

PLSC 30600 - Lab 8 - Regression Discontinuity Design

02/28/2025

Meyersson (2014) - “Islamic Rule and the Empowerment of the Poor and Pious”

In this lab, we will illustrate how to conduct RD analysis with the `rdrobust` packages. The data comes from Meyersson (2014), and can be downloaded from: https://github.com/rdpackages-replication/CIT_2020_CUP/blob/master/CIT_2020_CUP_polecon.dta. Note that all the codes in this R file can be found from Cattaneo et al. (2019), which is a very nice handbook on the practical guide of running RD analysis.

Meyersson (2014) studies the effect of electing Islamic party on women’s education. The variables in the datasets are:

- **Y** - educational attainment of women, measured as the percentage of women aged 15 to 20 in 2000 who had completed high school by 2000
- **X** - vote margin obtained by the Islamic party in the 1994 Turkish mayoral elections, measured as the vote percentage obtained by the Islamic party minus the vote percentage obtained by its strongest secular party opponent.
- **T** - electoral victory of the Islamic party in 1994
- **lpop1994** - Log Population in 1994
- **partycount** - Number of Parties Receiving Votes in 1994
- **vshr_islam1994** - Islamic Vote Percentage in 1994
- **i89** - Islamic Mayor in 1989
- **merkezp** - Province Center Indicator
- **merkezi** - District Center Indicator

```
# load data from Meyersson (2014, ECTA)
meyersson_2014ecta <- read_dta("meyersson_2014ecta.dta")

# specify outcome, running variable, and treatment variable
Y <- meyersson_2014ecta$Y
X <- meyersson_2014ecta$X
T <- meyersson_2014ecta$T

# Analyzing the running variable
meyersson_2014ecta %>%
  group_by(T) %>%
  summarize(count = n(),
            vote_margin = mean(X))

## # A tibble: 2 x 3
##       T count vote_margin
##   <dbl> <int>      <dbl>
## 1     0  2314      -33.4
```

```
## 2      1    315      10.3
```

RD validity tests

The first validity test is to test whether or not the density of the running variable is continuous at the cutoff. The idea is that if people can manipulate the running variable to sort themselves to a side where they expect benefits, we would observe discontinuity of the density of the running variables at the cutoff. In Meyersson (2014), we fail to reject the null that there is a manipulation of running variable.

