

Causalhw1

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Part 1 Find the github repo named RDD1 at the following github link

<https://github.com/Fjolle/RDD1>

Part 2 Summary of the paper: The paper Punishment and Deterrence: Evidence from Drunk Driving by Benjamin Hansen studies the effects of punishments in deterrence from drunk driving. Hansen demonstrates the results by comparing two different driving under influence (DUI) thresholds. He distinguishes the two cutoff levels as follows: A blood alcohol content (BAC) level above 0.08 is considered a DUI, while a BAC level above 0.15 is considered an aggravated DUI. The aggravated DUI results in higher punishments as compared to DUI. He finds out that, broadly speaking, higher punishments and sanctions result in smaller number of future drunk driving. Moreover, BAC above the level threshold set face higher punishments and sanctions if repeated in the future. The paper restricts attention to drivers above the legal drinking age. Moreover, certain demographics, such as age, gender, accident and race are considered to check whether or not covariates are balanced at the threshold level of 0.08 and 0.15. He finds out that the demographic factors are stable across the dui punishments. The stable results indicate that the characteristics considered provide credibility that the regression discontinuity design gives unbiased estimates. This finding implies that neither the drunk driver nor the police officer are able to manipulate testing at the cutoff points of 0.08 and 0.15.

A major question that the paper tries to answer is whether or not bac limits reduce future drunk driving. The author studies this question by estimating the effect of having bac over the dui limit on recidivism within four years of the initial offense. The 4 year time period is chosen for capturing the medium run effect of punishment on the likelihood of recidivism. Recidivism acts as an indicator variable in the data set, taking the value of 0 if the drivers are not pulled over for being suspected of drunk driving, and 1 if the drivers are subjected to a test or refuse a test by the police officer within four years of the original stop.

He finds out that drivers found to have a bac level about the 0.08 threshold decrease recidivism by 2 percentage points during the four-year follow-up window. Moreover, drivers with prior tests reduce recidivism by a larger margin within the 4 year period than drivers without prior tests. This is likely the result of the penalties being much higher for drivers being caught drunk driving for the second time.

Considering all drunk drivers above the legal drinking age, those with a bac over the 0.08 threshold show a decrease in likelihood of recidivism. The largest decrease in likelihood of recidivism is the bac level between 0.08 and 0.15. This shows that having a bac over the dui threshold decreases the likelihood of drunk driving in the future. Moreover, having a bac results in reduced future accidents. Additionally, drivers with at least one prior test are less likely to refuse a breath test. This is potentially due to the offenders having learned from experience that refusing to take a breath test could result in higher punishments. Drivers with no prior tests, on the other hand, show no change in their probability of refusing the breath test. Further, Hansen finds that drivers with a prior test are less likely to be pulled over for a second time.

Various sanctions and punishments affect how severe each bac limit is. Hansen finds that a 10% increase in sanctions and punishments is associated with a 2.3% decrease in drunk driving. He further considers different channels of drunk driving related to criminality as a potential explanation of the reduction in recidivism.

Between incapacitation, rehabilitation and deterrence, the latter shows to be the most effective channel. Based on the rational model of criminality, likelihood of recidivism as a DUI increases, decreases as sanctions and punishments increase. However, contrary to the rational model of criminality, likelihood of recidivism as the aggravated DUI increases, decreases with an increase in punishments and sanctions.

Hansen concludes by suggesting that a larger amount of resources through advertisement and public service announcements be spent to inform the 0.15 threshold group, provided that this group is responsible for the largest number of fatalities in the society.

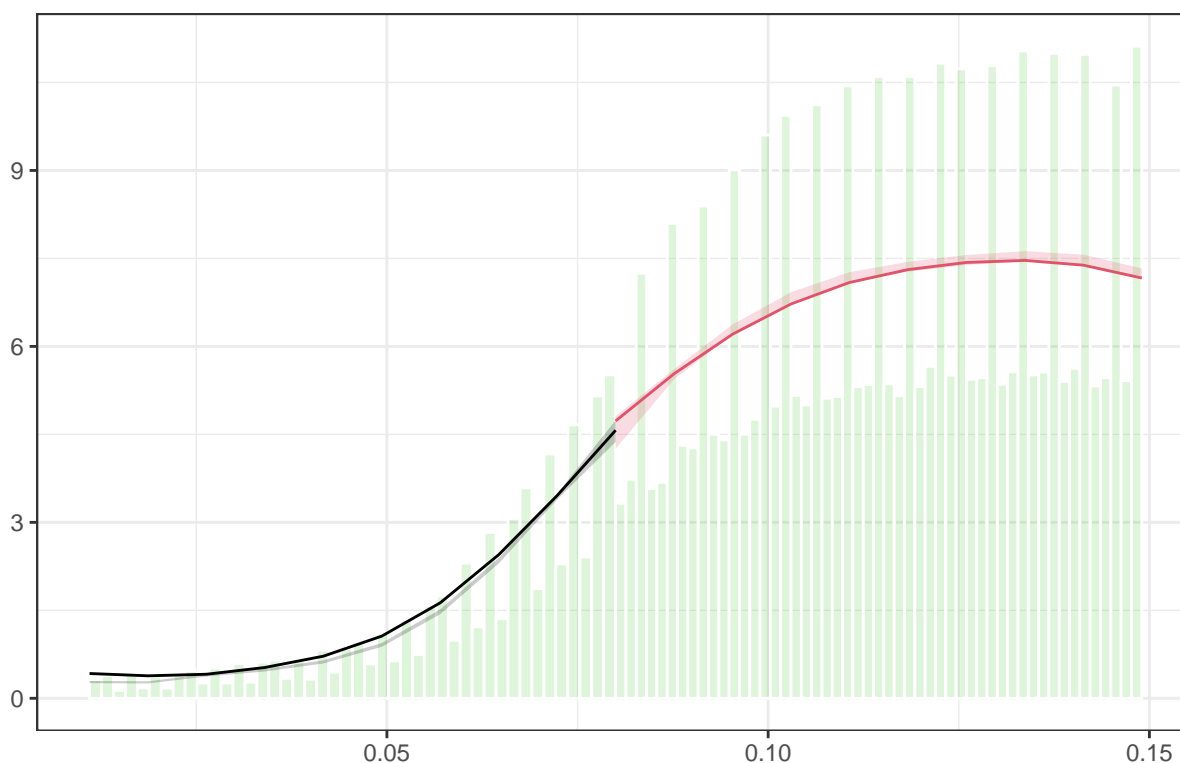
```
knitr::opts_chunk$set(echo = FALSE)
```

```
library(rddensity)
library(tidyverse)
library(cli)
library(haven)
library(rmarkdown)
library(haven)
library(stargazer)
library(estimatr)
library(rdd)
library(rdrobust)
library(multilevelPSA)
library(cobalt)
library(MatchIt)
library(optmatch)
library(jtools)
library(ggplot2)
library(cobalt)
library(plyr)
library(plotly)
library(knitr)
library(RDHonest)
```

```
hansen_dwi$dui=ifelse(hansen_dwi$bac1>=0.08,1,0)
```

