Replication - Punishment and Deterrence: Evidence from Drunk Driving by Benjamin Hansen

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1 Brief Summary

Hansen's paper addresses a question regarding whether punishments and sanctions are effective in reducing future drunk driving. He uses the theoretical result from Becker (1968), that suggests that criminals behave rationally when committing crimes by evaluating expected costs and benefits. The author analyzes administrative records from 1999 to 2007 from the state of Washington, where, during that time period, a blood alcohol content (BAC) above 0.08 was considered driving under the influence (DUI), while a BAC above 0.15 was considered an aggravated DUI. In order to evaluate the causal effect of having the 0.08 and 0.15 thresholds on recidivism, he examines other two mechanisms that, as well as deterrence, arise from theories of criminality and might affect recidivism: incapacitation and rehabilitation.

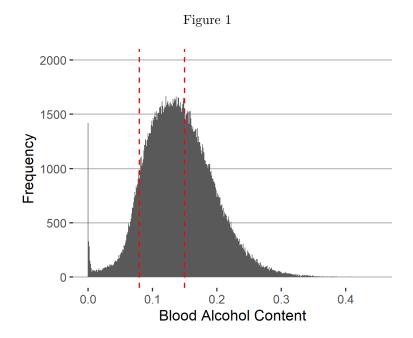
The data is consisted of records on 512,964 DUI BAC tests, and foccuses on individuals above the legal drinking age, since different cutoffs apply to those under 21. Given the characteristics of the BAC tests, the author argues that the inability of individuals to manipulate BAC allows for a quasi-experiment. Assuming that it is locally random for a drunk driver to have a BAC barely below or barely above the threshold, he uses the specific cutoffs to use a regression discontinuity design in order to test the effect of the punishments on recidivism.

Hansen finds evidence that having a BAC above the DUI threshold is associated with a 2 percentage point decrease in recidivism over the next four years, while having a BAC above the aggravated DUI treshhold is associated with one additional percentage point decrease in recidivism, which offers evidence of the causal effect of punishments and sanctions in reducing recidivism among drunk drivers.

2 Replication

Given the the particular research design, the first step of the replication was to check for any evidence of sorting on the running variable. In order to do that, I plotted a histogram to visualize the frequency distribution of the BAC test results.

If drivers were able to manipulate their test results, we would expect to see an exceptional increase in the frequency near the left side of the thresholds. However, as we can observe in Figure 1, the graph doesn't show any evidence of manipulation. This is particularly relevant because, had drunk drivers been able to control their BAC, the division between treatment and control group at the cutoff wouldn't be locally random.



Now, we need to test for covariate balance, by estimating the equation

$$y_i = \alpha_1 DUI_i + \alpha_2 BAC_i + \alpha_3 BAC_i \times DUI_i + u_i$$

with each of the control variables being specified as the dependent variable.

This procedure is important because, when trying to measure the causal effect of an intervention, we are implicitly assuming that all the other variables that affect the outcome, observed and unobserved, are not changing at the threshold.[1] Comparative statics methodological concept only describe the effect of an explanatory variable on the response variable when holding all else fixed.

Table 1 summarizes the coefficients associated with the cutoff yielded by each of the 4 regressions. On Panel A, all available observations were used,

while for Panel B it was set a bandwidth of ± 0.05 with a rectangular kernel for weighting. The results differ from those found by the authors, since we reject the null hypothesis of covariate balance for Age and Accident. It is not clear why we are finding different results, but the difference could be due to the fact that the dataset has less observations with $0.03 \leq \text{BAC} \leq 0.13$ than the one that the author used.

Table 1

Panel A. All observations			
Male	White	Age	Accident
0.031*** (0.007)	0.003 (0.006)	-7.787^{***} (0.204)	-0.219^{***} (0.006)
0.79 214,558	0.86 $214,558$	34.96 214,558	0.15 214,558
Panel B. $0.03 \leq BAC \leq 0.13$			
Male	White	Age	Accident
-0.018 (0.020)	0.004 (0.017)	-6.224^{***} (0.564)	-0.154^{***} (0.015)
0.79 89,967	0.85 89,967	34.17 89,967	0.1 89,967
	0.031*** (0.007) 0.79 214,558 Male -0.018 (0.020) 0.79	Male White 0.031*** 0.003 (0.007) (0.006) 0.79 0.86 214,558 214,558 Panel B. 0.0 Male White -0.018 0.004 (0.020) (0.017) 0.79 0.85	Male White Age 0.031^{***} 0.003 -7.787^{***} (0.007) (0.006) (0.204) 0.79 0.86 34.96 $214,558$ $214,558$ $214,558$ Panel B. $0.03 \le BAC \le 0$ $0.004 \le BAC \le 0$ Male White Age -0.018 0.004 -6.224^{***} (0.020) (0.017) (0.564) 0.79 0.85 34.17

Note:

*p<0.1; **p<0.05; ***p<0.01

Figure 2 illustrates the conditional mean with the fitted values from a linear model for the regressions specified above with a 95% confidence interval band.

Figure 3 illustrates the conditional mean with the fitted values from a quadratic model for the regressions specified above with a 95% confidence interval band.

We can observe from the graphs that, even though some covariates show a different slope after the cutoff, none of them show an extreme jump that would affect the conditional mean at the margin. The graphs look similar to those presented by the author, which corroborates his argument.