- Running variable test

```
# test H0: the density of the running variable is continuous at the cutoff
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

## Warning in summary.CJMrddensity(out): There are repeated observations. Point
## estimates and standard errors have been adjusted. Use option massPoints=FALSE
## to suppress this feature.

##
## P-values of binomial tests (H0: p=0.5).
##
## Window Length / 2    <c    >=c    P>|T|
## 0.874                20     26     0.4614
## 1.748                42     49     0.5296
## 2.622                70     63     0.6030
## 3.496                95     81     0.3271
## 4.370               131     98     0.0342
## 5.245               155    112     0.0100
## 6.119               183    131     0.0039
## 6.993               209    148     0.0015
## 7.867               229    160     0.0005
## 8.741               257    173     0.0001
```

```
# plot the raw counts of running variable
bw_left <- as.numeric(rddensity(X)$h[1]) #BW est. (h)      30.539      28.287
bw_right <- as.numeric(rddensity(X)$h[2])
```

```

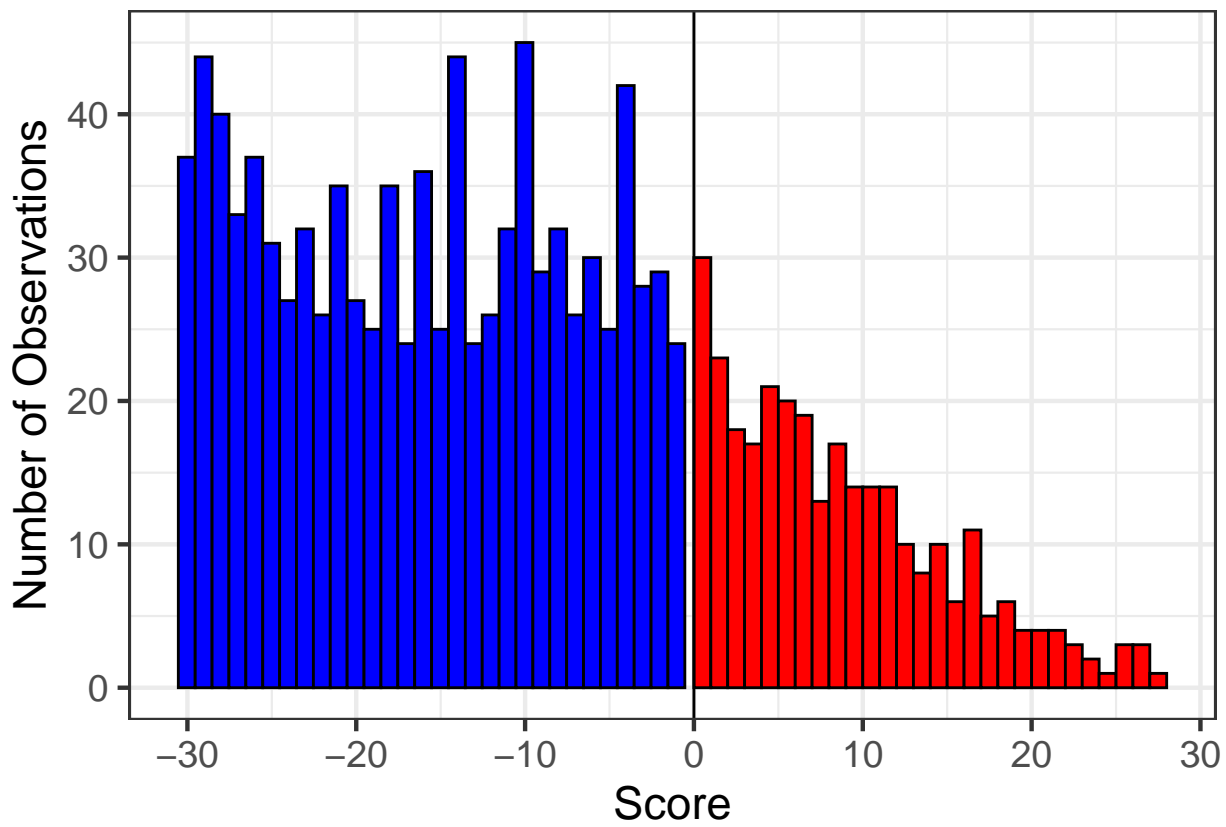
tempdata <- as.data.frame(X)
colnames(tempdata) = c("v1")
plot2 <- ggplot(data=tempdata, aes(tempdata$v1)) +
  theme_bw(base_size = 17) +
  geom_histogram(data = tempdata,
    aes(x = v1, y= ..count..),
    breaks = seq(-bw_left, 0, 1),
    fill = "blue",
    col = "black",
    alpha = 1) +
  geom_histogram(data = tempdata,
    aes(x = v1, y= ..count..),
    breaks = seq(0, bw_right, 1),
    fill = "red",
    col = "black",
    alpha = 1) +
  labs(x = "Score", y = "Number of Observations") +
  geom_vline(xintercept = 0, color = "black")
plot2

```

```

## Warning: The dot-dot notation (`..count..`) was deprecated in ggplot2 3.4.0.
## i Please use `after_stat(count)` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.