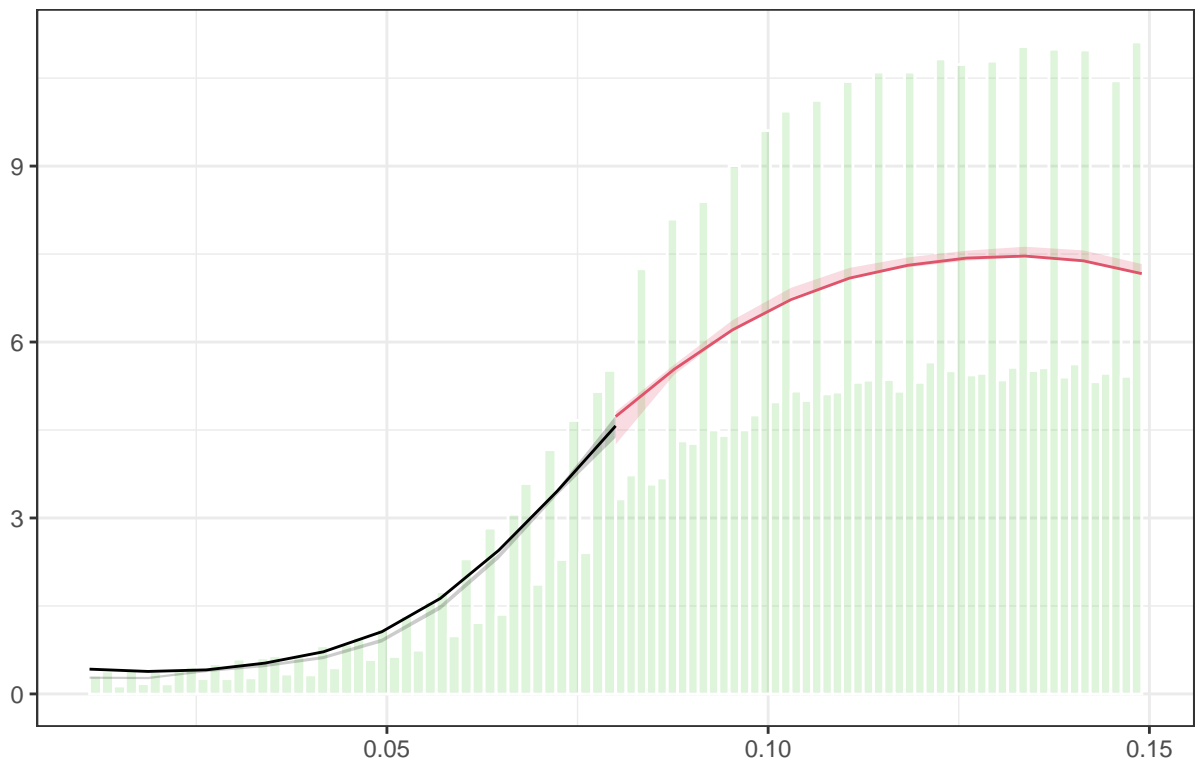
```
density <- rddensity(hansen_dwi$bac1, c = 0.08)
```

```
rdplotdensity(density, hansen_dwi$bac1)
```



