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Replication of Hansen (2015) Punishment and Deterrence: Evidence from Drunk Driving

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In the study *Punishment and Deterrence: Evidence from Drunk Driving* **(Hansen, 2015)**, Hansen investigated the effect of punishments and sanctions on reducing repeat drunk driving. The study implemented a quasi-experimental design, utilising the administrative records from 1995 to 2011 of the state of Washington, U.S., where two thresholds of blood alcohol content (BAC) are used to determine the status of driving under the influence (DUI). Specifically, a driver with a measured BAC over 0.08 is considered a case of DUI and will be punished via measures such as fines, jail time, and driving license suspension. One with a BAC over 0.15 is considered a case of aggravated DUI, to which more severe punishments and sanctions are applied. Since BAC measure has clear-cut numeric thresholds for determining whether a driver will receive harsher punishments, and neither drivers or police can manipulate this measure, Hansen applied a regression discontinuity design to analyse the data **(expand on the justification of using RDD)**. He hypothesized that receiving harsher punishments and sanctions at both thresholds would reduce offenders' future recidivism of DUI. He further applied the RDD to analyse the effect of receiving harsher punishments on the degree of deterrence, incapacitation, and rehabilitation in order to identify the mechanism through which harsher punishments might reduce recidivism **(check the paper to see whether this sentence is precise)**.

Ideally also the results

The present study aims to replicate the findings from **Hansen (2015)** using regression discontinuity design applied to a similar data **(what is it exactly…)**. It will be focused on estimating the effect of receiving punishments on reducing recidivism at the 0.08 BAC threshold only. The paper proceeds as follows. Section 1 discusses the econometric method and assumptions underlying its application to the current data. Section 2 presents the main results, and Section 3 discusses critiques and extensions to the original study. Section 4 concludes.

1 Methods and Assumptions

1.1 Assumptions of the regression discontinuity design

The present study applies the regression discontinuity design to the data provided by the class instructor. Several assumptions need to be met so that the regression discontinuity design can give accurate estimates. First, people need to be randomly assigned to receiving punishment at the BAC threshold. In other words, neither the drivers nor the police can manipulate the BAC level and thus whether one will receive punishment. **Hansen (2015)** has already given a plausible theoretical justification for this assumption. Empirically, I plot the distribution of BAC and test for discontinuity in its distribution at the threshold. Figure 1 shows the distribution of BAC level. Based on a recently developed local polynomial density estimator **(CJM, 2020)**, the hypothesis that the distribution is continuous at 0.08 cannot be rejected at the alpha level of 0.05 (p = 0.890). Therefore, there is no evidence for the existence of manipulation on the BAC level.

