Quant II

Lab 9: RDD

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April 6, 2023

Today's plan

- RDD implementation: local regression approach
- Material from Cattaneo, Idrobo, and Titiunik (2020)
- packages: `rdrobust`, `rddensity`, `rdlocrand` (available in both Stata and R format)
- Next week
  - Extensions: fuzzy RDD, local randomization approach
  - Topics in RDD: GRDD, Diff-in-disc etc

Working example: Meyersson (2014)

Econometrica, Vol. 82, No. 1 (January, 2014), 229–269

ISLAMIC RULE AND THE EMPOWERMENT OF THE POOR AND PIOUS

BY ERIK MEYERSSON[1]

Does Islamic political control affect women's empowerment? Several countries have recently experienced Islamic parties coming to power through democratic elections. Due to strong support among religious conservatives, constituencies with Islamic rule often tend to exhibit poor women's rights. Whether this reflects a causal relationship or a spurious one has so far gone unexplored. I provide the first piece of evidence using a new and unique data set of Turkish municipalities. In 1994, an Islamic party won multiple municipal mayor seats across the country. Using a regression discontinuity (RD) design, I compare municipalities where this Islamic party barely won or lost elections. Despite negative raw correlations, the RD results reveal that, over a period of six years, Islamic rule increased female secular high school education. Corresponding effects for men are systematically smaller and less precise. In the longer run, the effect on female education remained persistent up to 17 years after, and also reduced adolescent marriages. An analysis of long-run political effects of Islamic rule shows increased female political participation and an overall decrease in Islamic political preferences. The results are consistent with an explanation that emphasizes the Islamic party's effectiveness in overcoming barriers to female entry for the poor and pious.

KEYWORDS: Political Islam, regression discontinuity, education.

Meyersson (2014)

Causal effects of interest:

- Victory of Islamic candidate on educational attainment of women

Elements:

- **Outcome (Y)**: percentage of women aged 15-20 in 2000 who had completed high school by 2000

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Elements:

- **Outcome (Y)**: percentage of women aged 15-20 in 2000 who had completed high school by 2000
- **Running variable (X)**: vote percentage of the Islamic party minus vote percentage of the strongest secular opponent
- **Treatment (T)**: 1 if Islamic party won in 1994, 0 otherwise

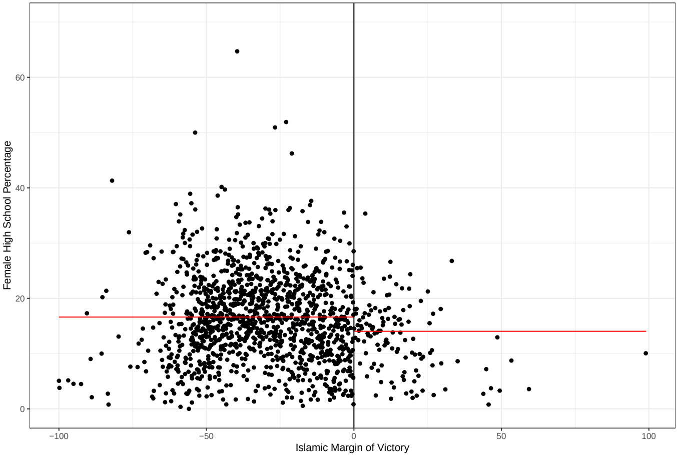
Set-up

```r
library(rdrobust); library(rddensity); library(haven)

# Import data and define variables
data <- read_dta("CIT_2019_Cambridge_polecon.dta")

Y <- data$Y
X <- data$X
T <- data$T
T_X <- T*X
```