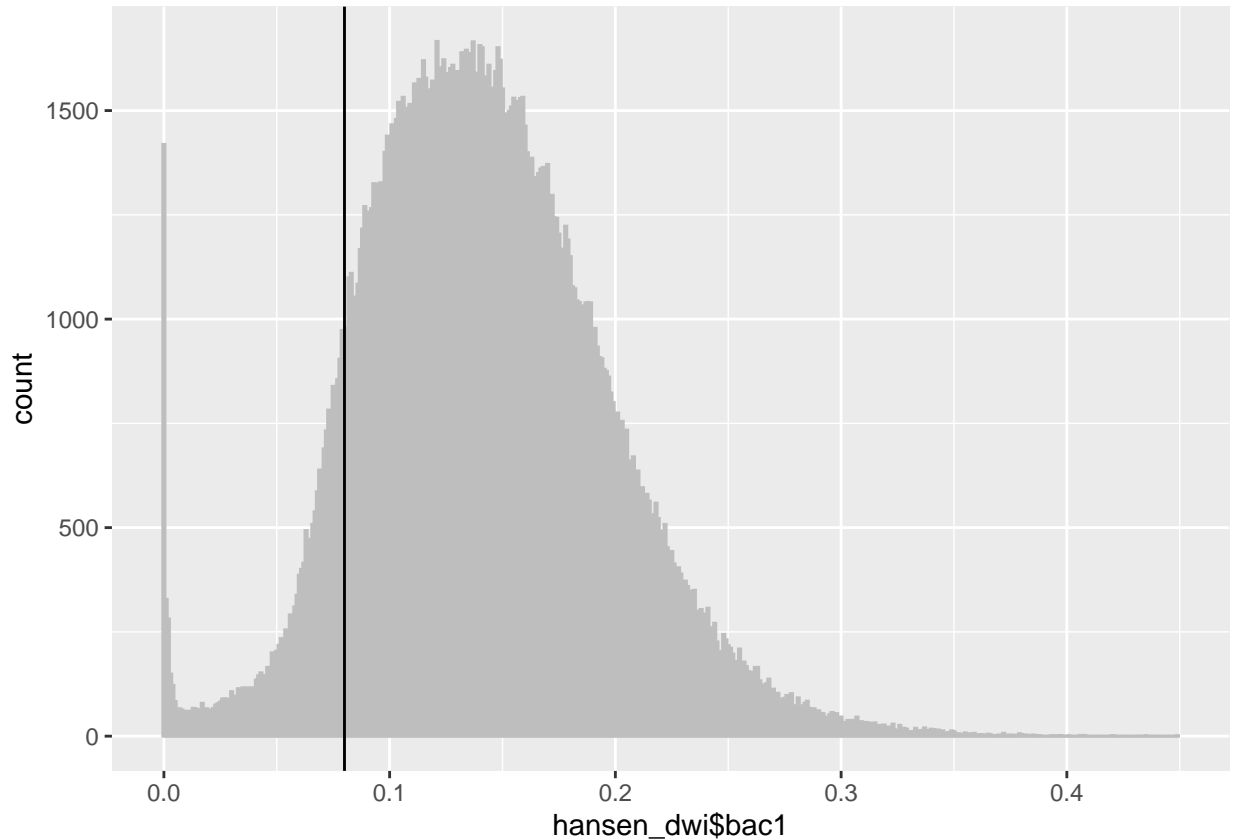
```
## $Est1
## Call: lpdensity
##
## Sample size                23010
## Polynomial order for point estimation (p=) 2
## Order of derivative estimated (v=) 1
## Polynomial order for confidence interval (q=) 3
## Kernel function            triangular
## Scaling factor             0.107239568040194
## Bandwidth method           user provided
##
## Use summary(...) to show estimates.
##
## $Estr
## Call: lpdensity
##
## Sample size                191548
## Polynomial order for point estimation (p=) 2
## Order of derivative estimated (v=) 1
## Polynomial order for confidence interval (q=) 3
## Kernel function            triangular
## Scaling factor             0.892755771193669
## Bandwidth method           user provided
##
## Use summary(...) to show estimates.
##
```

```
## $Estplot
```



```
ggplot(hansen_dwi, aes(x=hansen_dwi$bac1))+  
  geom_histogram(binwidth=0.001, color="gray")+  
  geom_vline(xintercept=0.08)
```

```
## Warning: Use of 'hansen_dwi$bac1' is discouraged. Use 'bac1' instead.
```



I use `rddensity` to check for manipulation on the running variable at the cutoff point of 0.08. The p-value of 0.8897 indicates that we cannot reject the null hypothesis that the density in the data is continuous at the cutoff point of 0.08. As such, there is no evidence of manipulation in the data. I also visually represent the rd density function, which appears to have a slight gap. However, the gap falls inside the confidence interval on both sides. Hence, no evidence of manipulation is found. The fairly smooth looking histogram is additional evidence that there isn't manipulation in the data. My findings coincide with the findings of the paper.

```
hansen_dwi_2 <- hansen_dwi %>%
  mutate(bac1_2 = bac1 - 0.08)

hansen_dwi2 <- hansen_dwi_2 %>%
  filter(bac1_2 >=-0.05 & bac1_2 <= 0.05)
#Check if covariates are balanced at the cutoff
m1 = lm(male ~ dui*bac1_2, data=hansen_dwi_2)
stargazer(m1, type = "text")
```

```
##
## =====
##               Dependent variable:
##            -----
##                   male
##            -----
## dui               0.006
##                   (0.004)
##
```

```
## bac1_2                0.218**
##                      (0.108)
##
## dui:bac1_2            -0.311***
##                      (0.110)
##
## Constant              0.791***
##                      (0.004)
##
## -----
## Observations          214,558
## R2                    0.0001
## Adjusted R2           0.0001
## Residual Std. Error    0.408 (df = 214554)
## F Statistic            9.428*** (df = 3; 214554)
## =====
## Note:                  *p<0.1; **p<0.05; ***p<0.01
```

```
m2 = lm(white ~ dui*bac1_2, data=hansen_dwi_2)
stargazer(m2, type = "text")
```

```
##
## =====
##                      Dependent variable:
##                      -----
##                      white
## -----
## dui                  0.004
##                      (0.004)
##
## bac1_2               0.154*
##                      (0.092)
##
## dui:bac1_2           0.017
##                      (0.093)
##
## Constant             0.847***
##                      (0.003)
##
## -----
## Observations          214,558
## R2                    0.001
## Adjusted R2           0.001
## Residual Std. Error    0.345 (df = 214554)
## F Statistic            58.401*** (df = 3; 214554)
## =====
## Note:                  *p<0.1; **p<0.05; ***p<0.01
```

```
m3 = lm(aged ~ dui*bac1_2, data=hansen_dwi_2)
stargazer(m3, type = "text")
```

```
##
## =====
```

```
##                               Dependent variable:
##                               -----
##                               aged
## -----
## dui                          -1.115***
##                               (0.117)
##
## bac1_2                       -56.361***
##                               (3.038)
##
## dui:bac1_2                   83.400***
##                               (3.089)
##
## Constant                     34.062***
##                               (0.107)
##
## -----
## Observations                 214,558
## R2                           0.013
## Adjusted R2                  0.013
## Residual Std. Error    11.431 (df = 214554)
## F Statistic             907.467*** (df = 3; 214554)
## =====
## Note:                       *p<0.1; **p<0.05; ***p<0.01
```

```
m4 = lm(acc ~ dui*bac1_2, data=hansen_dwi_2)
```

```
stargazer(m1,m2,m3,m4, type = "text")
```

```
##
## =====
##                               Dependent variable:
##                               -----
##                               male      white      aged      acc
##                               (1)       (2)       (3)       (4)
## -----
## dui                          0.006      0.004     -1.115***   -0.007*
##                               (0.004)   (0.004)   (0.117)    (0.004)
##
## bac1_2                      0.218**   0.154*   -56.361*** -1.540***
##                               (0.108)   (0.092)   (3.038)    (0.093)
##
## dui:bac1_2                  -0.311*** 0.017   83.400***  2.656***
##                               (0.110)   (0.093)   (3.089)    (0.095)
##
## Constant                    0.791*** 0.847*** 34.062***  0.078***
##                               (0.004)   (0.003)   (0.107)    (0.003)
##
## -----
## Observations                214,558   214,558   214,558    214,558
## R2                          0.0001     0.001     0.013       0.021
## Adjusted R2                 0.0001     0.001     0.013       0.021
## Residual Std. Error (df = 214554) 0.408     0.345     11.431      0.351
```

```
## F Statistic (df = 3; 214554)      9.428***  58.401*** 907.467*** 1,566.761***
## =====
## Note:                          *p<0.1; **p<0.05; ***p<0.01
```