```



```

# plot the density of the running variable
# "IMSE" stands for Integrated Mean Squared Error.
# The "lpdensity" function (Local Polynomial Density Estimation) will automatically select the bandwidth
# The ratio  $\text{sum}(X < 0 \ \& \ X \geq -\text{bw\_left}) / \text{length}(X)$  scales the density estimate according to the proportion

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))

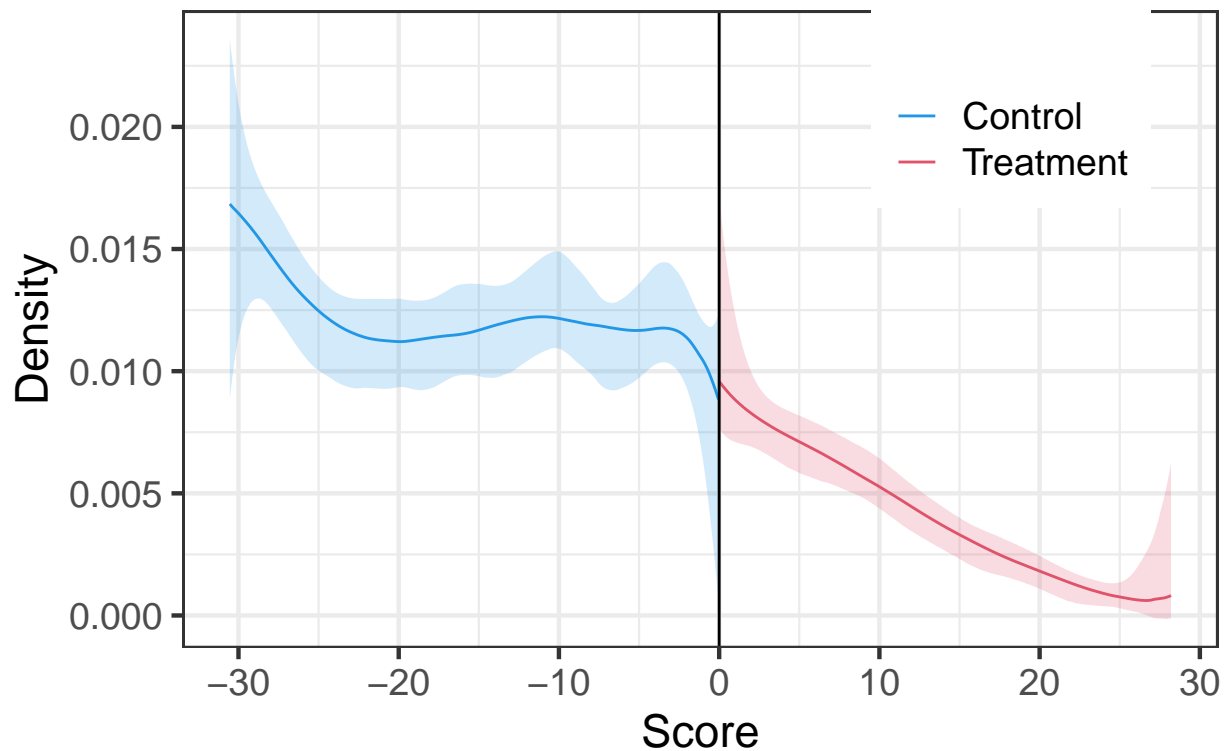
est2 <- lpdensity(data = X[X >= 0 & X <= bw_right],
                  grid = seq(0, bw_right, 0.1),
                  bwselect = "IMSE",
                  scale = sum(X >= 0 & X <= bw_right) / length(X))

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

## Warning: A numeric `legend.position` argument in `theme()` was deprecated in ggplot2
## 3.5.0.
## i Please use the `legend.position.inside` argument of `theme()` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.

plot1

