PROBLEM SET 2

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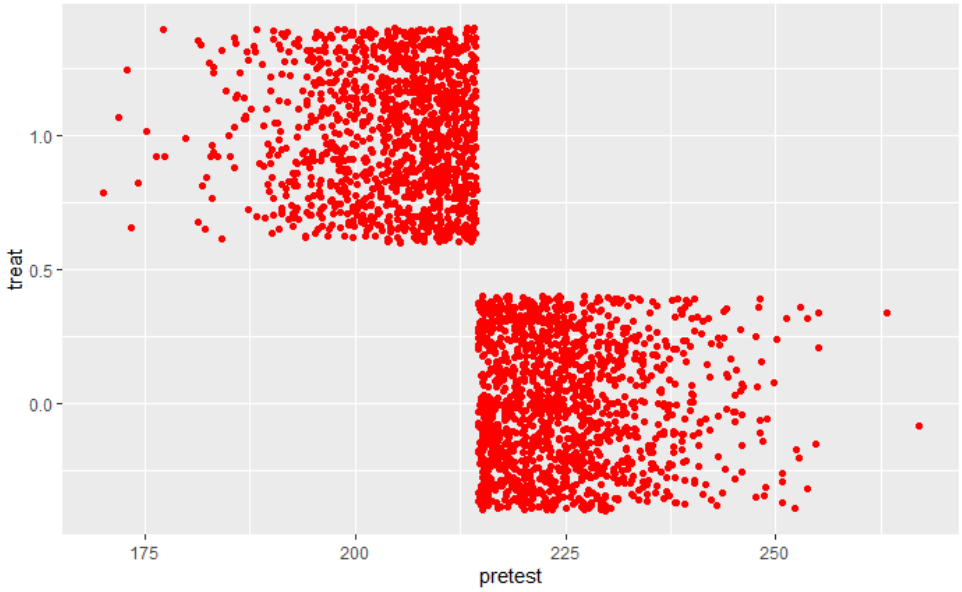
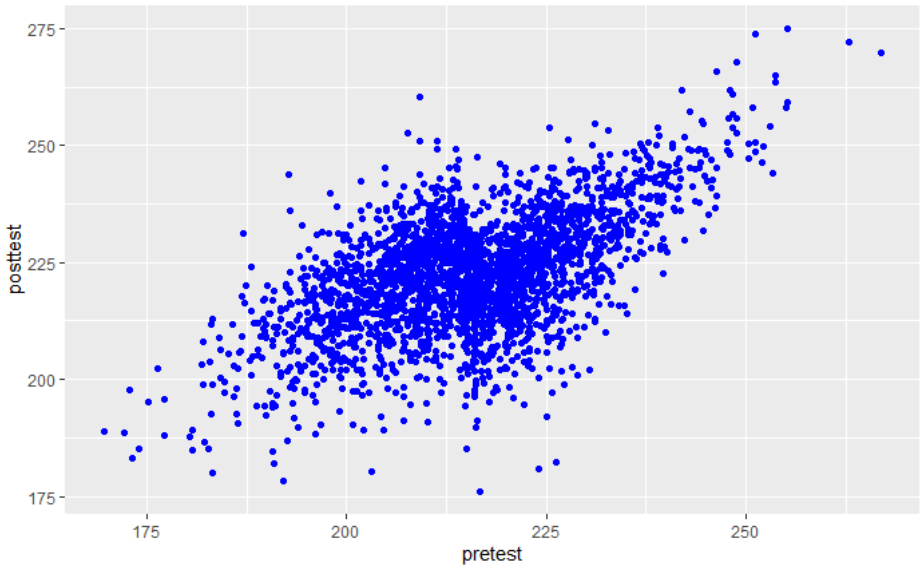
1. Plot treatment as a function of the running variable. Does the graph justify sharp RDD?



Yes, the plot does justify sharp RDD. This is because tutoring treatment is determined by how well a student did on the pretest. No student that scored at or above 215 gained treatment while every student below 215 received treatment. This creates a binary split between students that received treatment and students that didn't based on the cutoff score for the pretest.

2. Plot the exam score as a function of the pre-test score. What do you observe, and does this justify the use of the pre-test as a running variable?