Visualization

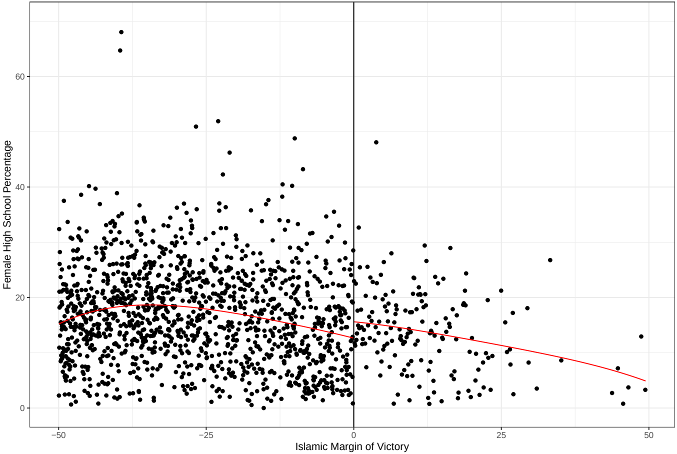
Visualization

```r
# Before we begin:
# ?rdplot

# Raw means comparison
rdplot(Y, X, nbins = c(2500, 500), p = 0, col.lines = "red", col.dots = "black", title = "",
       x.label = "Islamic Margin of Victory", y.label = "Female High School Percentage", y.lim = c(0,70))
```



Visualization

```
# Local means comparison
rdplot(Y[abs(X) <= 50], X[abs(X) <= 50], nbins = c(2500, 500), p = 4, col.lines = "red", col.dots = "black",
       title = "", x.label = "Islamic Margin of Victory", y.label = "Female High School Percentage",
       y.lim = c(0,70))
```



Binning

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- Overlay global polynomial fit of the outcome on the running variable, estimated **separately** on each side of the cutoff and using the **raw data**

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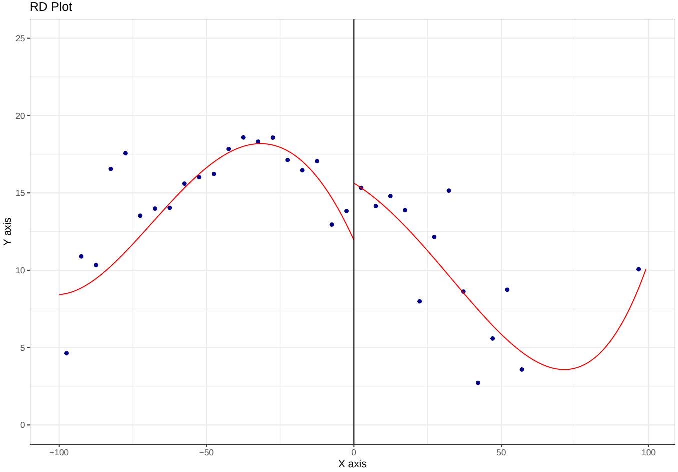
- `rdrobust::rdplot` does it automatically

Binning

Set bin size manually: evenly-spaced.

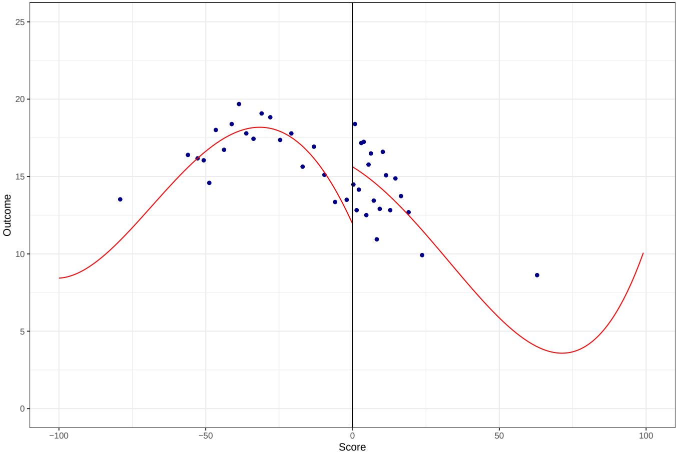
```
# Default is 4th polynomial degree on each side
rdplot(Y, X, nbins = c(20,20), binselect = "es", y.lim = c(0,25))
```



Principled binning

Quantile-spaced bins: retain information about actual data distribution, reduce discretion