For creating a covariate balance table I first re-centered the data around 0 and considered a bandwidth of 0.05 for bac1. We fail to reject the null hypothesis that there is no difference between the treatment and control group. That is, we do not have enough evidence to conclude that demographic factors (male, white, age, accident) considered are unrelated to the 0.08 cutoff. This is indicative of the fact that the characteristics considered are balanced across BAC levels. This balance in the covariates makes unbiased estimates on recidivism possible.

My findings are very similar to those of Hansen's in table 2 with negligible differences except for the variable "aged". To get the same coefficient as that of Hansen's for the age variable we could divide the variable by 100, moving the coefficient two decimal places to the right.

```
categories <- hansen_dwi$bac1
hansen_dwi2 <- hansen_dwi %>%
  filter(bac1 >= 0 & bac1 <= 0.2)

male <- split(hansen_dwi2$male, cut(hansen_dwi2$bac1, 191)) %>%
  lapply(mean) %>%
  unlist()
agg_hansen_dwi_male <- data.frame(male = male, bac1 = seq(0.01, 0.2, by = 0.001))

white <- split(hansen_dwi2$white, cut(hansen_dwi2$bac1, 191)) %>%
  lapply(mean) %>%
  unlist()
agg_hansen_dwi_white <- data.frame(white = white, bac1 = seq(0.01, 0.2, by = 0.001))

acc <- split(hansen_dwi2$acc, cut(hansen_dwi2$bac1, 191)) %>%
  lapply(mean) %>%
  unlist()
agg_hansen_dwi_acc <- data.frame(acc = acc, bac1 = seq(0.01, 0.2, by = 0.001))

aged <- split(hansen_dwi2$aged, cut(hansen_dwi2$bac1, 191)) %>%
  lapply(mean) %>%
  unlist()
agg_hansen_dwi_aged <- data.frame(aged = aged, bac1 = seq(0.01, 0.2, by = 0.001))
hansen_dwi2 <- hansen_dwi2 %>%
  mutate(gg_group = case_when(bac1 > 0.08 ~ 1, TRUE ~ 0))

#Male
linear_male <- ggplot(hansen_dwi2, aes(bac1, male)) +
  geom_point(aes(x = bac1, y = male), data = agg_hansen_dwi_male) +
  geom_vline(xintercept = 0.08, colour = "grey", linetype = 2) +
  stat_smooth(aes(bac1, male, group = gg_group), method = "lm") +
  labs(x = "BAC")
quadratic_male <- ggplot(hansen_dwi2, aes(bac1, male)) +
  geom_point(aes(x = bac1, y = male), data = agg_hansen_dwi_male) +
  geom_vline(xintercept = 0.08, colour = "grey", linetype = 2) +
  stat_smooth(aes(bac1, male, group = gg_group), method = "lm",
    formula = y ~ x + I(x^2)) +
  labs(x = "BAC")
#White
```



```

linear_white <- ggplot(hansen_dwi2, aes(bac1, white)) +
  geom_point(aes(x = bac1, y = white), data = agg_hansen_dwi_white) +
  geom_vline(xintercept = 0.08, colour = "grey", linetype = 2) +
  stat_smooth(aes(bac1, white, group = gg_group), method = "lm") +
  labs(x = "BAC")
quadratic_white <- ggplot(hansen_dwi2, aes(bac1, white)) +
  geom_point(aes(x = bac1, y = white), data = agg_hansen_dwi_white) +
  geom_vline(xintercept = 0.08, colour = "grey", linetype = 2) +
  stat_smooth(aes(bac1, white, group = gg_group), method = "lm",
    formula = y ~ x + I(x^2)) +
  labs(x = "BAC")
#Accident
linear_acc <- ggplot(hansen_dwi2, aes(bac1, acc)) +
  geom_point(aes(x = bac1, y = acc), data = agg_hansen_dwi_acc) +
  geom_vline(xintercept = 0.08, colour = "grey", linetype = 2) +
  stat_smooth(aes(bac1, acc, group = gg_group), method = "lm") +
  labs(x = "BAC")
quadratic_acc <- ggplot(hansen_dwi2, aes(bac1, acc)) +
  geom_point(aes(x = bac1, y = acc), data = agg_hansen_dwi_acc) +
  geom_vline(xintercept = 0.08, colour = "grey", linetype = 2) +
  stat_smooth(aes(bac1, acc, group = gg_group), method = "lm",
    formula = y ~ x + I(x^2)) +
  labs(x = "BAC")
#Age
linear_age <- ggplot(hansen_dwi2, aes(bac1, aged)) +
  geom_point(aes(x = bac1, y = aged), data = agg_hansen_dwi_aged) +
  geom_vline(xintercept = 0.08, colour = "grey", linetype = 2) +
  stat_smooth(aes(bac1, aged, group = gg_group), method = "lm") +
  labs(x = "BAC")
quadratic_age <- ggplot(hansen_dwi2, aes(bac1, aged)) +
  geom_point(aes(x = bac1, y = aged), data = agg_hansen_dwi_aged) +
  geom_vline(xintercept = 0.08, colour = "grey", linetype = 2) +
  stat_smooth(aes(bac1, aged, group = gg_group), method = "lm",
    formula = y ~ x + I(x^2)) +
  labs(x = "BAC")