```



- Covariates variation test

The other RD validity test is to test whether or not pre-treatment covariates vary smoothly at the threshold. The idea is that if individuals cannot perfectly manipulate the running variable near the threshold, then, there should be no systematic differences on pre-treatment covariates around the threshold.

```
# Log Population in 1994
out <- rdrobust(meyersson_2014ecta$lpop1994, X)
summary(out)
```

```
## Sharp RD estimates using local polynomial regression.
```

```
##
## Number of Obs.                2629
## BW type                      mserd
## Kernel                      Triangular
## VCE method                   NN
##
## Number of Obs.                2314          315
## Eff. Number of Obs.          400           233
## Order est. (p)                1             1
## Order bias (q)               2             2
## BW est. (h)                  13.320        13.320
## BW bias (b)                  21.368        21.368
## rho (h/b)                    0.623         0.623
## Unique Obs.                  2311          315
##
```

```
## =====
##      Method      Coef. Std. Err.      z    P>|z|    [ 95% C.I. ]
## =====
## Conventional    0.012    0.278    0.045    0.964    [-0.532 , 0.557]
## Robust          -        -    0.001    0.999    [-0.644 , 0.645]
```

```
## =====
# Number of Parties Receiving Votes in 1994
out <- rdrobust(meyersson_2014ecta$partycount, X)
summary(out)

## Sharp RD estimates using local polynomial regression.
##
## Number of Obs.                2629
## BW type                       mserd
## Kernel                        Triangular
## VCE method                    NN
##
## Number of Obs.                2314            315
## Eff. Number of Obs.          373            223
## Order est. (p)                1              1
## Order bias (q)                2              2
## BW est. (h)                   12.166         12.166
## BW bias (b)                   20.064         20.064
## rho (h/b)                     0.606         0.606
## Unique Obs.                   2311            315
##
## =====
##           Method      Coef. Std. Err.      z    P>|z|      [ 95% C.I. ]
## =====
##   Conventional   -0.168    0.478   -0.351    0.726   [-1.105 , 0.769]
##       Robust        -         -   -0.429    0.668   [-1.357 , 0.869]
## =====

# Islamic Vote Percentage in 1994
out <- rdrobust(meyersson_2014ecta$vshr_islam1994, X)
summary(out)

## Sharp RD estimates using local polynomial regression.
##
## Number of Obs.                2629
## BW type                       mserd
## Kernel                        Triangular
## VCE method                    NN
##
## Number of Obs.                2314            315
## Eff. Number of Obs.          430            238
## Order est. (p)                1              1
## Order bias (q)                2              2
## BW est. (h)                   13.940         13.940
## BW bias (b)                   22.475         22.475
## rho (h/b)                     0.620         0.620
## Unique Obs.                   2311            315
##
## =====
##           Method      Coef. Std. Err.      z    P>|z|      [ 95% C.I. ]
## =====
##   Conventional    0.603    1.479    0.408    0.683   [-2.296 , 3.503]
##       Robust        -         -    0.370    0.711   [-2.794 , 4.095]
## =====
```

```
# Islamic Mayor in 1989
```

```
out <- rdrobust(meyersson_2014ecta$i189, X)
```

```
summary(out)
```

```
## Sharp RD estimates using local polynomial regression.
```

```
##
```

```
## Number of Obs.          1908
```

```
## BW type                  mserd
```

```
## Kernel                   Triangular
```

```
## VCE method              NN
```

```
##
```

```
## Number of Obs.          1683      225
```

```
## Eff. Number of Obs.     269      149
```

```
## Order est. (p)          1          1
```

```
## Order bias (q)          2          2
```

```
## BW est. (h)             11.783     11.783
```

```
## BW bias (b)             20.559     20.559
```

```
## rho (h/b)               0.573     0.573
```

```
## Unique Obs.            1681      225
```

```
##
```

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

```
##      Method      Coef. Std. Err.      z    P>|z|      [ 95% C.I. ]
```

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

```
## Conventional    0.053    0.067    0.800    0.424    [-0.077 , 0.184]
```

```
## Robust          -        -    0.967    0.333    [-0.077 , 0.228]
```

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

```
# Province Center Indicator
```

```
out <- rdrobust(meyersson_2014ecta$merkezp, X)
```

```
summary(out)
```

```
## Sharp RD estimates using local polynomial regression.
```

```
##
```

```
## Number of Obs.          2629
```

```
## BW type                  mserd
```

```
## Kernel                   Triangular
```

```
## VCE method              NN
```

```
##
```

```
## Number of Obs.          2314      315
```

```
## Eff. Number of Obs.     358      216
```

```
## Order est. (p)          1          1
```

```
## Order bias (q)          2          2
```

```
## BW est. (h)             11.557     11.557
```

```
## BW bias (b)             18.908     18.908
```

```
## rho (h/b)               0.611     0.611
```

```
## Unique Obs.            2311      315
```

```
##
```

