If we estimate the causal effect in this case using difference-in-differences, even though parallel trends is violated, how much would our effect be off by? (note you won’t be able to give a specific number)

Answer: Based on the formula of DID: Effect of Treatment + Other Treated Group Changes-Other Untreated Group Changes, I think the amount of effects off by depends on the difference between Other Treated Group Changes and Other Untreated Group Changes. The greater the difference, the greater the effect will be off by.

1. Consider the below graph showing the average outcome for treated and control groups in the leadup to treatment (indicated by the dashed line), and also after treatment.  
   Chart, line chart

   Description automatically generated
   1. Based on the prior trend, does it seem likely that parallel trends holds in this instance?

Answer: Based on the shrinking gap between treated group and control group before the treatment, these two groups might not have similar trajectories for the dependent variable before treatment, so it seems likely that parallel trends does not hold in this instance.

* 1. If we estimate difference-in-differences anyway, are we likely to overestimate the actual causal effect, underestimate it, or get it right on average?

Answer: We are likely to underestimate the actual causal effect.

1. In mid-2020, during the COVID-19 pandemic, different countries pursued different courses of action. Some locked down fully, imposing harsh penalties to most people for leaving the house outside certain proscribed times. Some were looser and only suggested staying at home, and some had hardly any restrictions at all. You notice that COVID rates tend to spike dramatically in different countries at seemingly-random times, and want to know if certain restrictions helped.  
     
   From March through May 2020, US and Canada COVID case rates followed similar trends (US rates were higher, but the trends were similar). You want to look at the effect of COVID restrictions enacted in Canada in late May 2020 on case rates. Is DID, with the US as a control group, a good way to estimate this effect? If not, what concerns would you have about this research design?

Answer: Though I think it is a good way to use DID to estimate this effect, there are still some concerns about this design, first, the evolution of COVID virus might make the case rate of COVID in the US suddenly rise around the time of restrictions enacted in Canada; second, the difference of the amount of international travels between Canada and the US might also make them violate the parallel trends.

1. Consider the below table of mean outcomes, and calculate the difference-in-difference effect of treatment. Write out the equation you used to calculate it (i.e. show how the four numbers in the table are combined to get the estimate)

|  |  |  |
| --- | --- | --- |
|  | Before | After |
| Treated | 5 | 9 |
| Untreated | 6 | 7.5 |

Answer: (AfterTreated – BeforeTreated) – (AfterUntreated-BeforeUntreated)=(9-5)-(7.5-6)=2.5

*How is it Performed?*

1. You are planning to estimate whether voter-protection laws increase voter turnout. You note that, in 2015, a lot of new voter-protection laws were enacted in some provinces but not in others. Conveniently, no new laws were enacted in 2012, 2014, or 2016, so you decide to use 2012 and 2014 as your “before” periods and 2016 as “after”.
   1. Which of the following best describes what you’d want to regress state-and-year level “voter turnout” measures on? Answer: iv.
      1. An indicator for whether the state is treated, and an indicator for whether the year is 2016.
      2. A set of fixed effects for state, and a set of fixed effects for year.
      3. An indicator for whether the state is treated, a set of fixed effects for year, and an indicator for whether the state is currently treated.
      4. A set of fixed effects for state, and for year, and an interaction between “is 2016” and “is a treated state”.
      5. This design should not be estimated using a regression.
   2. Unless you chose the final option in the previous question, specify which coefficient in that regression would give you the DID estimate.

Answer: The coefficient of the interaction between “is 2016” and “is a treated state”. (The coefficient of the “Treated” term.)

1. You are looking at a difference-in-difference design to estimate the effect of providing laptops to school children on their test scores. Look at the below regression output, in which “Treated” is an indicator that the school received laptops in 2008 as part of a new program (the untreated group did not receive any laptops until years after the sample window for this study ended), and “After” is an indicator for being after the year 2008.  
     
   Using the table, fill in the blanks in the sentence “Assuming that \_\_the treated schools groups and the untreated schools groups hold the parallel trends\_\_\_, the effect of laptops on test scores was \_\_5.034 (the provision of laptops for school children would lead to a increase in children’s test scores which is 5.034 larger in treated schools than it was in the untreated schools) \_\_, and this effect (was/was not) statistically significant at the 95% level.”

|  |  |
| --- | --- |
|  | **Test Scores** |
| (Intercept) | 80.342\*\*\* |
|  | (0.501) |
| After | 3.369\*\*\* |
|  | (0.696) |
| Treated | 4.116\*\*\* |
|  | (0.718) |
| After× Treated | 5.034\*\*\* |
|  | (0.993) |
| Num.Obs. | 1523 |
|  | 0.188 |
| Standard errors in parentheses.  + p < 0.1, \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001 | |

1. A standard “prior trends” test might estimate a regression using the model (only using data from before-treatment), where is a time variable, is an indicator for being in the treated group, and is an outcome variable, and look for a large/significant estimate of . Explain why this test is performed, and specifically what it shows.

Answer: A prior trends test is trying look whether the treated groups and the untreated groups already had differing trends in the leadup to the period where treatment occurred. Therefore, if a design passes the prior trends test, there should be no significant difference between treated groups and untreated groups before treatment, which can be seen from the significant estimate of In the regression model, the interaction term implies whether the time trend is different in different groups. Therefore, we need to look for a large significant estimate of If we cannot find a significant estimate of , it means that this design is likely to succeed in the prior trends test.

1. Consider the below graph with estimates from a dynamic difference-in-differences model for a treatment that occurs between periods 4 and 5, with 95% confidence intervals shown.  
   Chart, line chart

   Description automatically generated
   1. What about this graph might make us concerned about our identification assumptions?

Answer: The effects in the periods before treatment should be around zero. However, from the graph we could see that the DID effects in period 1 and period 2 is over zero, which means that there might be some other changes/differences/time trends among these treated and untreated groups before treatment, which implies the violation of identification assumptions.

* 1. Ignoring any concerns we have, what would we say is the effect of treatment on Y in this case? (note the height of the line in period 5 is about 3, in period 6 is about 1, and in period 7 is about .5).

Answer: The effect of treatment on Y is positive and fading out as time passes.

1. Chapter 18.2.5 points out a problem with two-way fixed effects in cases where treatment is not all assigned at the same time, but rather different groups get treated at different times (a “rollout” design). In these designs, two-way fixed effects treats “already-treated” units, who were treated in earlier periods, as “control” units, as though they hadn’t gotten treated at all. However, there’s nothing theoretically wrong about using an already-treated unit as a control; the DID assumptions don’t require that the control group be untreated, just that the gap between treated and control doesn’t change when the treated group’s treatment goes into effect. Why are we so concerned, then, about using an already-treated group as a control? You can answer generally, or use as an example a DID with only two groups – an already-treated group and a newly-treated group. (hint: to do the example, try assuming the treatment only has an effect for the single period after treatment, and the already-treated group is treated exactly one period before the treated group)

It might break the parallel trends if the effect itself is dynamic or the treatment effect varies across groups or the effect will get stronger/weaker overtime, then the “already treated” group will have different trends from the treated group before the treatment of the treated group because they are in different periods of receiving treatment. The effect of the treatment on the “already treated” group as control groups might make the violation of parallel trends in the case that different groups get treated at different times.

Coding (which includes any how-the-pros-do-it questions)