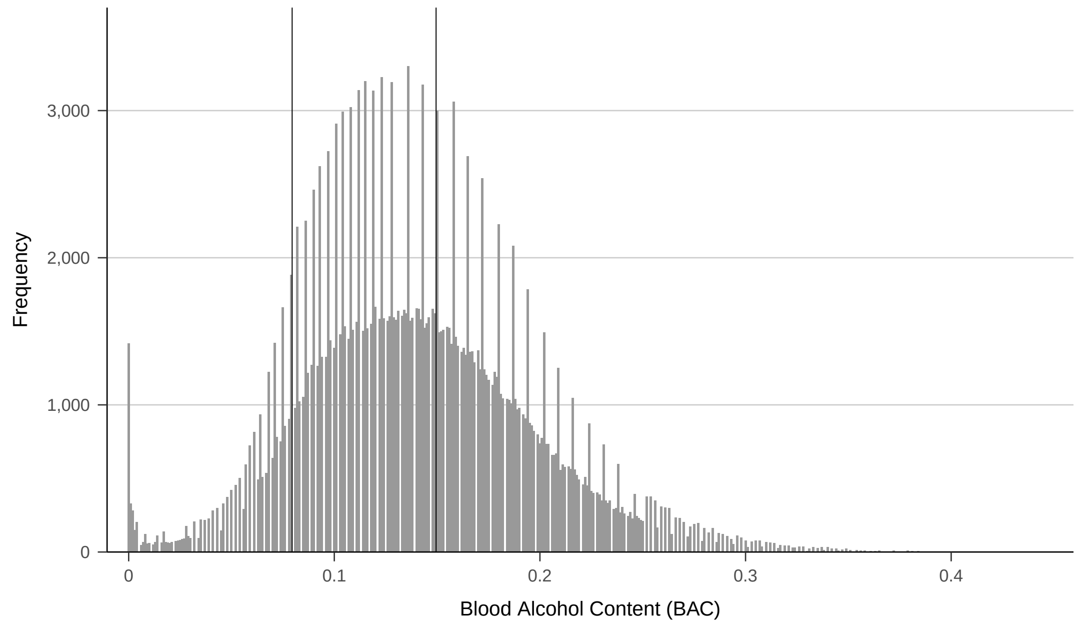

Figure 1: Histogram of blood alcohol content as a continuous variable. The blood alcohol content is plotted as a continuous variable with a bin width of 0.001, the precision used on the breathalysers. The y-axis represents the frequency of observations in each bin. The vertical black lines represent the two thresholds at 0.08 and 0.15.

The second assumption is that the running variable should not contain non-random heaping, which can lead to biased estimates in regression discontinuity models **(Barreca et al., 2011)**. In other words, BAC should not be much more likely to take certain values than others. Based on Figure 1, this assumption seems to be violated. Curiously, when BAC is plotted as a discrete variable, non-random heaping disappears (Figure 2). A closer inspection of the data suggests that this is probably due to the lack of precision in BAC in the current data. Many BAC values deviate by a very small amount from the values that are supposed to be given by the breathalysers (i.e., precise to three digits after the decimal point). Some bins have a value at the left boundary deviating upwards and a value at the right boundary deviating downwards. Such bins will contain a larger number of observations than other bins and thus leads to heaping. This would not occur if the data records the values precisely so that the number of observations are rightly separated into and plotted by two bins, or if we treat BAC as discrete and give each value its own bin. **(consider using a simulation to justify this claim?)**

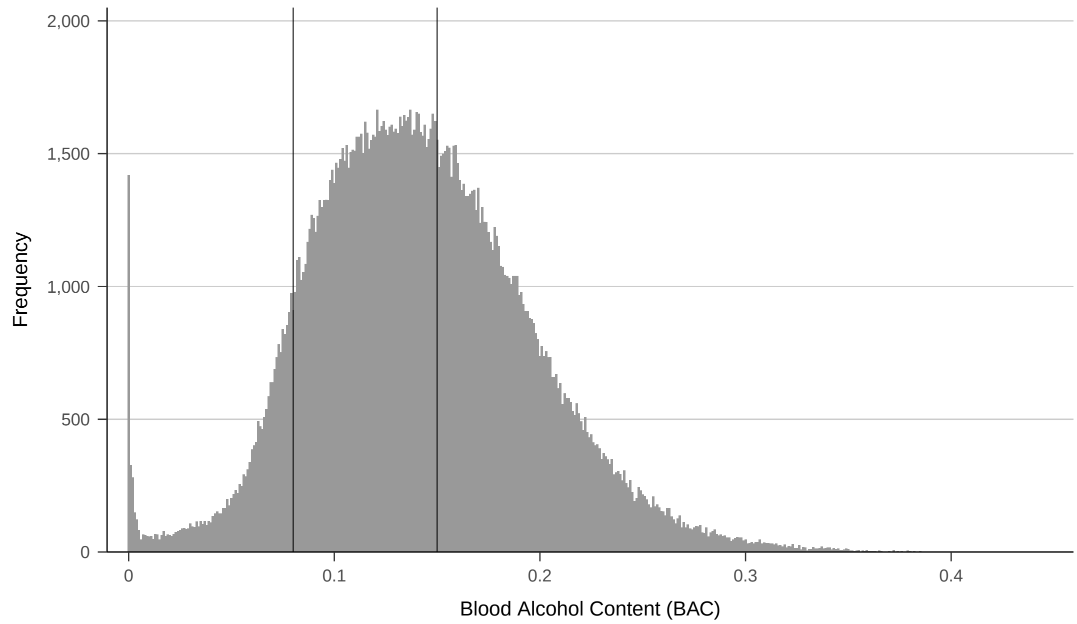

Figure 2: Histogram of blood alcohol content as a discrete variable. The blood alcohol content is plotted as a discrete variable with a bin width of 0.001, the precision used on the breathalysers. The y-axis represents the frequency of observations in each bin. The vertical black lines represent the two thresholds at 0.08 and 0.15.