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

```
##      Method      Coef. Std. Err.      z    P>|z|      [ 95% C.I. ]
```

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

```
## Conventional    0.029    0.037    0.788    0.431    [-0.044 , 0.103]
```

```
## Robust          -        -    0.511    0.609    [-0.064 , 0.109]
```

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

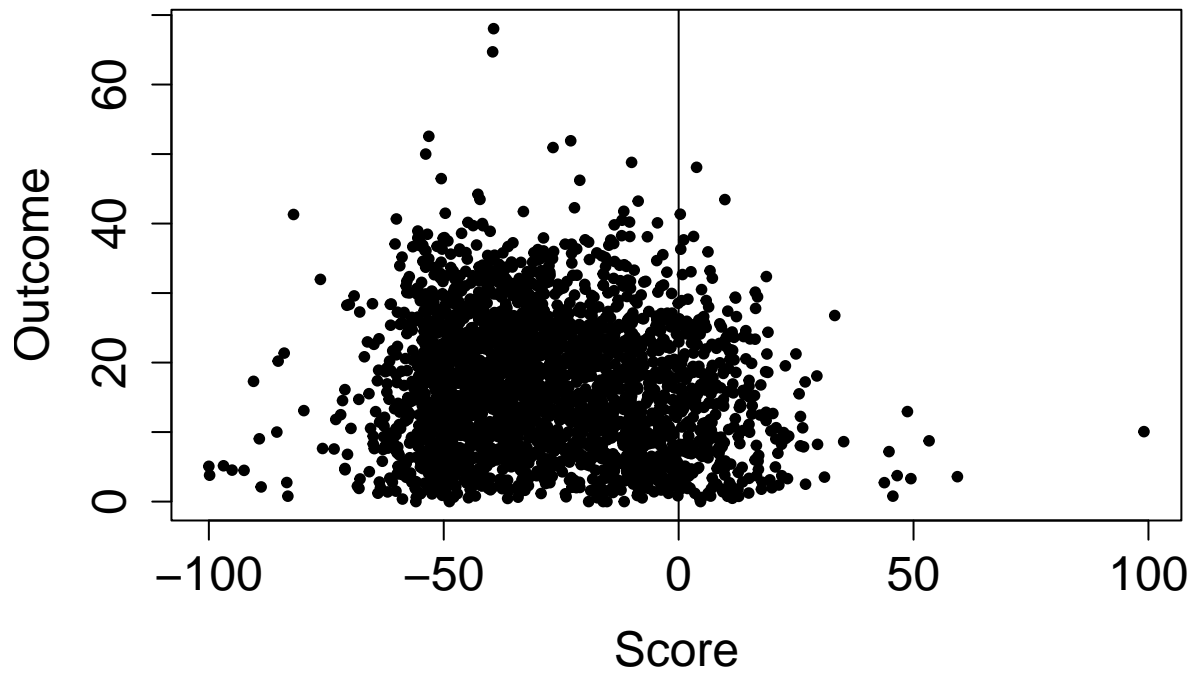
```
# District Center Indicator
out <- rdrobust(meyersson_2014ecta$merkezi, X)
summary(out)
```

```
## Sharp RD estimates using local polynomial regression.
##
## Number of Obs.                2629
## BW type                      mserd
## Kernel                      Triangular
## VCE method                   NN
##
## Number of Obs.                2314            315
## Eff. Number of Obs.          394            230
## Order est. (p)                1              1
## Order bias (q)                2              2
## BW est. (h)                  13.033          13.033
## BW bias (b)                  20.764          20.764
## rho (h/b)                    0.628          0.628
## Unique Obs.                  2311            315
##
## =====
##      Method      Coef. Std. Err.      z    P>|z|      [ 95% C.I. ]
## =====
##   Conventional   -0.067    0.089   -0.757    0.449   [-0.241 , 0.107]
##      Robust       -         -    -0.735    0.462   [-0.285 , 0.130]
## =====
```

