EDUC 2360
Spring 2019
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Problem Set 3 Answers

As before, I wanted to provide you with three things:

(1) The STATA code I used for each question
(2) The answers
(3) An abbreviated response to any question

For each response, I provide the code (in bold), the key results (if any) and then some text. Obviously, there are many ways to respond to a question, and many ways you could program STATA to get the same result. This "Answer Key" represents one set of answers, but there are other equally-worthy responses. Please do not view these as the only "right" answer to the questions.

Part 1: *Estimate the average treatment effect using an interrupted time-series design. Instead of restricting your focus to 2010 and 2011 as you did in the difference-in-differences approach, use the full dataset across all years.*

1. *[5 points] First, write out the statistical model for a simple interrupted time-series design using only turnaround schools. Define your variables and explain which parameter in your model represents the treatment effect. {In other words, create a model that examines whether there is a disruption in the time trend for turnarounds in 2011. You should use a linear time trend. Centering your year variable will also help.}*

$Y_i = \beta_0 + \beta_1 YEAR\_NEW_i + \beta_2 AFTER_i + \beta_3 YEAR\_NEW * AFTER_i + \varepsilon_i,$

Where $YEAR\_NEW_i$ is a version of year centered at 0 in 2011.

We fit this model only among turnaround schools. Here, coefficient β_1 represents the time trend before the treatment, $\beta_1 + \beta_3$ represents the time trend after the treatment, and β_2 represents the disruption in the time trend in 2011. This is the effect of being a turnaround school on student test scores.

2. *[5 points] Fit the model using STATA. What do you find? What is the estimated treatment effect in 2011 and why? What is the estimated treatment effect in 2013 (two years after the treatment was implemented) and why?*

```
gen year_new = year-2011
gen after= year>=2011
gen year_new_after= year_new*after
reg math_std year_new after year_new_after if turnaround==1
```

We find that being a turnaround school improves a school's test scores by 0.56 SD ($p<0.001$). The estimated treatment effect in 2013 is $\beta_2 + 2 * \beta_3$, which is 0.56 + 2*.14= 0.84 SD.

3. *[5 points] Now, modify your model in (2) by including the fixed effects of school (use the* ***schoolid*** *variable). What is your new estimated treatment effect? How does this change your interpretation of the treatment effect substantively?*

areg math_std year_new after year_new_after if turnaround==1, absorb(schoolid)

Including school fixed effects restricts our comparisons to "within-school" variation. Including school fixed effects in the model barely changes the parameter estimate, as we now we find that being a turnaround school improves a school's test scores by 0.55 SD ($p<0.001$). In other words, using each school as its own comparison group and accounting for the overall trend in student achievement over time, we still find that being a turnaround school improves student test scores. Most importantly, this approach helps to make our estimates more precise. The fact that the estimated treatment effect remains so similar whether or not we include school fixed effects also helps lend credence to our findings that this estimate actually represents a causal effect.

4. *Modify your ITS model in (2) by adding in a non-equivalent non-treatment comparison group. Again, this comparison group will be all other schools in MA (non-turnarounds).*
    a. *[10 points] Write out your statistical model.*

$$Y_i = \beta_0 + \beta_1 YEAR\_NEW_i + \beta_2 AFTER_i + \beta_3 YEAR\_NEW * AFTER_i + \beta_4 TURN_i + \beta_5 YEAR\_NEW * TURN_i + \beta_6 AFTER * TURN_i + \beta_7 YEAR\_NEW * AFTER * TURN_i + \varepsilon_i$$

    b. *[5 points] Which parameter in (4a) represents your estimate of the average treatment effect in 2011 and why?*

The average treatment effect would be the coefficient on $AFTER * TURN_i, \beta_6$, because it represents the relative difference in the disruption in the time trend for turnaround schools.

    c. *[5 points] Fit the model in STATA. What is the estimated treatment effect in this analysis?*

gen year_new_turnaround= year_new*turnaround
gen after_turnaround= after*turnaround
gen year_new_after_turnaround= year_new*after*turnaround
reg math_std year_new after year_new_after turnaround year_new_turnaround after_turnaround year_new_after_turnaround

We find that being a turnaround school increases student achievement by 0.60 SD ($p<0.001$).

d. [5 points] Explain why you might want to add this comparison group.

