Regression Discontinuity 2: Implementation in R

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Close election design

Question and Estimation strategy

- Lee, D.S., Moretti, E., and M. Butler, 2004, Do Voters Affect or Elect Policies? Evidence from the U.S. House, Quarterly Journal of Economics 119, 807-859.
- Do voters affect policy itself or do they just select politician?
- The roll-call voting record RC_t of the representative in the district following the election t can be written as

$$RC_t = (1 - D_t)y_t + D_t x_t,$$

  - D_t: indicator variable for whether the Democrat won election t
  - x_t (y_t): the policy implemented by the Democrat (the Repulican) at t

- Under some conditions, it can be expressed as

$$RC_t = constant + \pi_0 P_t^* + \pi_1 D_t + \epsilon_t \quad (1)$$
$$RC_{t+1} = constant + \pi_0 P_{t+1}^* + \pi_1 D_{t+1} + \epsilon_{t+1} \quad (2)$$

  - P_t^*: voters' underlying popularity (the electoral strength) of the Democrat. It is defined as the probability that party D will win if parties D and R are expected to choose their blis points, not moderating points.

- **What we try to know** is whether $\pi_0 = 0$ or $\pi_1 = 0$, or neither, meaning what affect representative's roll-call voting, in other words, politician's decision.
    - If $\pi_1 = 0$, the roll-call voting of the representative in the district does not vary regarless of who wins (called **Complete Convergence**). That is both parties choose the exactly same policy. The policy position is determined only by the voter's underlying popularity.
    - If $\pi_0 = 0$, the roll-call voting of the representative in the district does not affected by voters' underlying popularity (called **Complete Divergence**). This can be interpretted that voters can not affect policy, but merely elect politicians' fixed policies.
    - If else, both parties select different policies, but voters can affect policy (called **Partial Convergence**).

- The problem is we cannot estimate equations (1) and (2), because we cannot observe P_t^*.
- This brings **two issues** to figure out in order to identify π_0 and π_1.

1. Simple comparison of RC_t between $D_t = 1$ and $D_t = 0$ without controlling on P_t^* leads endogeneity bias, since P_t^* tends to be higher among $D_t = 1$.
   $\Rightarrow$ We need to somehow control P_t^* $\Rightarrow$ **RDD**
   - By focusing on close elections (when voteshares of both parties are very tight), we can compare the cases between when $D_t = 1$ and $D_t = 0$, fixing P_t^* constant. $\Rightarrow$ Being able to identify π_1.
2. Because P_t^* is directly unobservable, we have to somehow find variation of P_t^* to identify π_0.
   $\Rightarrow$ **Incumbency advantage**
   - The random assignment of who wins in the first election generates random assignment in which candidate has greater electoral strength for the next election. $\Rightarrow$ This requires **two period analysis.**

Identification

- The conditional expectation of equation (2) is:

$$\begin{aligned}\lim_{v \downarrow 0.5} E[RC_{t+1}|V_t = v] &= constant + \pi_0 E[P^*_{t+1}|D_t = 1, V_t = 0.5] \\ &\quad + \pi_1 E[D_{t+1}|D_t = 1, V_t = 0.5] \\ &= constant + \pi_0 P^{*D}_{t+1} + \pi_1 P^D_{t+1}\end{aligned}$$

$$\begin{aligned}\lim_{v \uparrow 0.5} E[RC_{t+1}|V_t = v] &= constant + \pi_0 E[P^*_{t+1}|D_t = 0, V_t = 0.5] \\ &\quad + \pi_1 E[D_{t+1}|D_t = 0, V_t = 0.5] \\ &= constant + \pi_0 P^{*R}_{t+1} + \pi_1 P^R_{t+1}\end{aligned}$$

  - V_t is voteshare of the Democrat in election t, and threshold is 0.5.
  - $P^{*D}_{t+1} \equiv E[P^*_{t+1}|D_t = 1, V_t = 0.5]$, $P^{*R}_{t+1} \equiv E[P^*_{t+1}|D_t = 0, V_t = 0.5]$
  - P^D_{t+1} (P^R_{t+1}) is equilibrium probability that Democrat wins in election t+1 when Democrat (Republican) won in election t.

Estimation

- When one could randomize D_t by restricting data close to the threshold,

$$\underbrace{E[RC_{t+1}|D_t = 1] - E[RC_{t+1}|D_t = 0]}_{\text{Observable}} = \pi_0(P^{*D}_{t+1} - P^{*R}_{t+1}) + \pi_1(P^{D}_{t+1} - P^{R}_{t+1})$$

$$\equiv \underbrace{\gamma}_{\text{Total effect of initial win on future roll call votes}} \qquad (3)$$

$$\underbrace{E[RC_t|D_t = 1] - E[RC_t|D_t = 0]}_{\text{Observable}} = \pi_1 \qquad (4)$$

$$\underbrace{E[D_{t+1}|D_t = 1] - E[D_{t+1}|D_t = 0]}_{\text{Observable}} = P^{D}_{t+1} - P^{R}_{t+1} \qquad (5)$$

- Therefore, $\pi_0(P^{*D}_{t+1} - P^{*R}_{t+1})$ can be estimated by $\gamma - \pi_1(P^{D}_{t+1} - P^{R}_{t+1})$

Data

- There are two main data sets in this project.
- The first is a measure of how liberal an official voted, broght from **ADA score** for 1946–1995. ADA varies from 0 to 100 for each representative. Higher scores correspond to a more “liberal” voting record.
- The running variable in this study is the vote share. That is the share of all votes that went to a Democrat across Congressional districts.
    - U. S. House elections are held every two years.

- **Panel data** (1946–1995 $\times$ all districs around the U.S.)
- Main variables
  - `score`: ADA score in Congressional session t of the representative elected at k (RC_t)
  - `democrat`: indicator whether the Democrat wins in election t (D_t)
  - `lagdemocrat`: indicator whether the Democrat wins in election t-1 (D_{t-1})
  - `demvoteshare`: voteshare at district k in election t (V_t)
  - `lagdemvoteshare`: voteshare at district k in the previous election, t-1 (V_{t-1})

- For example, one specific row of the dataset has the voteshares and the results of the November 1992 election (period t) and the November 1990 election (period t-1) at district k, and the ADA score of 1993–1994 Congressional session (period t).

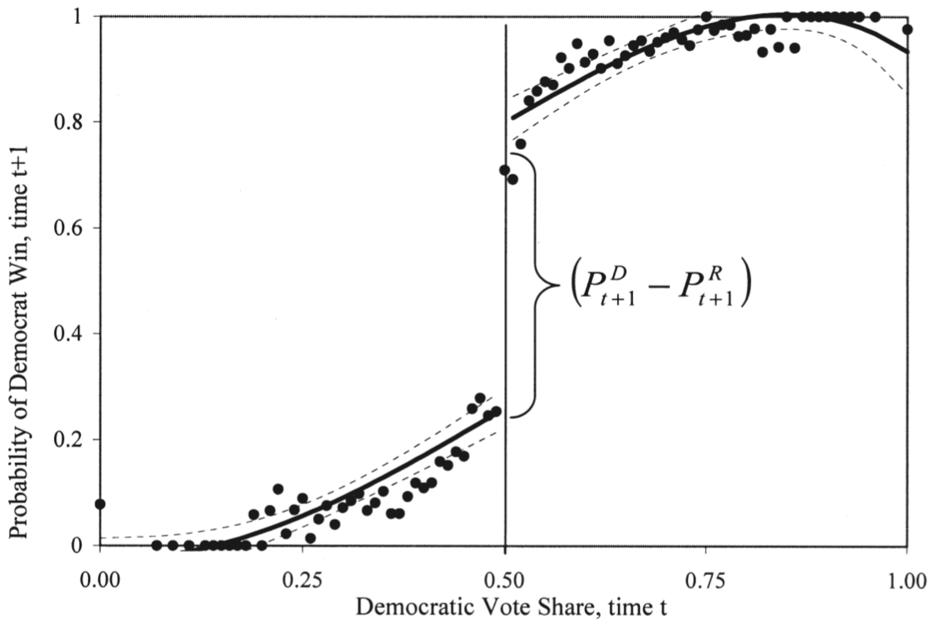
Graphical Analysis

Graphical Analysis

- Results of the analysis will be seen later. Here, we learn how to implement graphical analysis first.
- **RD analyses hinge on their graphical analyses.**
- always start with visual inspection to check which model (e.g. linear or nonlinear) is plausible.