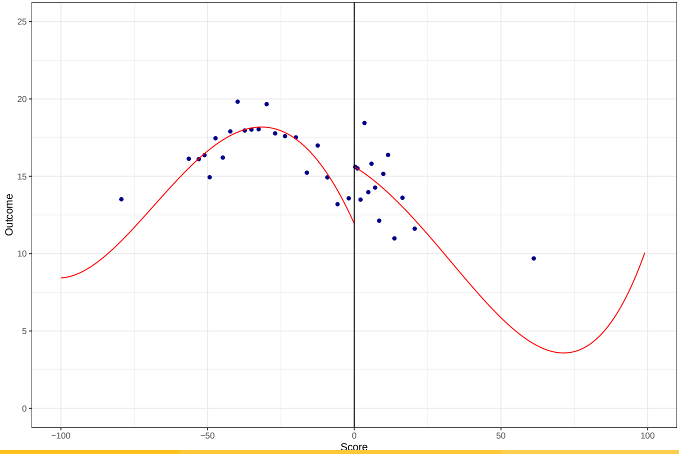
```
rdplot(Y, X, nbins = c(20,20), binselect = 'qs', x.label = 'Score',
       y.label = 'Outcome', title = '', x.lim = c(-100,100), y.lim = c(0,25))
```



Principled binning

Data-driven approach: minimize IMSE of local means estimator (optimize along bias-variance)

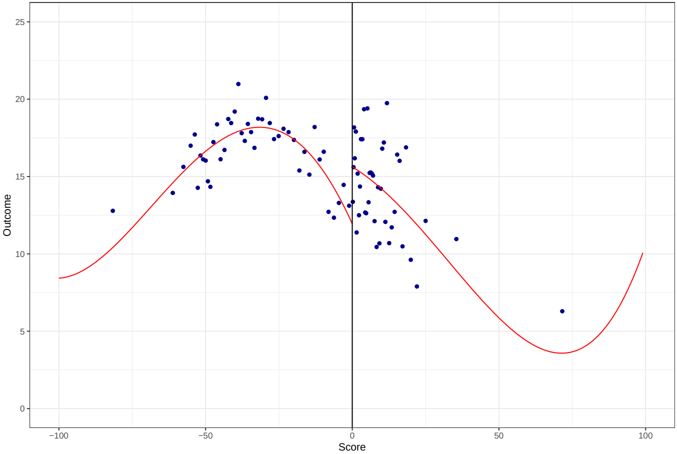
```
rdplot(Y, X, binselect = 'qs', x.label = 'Score',
      y.label = 'Outcome', title = '', x.lim = c(-100,100), y.lim = c(0,25))
```



Principled binning

Mimicking variance: choose number of bins so that the variability of means "mimicks" that of the raw data.

```
rdplot(Y, X, binselect = 'qsmv', x.label = 'Score',
       y.label = 'Outcome', title = '', x.lim = c(-100,100), y.lim = c(0,25))
```



Binning in sum

"Which method of implementation is most appropriate depends on the researcher's particular goal, for example, illustrating/testing for the overall functional form versus showing the variability of the data. We recommend to start with MV bins to better illustrate the variability of the outcome as a function of the score, ideally comparing ES and QS bins to highlight the distributional features of the score. Then, if needed, the researcher can select the number of bins to be IMSE-optimal in order to explore the global features of the regression function." (Cattaneo, Idrobo, and Titiunik 2020)

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Continuity-based framework

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- In practice, observations never have the cutoff value
- Approximate CEF on both sides of cutoff
- Global approximations: good for plots (descriptions), not suitable for causal effect estimation: Gelman and Imbens (2019)
- Best current practice: local polynomial functions with low order near cutoff

