

# Tutorial Week 11: Instrumental Variable (IV) Analysis and RDD

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## 1 Setup and Package Loading

```
# Install packages if needed
packages <- c("AER", "haven", "dplyr", "ggplot2", "stargazer",
            "boot", "lmtest", "sandwich", "knitr", "kableExtra",
            "rdrobust", "rddensity", "rdlocrand")

for (pkg in packages) {
  if (!require(pkg, character.only = TRUE)) {
    install.packages(pkg)
    library(pkg, character.only = TRUE)
  }
}
```

## 2 Load Data

```

# Load the AJR (2001) replication data
ajr_data <- haven::read_dta("acemoglu.dta")
cat("Observations:", nrow(ajr_data), "\n")

## Observations: 64
cat("Variables:", ncol(ajr_data), "\n")

## Variables: 31

```

### 3 Problem 1: Instrumental Variable Analysis

#### 3.1 Q1. Writing and Estimating the IV Model (10 pts)

1. Write down the two-equation IV system (first stage and second stage).

Define explicitly:

- $Y_i$ : outcome
- $T_i$ : endogenous regressor
- $Z_i$ : instrument
- $X_i$ : controls

2. Estimate the following:

- First stage:

$$T_i = \alpha_1 + \beta_1 Z_i + \mathbf{X}'_i \gamma_1 + \varepsilon_{1i}$$

- Reduced form:

$$Y_i = \alpha_2 + \delta_1 Z_i + \mathbf{X}'_i \gamma_2 + \varepsilon_{2i}$$

- 2SLS:

$$Y_i = \alpha_3 + \beta_2 T_i + \mathbf{X}'_i \gamma_3 + \varepsilon_{3i}$$

3. Report and interpret:

- The reduced-form coefficient on  $Z_i$ .
- The first-stage coefficient on  $Z_i$ .
- The **first-stage F-statistic**. Is it above the rule-of-thumb threshold of  $\approx 10$ ?
- The 2SLS estimate of the effect of  $T_i$  on  $Y_i$ . Is it statistically significant?

#### 3.2 Q2. Randomization and Resampling (10 pts)

##### 3.2.1 Q2(a). Permutation Test

1. State the null hypothesis being tested.

2. Conduct a **permutation test** for the IV coefficient:

- Shuffle the endogenous variable (or fitted values) while holding other variables fixed.
- Re-estimate the IV model for each permutation.
- Construct the empirical null distribution.
- Report the **permutation p-value**.

3. Compare this p-value to the **normal-approximation p-value** from your 2SLS output.

Discuss any differences and what they imply for small-sample IV inference.

### 3.2.2 Q2(b). Bootstrap Confidence Intervals

Using bootstrap resampling of observations:

1. Generate bootstrap 2SLS estimates of the coefficient on  $T_i$ .
2. Construct three 95% confidence intervals:
  - Efron percentile
  - Bias-corrected (BC—google this one.)
3. Compare the three CIs:
  - Do they include zero?
  - Are they wider or narrower?
  - What does this imply about the sampling distribution?

### 3.2.3 Q2(c). Conceptual: Permutation vs Bootstrap

Explain—precisely—what the **permutation test** and the **bootstrap** each measure.

What is held fixed? What is resampled?

Why do they answer conceptually different questions?

## 3.3 Q3. Instrument Validity and Timing (10 pts)

### 3.3.1 Q3.1 Causal Priority in AJR's Theory

Why settler mortality must be causally prior to institutions:

[Write your answer here]

Key points to address:

- The logic of instrumental variables requires that  $Z \rightarrow T \rightarrow Y$  (no reverse causation)
- In AJR's theory, high settler mortality  $\rightarrow$  extractive institutions  $\rightarrow$  lower growth
- If institutions could affect mortality rates retroactively, the IV assumption fails
- The exclusion restriction requires mortality affects GDP ONLY through institutions

### 3.3.2 Q3.2 Timing Problems

Issues with timing of settler mortality measurements:

[Write your answer here]

Address each IV assumption:

**Relevance (First-stage):**

- Why does measurement timing affect the strength of the first stage?
- Consider data availability and measurement error

**Exclusion Restriction:**

- If mortality was measured long after colonization, what other channels might exist?
- Could later mortality reflect economic conditions rather than cause them?

**Independence:**

- Are there confounders that affect both late-measured mortality and outcomes?

- Geographic or climatic factors?

### **3.3.3 Q3.3 Assessment of AJR Results**

Based on your analysis:

**Your assessment:**

[Write your answer here]

Consider:

- Is the first stage strong enough?
- Are the IV assumptions plausible given the timing issues?
- What are the main threats to validity?
- Would you believe the causal interpretation?

## **3.4 Q4. Albouy's Critique of AJR (10 pts)**

### **3.4.1 Q4(a). Measurement Problems**

Key measurement issues raised by Albouy (2012):

- 1.
- 2.