Outcomes by the running variables

- First, we try to create this figure from the article.



- The dependent variable is probability of Democrat victory in election t+1 and the independent is voteshare in election t.
- Then, we will see what happens when we change bandwidth and functional form.

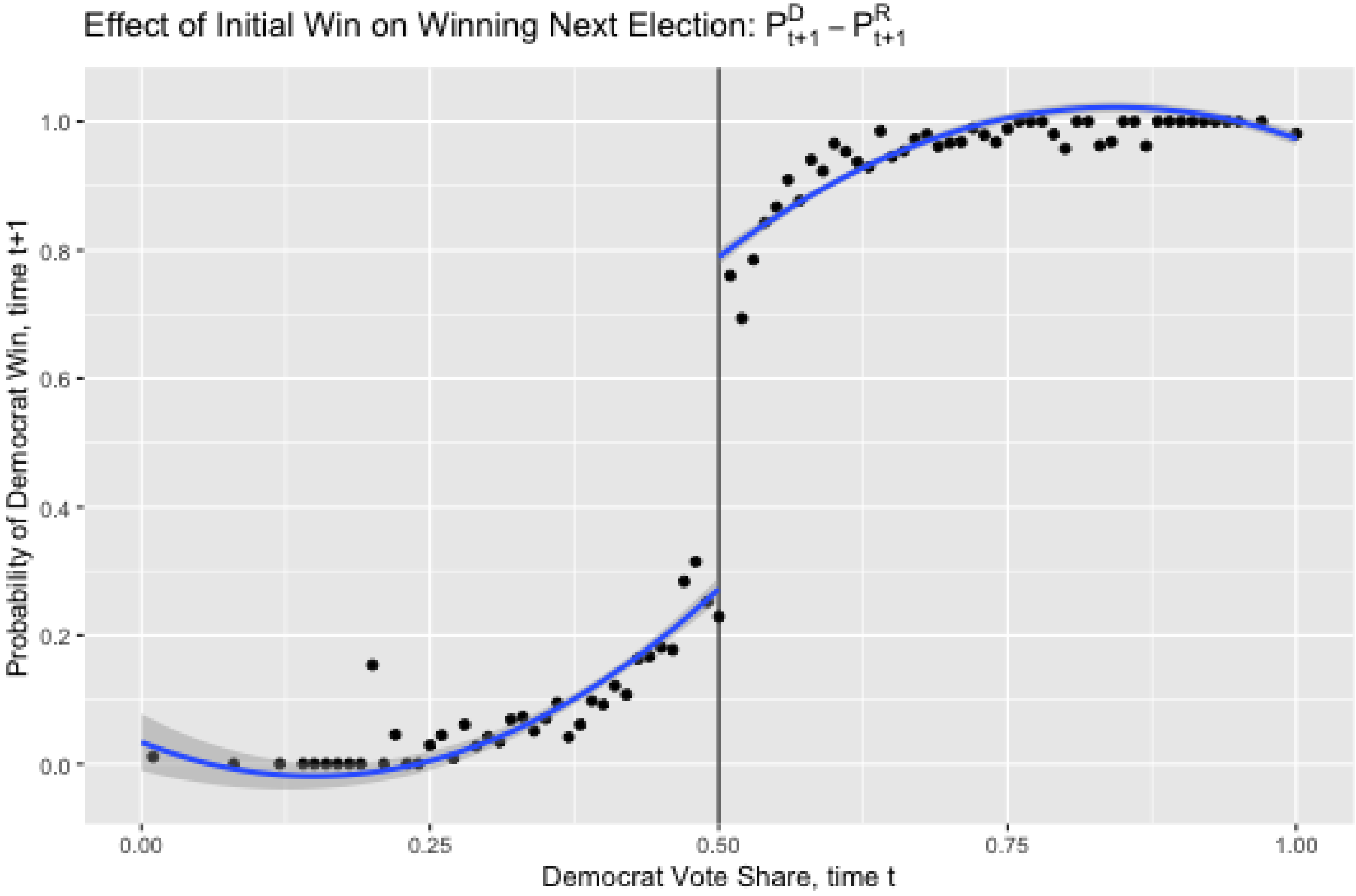
```r
library(tidyverse)
library(haven)
library(estimatr)
library(texreg)
library(latex2exp)

# Download data
read_data <- function(df)
{
  full_path <- paste("https://raw.github.com/scunning1975/mixtape/master/",
                     df, sep = "")
  df <- read_dta(full_path)
  return(df)
}

lmb_data <- read_data("lmb-data.dta")
```

- First, you have more than 10,000 data points, so reduce them for scatter plot.

```
#aggregating the data
# calculate mean value for every 0.01 voteshare
demmeans <- split(lmb_data$democrat, cut(lmb_data$lagdemvoteshare, 100)) %>%
  lapply(mean) %>%
  unlist()

#createing new data frame for plotting
agg_lmb_data <- data.frame(democrat = demmeans, lagdemvoteshare = seq(0.01,1, by = 0.01))
```

Quadratic fitting in all data

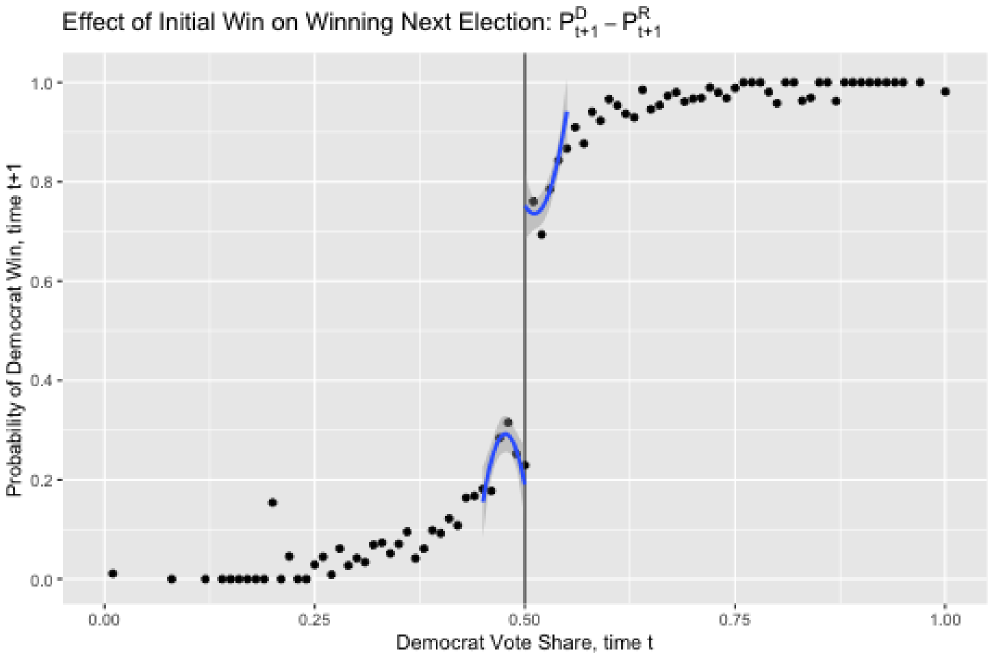
```r
#grouping above or below threshold
lmb_data <- lmb_data %>%
  mutate(gg_group = if_else(lagdemvoteshare > 0.5, 1,0))


#plotting
gg_srd = ggplot(data=lmb_data, aes(lagdemvoteshare, democrat)) +
    geom_point(aes(x = lagdemvoteshare, y = democrat), data = agg_lmb_data)  +
    xlim(0,1) + ylim(-0.1,1.1) +
    geom_vline(xintercept = 0.5) +
    xlab("Democrat Vote Share, time t") +
    ylab("Probability of Democrat Win, time t+1") +
    scale_y_continuous(breaks=seq(0,1,0.2)) +
    ggtitle(TeX("Effect of Initial Win on Winning Next Election: $\\P^D_{t+1} - P^R_{t+1}$"))

gg_srd + stat_smooth(aes(lagdemvoteshare, democrat, group = gg_group),
                     method = "lm", formula = y ~ x + I(x^2))
```