Finally, in order to evaluate the effect of the threshold on recidivism, we estimated the model's equation with the four control variables (being X_i the vector of covariates) and three different specifications for the dummy variable DUI:

$$\begin{aligned} \text{Linear}: \mathbf{y}_i &= \mathbf{X}'_i \gamma + \alpha_1 \mathbf{D} \mathbf{U} \mathbf{I}_i + \alpha_2 \mathbf{B} \mathbf{A} \mathbf{C}_i + \mathbf{u}_i \\ \text{Interaction}: \mathbf{y}_i &= \mathbf{X}'_i \gamma + \alpha_1 \mathbf{D} \mathbf{U} \mathbf{I}_i + \alpha_2 \mathbf{B} \mathbf{A} \mathbf{C}_i + \alpha_3 \mathbf{B} \mathbf{A} \mathbf{C}_i \times \mathbf{D} \mathbf{U} \mathbf{I}_i + \mathbf{u}_i \\ \text{Quadratic}: \mathbf{y}_i &= \mathbf{X}'_i \gamma + \alpha_1 \mathbf{D} \mathbf{U} \mathbf{I}_i + \alpha_2 \mathbf{B} \mathbf{A} \mathbf{C}_i + \alpha_3 \mathbf{B} \mathbf{A} \mathbf{C}_i \times \mathbf{D} \mathbf{U} \mathbf{I}_i + \alpha_4 \mathbf{B} \mathbf{A} \mathbf{C}^2_i + \alpha_5 \mathbf{B} \mathbf{A} \mathbf{C}^2_i \times \mathbf{D} \mathbf{U} \mathbf{I}_i + \mathbf{u}_i \end{aligned}$$

Figure 2

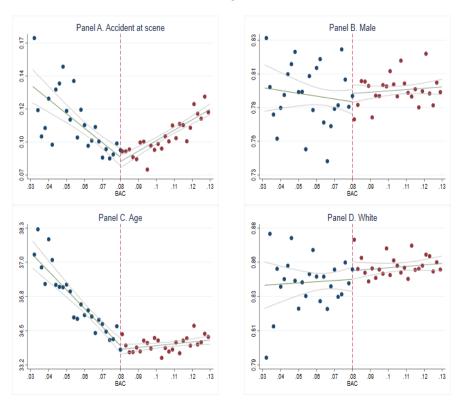


Table 2 summarizes the output of the regression of recidivism using the linear, interaction and quadratic model specified above. On Panel A, a bandwidth of ± 0.05 was used with a rectangular kernel for weighting while while, for Panel B, a bandwidth of ± 0.025 was used with a rectangular kernel for weighting.

The regression discontinuity estimates slightly changes fro Panel A to Panel B, but both yield a statistically significant coefficient for the DUI variable in the Interaction model, providing evidence that being charged for DUI decreases the probability of recidivism in the future.

To illustrate the results found on the regression discontinuity estimates, Figure 4 shows a substantial decrease in recidivism right after the cutoff, providing evidence that the increase in punishments and sanctions is effective in reducing future drunk driving.

References

[1] S. Cunningham. Causal Inference: The Mixtape. 2020.

Table 2

Panel A. 0	$0.03 \le BAC \le 0.03$.13 bandwidth
	Recidivism	
Linear	Interaction	Quadratic
-0.027^{***} (0.004)	-0.059^{***} (0.015)	0.113 (0.085)
0.11 89,967 Panel B. 0.0	$ \begin{array}{c} 0.11 \\ 89,967 \\ 055 \le BAC \le 0. \end{array} $	0.11 89,967 105 bandwidtl
	Recidivism	
Linear	Interaction	Quadratic
-0.022^{***} (0.006)	-0.069^{**} (0.034)	0.270 (0.406)
0.11 47,205	0.11 47,205	0.11 47,205
	Linear -0.027*** (0.004) 0.11 89,967 Panel B. 0.0 Linear -0.022*** (0.006)	$\begin{array}{c cccc} \mbox{Linear} & \mbox{Interaction} \\ -0.027^{***} & -0.059^{***} \\ (0.004) & (0.015) \\ \hline \\ 0.11 & 0.11 \\ 89,967 & 89,967 \\ \hline \mbox{Panel B. } 0.055 \leq \mbox{BAC} \leq 0. \\ \hline \mbox{Recidivism} \\ \hline \mbox{Linear} & \mbox{Interaction} \\ -0.022^{***} & -0.069^{**} \\ (0.006) & (0.034) \\ \hline \\ 0.11 & 0.11 \\ \hline \end{array}$

Note:

*p<0.1; **p<0.05; ***p<0.01

Figure 3

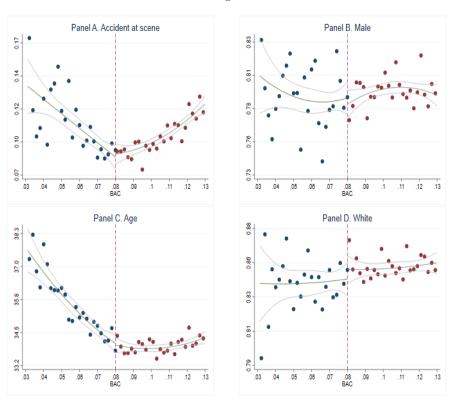


Figure 4