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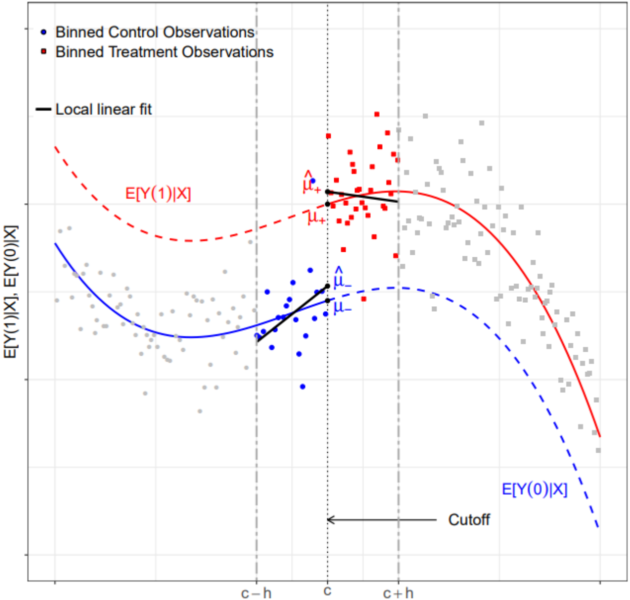
$$\hat{Y}_i = \hat{\mu}_+ + \hat{\mu}_{+,1}(X_i - c) + \hat{\mu}_{+,2}(X_i - c)^2 + ... + \hat{\mu}_{+,p}(X_i - c)^p$$
$$\hat{Y}_i = \hat{\mu}_- + \hat{\mu}_{-,1}(X_i - c) + \hat{\mu}_{-,2}(X_i - c)^2 + ... + \hat{\mu}_{-,p}(X_i - c)^p$$

- Calculate the sharp RD estimate: $\hat{\tau}_{SRD} = \hat{\mu}_+ - \hat{\mu}_-$, the difference of the two functions when $X_i = c$

Estimation of causal effects



Parameters

Relevant parameters

- **Kernel**: triangular one is recommended (weight $= 0$ outside h and $\uparrow$ as we get closer to c) and default in `rdrobust`. Alternatives: Uniform and Epanechnikov

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- **Bandwidth**: the most important thing. Usually chosen by a data-driven approach to minimize the MSE of the local polynomial point estimator
- `rdrobust:rdbwselect` selects a variety of optimal bandwidths. Either stand-alone or called from inside `rdrobust` using the option `bwselect`
- **Polynomial order**: low to avoid overfitting, generally local linear is the default choice

Estimation

```r
# By default c = 0
out <- rdrobust(Y, X, kernel = "uniform", p = 1, h = 20)
summary(out)
```

```
## Call: rdrobust
##
## Number of Obs.                 2629
## BW type                      Manual
## Kernel                      Uniform
## VCE method                       NN
##
## Number of Obs.                 2314          315
## Eff. Number of Obs.             608          280
## Order est. (p)                    1            1
## Order bias  (q)                   2            2
## BW est. (h)                  20.000       20.000
## BW bias (b)                  20.000       20.000
## rho (h/b)                     1.000        1.000
## Unique Obs.                    2311          315
##
## =============================================================================
##         Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
## =============================================================================
##   Conventional     2.927     1.235     2.371     0.018     [0.507 , 5.347]
##         Robust         -         -     1.636     0.102    [-0.582 , 6.471]
## =============================================================================
```

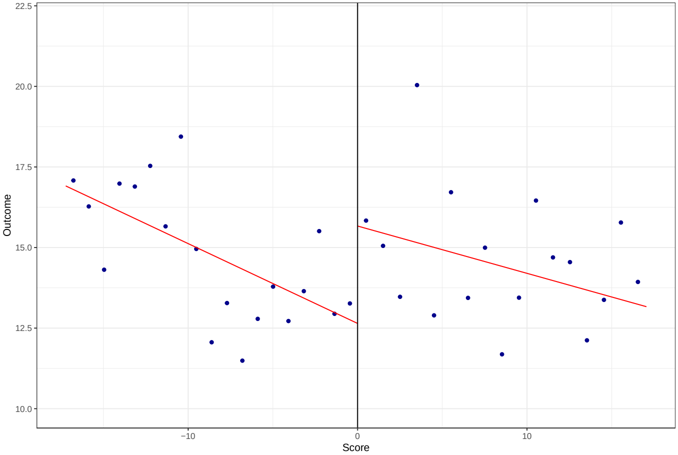
Estimation

```r
# Choose h to minimize MSE
out <- rdrobust(Y, X, kernel = "triangular", p = 1, bwselect = "mserd")
summary(out)
```

```
## Call: rdrobust
##
## Number of Obs.                 2629
## BW type                       mserd
## Kernel                   Triangular
## VCE method                       NN
##
## Number of Obs.                 2314          315
## Eff. Number of Obs.             529          266
## Order est. (p)                    1            1
## Order bias  (q)                   2            2
## BW est. (h)                  17.240       17.240
## BW bias (b)                  28.576       28.576
## rho (h/b)                     0.603        0.603
## Unique Obs.                    2311          315
##
## ====================================================================
##         Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
## ====================================================================
##   Conventional     3.020     1.427     2.116     0.034     [0.223 , 5.816]
##         Robust         -         -     1.776     0.076    [-0.309 , 6.276]
## ====================================================================
```