Effect of Initial Win on Winning Next Election: $P^D_{t+1} - P^R_{t+1}$
Probability of Democrat Win, time t+1
1.0
0.8
0.6
0.4
0.2
0.0
0.00
0.25
0.50
0.75
1.00
Democrat Vote Share, time t

Quadratic fitting; limited to +/- 0.05

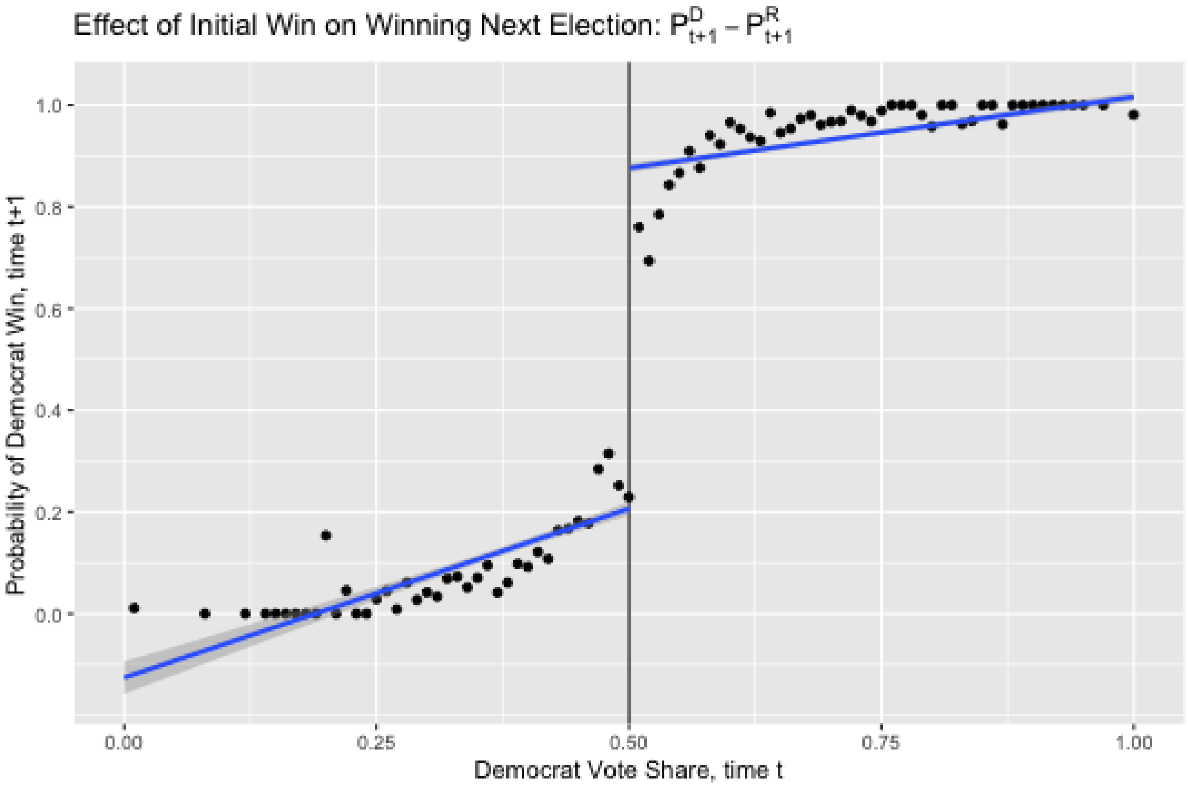
```
gg_srd + stat_smooth(data=lmb_data %>% filter(lagdemvoteshare>.45 & lagdemvoteshare<.55),
                     aes(lagdemvoteshare,  democrat, group = gg_group),
                     method = "lm", formula = y ~ x + I(x^2))
```



- Notice that confidence interval widens. But, lines fit plots better.

Linear different slops

```
gg_srd + stat_smooth(aes(lagdemvoteshare,  democrat, group = gg_group), method = "lm")
```

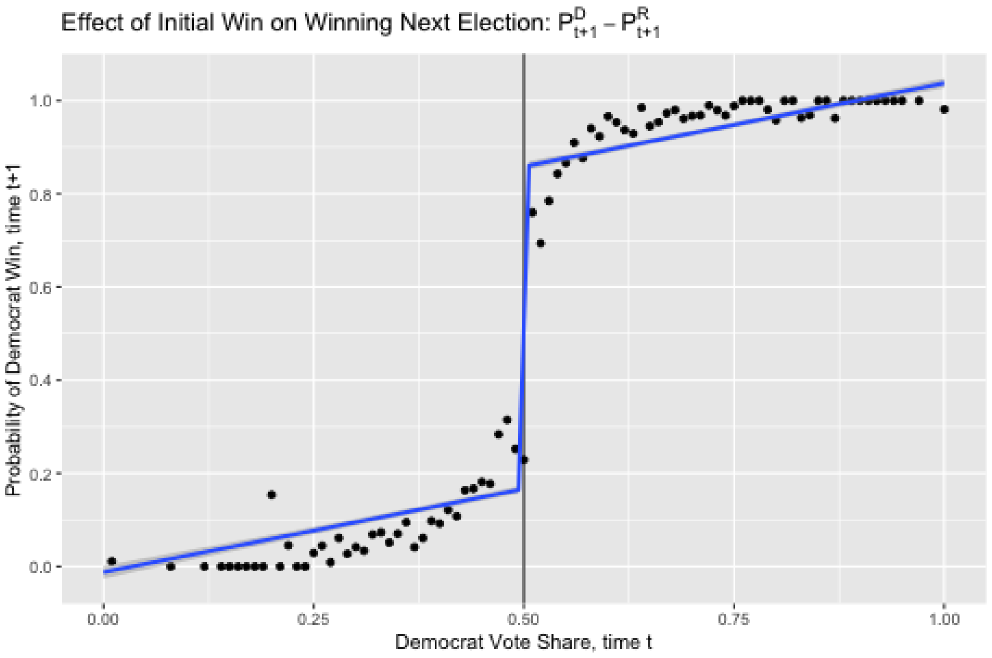


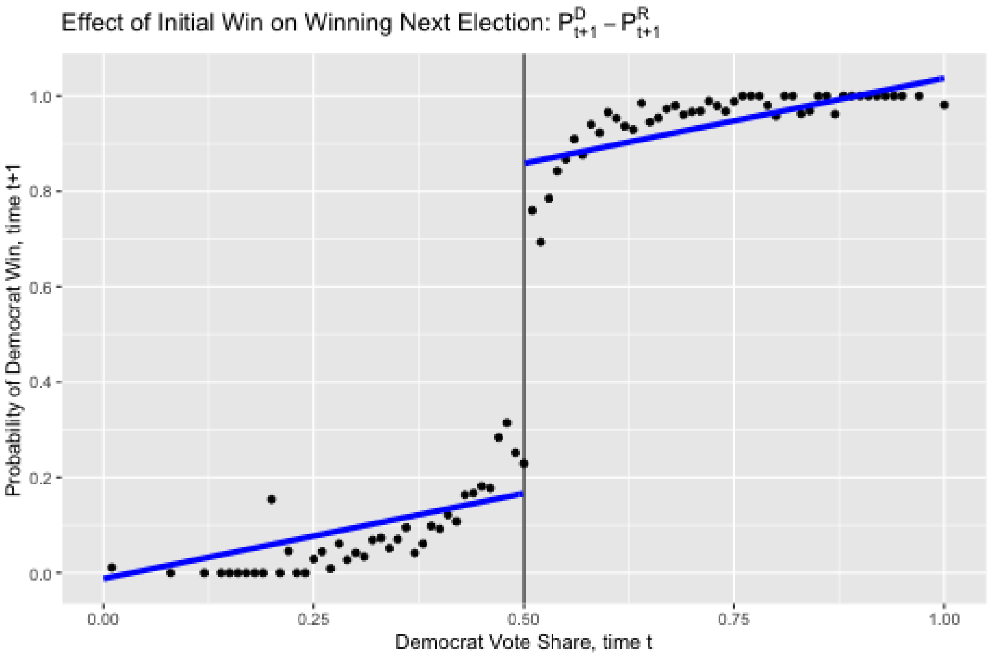
Linear common slop

```
gg_srd + stat_smooth(data=lmb_data, aes(lagdemvoteshare,  democrat),
                     method = "lm", formula = y ~ x + I(x > 0.5))
```

- Alternatively, this can avoid showing line across the threshold.