1.2 The model

The present study utilises a local linear regression model with a rectangular kernel weight function to estimate the effect of receiving punishments at the threshold on recidivism. For sensitivity analyses, the models are re-estimated using second-order polynomials and triangle kernel function). The model is specified by the following function:

$$R_i = \alpha + \beta_1 DUI_i + \beta_2 BAC_i + \beta_3 DUI_i \times BAC_i + \tau Z_i + \epsilon_i \tag{1}$$

where the variable DUI_i is an indicator of whether BAC is above the 0.08 threshold, BAC_i is the measure of BAC level, R_i is an indicator of recidivism, and Z_i is a vector of control variables. The variable BAC_i in the model is centered around the threshold value of 0.08 so that the coefficients directly reflect the estimates of the effect.

1.3 Inclusion of control variables

In order to determine whether any covariates should be included in the model, I run preliminary analyses on the effect of receiving punishments at the threshold on four predetermined characteristics, including three demographic variables (gender, race, and age) and the BAC test being conducted in a traffic accident. The analyses use the same local linear regression model specified in equation (1), with a bandwidth of 0.05 and no kernel weight function. As Table 1 shows, I fail to reject any of the null hypotheses that predetermined

Table 1: Regression Discontinuity Estimates of the Effect of Receiving Punishments at the 0.08 BAC Threshold on Predetermined Characteristics

	Male	White	Age	Accident
DUI	0.006	0.006	–0.141	–0.003
	(0.006)	(0.005)	(0.164)	(0.004)
Mean	0.784	0.846	0.085	33.99
Num. of Obs.	89,967	89,967	89,967	89,967

Note. Regression discontinuity based estimates of the effect of receiving punishments at the 0.08 BAC threshold on four predetermined characteristics. All models use a bandwidth of 0.05 and a rectangular kernel weight function. Counterfactual predictions of mean recidivism is calculated at the 0.079 BAC threshold. Heteroscedasticity-robust standard errors are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

characteristics remained the same at the threshold. This indicates that gender, race, age, and the BAC test being conducted in a traffic accident, on average, were not different between people who did not receive punishments and those who received punishments at the threshold. According to **Calonico et al. (2019)**, I will include the four predetermined characteristics in regression discontinuity models to improve the estimation precision of the effects of receiving punishments at the threshold on recidivism.

2 Results

2.1 The Effect of Punishments on Recidivism

Table 2 reports the estimated effect of receiving punishments at the threshold on recidivism. Local linear regression model with a rectangular kernel function gives the estimate that receiving punishments at the 0.08 BAC threshold decreases recidivism by 2.4 percentage points, which is statistically significant at the alpha level of 0.01. Local second-order polynomial with a rectangular kernel function gives an estimate of a decrease in recidivism by 1.4 percentage points, which is statistically significant at the alpha level of 0.05. These estimates are consistent across both bandwidths and across models with different types of kernel functions.

Figure 3 plots means of recidivism in bins and predicted recidivism based on linear regression models or second-order polynomials using observations within the interval $BAC \in [0.06, 0.11]$. Panel A and B and Panel C and D use different methods for binning observations and representing confidence intervals to ensure the robustness of the visual evidence (See the figure caption). All panels show an apparent drop in recidivism at the BAC threshold of 0.08. This visually indicates that there is an effect of receiving punishments at the BAC threshold in decreasing recidivism.

Table 2: Regression Discontinuity Estimates of the Effect of Receiving Punishments at the 0.08 BAC Threshold on Recidivism

	Rectangular kernel		Triangular kernel	
	Linear	Quadratic	Linear	Quadratic
A. DUI ∈ [0.03, 0.13]				
DUI	–0.024***	–0.014**	–0.020***	–0.014**
	(0.004)	(0.006)	(0.005)	(0.006)
Mean	0.104	0.099	0.100	0.099
Controls	Yes	Yes	Yes	Yes
Num. of Obs.	89,967	89,967	89,967	89,967
B. DUI ∈ [0.055, 0.105]				
DUI	–0.021***	–0.014*	–0.018***	–0.016*
	(0.006)	(0.008)	(0.006)	(0.009)
Mean	0.101	0.098	0.101	0.100
Controls	Yes	Yes	Yes	Yes
Num. of Obs.	46,957	46,957	46,957	46,957