**Why they matter for IV validity:**

[Your answer]

### **3.4.2 Q4(b). Violations of IV Assumptions**

**Relevance:**

Albouy's argument:

[Your answer]

**Independence:**

Albouy's argument:

[Your answer]

**Exclusion Restriction:**

Albouy's argument:

[Your answer]

### **3.4.3 Q4(c). Sensitivity and Data Corrections**

After Albouy reconstructs and corrects the mortality data:

**Effects on:**

1. **First stage:** [Your answer - what happens to F-statistic and coefficient?]
2. **Reduced form:** [Your answer - does the relationship weaken?]
3. **2SLS estimates:** [Your answer - how do the causal estimates change?]

**What this reveals about stability:**

[Your answer - are the AJR findings robust or fragile?]

### 3.4.4 Q4(d). Interpretation

Do you believe the AJR conclusions still hold?

[Your answer]

Or do the methodological issues undermine the core causal claim?

[Your answer]

**Justification:**

[Provide clear reasoning based on:

- The strength of Albouy's critique
- Your replication results
- The plausibility of IV assumptions
- The sensitivity of findings to data corrections]

## 4 Problem 2: Regression Discontinuity Design

### 4.1 Part A - Data Loading and Setup

```
# Load RD data
data <- read.csv("CTV_2020_Sage.csv")

# Define outcome, running variable, and covariates
Y <- data$mv_incpartyfor1
X <- data$mv_incparty

covs <- data[, c("pibpc", "population", "numpar_candidates_eff",
                 "party_DEM_wonlag1_b1", "party_PSDB_wonlag1_b1",
                 "party_PT_wonlag1_b1", "party_PMDB_wonlag1_b1")]
covsnm <- c("GDP per capita", "Population", "No. Effective Parties",
            "DEM Victory t-1", "PSDB Victory t-1", "PT Victory t-1", "PMDB Victory t-1")

cat("RDD data loaded successfully!\n")

## RDD data loaded successfully!
cat("Observations:", nrow(data), "\n")

## Observations: 27455
cat("Running variable (X): Incumbent Party's Margin of Victory\n")

## Running variable (X): Incumbent Party's Margin of Victory
cat("Outcome variable (Y): Incumbent Party Victory at t+1\n")

## Outcome variable (Y): Incumbent Party Victory at t+1
```

