Casual Inference Replication 1/ NAME: KAO, HSUAN-CHEN/ UT EID: HK25348

Q1: Github: https://github.com/justinkao44/RDD.git

Q2: summarize the paper

This paper focuses on whether punishments and sanctions on driving under the influence make an effective influence on decreasing drunk driving. The author claims that this finding is essential to improve society's social welfare and reduce the percentage of recidivism. When it comes to the model's mechanism, the property of the quantifiable characteristics of BAC allows the authors to apply a local linear regression discontinuity design to do the estimation. To construct the model, he utilizes administrative records on 512,964 DUI BAC tests in Washington from 1999 to 2007. The core reason is that BAC thresholds are the same after 1999, which is 0.08 and 0.15 aggravated.

He finds evidence that a 10 percent increase in sanctions and punishments is associated with a 2.3 percent decline in drunk driving. The evidence also shows that demographic indicators such as age, race, and gender keep constant in the DUI punishment thresholds. The identification strategy allows the slopes changes at the specific DUI =0.08 and severe DUI =0.15 threshold. Under the processing, they assume recidivism must decrease at specific points if punishment and sanctions are in effect, which is meet our expectations.

To sum up, the conclusion says that people have lower possibilities to repeatedly drunk drive. The estimates suggest having a BAC over the 0.08 legal limit corresponds with a two percentage point decline in repeat drunk driving over the next four years. Likewise, having a BAC over the 0.15 enhanced punishment limit is associated with a further one percentage point decline in repeat drunk driving. Hence, the project exhibits that the punishment and sanctions absolutely have the advantages of reducing repeatedly drunk drivers in the long run and the short run for both 0.08 DUI threshold and 0.15 aggravated DUI.

Q3:

In order to only focus on the 0.08 BAC cutoff, I ignore the 0.15 cutoff for all this analysis. Then create a dummy equaling 1 if bac1>= 0.08 and 0 otherwise.

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***bacc as our dummy variable***
. gen bacc=0

. replace bacc=1 if bac1>=0.08

. hist bac1
(bin=53, start=0, width=.0084717)
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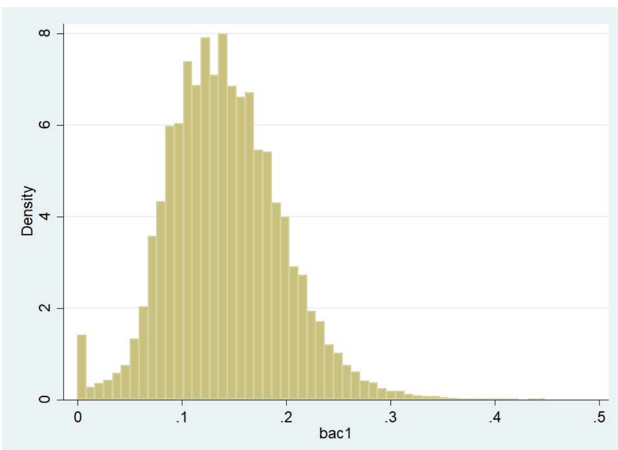
Q4:
In order to decide whether people are capable of manipulating their blood alcohol content (bac1), it is useful to use the McCrary test to figure out. Also, as was discussed in the class, we can use the visualization by sorting for running variables to confirm the density weather meet our expectation. After the comparison, we found out that the graph that made by ourselves is not so far from the author's paper(figure 1.) The only difference based on the graph would be the difference in the vertical axis. The vertical axis in our graph is the density rather than the frequency of BAC. From my perspective, I want to assume it complies with the normal distribution. However, a bit of the right-skewed would be caused by the zero points. All in all, there is no obvious evidence for the human manipulation of the dataset.



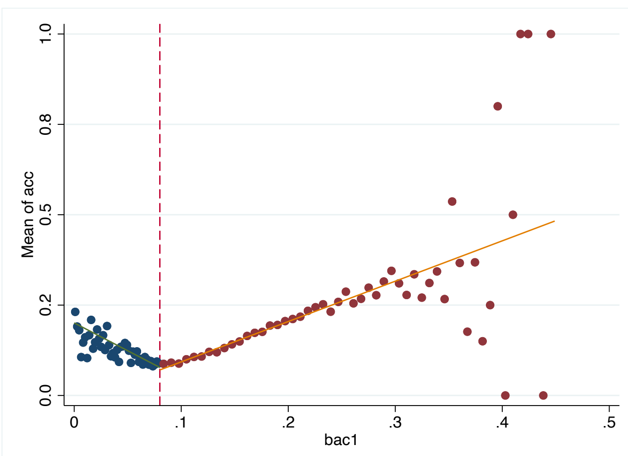
Q5:
The equation(1)
bacc = β0 + β1white + β2male + β3aged + β4acc + u
The equation(2)
recidivism = α0 + α1male + α2white + α3aged + α4acc + α5bac1 + α6bacc + α7bacc ∗ bac1

As a requirement, we recreate table 2 panel A but only white male, age, and accident (acc) as dependent variables. We could see the results in the below table after we recreate Table 2 Panel A. If we make the comparison of the result we obtain to the table in Hansen's paper, we might find that covariates are balancing at the cutoff. This result seems to keep the same at the thresholds depends on the setting of equation 1.