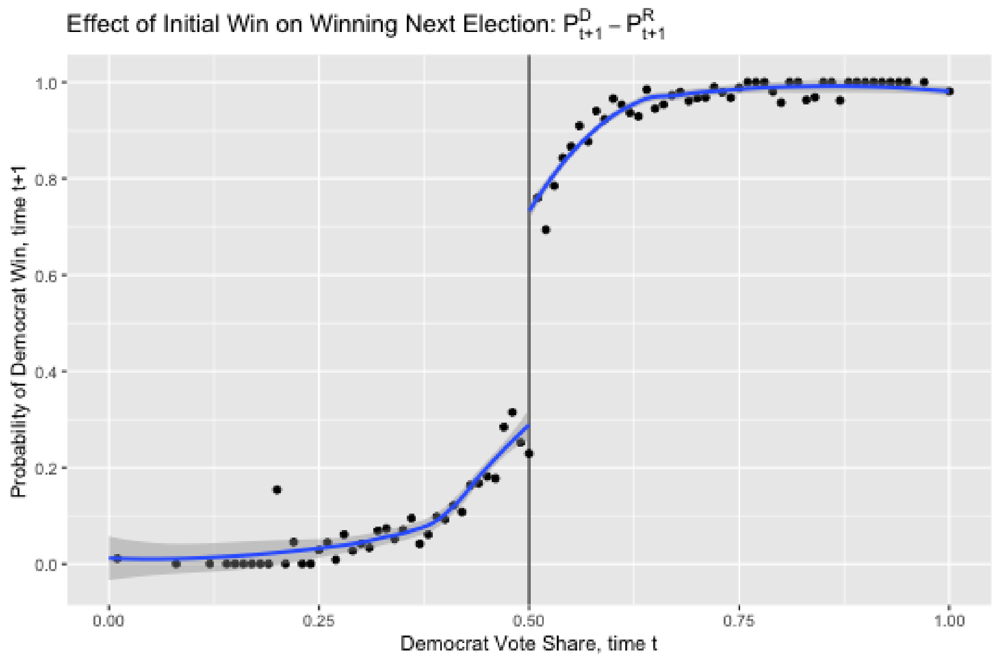
```
lm_tmp <- lm(democrat ~ lagdemvoteshare + I(lagdemvoteshare>0.5), data = lmb_data)
lm_fun <- function(x) predict(lm_tmp, data.frame(lagdemvoteshare = x)) #output is predicted democra
gg_srd +
stat_function(
  data = data.frame(x = c(0, 1),y = c(0, 1)),aes(x = x,y=y),
  fun = lm_fun,xlim = c(0,0.499),
  col="blue",size = 1.5) +
stat_function(
  data = data.frame(x = c(0, 1),y = c(0, 1)),aes(x = x,y=y),
  fun = lm_fun,xlim = c(0.501,1),
  col="blue", size = 1.5 )
```


Effect of Initial Win on Winning Next Election: $P^D_{t+1} - P^R_{t+1}$
Probability of Democrat Win, time t+1
Democrat Vote Share, time t
0.0
0.2
0.4
0.6
0.8
1.0
0.00
0.25
0.50
0.75
1.00


Effect of Initial Win on Winning Next Election: $P^D_{t+1} - P^R_{t+1}$
Probability of Democrat Win, time t+1
Democrat Vote Share, time t
0.0
0.2
0.4
0.6
0.8
1.0
0.00
0.25
0.50
0.75
1.00

Loess fitting

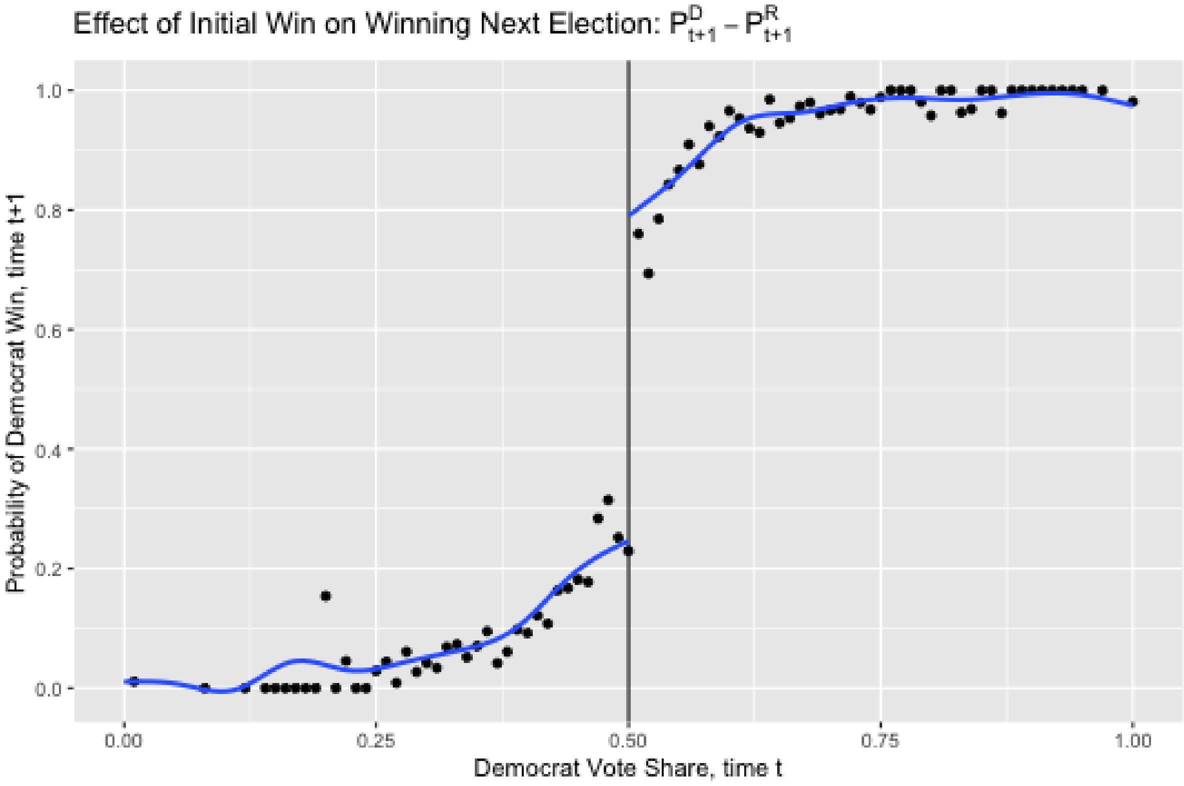
```
gg_srd + stat_smooth(aes(lagdemvoteshare, democrat, group = gg_group), method = "loess")
```



- Compared to the quadratic case, variance gets bigger but the prediction fits the points better.

Kernel-weighted local polynomial regressions

```
library(stats)

smooth_dem0 <- lmb_data %>%
  filter(lagdemvoteshare < 0.5) %>%
  dplyr::select(democrat, lagdemvoteshare) %>%
  na.omit()

smooth_dem0 <- as_tibble(ksmooth(smooth_dem0$lagdemvoteshare, smooth_dem0$democrat,
                                 kernel = "box", bandwidth = 0.1))


smooth_dem1 <- lmb_data %>%
  filter(lagdemvoteshare >= 0.5) %>%
  dplyr::select(democrat, lagdemvoteshare) %>%
  na.omit()
smooth_dem1 <- as_tibble(ksmooth(smooth_dem1$lagdemvoteshare, smooth_dem1$democrat,
                                 kernel = "box", bandwidth = 0.1))

gg_srd  +
  geom_smooth(aes(x, y), data = smooth_dem0) +
  geom_smooth(aes(x, y), data = smooth_dem1)
```


Effect of Initial Win on Winning Next Election: $P^{D}_{t+1} - P^{R}_{t+1}$
Probability of Democrat Win, time t+1
Democrat Vote Share, time t
0.0
0.2
0.4
0.6
0.8
1.0
0.00
0.25
0.50
0.75
1.00

Model and Bandwidth selection - bias-variance tradeoff

- How should we pick the “right” model and bandwidth?