Note. Regression discontinuity based estimates of the effect of receiving punishments at the 0.08 BAC threshold on recidivism. Panel A presents estimates based on a 0.05 bandwidth, and Panel B presents estimates based on a 0.025 bandwidth. The table includes results from both linear and quadratic models, with either a rectangular or a triangular kernel weight function. Controls include individuals' gender, race, age, and an indicator of whether the BAC test was conducted in a traffic accident. Counterfactual predictions of mean recidivism are calculated at the 0.079 BAC threshold and mean age of the respective populations, averaging over individuals' gender and race, as well as over whether the BAC testing was conducted in an accident. Heteroscedasticity-robust standard errors are in parentheses. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

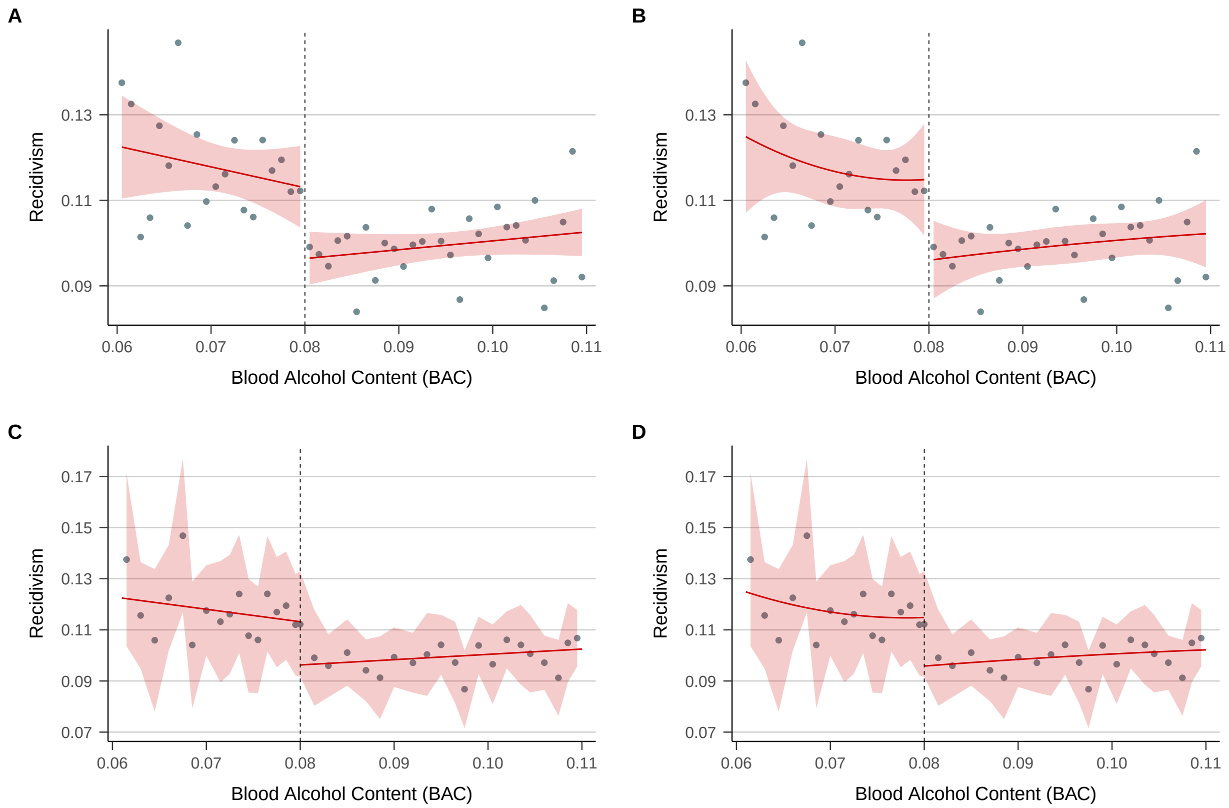

Figure 3: Regression Discontinuity Plot of the Effect of Receiving Punishments at the 0.08 BAC Threshold on Recidivism. Plot of means of recidivism in bins and predicted recidivism using simple regression models. In plotting the binned means (gray points), Panel A and B choose the number of bins on each side of the threshold using the formula $bins = min\{\sqrt{n}, 10 \times \frac{\ln n}{\ln 10}\}$, while Panel C and D choose the number using quantile spaced binning **(Calonico et al., 2015)**. For the confidence intervals (shaded areas in red), Panel A and B plot the 95% confidence interval of the regression models, while Panel C and D plot the 95% confidence interval of each bin. For the regression models (red lines), Panel A and C plot the best fitted linear model, while Panel B and D plot the best fitted second-order polynomial. All panels plot the data within the interval $BAC \in [0.06, 0.11]$. The vertical dashed lines represent the BAC threshold at 0.08.