### 4.2 Part B - Falsification Analysis

#### 4.2.1 Density Test

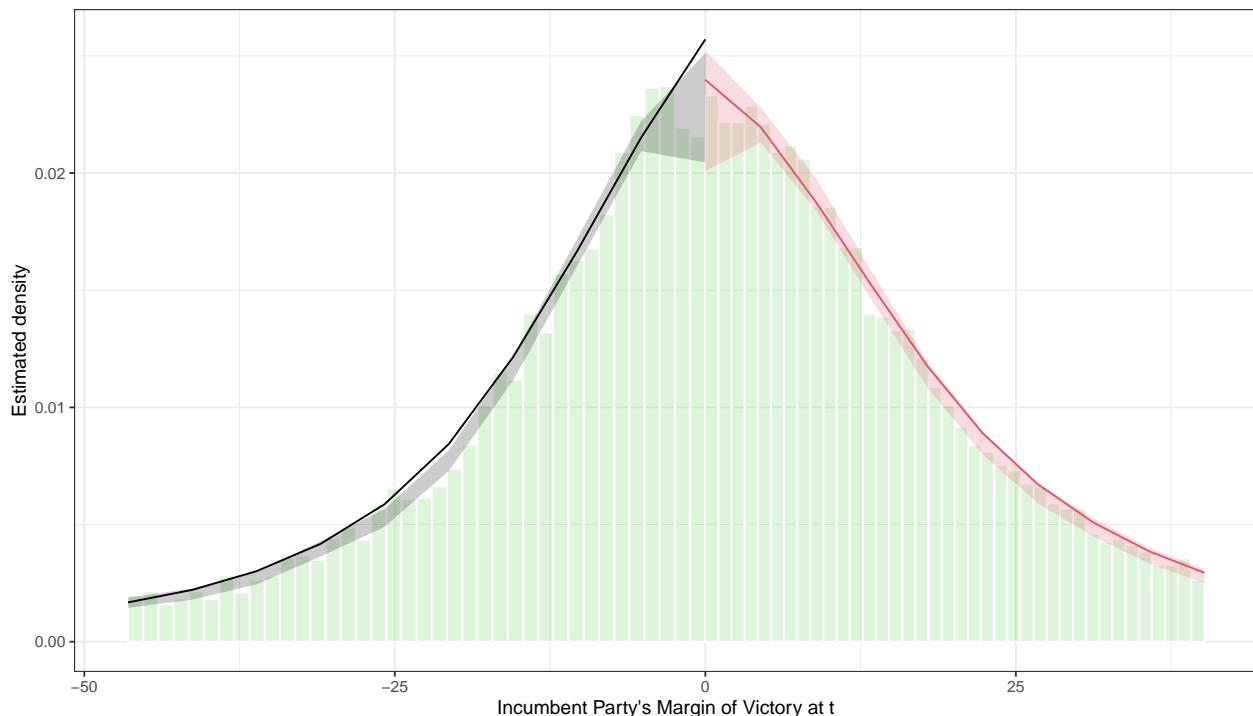
```
# McCrary density test using rddensity
rddens <- rddensity(X)
summary(rddens)
```

```

##
## Manipulation testing using local polynomial density estimation.
##
## Number of obs = 13308
## Model = unrestricted
## Kernel = triangular
## BW method = estimated
## VCE method = jackknife
##
## c = 0 Left of c Right of c
## Number of obs 6088 7220
## Eff. Number of obs 3852 3590
## Order est. (p) 2 2
## Order bias (q) 3 3
## BW est. (h) 15.493 13.392
##
## Method T P > |T|
## Robust -0.0757 0.9397
##
## P-values of binomial tests (H0: p=0.5).
##
## Window Length / 2 <c >=c P>|T|
## 0.098 20 26 0.4614
## 0.195 53 50 0.8439
## 0.293 80 77 0.8732
## 0.390 112 114 0.9470
## 0.488 141 140 1.0000
## 0.585 180 184 0.8751
## 0.683 199 213 0.5219
## 0.780 231 240 0.7125
## 0.878 254 267 0.5991
## 0.975 278 296 0.4780

# Plot the density
rdplotdensity(rddens, X = data$mv_incparty[!is.na(data$mv_incparty)],
              xlab = "Incumbent Party's Margin of Victory at t",
              ylab = "Estimated density")

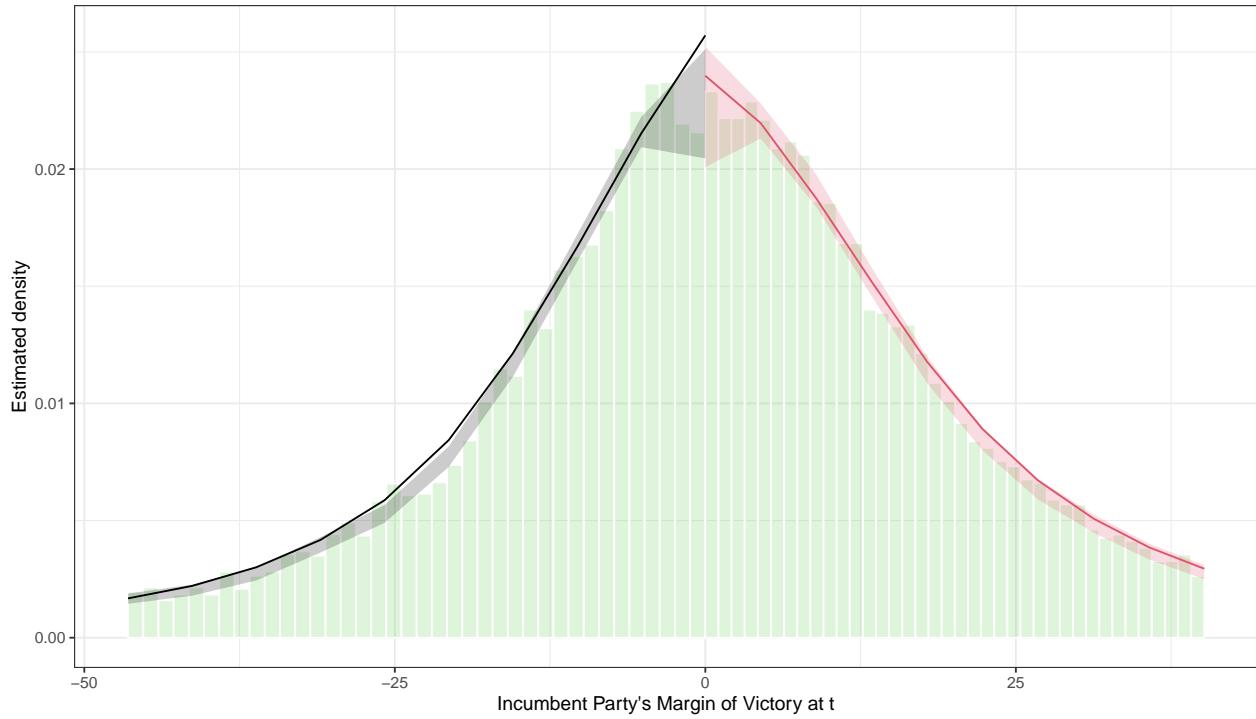
```



```

## $Estl
## Call: lpdensity
##
## Sample size                               6088
## 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                          0.457503569549861
## Bandwidth method                        user provided
##
## Use summary(...) to show estimates.
##
## $Estr
## Call: lpdensity
##
## Sample size                               7220
## 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                          0.542571578868265
## Bandwidth method                        user provided
##
## Use summary(...) to show estimates.
##
## $Estplot

```



#### Interpretation:

The density test checks whether there is evidence of manipulation around the threshold (margin of victory = 0). A significant discontinuity in the density would suggest that parties can manipulate their vote margins to barely win elections, which would violate the RD identifying assumptions.