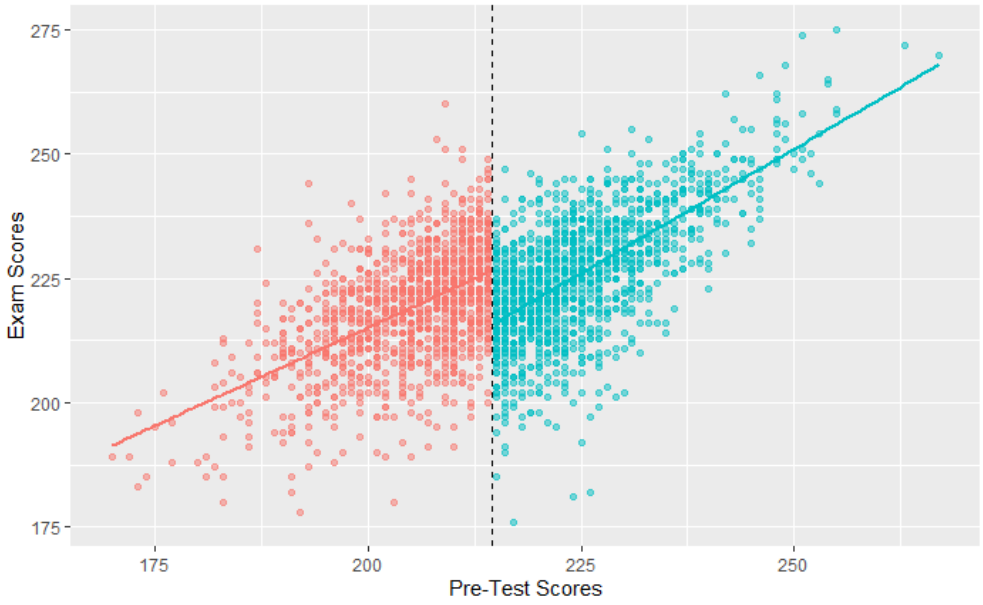


With this graph, we observe a linear, positive correlation between pretest score exam score. This justifies the use of the pretest as a running variable because the pretest is an accurate predictor of the exam score.

3. Estimate the treatment effect at the threshold using a linear model with common slopes for treated and control units. Implement with an OLS regression of the exam score on the indicator for tutoring and the pre-test score. Under what assumptions does this estimation strategy obtain a consistent estimate of the causal effect? Provide a plot of the exam scores (y-axis) and the pre-test scores (x-axis) in which you show the regression fits and the underlying scatterplot of the data. Interpret your estimate.

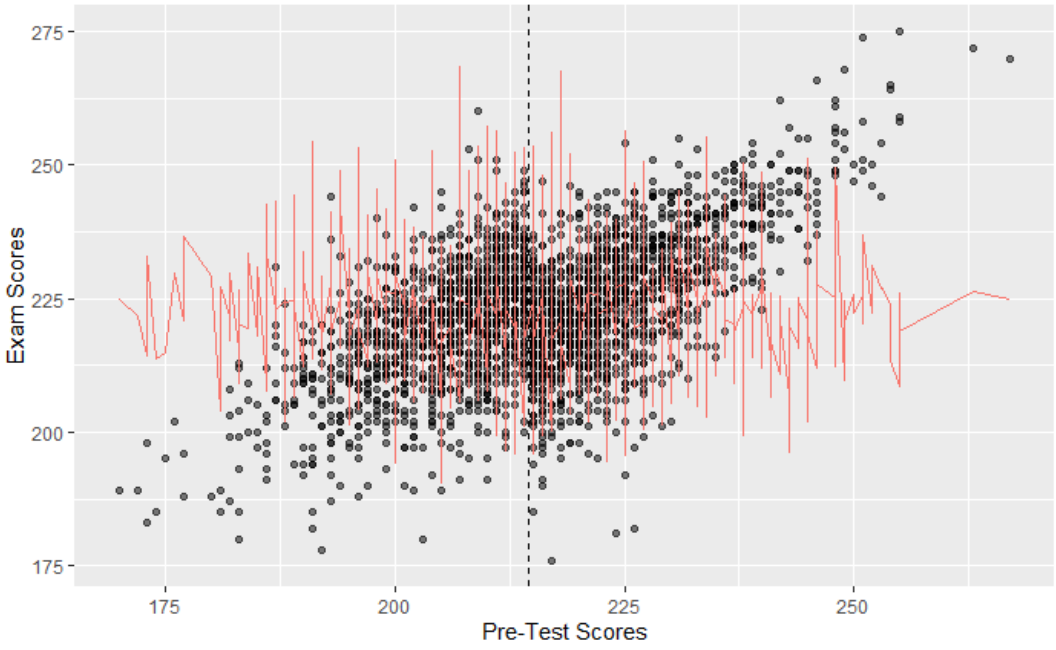
Treatment effect is approximately 8.3 points. This estimation strategy obtains a consistent estimate of the causal effect under the following assumptions: Students who score 214 are pretty similar to students who score 215.