Illustrate the main effect

```
bw <- out$bws[1,1]
rdplot(Y[abs(X)<=bw], X[abs(X)<=bw], p = 1, kernel = 'triangular',
       x.label = 'Score', y.label = 'Outcome', title = '', y.lim = c(10,22))
```



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- One can:
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- Incorporate extra variability from bias removal in the SE estimate

Inference

Table 3: Local Polynomial Confidence Intervals

	Centered at	Standard Error
Conventional: $\mathtt{CI}_{\mathtt{us}}$	$\hat{\tau}_{\mathtt{SRD}}$	$\sqrt{\hat{\mathscr{V}}}$
Bias-Corrected: $\mathtt{CI}_{\mathtt{bc}}$	$\hat{\tau}_{\mathtt{SRD}} - \hat{\mathscr{B}}$	$\sqrt{\hat{\mathscr{V}}}$
Robust bias-corrected: $\mathtt{CI}_{\mathtt{rbc}}$	$\hat{\tau}_{\mathtt{SRD}} - \hat{\mathscr{B}}$	$\sqrt{\hat{\mathscr{V}}_{\mathtt{bc}}}$

Inference

- Robust bias correction enables to do valid inference using the same bandwidth used for the point estimate

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- Robust bias correction enables to do valid inference using the same bandwidth used for the point estimate
- Another approach: use a different bandwidth for SE calculation

Inference

```r
out <- rdrobust(Y, X, kernel = 'triangular',  p = 1, bwselect = 'mserd', all = TRUE)
summary(out)
```

```
## Call: rdrobust
##
## Number of Obs.                 2629
## BW type                       mserd
## Kernel                   Triangular
## VCE method                       NN
##
## Number of Obs.                 2314          315
## Eff. Number of Obs.             529          266
## Order est. (p)                    1            1
## Order bias  (q)                   2            2
## BW est. (h)                  17.240       17.240
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##
## =============================================================================
##         Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
## =============================================================================
##   Conventional     3.020     1.427     2.116     0.034     [0.223 , 5.816]
## Bias-Corrected     2.983     1.427     2.090     0.037     [0.186 , 5.780]
##         Robust     2.983     1.680     1.776     0.076    [-0.309 , 6.276]
## =============================================================================
```

RDD assumption violations

- Key ID assumption: potential outcomes continuous at the cutoff

$$\lim_{x \to c^+} E[Y_i(j)|X = x] = \lim_{x \to c^-} E[Y_i(j)|X = x] = E[Y_i(j)|X = c], j \in (0, 1)$$

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- There are instances where this assumption can be plausibly violated.

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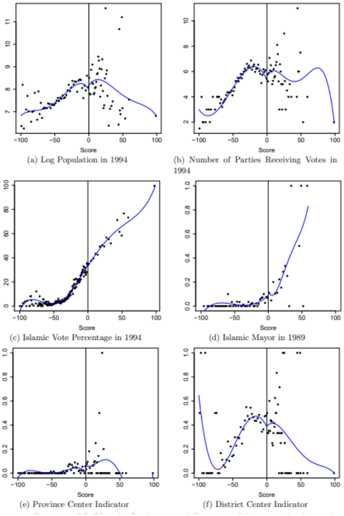
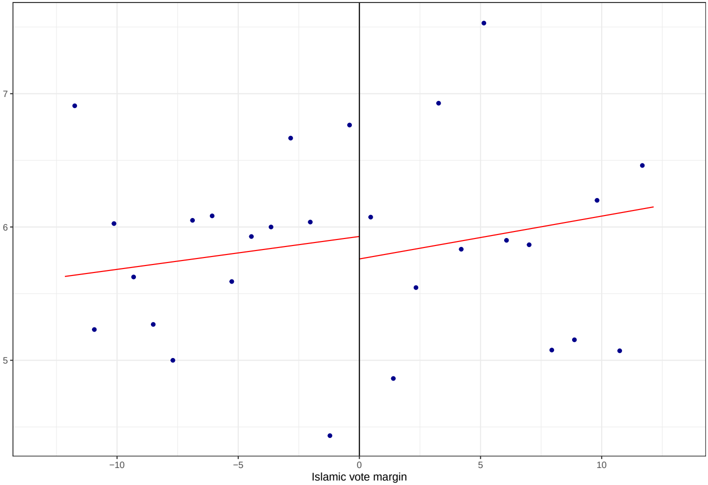
- Check for discontinuities in observable variables that we would expect to be continuous: typically pre-treatment covariates
- Placebos