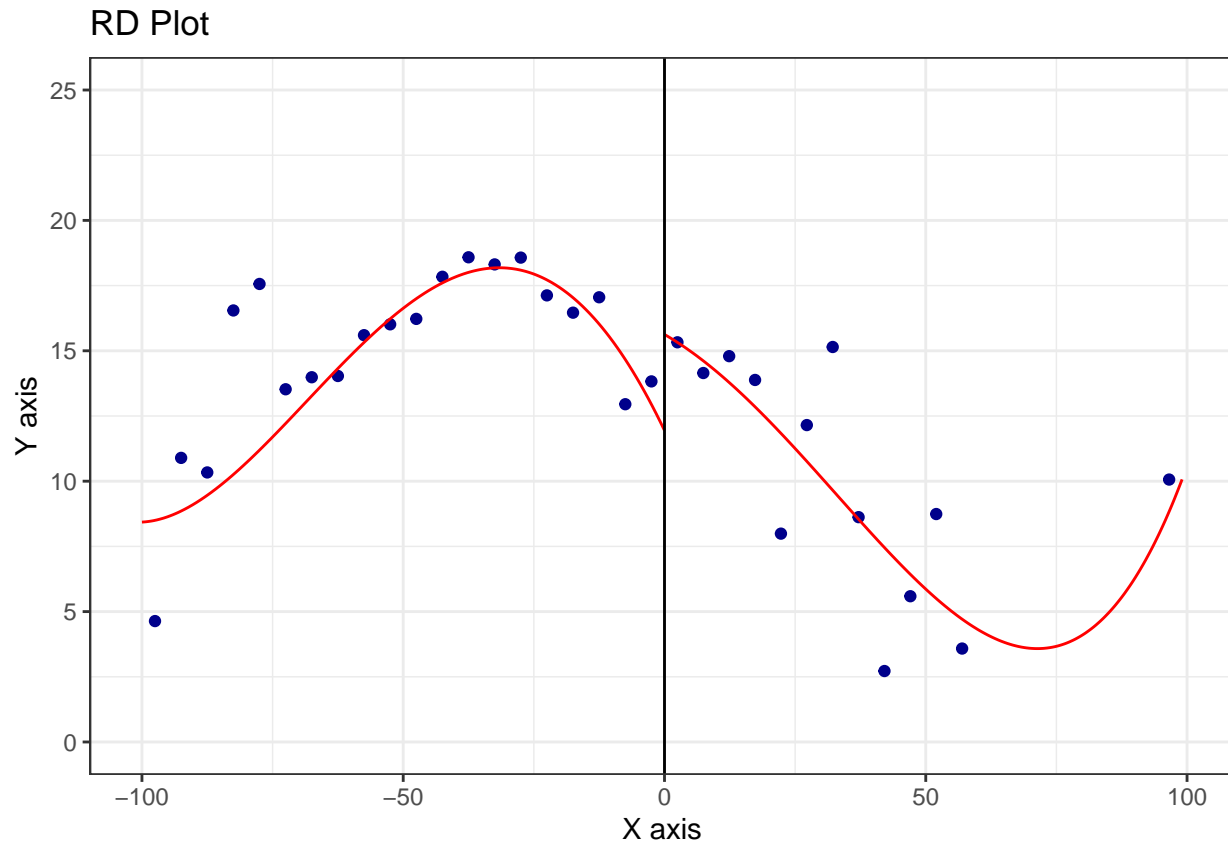
Using RD Plots to Present the Results Visually

Before using regression to present the RD results, it is often useful to draw the plot to show the readers that there is a jump of the outcome at the cutoff. We can use the `rdplot` package to draw such plot. From the plot that uses Meyersson (2014) data, we can see that there is graphical evidence that electing Islamic part increases woman's education.

```
# plot the raw data
plot(X,
      Y,
      xlab = "Score",
      ylab = "Outcome",
      col = 1,
      pch = 20,
      cex.axis = 1.5,
      cex.lab = 1.5)
abline(v=0)
```

```
# use rdplot package to draw plot with evenly spaced bins  
# the bins will be equally spaced on both sides of the cutoff.  
out <- rdplot(Y,  
  X,  
  nbins = c(20,20),  
  binselect = 'es',  
  y.lim = c(0,25))
```