- There’s always a **trade-off between bias and variance** when choosing bandwidth and polynomial length.
  - Bias: distance between your prediction and true value
  - Variance: width of your prediction
  - The shorter the window and the more flexible (e.g. higher-order polynomials) the model, the lower the bias, but because you have less data, the variance in your estimate increases.

- Always, it's important to show robustness.

- Model selection
    - Higher-order polynomials can lead to overfitting (Gelman and Imbens 2019). They recommend using local linear regressions with linear and quadratic forms only.
    - Local linear regression with a kernel smoother is a popular choice
- Bandwidth selection:
    - Optimal bandwidth selection: Imbens and Kalyanaraman (2011), Calonico, Cattaneo, and Titiunik (2014) **implimentation will be at the last slide**
    - Cross validation: Imbens and Lemieux (2008)

Quantitative analysis

Quantitative analysis

- Our next goal is to replicate the quantitaive results of Lee, Moretti, and Butler (2004) in the table below.

	γ	π_1	$P^D_{t+1} - P^R_{t+1}$	$\pi_1(P^D_{t+1} - P^R_{t+1})$	$\pi_0(P^{*D}_{t+1} - P^{*R}_{t+1})$
Variable	ADA_{t+1}	ADA_t	DEM_{t+1}		
Estimated gap	21.2 (1.9)	47.6 (1.3)	0.48 (0.02)		
				22.84 (2.2)	-1.64 (2.0)

- The analysis restrics only observations where the Democrat voteshare is between 48 percent and 52 percent, so that the number of observations is 915.
- From the second column, complete convergence is rejected.
- The last column of the statistical insignificance shows that voters primarily elect policies rather than affect policies.
- **Complete divergence** is supported by this analysis.

```r
# Restrict data containg the Democrat vote share between 48 percent and 52 percent
# `lagdemvoteshare` is the Dem. voteshare of the t-1 period
lmb_subset <- lmb_data %>%
  filter(lagdemvoteshare>.48 & lagdemvoteshare<.52)

# E[ADA_{t+1}|D_t] = \gamma
lm_1 <- lm_robust(score ~ lagdemocrat, data = lmb_subset, se_type = "HC1")
# E[ADA_{t}|D_t] = \pi_1
lm_2 <- lm_robust(score ~ democrat, data = lmb_subset, se_type = "HC1")
# E[D_{t+1}|D_t] = P_{t+1}^D - P_{t+1}^R
lm_3 <- lm_robust(democrat ~ lagdemocrat, data = lmb_subset, se_type = "HC1")

screenreg(l = list(lm_1, lm_2,lm_3),
          digits = 2,
          # caption = 'title',
          custom.model.names = c("ADA_t+1", "ADA_t", "DEM_t+1"),
          include.ci = F,
          include.rsquared = FALSE, include.adjrs = FALSE, include.nobs = T,
          include.pvalues = FALSE, include.df = FALSE, include.rmse = FALSE,
          custom.coef.map = list("lagdemocrat"="lagdemocrat","democrat"="democrat"),
          # select coefficients to report
          stars = numeric(0))
```

```
##
## ======================================
##                ADA_t+1  ADA_t    DEM_t+1
## --------------------------------------
## lagdemocrat    21.28              0.48
##               (1.95)            (0.03)
## democrat                47.71
##                        (1.36)
## --------------------------------------
## Num. obs.     915      915      915
## ======================================
```

- The results are slightly different. But ignore that for now.
- From now on, we will see how the results depend on **bandwidth** and **fanctional form**.

Same specification in all the data

```r
#using all data (note data used is lmb_data, not lmb_subset)

lm_1 <- lm_robust(score ~ lagdemocrat, data = lmb_data, se_type = "HC1")
lm_2 <- lm_robust(score ~ democrat, data = lmb_data, se_type = "HC1")
lm_3 <- lm_robust(democrat ~ lagdemocrat, data = lmb_data, se_type = "HC1")

screenreg(l = list(lm_1, lm_2,lm_3),
          digits = 2,
          # caption = 'title',
          custom.model.names = c("ADA_t+1", "ADA_t", "DEM_t+1"),
          include.ci = F,
          include.rsquared = FALSE, include.adjrs = FALSE, include.nobs = T,
          include.pvalues = FALSE, include.df = FALSE, include.rmse = FALSE,
          custom.coef.map = list("lagdemocrat"="lagdemocrat","democrat"="democrat"),
          # select coefficients to report
          stars = numeric(0))
```

```
##
## =============================================
##                ADA_t+1    ADA_t      DEM_t+1
## ---------------------------------------------
## lagdemocrat     31.51                  0.82
##                 (0.48)                (0.01)
## democrat                   40.76
##                            (0.42)
## ---------------------------------------------
## Num. obs.    13588      13588      13588
## =============================================
```

- Here we see that simply running the regression yields different estimates when we include data far from the cutoff itself.

Controls for the running variable & Recentering of the running variable

- We will simply subtract 0.5 from the running variable.

```r
# Recentering
lmb_data <- lmb_data %>%
  mutate(demvoteshare_c = demvoteshare - 0.5)

lm_1 <- lm_robust(score ~ lagdemocrat + demvoteshare_c, data = lmb_data, se_type = "HC1")
lm_2 <- lm_robust(score ~ democrat + demvoteshare_c, data = lmb_data, se_type = "HC1")
lm_3 <- lm_robust(democrat ~ lagdemocrat + demvoteshare_c, data = lmb_data, se_type = "HC1")

screenreg(l = list(lm_1, lm_2,lm_3),
          digits = 2,
          # caption = 'title',
          custom.model.names = c("ADA_t+1", "ADA_t", "DEM_t+1"),
          include.ci = F,
          include.rsquared = FALSE, include.adjrs = FALSE, include.nobs = T,
          include.pvalues = FALSE, include.df = FALSE, include.rmse = FALSE,
          custom.coef.map = list("lagdemocrat"="lagdemocrat","democrat"="democrat"),
          # select coefficients to report
          stars = numeric(0))
```

```
##
## ================================================
##                ADA_t+1    ADA_t      DEM_t+1
## ------------------------------------------------
## lagdemocrat     33.45                   0.55
##                 (0.85)                 (0.01)
## democrat                    58.50
##                             (0.66)
## ------------------------------------------------
## Num. obs.    13577      13577      13577
## ================================================
```

Different slopes on either side of the discontinuity

- How to impliment a regression line to be on either side, which means necessarily that we have two lines left and right of the discontinuity? $\Rightarrow$ **Interaction**

```
lm_1 <- lm_robust(score ~ lagdemocrat*demvoteshare_c,
                  data = lmb_data, se_type = "HC1")
lm_2 <- lm_robust(score ~ democrat*demvoteshare_c,
                  data = lmb_data, se_type = "HC1")
lm_3 <- lm_robust(democrat ~ lagdemocrat*demvoteshare_c,
                  data = lmb_data, se_type = "HC1")

screenreg(l = list(lm_1, lm_2,lm_3),
          digits = 2,
          # caption = 'title',
          custom.model.names = c("ADA_t+1", "ADA_t", "DEM_t+1"),
          include.ci = F,
          include.rsquared = FALSE, include.adjrs = FALSE, include.nobs = T,
          include.pvalues = FALSE, include.df = FALSE, include.rmse = FALSE,
          custom.coef.map = list("lagdemocrat"="lagdemocrat","democrat"="democrat"),
          # select coefficients to report
          stars = numeric(0))
```

```
##
## =============================================
##                ADA_t+1    ADA_t      DEM_t+1
## ---------------------------------------------
## lagdemocrat     30.51                  0.53
##                 (0.82)                (0.01)
## democrat                   55.43
##                            (0.64)
## ---------------------------------------------
## Num. obs.    13577      13577      13577
## =============================================
```