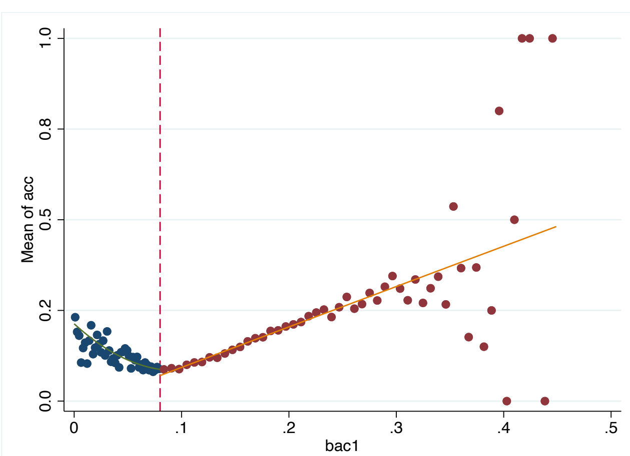
Table 2	Male	White	Age	Accident
Panel A. DUI threshold	0.004	0.017	-0.0004	0.028
	(0.002)	(0.002)	(0.000)	(0.002)
Mean (at 0.892)	0.79	0.862	34.957	0.147
Controls	No	No	No	No
Observations	214,558	214,558	214,558	214,558

Q6:
I use the following result to make the comparison to Hansen's paper. Though we only set for the one threshold 0.08, the result seems very similar. Also, if we only focus on the curve between 0-0.2 for both linear and quadratic equations, the degree of the similarity is much close to Hansen's result.

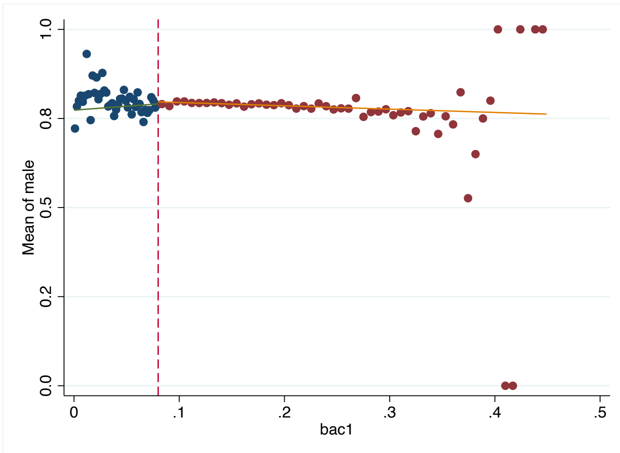
cmogram acc bac1, cut(0.08) scatter line(0.08) lfit



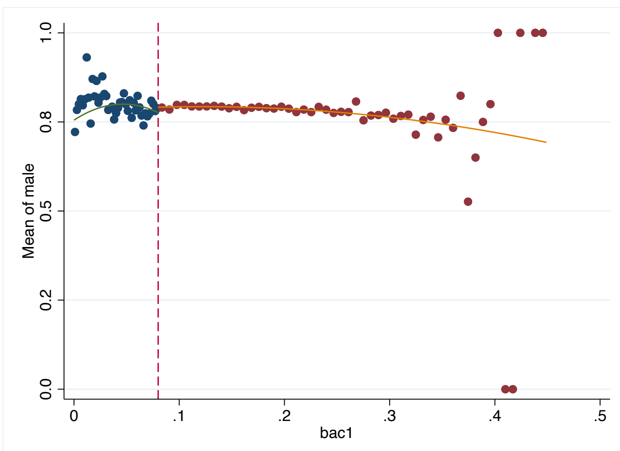
cmogram acc bac1, cut(0.08) scatter line(0.08) qfit