4. Repeat the exercise from question 3, but this time include both the pre-test variable and the square of the pre-test variable in the regression. Does the estimate change much? And is that consistent with your expectation, given your answer to question 2?



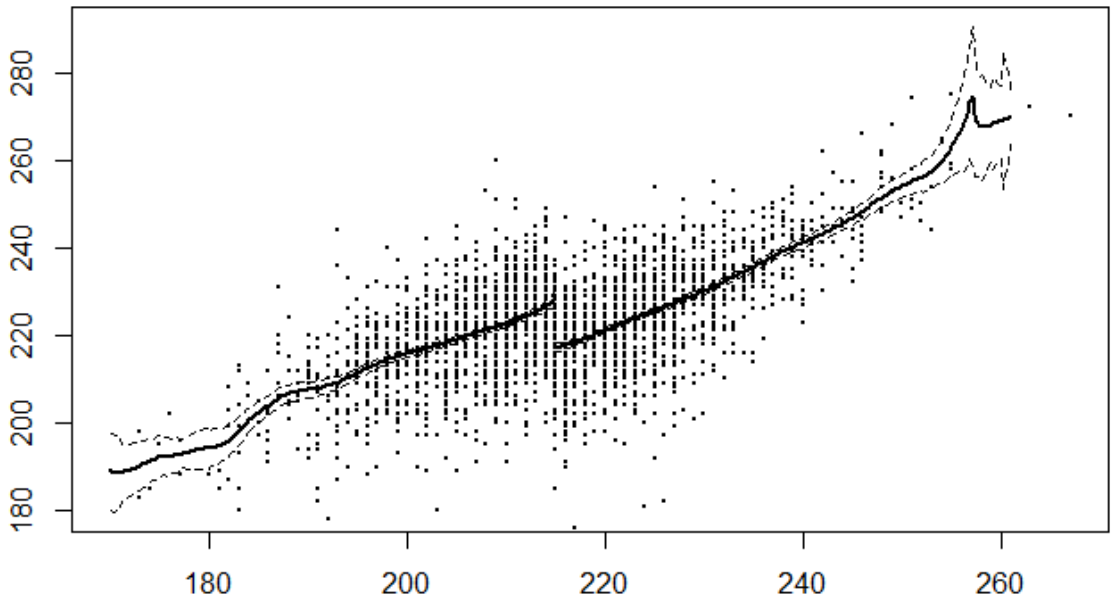
The estimate does not change much. This is to be expected because the exam scores are linearly correlated with pre test scores

5. Again repeat the exercise from question 3, but this time include the control variables that are provided in the dataset. Interpret any differences you see.



The results are that the prediction regresses towards and around the mean. The predictions are also very noisy and over-fitted. This is probably the result of controlling for every variable.

6. Use the rdd package in R to estimate the treatment effect using a local linear regression with a triangular kernel. Note that the function RDestimate automatically uses the Imbens-Kalyanamaran optimal bandwidth calculation. Report your estimate for the treatment effect and an estimate of uncertainty.



Using the rdd package, the treatment coefficient was found to have a magnitude of 10.67, and the uncertainty was 1.26 based on the standard error.

7. How do the estimates of the treatment effect differ across your results for questions 3-6? In other words, how robust are the results to different specifications of the regression?

As seen in the below table, the treatment effects are relatively similar across Questions 3, 4 and 5. Question 6 has a higher treatment effect at 10.65. The fact that these treatment effects do not vary by much indicates the results are relatively robust to the different specifications of the regression.