```

```

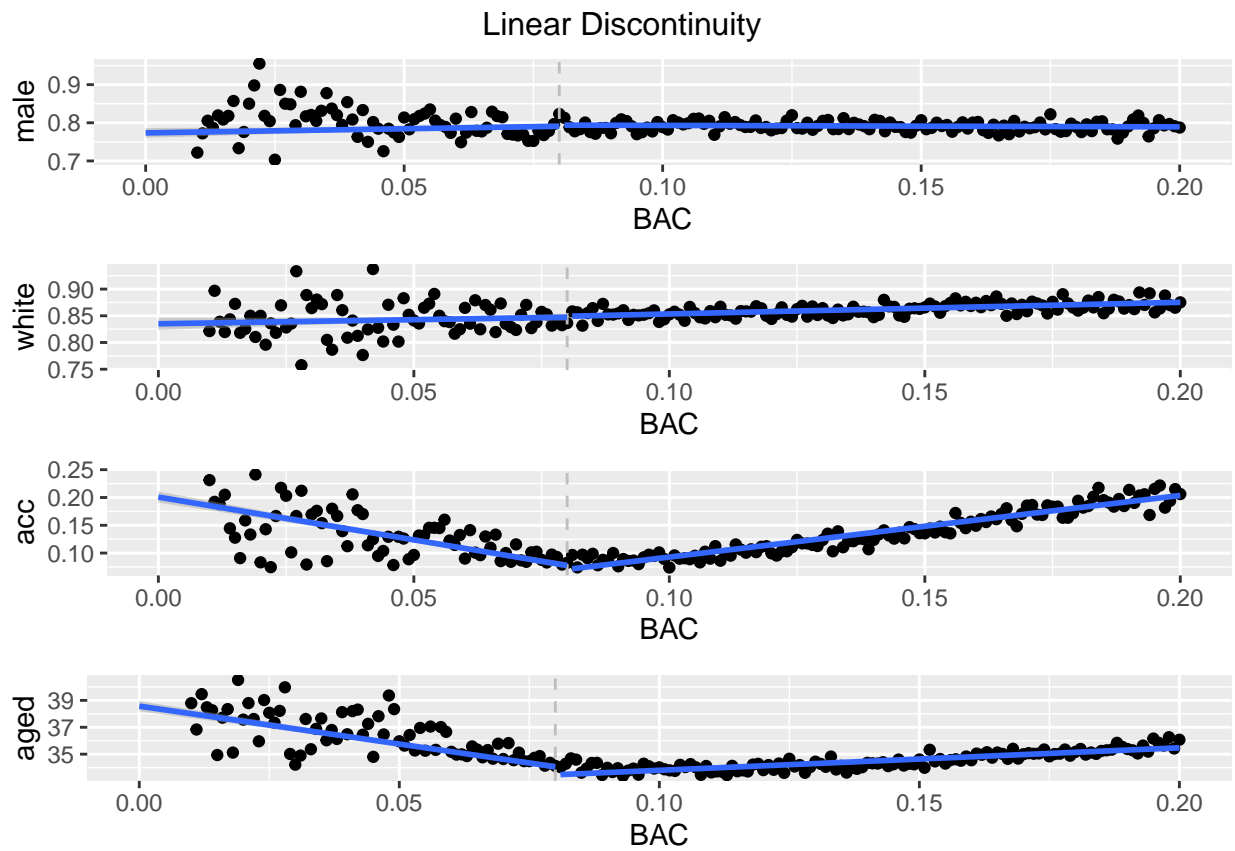
library(gridExtra)
grid.arrange(linear_male, linear_white, linear_acc,
  linear_age, nrow=4, top="Linear Discontinuity")