2.2 Robustness

Since there seems to be non-random heaping in the current data (Figure 1), this section will use donut regression discontinuity models to investigate the robustness of the results presented in the last section. Donut regression discontinuity models entirely drop the observations near the threshold. Under appropriate assumptions, they are effective in preventing a heap just at the threshold from biasing the estimates **(Barreca et al., 2011)**.

For the present study, I drop the observations in the interval $BAC \in [0.079, 0.081]$, and re-estimate local linear and quadratic models with either a rectangular or a triangular kernel weight function. It is worth stressing that robustness test using local polynomials is especially important in a donut regression discontinuity design. This is because a donut regression model gets rid of the very observations on which the estimates of local average effects rely upon. The estimates given by donut regression models are essentially

Table 3: Donut Regression Discontinuity Estimates of the Effect of Receiving Punishments at the 0.08 BAC Threshold on Recidivism

	Rectangular kernel		Triangular kernel	
	Linear	Quadratic	Linear	Quadratic
A. DUI ∈ [0.03, 0.13]				
DUI	–0.026***	–0.014*	–0.022***	–0.018**
	(0.005)	(0.007)	(0.005)	(0.006)
Mean	0.105	0.099	0.102	0.101
Controls	Yes	Yes	Yes	Yes
Num. of Obs.	88,085	88,085	88,085	88,085
B. DUI ∈ [0.055, 0.105]				
DUI	–0.022***	–0.015	–0.020***	–0.020
	(0.007)	(0.011)	(0.007)	(0.012)
Mean	0.103	0.099	0.103	0.104
Controls	Yes	Yes	Yes	Yes
Num. of Obs.	45,075	45,075	45,075	45,075

Note. Regression discontinuity based estimates of the effect of receiving punishments at the 0.08 BAC threshold on recidivism after dropping observations in the interval [0.079, 0.081]. Panel A presents estimates based on a 0.05 bandwidth, and Panel B presents estimates based on a 0.025 bandwidth. The table includes results from both linear and quadratic models, with either a rectangular or a triangular kernel weight function. Controls include individuals' gender, race, age, and an indicator of whether the BAC test was conducted in a traffic accident. Counterfactual predictions of mean recidivism are calculated at the 0.079 BAC threshold and mean age of the respective populations, averaging over individuals' gender and race, as well as over whether the BAC testing was conducted in an accident. Heteroscedasticity-robust standard errors are in parentheses. $^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$.

based on models' extrapolation over the region of the donut **(Dowd, 2021)** and may be especially sensitive to the assumptions about the underlying functional form **(Consider justifying this using a simulation)**. Using polynomials with different orders can ensure the robustness of the results over different functional assumptions.

The results from donut regression discontinuity models are presented in Table 3. According to the local linear regression model with a rectangular kernel function, receiving punishments at the threshold decreases recidivism by 2.6 percentage points and is statistically significant at the alpha level of 0.01. According to the local second-order polynomial with a rectangular kernel function, receiving punishments at the threshold decreases recidivism by 1.4 percentage points and is statistically significant at the alpha level of 0.1. These estimates are consistent across both bandwidths and across models with different types of kernel functions, except for not being statistically significant in quadratic models estimated with narrower bandwidth of 0.025. Therefore, the results given by donut regression discontinuity models are essentially identical with those given by ordinary models presents in the last section.

3 Discussion, Critique and Extension

Using a regression discontinuity design, the present study aims to replicate the findings of **Hansen (2015)** about the effect of punishments and sanctions on reducing repeat drunk driving. Specifically, the present study focuses on testing whether receiving punishments at the 0.08 Blood Alcohol Content (BAC) threshold reduces future recidivism of drunk driving with a local linear regression model. The findings show that receiving punishments at the threshold reduces recidivism by up to 2.4 percentage points [1]. Robustness test based on local second-order polynomials show that receiving punishments at the threshold reduces recidivism by up to 1.6 percentage points [2]. These estimates are consistent with those given by models that take into account non-random heaping in the data.

The findings of the present study successfully replicate the main results of **Hansen (2015)**.

4 Conclusion

[1] The average estimated effect is 2.1 percentage points. The average estimate is calculated over models based on different bandwidths and with different kernel functions, assuming equal weights of estimates.

[2] The average estimated effect is 1.5 percentage points.