Different quadratic regressions in all data

```
lmb_data <- lmb_data %>%
  mutate(demvoteshare_sq = demvoteshare_c^2)

lm_1 <- lm_robust(score ~ lagdemocrat*demvoteshare_c + lagdemocrat*demvoteshare_sq,
                  data = lmb_data, se_type = "HC1")
lm_2 <- lm_robust(score ~ democrat*demvoteshare_c + democrat*demvoteshare_sq,
                  data = lmb_data, se_type = "HC1")
lm_3 <- lm_robust(democrat ~ lagdemocrat*demvoteshare_c + lagdemocrat*demvoteshare_sq,
                  data = lmb_data, se_type = "HC1")


screenreg(l = list(lm_1, lm_2,lm_3),
          digits = 2,
          # caption = 'title',
          custom.model.names = c("ADA_t+1", "ADA_t", "DEM_t+1"),
          include.ci = F,
          include.rsquared = FALSE, include.adjrs = FALSE, include.nobs = T,
          include.pvalues = FALSE, include.df = FALSE, include.rmse = FALSE,
          custom.coef.map = list("lagdemocrat"="lagdemocrat","democrat"="democrat"),
          # select coefficients to report
          stars = numeric(0))
```

```
##
## ===============================================
##               ADA_t+1    ADA_t      DEM_t+1
## -----------------------------------------------
## lagdemocrat     13.03                  0.32
##                 (1.27)                (0.02)
## democrat                   44.40
##                            (0.91)
## -----------------------------------------------
## Num. obs.    13577      13577      13577
## ===============================================
```

- The larger standard error due to the longer polynomial term.

Different quadratic regression; limited to +/- 0.05

```
lmb_subset <- lmb_data %>%
  filter(demvoteshare > .45 & demvoteshare < .55) %>%
  mutate(demvoteshare_sq = demvoteshare_c^2)

lm_1 <- lm_robust(score ~ lagdemocrat*demvoteshare_c + lagdemocrat*demvoteshare_sq,
                  data = lmb_subset, se_type = "HC1")
lm_2 <- lm_robust(score ~ democrat*demvoteshare_c + democrat*demvoteshare_sq,
                  data = lmb_subset, se_type = "HC1")
lm_3 <- lm_robust(democrat ~ lagdemocrat*demvoteshare_c + lagdemocrat*demvoteshare_sq,
                  data = lmb_subset, se_type = "HC1")

screenreg(l = list(lm_1, lm_2,lm_3),
          digits = 2,
          # caption = 'title',
          custom.model.names = c("ADA_t+1", "ADA_t", "DEM_t+1"),
          include.ci = F,
          include.rsquared = FALSE, include.adjrs = FALSE, include.nobs = T,
          include.pvalues = FALSE, include.df = FALSE, include.rmse = FALSE,
          custom.coef.map = list("lagdemocrat"="lagdemocrat","democrat"="democrat"),
          # select coefficients to report
          stars = numeric(0))
```

```
##
## =========================================
##               ADA_t+1   ADA_t     DEM_t+1
## -----------------------------------------
## lagdemocrat     7.35                0.17
##               (1.59)              (0.02)
## democrat                 45.19
##                          (2.68)
## -----------------------------------------
## Num. obs.    2387      2387      2387
## =========================================
```

Optimal bandwidth by `rdrobust`

- The method of optimal bandwidth selection (Calonico, Cattaneo, and Titiunik 2014) can be implemented with the user-created `rdrobust` command.
- These methods ultimately choose optimal bandwidths that may differ left and right of the cutoff based on some bias-variance trade-off.

```r
# install.packages("rdrobust")
library(rdrobust)

rdr <- rdrobust(y = lmb_data$score,
                x = lmb_data$demvoteshare, c = 0.5)
summary(rdr)
```

```
## [1] "Mass points detected in the running variable."

## Call: rdrobust
##
## Number of Obs.                   13577
## BW type                          mserd
## Kernel                      Triangular
## VCE method                          NN
##
## Number of Obs.                   5480         8097
## Eff. Number of Obs.              2112         1893
## Order est. (p)                      1            1
## Order bias  (q)                     2            2
## BW est. (h)                     0.086        0.086
## BW bias (b)                     0.141        0.141
## rho (h/b)                       0.609        0.609
## Unique Obs.                      2770         3351
##
## =============================================================================
##         Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
## =============================================================================
##   Conventional    46.491     1.241    37.477     0.000    [44.060 , 48.923]
##         Robust         -         -    31.425     0.000    [43.293 , 49.052]
## =============================================================================
```

Covariate test

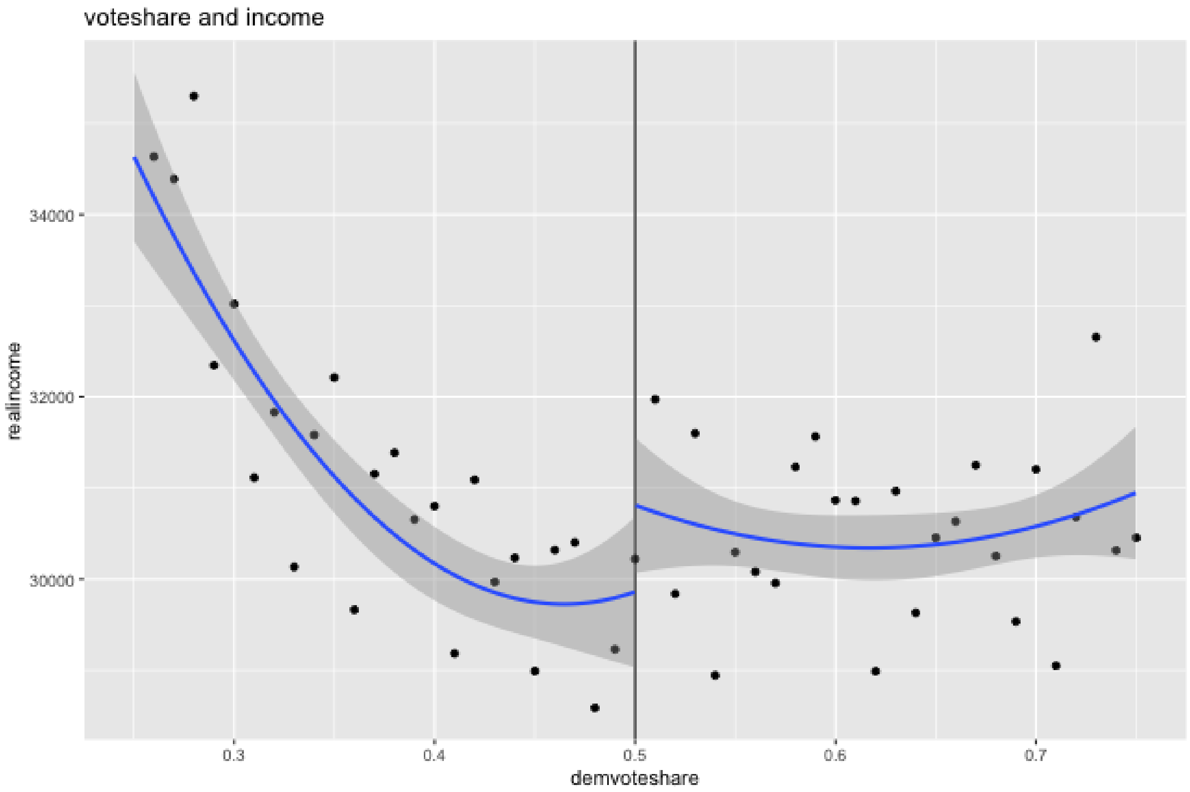
Covariates by the running variables

- We use income (`realincome`) as covariates.
- We limit window of voteshare from 0.25 to 0.75.

```
#aggregating the data
lmb_subset = lmb_data %>%
    dplyr::select(realincome,demvoteshare) %>%
    filter(demvoteshare>.25 & demvoteshare<.75) %>%
    na.omit()

#calculate mean value for every 0.01 voteshare
demmeans <- split(lmb_subset$realincome, cut(lmb_subset$demvoteshare, 50)) %>%
  lapply(mean) %>%
  unlist()

#createing new data frame for plotting
agg_lmb_data <- data.frame(income = demmeans, demvoteshare = seq(0.26, 0.75, by = 0.01))
```