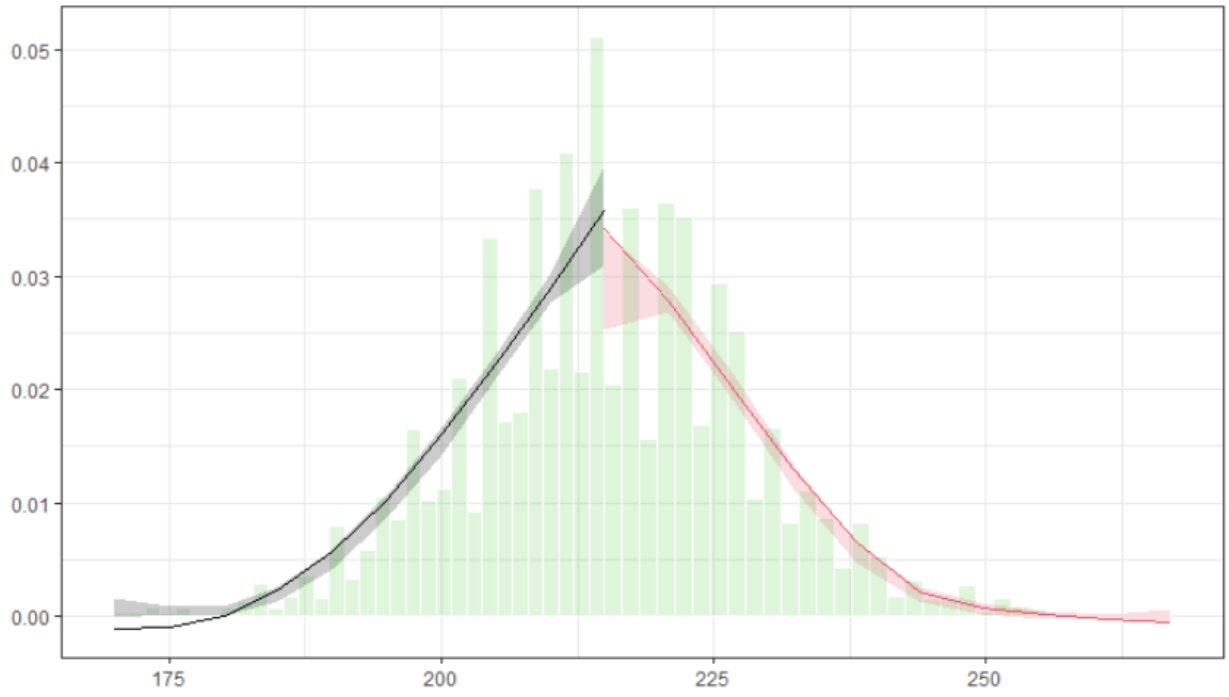
Result	Question 3	Question 4	Question 5	Question 6
Treatment Effect Estimates	8.3	8.3	7.2	10.65

8. Plot the age variable as a function of the running variable. What should this graph look like for RDD to be a valid research design? What do you see?

For RDD to be a valid approach for research design, there should be a similar amount of data points on both sides of the threshold. Because Age is not affected by the threshold in the pretest, there is not a divide point where one can properly use RDD to determine the effect of the treatment.

9. One issue with RDD is manipulation, i.e., sorting around the cutoff threshold in the running variable. Plot a histogram of the running variable, drawing a vertical line at the cutoff. What would sorting around this cutoff point look like? What do you see? Use the rdplotdensityfunction in R to evaluate the statistical significance of any changes.

Sorting around this cutoff point would look as if there were many more variables on one side than the other. This would insinuate that manipulation of the running variable has occurred. In this plot, we do not see any evidence for manipulation because there seems to be a similar amount of students on both sides of the threshold, therefore, the gap between values on the left and right of the threshold is not large enough to reject the null.



10. Use OLS to regress suicides on the treatment indicator and the control variables (income,poverty, and population). Interpret your results. Under what conditions does this provide an unbiased estimate of the causal effect?

The estimate of the causal effect is unbiased when the treatment and control groups would have moved in parallel absence of treatment (Parallel Trends). The key assumption is that the treatment and control groups move in parallel, they do not need to be similar, just parallel trends assumptions to hold true. The difference between the control and treated group, or treatment effect, is 1.40.

11. Estimate the treatment effect with differences-in-differences by regressing suicides on the treatment indicator, state fixed effects, and year fixed effects. In a second regression, also include the control variables. Interpret your results.