(a) Log Population in 1994
(b) Number of Parties Receiving Votes in 1994
(c) Islamic Vote Percentage in 1994
(d) Islamic Mayor in 1989
(e) Province Center Indicator
(f) District Center Indicator
Score

RDD with placebo outcomes

```
bw <- rdrobust(data$partycount, X)$bws[1, 1]
xlim <- ceiling(bw)
rdplot(data$partycount[abs(X) <= bw], X[abs(X) <= bw],
       p = 1, kernel = "triangular", x.lim = c(-xlim, xlim), x.label = "Islamic vote margin", y.label = "", tit
```



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  - R: `DCdensity` in the package `rdd`

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  - Stata and R:`rddensity`

Density tests

```r
library(rddensity)

out <- rddensity(X)
summary(out)
```

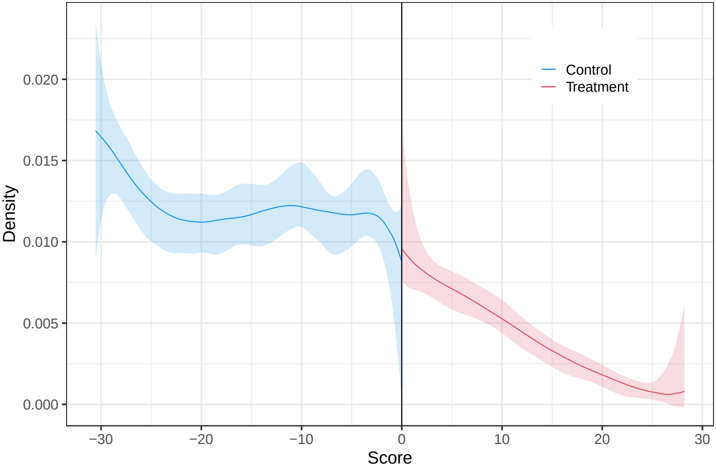
```
##
## Manipulation testing using local polynomial density estimation.
##
## Number of obs =       2629
## Model =               unrestricted
## Kernel =              triangular
## BW method =           estimated
## VCE method =          jackknife
##
## c = 0                 Left of c           Right of c
## Number of obs         2314                315
## Eff. Number of obs    965                 301
## Order est. (p)        2                   2
## Order bias (q)        3                   3
## BW est. (h)           30.539              28.287
##
## Method                T                   P > |T|
## Robust                -1.3937             0.1634
##
##
## P-values of binomial tests (H0: p=0.5).
##
## Window Length / 2          <c     >=c    P>|T|
## 0.426                      11       9    0.8238
## 0.852                      18      26    0.2912
## 1.278                      32      34    0.9022
## 1.704                      42      48    0.5984
## 2.130                      52      57    0.7018
```

Density tests

```r
library(lpdensity)

bw_left <- as.numeric(rddensity(X)$h[1])
bw_right <- as.numeric(rddensity(X)$h[2])

est1 <- lpdensity(data = X[X < 0 & X >= -bw_left], grid = seq(-bw_left, 0,
                                                            0.1),
                  bwselect = "IMSE", scale = sum(X < 0 & X >= -bw_left) / length(X))

est2 <- lpdensity(data = X[X >= 0 & X <= bw_right], grid = seq(0, bw_right,
                                                             0.1),
                  bwselect = "IMSE", scale = sum(X >= 0 & X <= bw_right) / length(X))
```