```

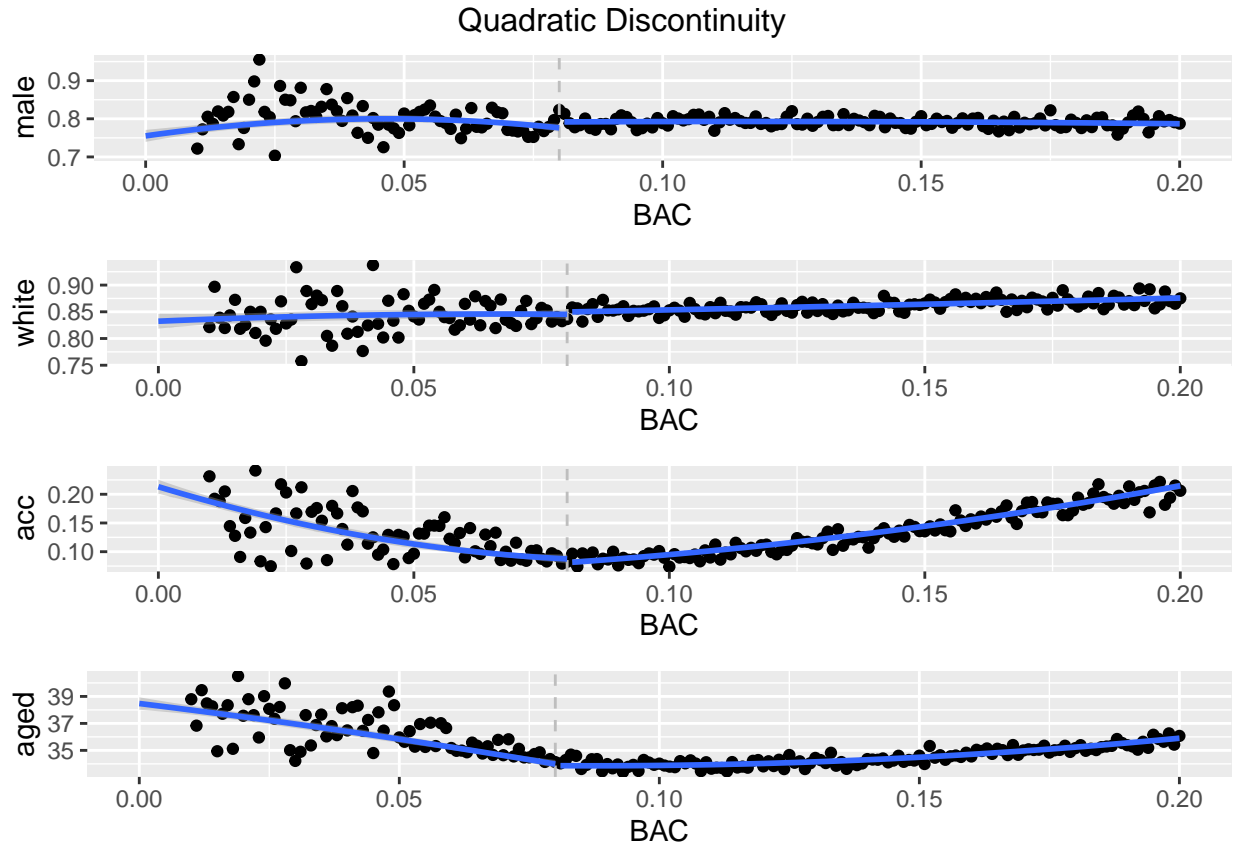
```

## 'geom_smooth()' using formula 'y ~ x'
## 'geom_smooth()' using formula 'y ~ x'
## 'geom_smooth()' using formula 'y ~ x'
## 'geom_smooth()' using formula 'y ~ x'

```



```
grid.arrange(quadratic_male, quadratic_white,  
             quadratic_acc, quadratic_age, nrow=4, top="Quadratic Discontinuity")
```



In part 6 I fit both the linear and quadratic regression lines based on the regressions with the covariates which we would expect to remain unchanged across punishment thresholds if offenders or police are unable to manipulate the running variable. This stability in the predetermined characteristics gives further credibility that the regression discontinuity design delivers unbiased estimates.

This finding is similar to that of Hansen's, letting us conclude that neither the drunk driver nor the police officer were able to manipulate testing at the 0.08 threshold.

```
RDeestimate(recidivism ~ bac1, cutpoint = 0.08, bw = 0.05, data=hansen_dwi)
```

```
##
## Call:
## RDeestimate(formula = recidivism ~ bac1, data = hansen_dwi, cutpoint = 0.08,
##   bw = 0.05)
##
## Coefficients:
##      LATE      Half-BW   Double-BW
## -0.01988  -0.01808  -0.02151
```

```
RDHonest(recidivism ~ bac1, cutoff = 0.08, h=0.05,
  kern="triangular", M=0.1, sclass="T", order = 1, data=hansen_dwi)
```

```
## Call:
## RDHonest(formula = recidivism ~ bac1, data = hansen_dwi, cutoff = 0.08,
##   M = 0.1, kern = "triangular", h = 0.05, sclass = "T", order = 1)
```

```

##
##
## Inference by se.method:
##      Estimate Maximum Bias Std. Error
## nn -0.01987723 4.049288e-05 0.00471454
##
## Confidence intervals:
## nn      (-0.0291179, -0.01063656), (-0.02767245, Inf), (-Inf, -0.01208201)
##
## Bandwidth: 0.05
## Number of effective observations: 18911.67

RDestimate(recidivism ~ bac1 | bac1*dui, cutpoint = 0.08, bw = 0.05, data=hansen_dwi)

##
## Call:
## RDestimate(formula = recidivism ~ bac1 | bac1 * dui, data = hansen_dwi,
##      cutpoint = 0.08, bw = 0.05)
##
## Coefficients:
##      LATE      Half-BW  Double-BW
## -0.01988   -0.01808   -0.02151

RDHonest(recidivism ~ bac1 + bac1*dui, cutoff = 0.08, h=0.05,
          kern="triangular", M=0.1, sclass="T", order = 1, data=hansen_dwi)

## Call:
## RDHonest(formula = recidivism ~ bac1 + bac1 * dui, data = hansen_dwi,
##      cutoff = 0.08, M = 0.1, kern = "triangular", h = 0.05, sclass = "T",
##      order = 1)
##
##
## Inference by se.method:
##      Estimate Maximum Bias Std. Error
## nn -0.01987723 4.049288e-05 0.00471454
##
## Confidence intervals:
## nn      (-0.0291179, -0.01063656), (-0.02767245, Inf), (-Inf, -0.01208201)
##
## Bandwidth: 0.05
## Number of effective observations: 18911.67

RDestimate(recidivism ~ bac1 | bac1*dui + (bac1^2)*dui, cutpoint = 0.08,
          bw = 0.05, data=hansen_dwi)

##
## Call:
## RDestimate(formula = recidivism ~ bac1 | bac1 * dui + (bac1^2) *
##      dui, data = hansen_dwi, cutpoint = 0.08, bw = 0.05)
##
## Coefficients:
##      LATE      Half-BW  Double-BW
## -0.01988   -0.01808   -0.02151