Essentially, this approach combines the logic of the interrupted time-series model and the difference-in-differences model. Using this approach strengthens our inferences compared to the other two models. Here, we are looking at the disruption in the time trend in both turnaround schools and non-turnaround schools in 2011. We focus on the relative difference in this disruption among turnaround schools. In other words, we now account for any disruptions in the time trend that are common across other schools in the state.

Part 2: *Now, estimate the same treatment effect using a regression-discontinuity design. First, restrict your dataset to the year 2011 (**keep if year==2011**). Remember, schools were assigned to be turnarounds or not based on their rank on the **rank** variable. Schools with ranks from 1 to 1326 are your "control" group, while schools with ranks from 1327 to 1356 are turnaround schools (your "treatment" group).*

5. *[10 points] Write out your regression-discontinuity model. Allow the relationship between **rank** and your outcome to vary above and below the cutoff. Define your variables and explain which parameter represents your average treatment effect and why?*

$Y_i = \beta_0 + \beta_1 RANK\_NEW_i + \beta_2 TURN_i + \beta_3 RANK\_NEWxTURN_i + \varepsilon_i$, where
$RANK\_NEW_i$ is a recentered version of *$RANK_i$*, such that the school with *RANK_NEW*=0 is the first turnaround school.

Here, we account for the relationship between a school's rank and their test score and look for the disruption at the cutoff. Parameter β_2 represents this disruption and it is thus our estimate of the average treatment effect.

6. *[5 points] What is the key identifying assumption in using this regression discontinuity design? How (in theory) might this assumption be violated?*

The key identifying assumption is that schools who just barely ranked above the cutoff (a rank of 1327) and schools who just barely ranked below the cutoff are "equal in expectation." This means that we are assuming that there is nothing very different about these schools other than the fact that schools just above the cutoff did not get the treatment of being designated a turnaround school, and schools just below the cutoff did get the treatment of being designated a turnaround school. Thus, this simulates a randomized experiment around the cutoff, and we can attribute any jump in outcomes at the threshold to the treatment. This might be violated if there was something else that was special about this cutoff, that may also be contributing to the jump in outcomes, or that somehow made these two groups around the cutoff no longer equal in expectation. For example, if schools could somehow manipulate their placement in rankings to move themselves from one side of the cutoff to another, this could bias results.

7. *[5 points] Fit this model in STATA. Implement it using schools in a window within 20 ranks above and below the cutoff. What is the estimated treatment effect in this analysis? How do you interpret this?*

```
keep if year==2011
summ rank if turnaround==1
gen rank_new=rank-1327
gen rank_new_turn = rank_new*turnaround
reg math_std rank_new turnaround rank_new_turn if rank_new>=-20 & rank_new<=20
```

Using a window of 20 schools on either side of the cutoff, we estimate that being a turnaround school increases student test scores by 0.97 SD ($p<0.001$).

8. *[5 points] A "window" of 20 rank points is pretty arbitrary. If your results are robust to the "window" used, your analysis will be stronger. Re-estimate your RDD model using four different "window" widths – 10 rank points above and below the cutoff, 15 points, 25 points, and 30 points. Create a table that presents the estimated treatment effect, standard error, and associated p-value for each of these window widths. In your judgment, are your results robust to the window you chose? Justify your answer thoroughly.*

```
reg math_std rank_new turnaround rank_new_turn if rank_new>=-10 & rank_new<=10

reg math_std rank_new turnaround rank_new_turn if rank_new>=-15 & rank_new<=15

reg math_std rank_new turnaround rank_new_turn if rank_new>=-25 & rank_new<=25

reg math_std rank_new turnaround rank_new_turn if rank_new>=-30 & rank_new<=30
```

Part 3:

9. *[10 points] You have estimated the effect of being identified as a turnaround school on student achievement in several different ways. In Problem Set 2, you used a difference-in-differences approach and estimated that being identified as a turnaround school increased student achievement by approximately* 0.6 *standard deviations, on average. In Question 4, you used a comparative interrupted time-series design. In Question 7, you used a regression-discontinuity design. What do you make of these three findings, taken together – did turnaround schools boost student achievement? How do you reconcile any differences between these estimates? Given these analyses, what would you recommend to a policymaker? Justify your answer thoroughly.*

   Here, you could answer in many different ways. For example, you could be convinced that this result is "real", or you could be skeptical that we have not addressed important threats to validity. You just need to have justified your answer thoroughly (using correct logic).