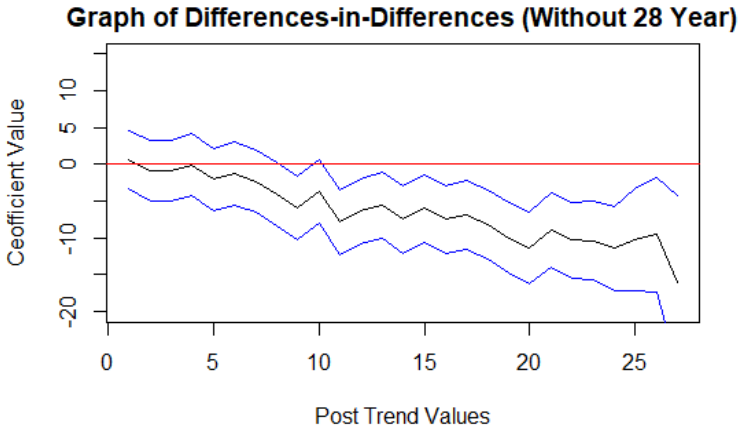
The treatment effect is -3.08 when considering the state (group) effects and the year (time) effects. The second regression with the addition of the control variables increases the treatment effect slightly to -2.66. Both values are significant therefore we can conclude that there is a significant difference between the control and treatment groups**.**

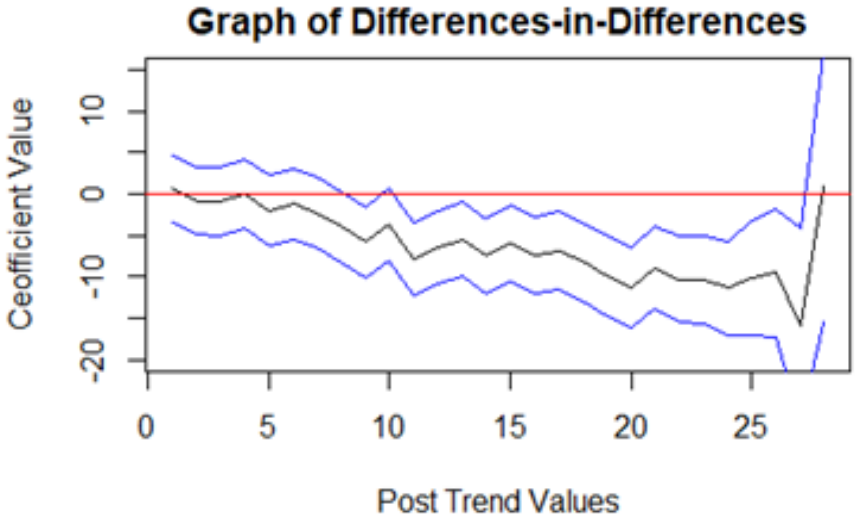
12. Re-estimate the model (without controls) excluding state-year observations for which the divorce law revisions have been in place longer than 2 years. This can be implemented by selecting observations with posttrend ≤ 2. Repeat the analysis, cutting off the sample after 5, 10, and 15 years of treatment. What do you observe, and what does this imply for the validity of the estimates obtained for the previous question?

Year Cutoff	Treatment Effect	Standard Error	P-value
<= 2	-2.04	1.39	0.14
<= 5	0.30	1.34	0.82
<= 10	0.26	1.23	0.83
<= 15	-1.15	1.14	0.31

The results of the treatment effects above for each year cutoff are not significant therefore we cannot conclude there was a significant difference between the control and treatment groups from the years less than or equal to 15 years after state divorce law revision. The validity of the estimates is not strong since each year cutoff had high p-values that were statistically insignificant.

13. Now estimate an event study model. Regress suicides on state fixed effects, year fixed effects,and fixed effects for the different values of posttrend. The last set of fixed effects is the object of interest. Plot the values of these fixed effects, along with a confidence interval, on a graph where posttrend is on the horizontal axis. Interpret the graph.





Based on the plot on the left, the fixed effect of posttrend has a negative effect on suicides. The suicide rate decreases each year after states implement divorce law revisions. This effect takes at least 7 years to happen as the significance of the p-values at and prior to the 7 year mark are insignificant. Therefore we can conclude that a state's law revision must be in place for around 7 years before there is a significant effect that decreases the suicide rate. Another factor to consider is that the 28 year mark post law revision was an outlier and statistically insignificant. We removed that datapoint from the plot to show the differences, the

plot on the right shows without the 28th year, that has a continual negative effect on suicides. There may be some error term that is not seen in the data skewing our results.

14. To check the parallel trends assumption, reestimate the model from the previous question, this time also including fixed effects for the different values of pretrend. Interpret the results. Do they support the validity of the event study approach to estimation?

The parallel trends assumptions on the pretend effect holds as none of the values of the coefficients were statistically significant. There is no evidence that the placebo (pretend effect) values are significantly different from 0. Therefore, we can conclude that the event study approach to estimation is valid.