Covariate test for income

```
#grouping above or below threshold
lmb_subset <- lmb_subset %>%
  mutate(gg_group = if_else(demvoteshare > 0.5, 1,0))

#plotting
ggplot(data=lmb_subset, aes(demvoteshare, realincome)) +
  geom_point(aes(x = demvoteshare, y = income), data = agg_lmb_data)  +
  geom_vline(xintercept = 0.5) +
  stat_smooth( aes(demvoteshare, realincome, group = gg_group), method = "lm", formula = y ~ x + I(x
```


voteshare and income
34000
32000
30000
realincome
0.3
0.4
0.5
0.6
0.7
demvoteshare

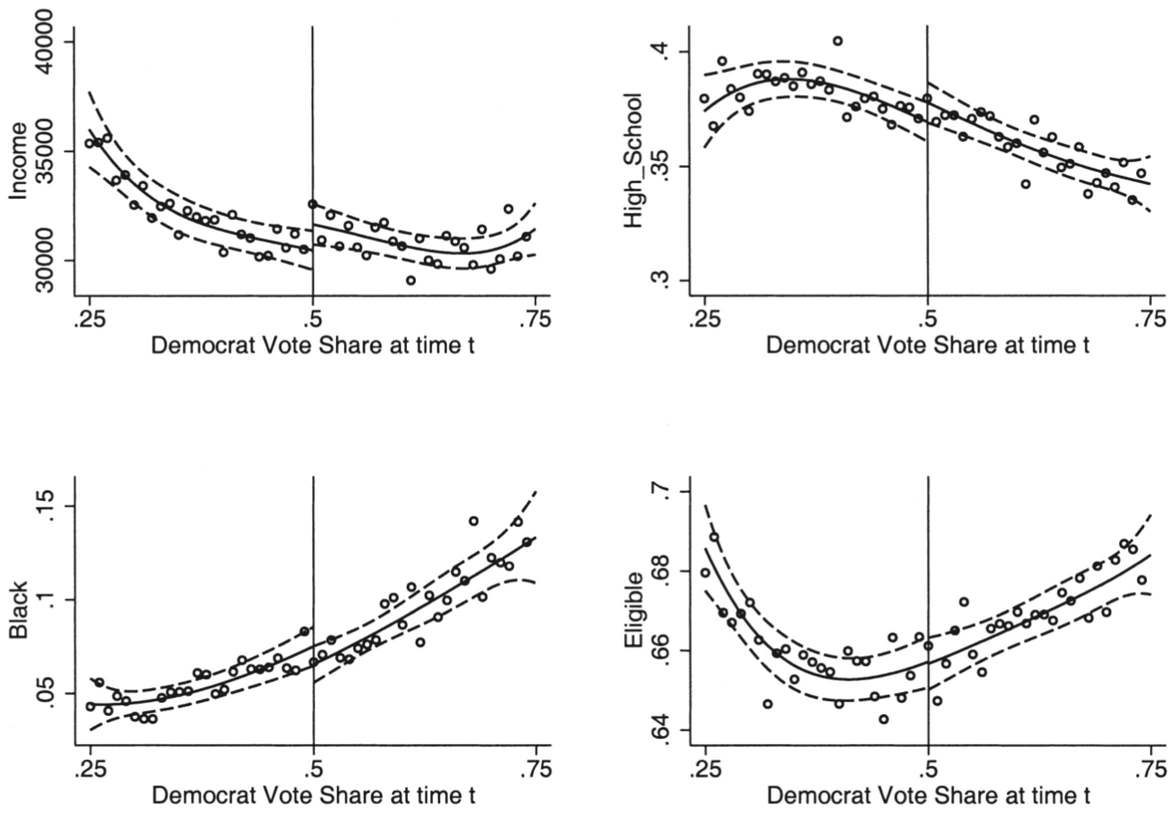
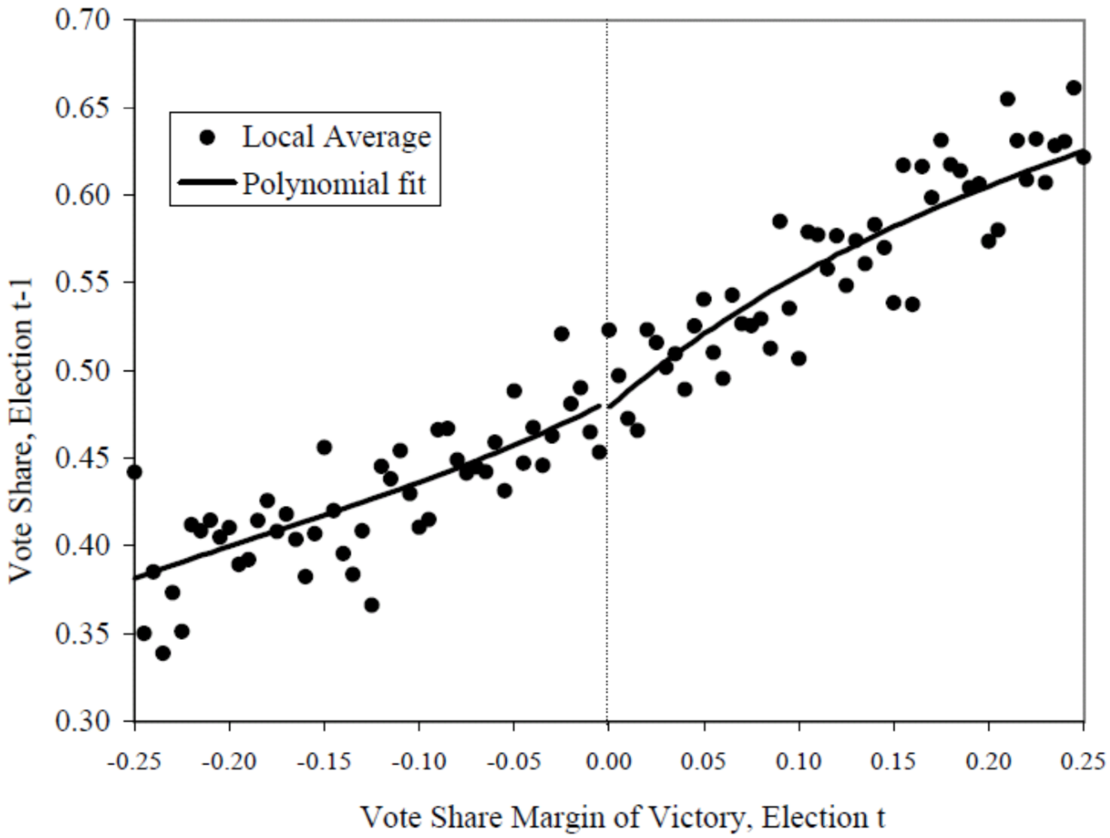