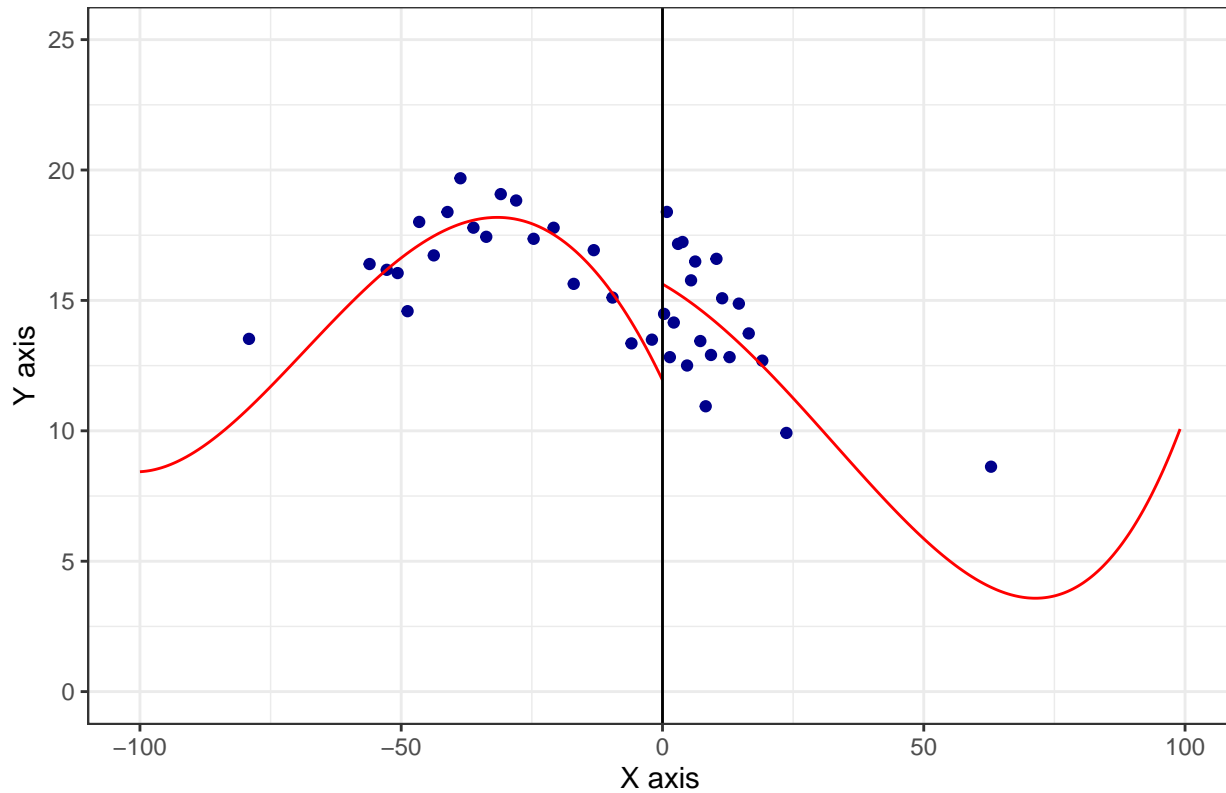
```
summary(out)
```

```
## Call: rdplot
##
## Number of Obs.          2629
## Kernel                  Uniform
##
## Number of Obs.          2314          315
## Eff. Number of Obs.     2314          315
## Order poly. fit (p)      4             4
## BW poly. fit (h)         100.000       99.051
## Number of bins scale     1             1
##
## Bins Selected            20            20
## Average Bin Length       5.000         4.953
## Median Bin Length        5.000         4.953
##
## IMSE-optimal bins        11            7
## Mimicking Variance bins   40           75
##
## Relative to IMSE-optimal:
## Implied scale            1.818         2.857
## WIMSE variance weight     0.143         0.041
## WIMSE bias weight         0.857         0.959
```

```
# use rdplot package to draw plot with quantile spaced bins
# the bins will contain an equal number of observations, making them "quantile-spaced."
out <- rdplot(Y,
```

```
X,
nbins = c(20,20),
binselect = 'qs',
y.lim = c(0,25))
```