```

```
RDHonest(recidivism ~ bac1 + bac1*dui + (bac1^2)*dui, cutoff = 0.08, h=0.05,
         kern="triangular", M=0.1, sclass="T", order = 1, data=hansen_dwi)
```

```
## Call:
## RDHonest(formula = recidivism ~ bac1 + bac1 * dui + (bac1^2) *
##      dui, data = hansen_dwi, cutoff = 0.08, M = 0.1, kern = "triangular",
##      h = 0.05, sclass = "T", order = 1)
##
##
## Inference by se.method:
##      Estimate Maximum Bias Std. Error
## nn -0.01987723 4.049288e-05 0.00471454
##
## Confidence intervals:
## nn      (-0.0291179, -0.01063656), (-0.02767245, Inf), (-Inf, -0.01208201)
##
## Bandwidth: 0.05
## Number of effective observations: 18911.67
```

```
RDestimate(recidivism ~ bac1, cutpoint = 0.08, bw = 0.025, data=hansen_dwi)
```

```
##
## Call:
## RDestimate(formula = recidivism ~ bac1, data = hansen_dwi, cutpoint = 0.08,
##      bw = 0.025)
##
## Coefficients:
##      LATE      Half-BW  Double-BW
## -0.01808   -0.01650   -0.01988
```

```
RDHonest(recidivism ~ bac1, cutoff = 0.08, h=0.025,
         kern="triangular", M=0.1, sclass="T", order = 1, data=hansen_dwi)
```

```
## Call:
## RDHonest(formula = recidivism ~ bac1, data = hansen_dwi, cutoff = 0.08,
##      M = 0.1, kern = "triangular", h = 0.025, sclass = "T", order = 1)
##
##
## Inference by se.method:
##      Estimate Maximum Bias Std. Error
## nn -0.018083 1.117077e-05 0.006263225
##
## Confidence intervals:
## nn      (-0.03035872, -0.005807286), (-0.02839626, Inf), (-Inf, -0.007769742)
##
## Bandwidth: 0.025
## Number of effective observations: 9811.295
```

```
RDestimate(recidivism ~ bac1 | bac1*dui, cutpoint = 0.08, bw = 0.025, data=hansen_dwi)
```

```
##
```

```
## Call:
## RDestimate(formula = recidivism ~ bac1 | bac1 * dui, data = hansen_dwi,
##      cutpoint = 0.08, bw = 0.025)
##
## Coefficients:
##      LATE      Half-BW  Double-BW
## -0.01808   -0.01650   -0.01988
```

```
RDHonest(recidivism ~ bac1 + bac1*dui, cutoff = 0.08, h=0.025,
          kern="triangular", M=0.1, sclass="T", order = 1, data=hansen_dwi)
```

```
## Call:
## RDHonest(formula = recidivism ~ bac1 + bac1 * dui, data = hansen_dwi,
##      cutoff = 0.08, M = 0.1, kern = "triangular", h = 0.025, sclass = "T",      order = 1)
##
##
## Inference by se.method:
##      Estimate Maximum Bias Std. Error
## nn -0.018083 1.117077e-05 0.006263225
##
## Confidence intervals:
## nn      (-0.03035872, -0.005807286), (-0.02839626, Inf), (-Inf, -0.007769742)
##
## Bandwidth: 0.025
## Number of effective observations: 9811.295
```

```
RDestimate(recidivism ~ bac1 | bac1*dui + (bac1^2)*dui,
            cutoff = 0.08, bw = 0.025, data=hansen_dwi)
```

```
##
## Call:
## RDestimate(formula = recidivism ~ bac1 | bac1 * dui + (bac1^2) *
##      dui, data = hansen_dwi, cutpoint = 0.08, bw = 0.025)
##
## Coefficients:
##      LATE      Half-BW  Double-BW
## -0.01808   -0.01650   -0.01988
```

```
RDHonest(recidivism ~ bac1 + bac1*dui + (bac1^2)*dui,
          cutoff = 0.08, h=0.025, kern="triangular",
          M=0.1, sclass="T", order = 1, data=hansen_dwi)
```

```
## Call:
## RDHonest(formula = recidivism ~ bac1 + bac1 * dui + (bac1^2) *
##      dui, data = hansen_dwi, cutoff = 0.08, M = 0.1, kern = "triangular",
##      h = 0.025, sclass = "T", order = 1)
##
##
## Inference by se.method:
##      Estimate Maximum Bias Std. Error
## nn -0.018083 1.117077e-05 0.006263225
##
```

```
## Confidence intervals:
## nn      (-0.03035872, -0.005807286), (-0.02839626, Inf), (-Inf, -0.007769742)
##
## Bandwidth: 0.025
## Number of effective observations: 9811.295
```