FIGURE III

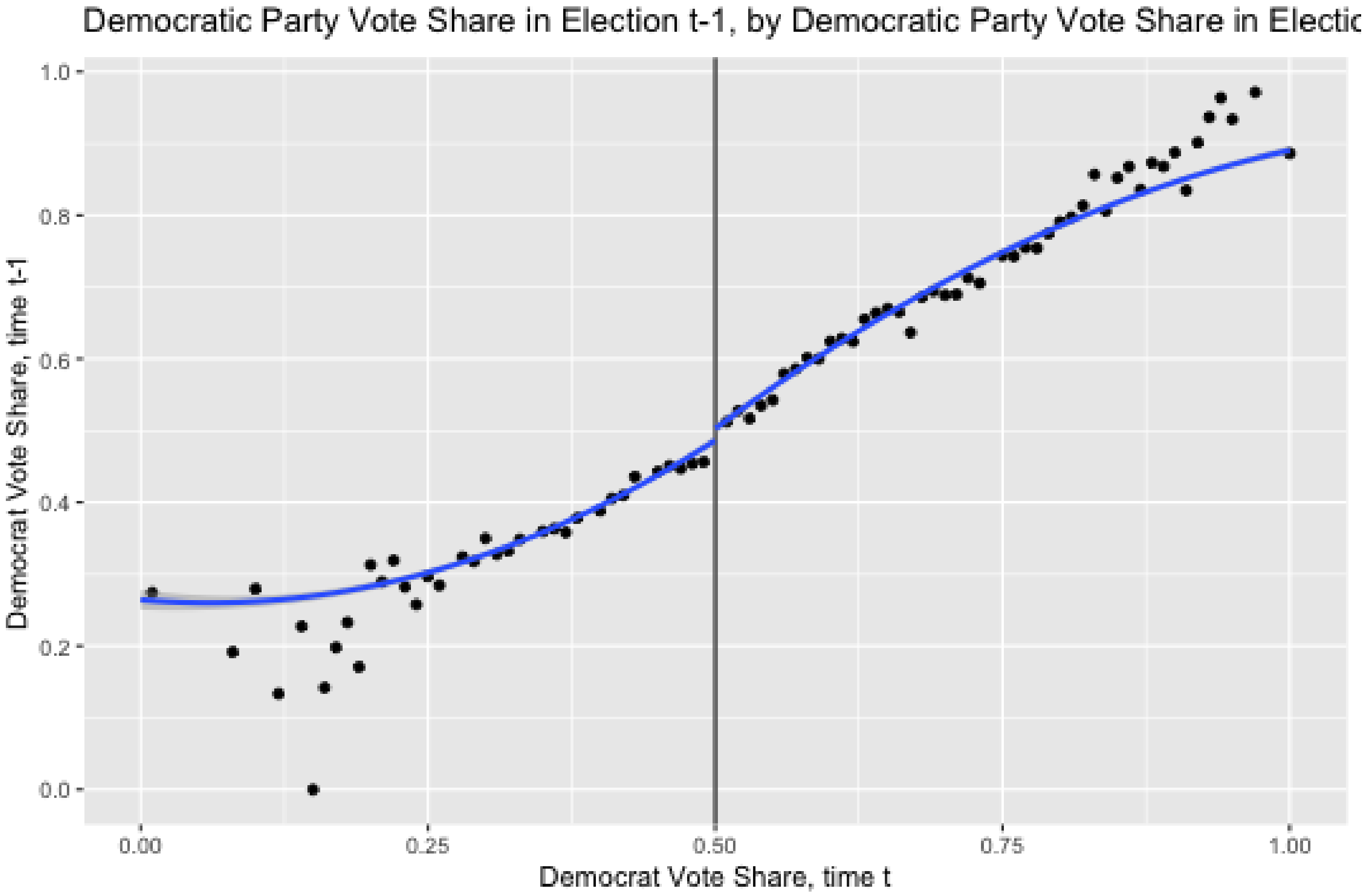
- The authors also did covariate tests with other variables such as percentage with high-school degree (`pcthighschl`), percentage black (`pctblack`), percentage eligible to vote (`votingpop/totpop`).



- t-1 period's outcome is also often used as a placebo.

Coding of placebo

```r
#aggregating the data
# calculate mean value for every 0.01 voteshare
demmeans <- split(lmb_data$lagdemvoteshare, cut(lmb_data$demvoteshare, 100)) %>%
  lapply(mean) %>%
  unlist()
#createing new data frame for plotting
agg_lmb_data <- data.frame(lagdemvoteshare=demmeans, demvoteshare = seq(0.01,1, by = 0.01))
#grouping above or below threshold
lmb_data <- lmb_data %>%
  mutate(gg_group = if_else(demvoteshare > 0.5, 1,0))


#plotting
ggplot(data=lmb_data, aes(demvoteshare, lagdemvoteshare)) +
    geom_point(aes(x = demvoteshare, y = lagdemvoteshare), data = agg_lmb_data)  +
    xlim(0,1) + ylim(-0.1,1.1) +
    geom_vline(xintercept = 0.5) +
    xlab("Democrat Vote Share, time t") +
    ylab("Democrat Vote Share, time t-1") +
    scale_y_continuous(breaks=seq(0,1,0.2)) +
    ggtitle(TeX("Democratic Party Vote Share in Election t-1, by Democratic Party Vote Share in Elec
                 method = "lm", formula = y ~ x + I(x^2))
```

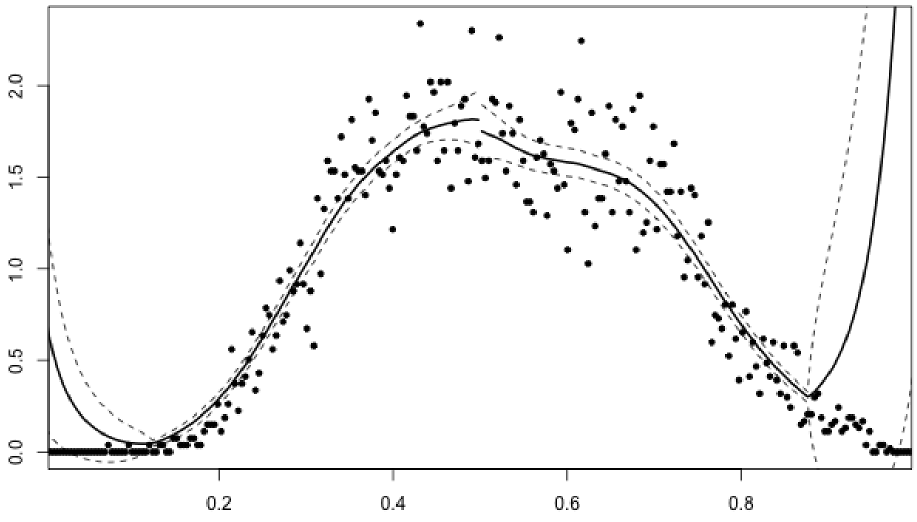

Democratic Party Vote Share in Election t-1, by Democratic Party Vote Share in Electic
1.0
0.8
0.6
0.4
0.2
0.0
Democrat Vote Share, time t-1
0.00
0.25
0.50
0.75
1.00
Democrat Vote Share, time t

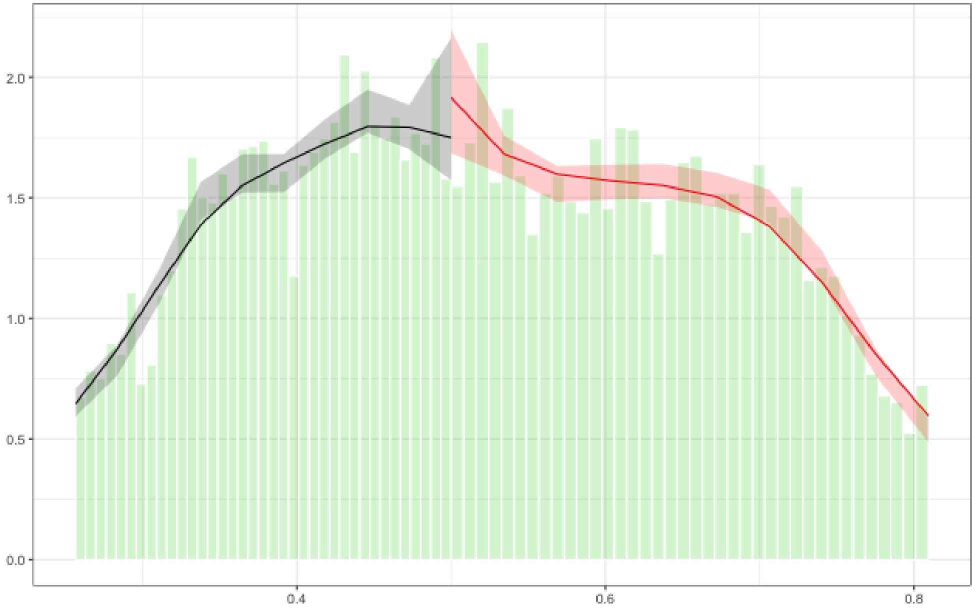
Density test

Density of the running variables

- McCrary density test
- We will implement this test using local polynomial density estimation (Cattaneo, Jansson, and Ma 2019).

```r
# install.packages("rddensity")
# install.packages("rdd")
library(rddensity)
library(rdd)

DCdensity(lmb_data$demvoteshare, cutpoint = 0.5)

density <- rddensity(lmb_data$demvoteshare, c = 0.5)
rdplotdensity(density, lmb_data$demvoteshare)
```





- No signs that there was manipulation in the running variable at the cutoff.