Density tests

```
library(ggplot2)
plot1 <- lpdensity.plot(est1, est2, CIshade = 0.2, lcol = c(4, 2), CIcol = c(4, 2), legendGroups = c("Control",
  labs(x = "Score", y = "Density") + geom_vline(xintercept = 0, color = "black") +
  theme_bw(base_size = 17)+theme(legend.position = c(0.8, 0.85))
plot1
```



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  - Other examples: "Pre-trend" coefficients in DiD are an example

RDD with placebo cutoffs

- So far, placebo outcomes: replace the outcome with one that should not be affected by treatment
  - If it is affected, evidence of confounding
  - Other examples: Balance tests in experiments
- Now placebo treatments: replace the treatment with one that by construction has no effect but the same confounding source
  - If there is effect, evidence of confounding also in the original treatment
  - Other examples: "Pre-trend" coefficients in DiD are an example
- In RDD: vary the cutoff where there should be no discontinuities

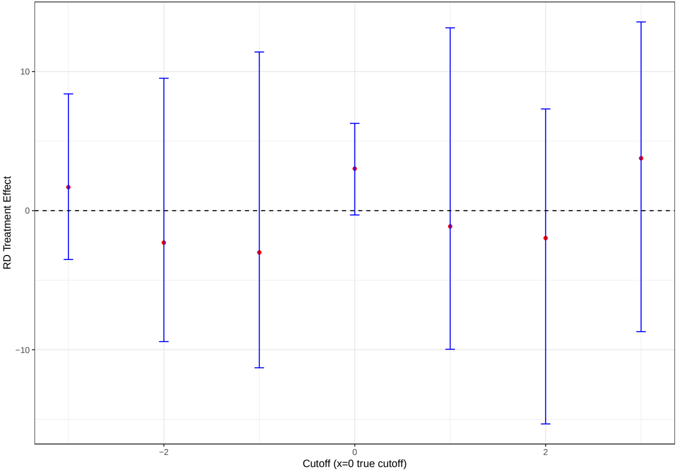
RDD with placebo cutoffs

```
placebo <- function(Y, X, new_cutoff){
  if (new_cutoff > 0){
    Y <- Y[X>=0]; X <- X[X>=0]
  }
  if (new_cutoff < 0){
    Y <- Y[X<0]; X <- X[X<0]
  }
  else{
    Y <- Y; X <- X
  }

  out <- rdrobust(Y, X, c = new_cutoff)
  coef <- out$coef["Conventional",]
  ll <- out$ci["Robust",1]
  ul <- out$ci["Robust",2]

  cbind(coef, ll, ul)
}

cutoffs <- as.list(c(-3:3))
(placebos <- do.call("rbind", lapply(cutoffs, function(i) placebo(Y, X, i))))
```

```
##           coef          ll        ul
## [1,]  1.687817  -3.5083421  8.397096
## [2,] -2.300012  -9.4137423  9.517862
## [3,] -3.004159 -11.2961682 11.407925
## [4,]  3.019526  -0.3092892  6.275769
## [5,] -1.130650  -9.9671538 13.146914
## [6,] -1.972790 -15.3333665  7.313371
## [7,]  3.766433  -8.6998298 13.569346
```

RDD with placebo cutoffs

```r
library(dplyr)
placebos %>% as.data.frame() %>% mutate(cutoff = -3:3) %>%
  ggplot(aes(x=cutoff, y=coef)) + geom_point(col="red") +
  geom_errorbar(aes(ymin=ll, ymax=ul), col="blue",width=0.1) +
  labs(y = "RD Treatment Effect", x = "Cutoff (x=0 true cutoff)") +
  geom_hline(yintercept=0, col="black", linetype = "dashed") + theme_bw()
```



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- Exclude points closer to the cutoff
- Vary the bandwidth in a neighborhood of the optimal bandwidth

Summing up

The standard practice includes:

- Graphical and formal placebo tests with covariates and other outcomes
- Density tests for sorting around the cutoff
- Perturbate the cutoff values
- Exclude observations near the cutoff
- Vary the bandwidth choice

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- CCFT recommend not to interact covariates with treatment indicator (allowing for different effects on the two sides requires stronger assumptions)
- In `rdrobust`: use the `covs` argument