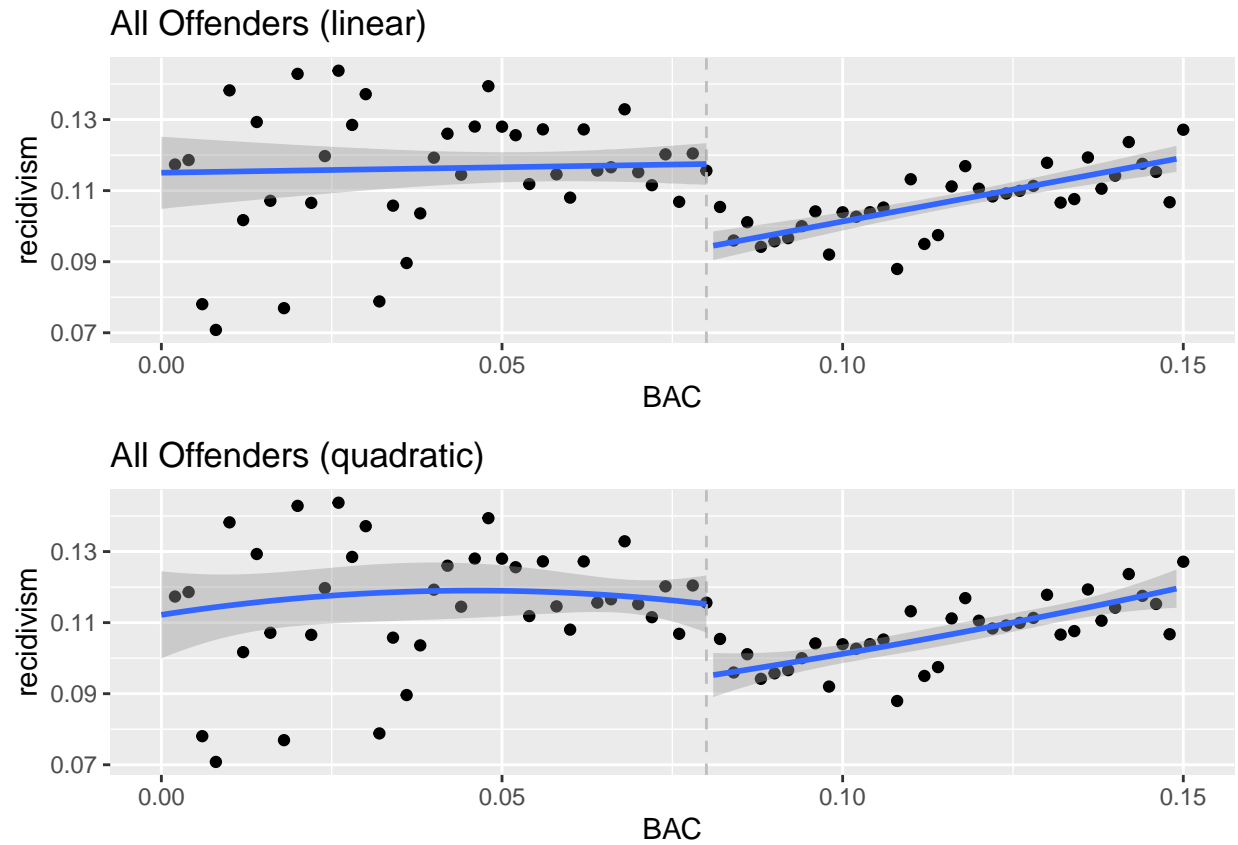
```
categories <- hansen_dwi$bac1
hansen_dwi3 <- hansen_dwi %>%
  filter(bac1 >= 0 & bac1 <= 0.15)
recid <- split(hansen_dwi3$recidivism, cut(hansen_dwi3$bac1, 75)) %>%
  lapply(mean) %>%
  unlist()
agg_hansen_dwi_recid <- data.frame(recidivism = recid,
                                   bac1 = seq(0.002, 0.15, by = 0.002))
hansen_dwi3 <- hansen_dwi3 %>%
  mutate(gg_group2 = case_when(bac1 > 0.08 ~ 1, TRUE ~ 0))

linear_recid <- ggplot(hansen_dwi3, aes(bac1, recidivism)) +
  geom_point(aes(x = bac1, y = recidivism), data = agg_hansen_dwi_recid) +
  geom_vline(xintercept = 0.08, colour = "grey", linetype = 2) +
  stat_smooth(aes(bac1, recidivism, group = gg_group2), method = "lm") +
  labs(x = "BAC", title = "All Offenders (linear)")

quadratic_recid <- ggplot(hansen_dwi3, aes(bac1, recidivism)) +
  geom_point(aes(x = bac1, y = recidivism), data = agg_hansen_dwi_recid) +
  geom_vline(xintercept = 0.08, colour = "grey", linetype = 2) +
  stat_smooth(aes(bac1, recidivism, group = gg_group2), method = "lm",
              formula = y ~ x + I(x^2)) +
  labs(x = "BAC", title = "All Offenders (quadratic)")
```

```
grid.arrange(linear_recid, quadratic_recid, nrow=2)
```

```
## 'geom_smooth()' using formula 'y ~ x'
```



Part 9

I test the hypothesis that there is no bunching and that the covariates are balanced at the 0.08 cutoff. From the covariate balance table as well as the local linear regressions I found that there are no unusual jumps or discontinuities in the plots. This is an indication that we are safe to apply the regression discontinuity method and get unbiased results for recidivism and ultimately getting reasonably believable results on the research question as to whether BAC limits reduce future drunk driving.