RD Plot



```
summary(out)
```

```
## Call: rdplot
##
## Number of Obs.          2629
## Kernel                  Uniform
##
## Number of Obs.          2314          315
## Eff. Number of Obs.     2314          315
## Order poly. fit (p)      4            4
## BW poly. fit (h)         100.000      99.051
## Number of bins scale     1            1
##
## Bins Selected            20           20
## Average Bin Length       4.995        4.950
## Median Bin Length        2.950        1.011
##
## IMSE-optimal bins        21           14
## Mimicking Variance bins  44           41
##
## Relative to IMSE-optimal:
## Implied scale            0.952        1.429
```

```
## WIMSE variance weight      0.537      0.255
## WIMSE bias weight          0.463      0.745
```

Regression Presentation of the RD estimator

We now proceed to use the `rdrobust` package to produce an estimate and the associated confidence interval of the RD estimand. The `rdrobust` package can use robust bias correction for constructing confidence intervals, which has smaller coverage errors than competing approaches. Overall, the results show that there is a positive effect of electing Islamic party on women's education. The results are significant at 10% level when not conditioning on covariates, and are significant at 5% level when conditioning on covariates.

```
# rdrobust without covariates
# the local polynomial order for density estimation is 1
# the method for bandwidth selection is "mserd" (Mean Squared Error - RD)
out <- rdrobust(Y,
               X,
               kernel = "triangular",
               p = 1,
               bwselect = "mserd",
               all = TRUE)

summary(out)
```

```
## Sharp RD estimates using local polynomial regression.
```

```
##
## 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]
## 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]
## =====
```

```
# rdrobust with covariates
Z <- cbind(meyersson_2014ecta$vshr_islam1994,
           meyersson_2014ecta$partycount,
           meyersson_2014ecta$lpop1994,
           meyersson_2014ecta$merkezi,
           meyersson_2014ecta$merkezp,
           meyersson_2014ecta$subbuyuk,
           meyersson_2014ecta$buyuk)
```

```
colnames(Z) <- c("vshr_islam1994",
                "partycount",
                "lpop1994",
                "merkezi",
                "merkezp",
                "subbuyuk",
                "buyuk")

out <- rdrobust(Y,
               X,
               covs = Z,
               kernel = 'triangular',
               scaleregul = 1,
               p = 1,
               bwselect = 'mserd',
               all = TRUE)

summary(out)
```

```
## Covariate-adjusted Sharp RD estimates using local polynomial regression.
```

```
##
## Number of Obs.                2629
## BW type                      mserd
## Kernel                      Triangular
## VCE method                  NN
##
## Number of Obs.                2314            315
## Eff. Number of Obs.          448            241
## Order est. (p)                1              1
## Order bias (q)                2              2
## BW est. (h)                   14.410         14.410
## BW bias (b)                   23.733         23.733
## rho (h/b)                     0.607         0.607
## Unique Obs.                   2311            315
```

```
##
## =====
##           Method      Coef. Std. Err.      z    P>|z|      [ 95% C.I. ]
## =====
##   Conventional      3.108      1.284      2.421    0.015    [0.592 , 5.624]
## Bias-Corrected      3.163      1.284      2.463    0.014    [0.646 , 5.679]
## Robust              3.163      1.515      2.088    0.037    [0.194 , 6.132]
## =====
```

Reference

Cattaneo, Matias D., Nicolás Idrobo, and Rocio Titiunik. “A Practical Introduction to Regression Discontinuity Designs: Foundations.” arXiv preprint arXiv:1911.09511 (2019).

Meyersson, Erik. “Islamic Rule and the Empowerment of the Poor and Pious.” *Econometrica* 82, no. 1 (2014): 229-269.