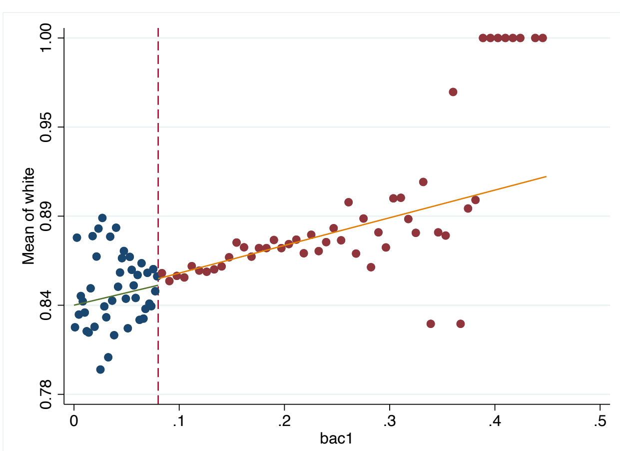
cmogram male bac1, cut(0.08) scatter line(0.08) lfit



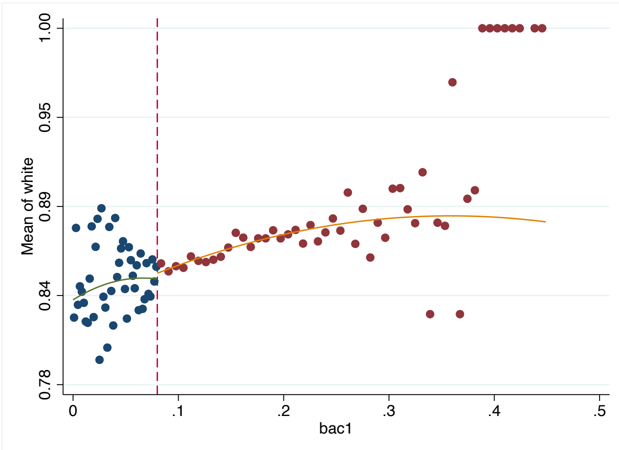
cmogram male bac1, cut(0.08) scatter line(0.08) qfit



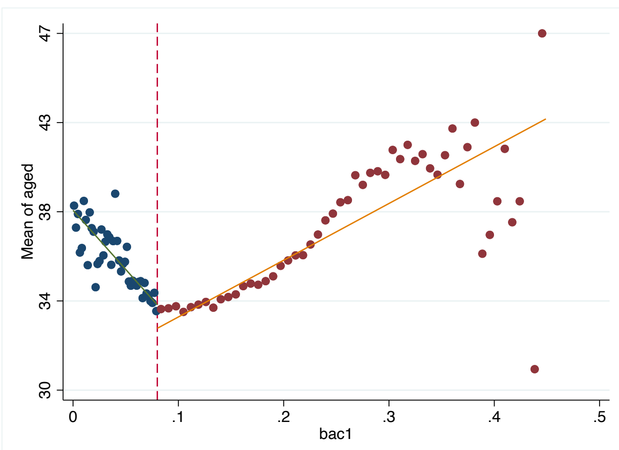
cmogram white bac1, cut(0.08) scatter line(0.08) lfit



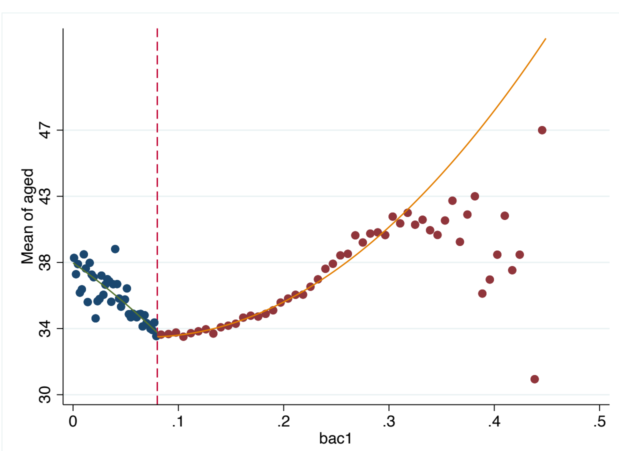
cmogram white bac1, cut(0.08) scatter line(0.08) qfit



cmogram aged bac1, cut(0.08) scatter line(0.08) lfit



cmogram aged bac1, cut(0.08) scatter line(0.08) qfit



Q7:
Equation 1: control for the bac1 linearly
Equation 2: interact bac1 with cutoff linearly
Equation 3: interact bac1 with cutoff linearly and as a quadratic

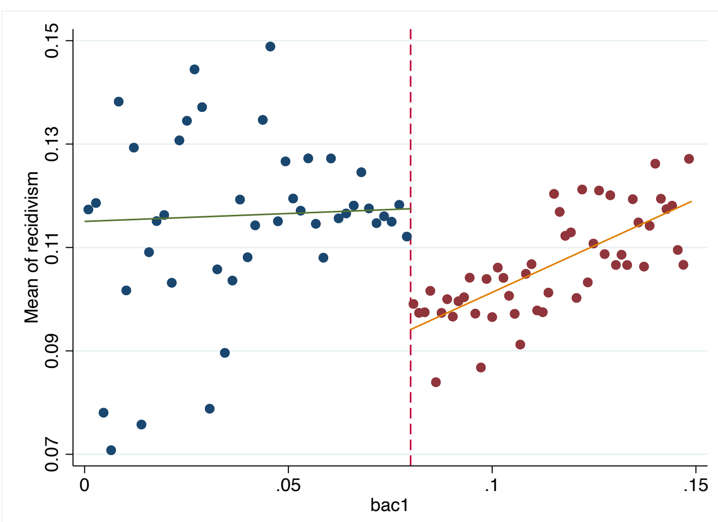
Table 3	Equation (1)	Equation (2)	Equation (3)
Panel A. BAC* ∈ [0.03, 0.13] *DUI	-0.075 (0.048)	-0.043 (0.187)	2.902** (0.092)
Controls	Yes	Yes	Yes
Observations	214,558	214,558	214,558
Panel B. BAC* ∈ [0.055, 0.105] *DUI	-0.476*** (0.111)	-0.196 (0.383)	6.167 (8.120)
Controls	Yes	Yes	Yes
Observations	214,558	214,558	214,558

*** Significant at the 1 percent level.

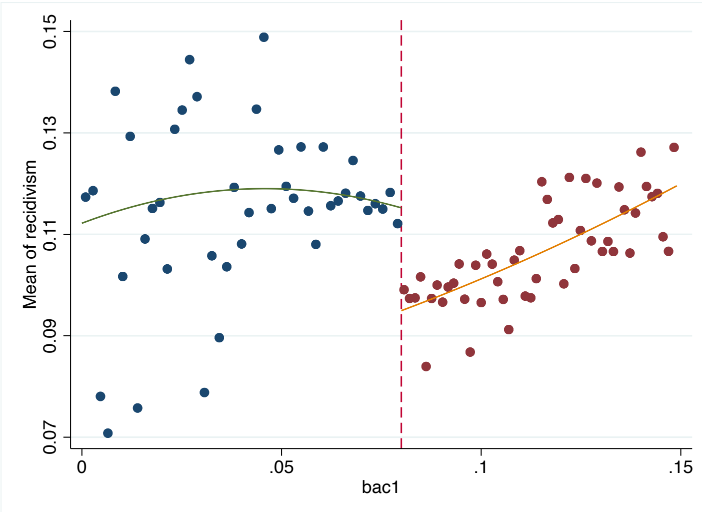
** Significant at the 5 percent level.

* Significant at the 10 percent level.

Q8:
(1)Fit linear fit using only observations with less than 0.15 bac on the bac1
:cmogram recidivism bac1 if bac1<0.15, cut(0.08) scatter line(0.08) lfit



(2)Fit quadratic fit using only observations with less than 0.15 bac on the bac1
:cmogram recidivism bac1 if bac1<0.15, cut(0.08) scatter line(0.08) qfit



Q9:
Alcohol abuse continues to be a significant problem not only in the USA but it is also severe in our home country. I am so happy to learn this whole project and try to agonize over whether the process would be possible to improve the drunk driver situation in my home country.

From this exercise, the purpose and hypothesis are to research whether punishments and sanctions can effectively decrease drunk driving in a certain threshold, which is 0.08 in this practice paper. The result obtained from our regression discontinuity is very close to Hansen's paper. However, if I have to conclude that I am confident of Hansen's result, I think we have to be more careful. First, the dataset of his and mine is not exactly the same, and this would result in the problem of proving the explanatory power of the punishment. But, my doubt is solely on the number of declination of recidivism; I am confident that the more harsh punishment would improve drunk driver's problem. Second, I believe that there is still a more strict test to precisely measure whether the model estimates our goal. Thus far, the mechanisms I had learned are not quite complete; hence, I doubt everything I had already done still not enough to make sure the paper's conclusion is perfect.

Though I had tried to figure out why our result in Q7 exhibits the statistically insignificant effect of punishment, I still believe that the intuitive sense would be the same as the real data, which means the penalty does really make a huge impact on reducing the DUI.

This replication is my first project to address the real issue in daily life. I believe that this causal inference training would help me delve into a more complicated issue successfully in the future.