#### 4.2.2 Covariate Balance Tests

```
# Test for balance in covariates at the threshold
for(c in 1:ncol(covs)){
  cat("\n==== Testing covariate:", covsnm[c], "====\n")
  rdr_cov <- rdrobust(covs[,c], X)
  print(summary(rdr_cov))

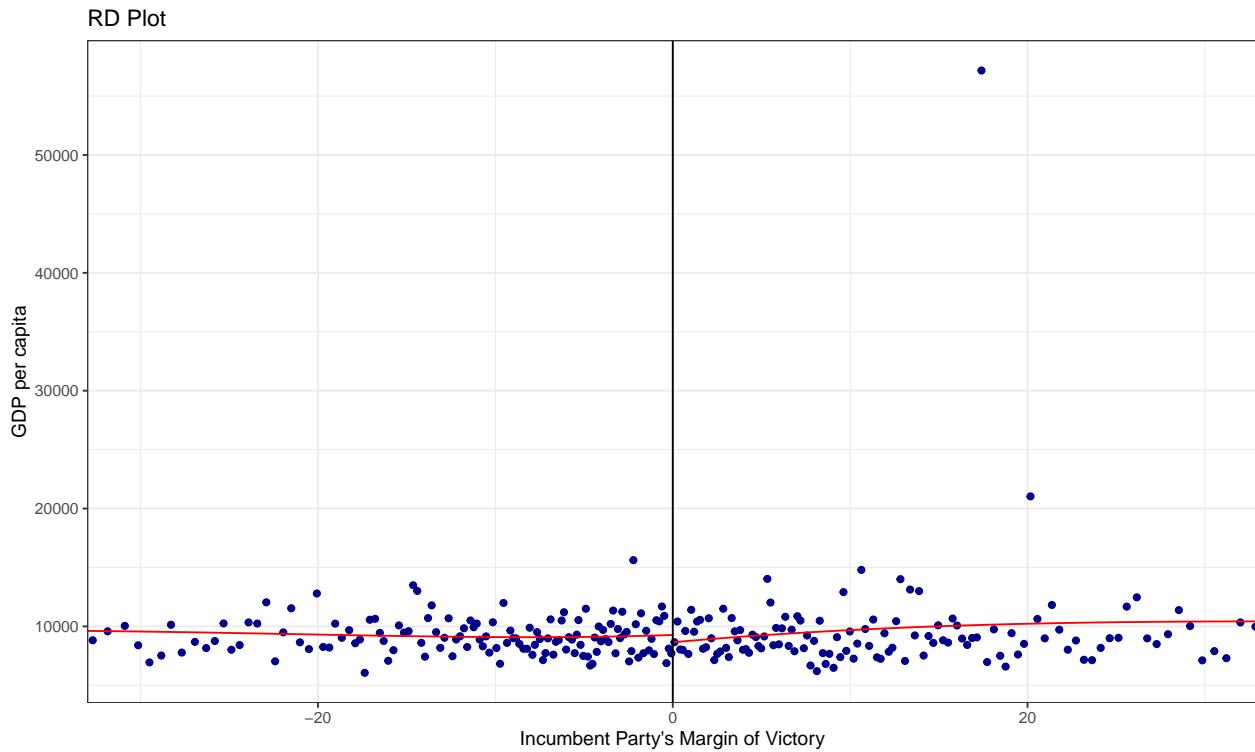
  # Create RD plot for this covariate
  rdplot(covs[,c], X,
         y.label = covsnm[c],
         x.label = "Incumbent Party's Margin of Victory",
         x.lim = c(-30, 30),
         binselect = "qsmv")
}

## 
## === Testing covariate: GDP per capita ===
## Sharp RD estimates using local polynomial regression.
##
## Number of Obs.          13278
## BW type                 mserd
## Kernel                  Triangular
## VCE method               NN
##
## Number of Obs.          6075      7203
```

```

## Eff. Number of Obs.          3626          3740
## Order est. (p)              1              1
## Order bias (q)              2              2
## BW est. (h)                 14.230        14.230
## BW bias (b)                27.423        27.423
## rho (h/b)                  0.519        0.519
## Unique Obs.                6021         6833
##
## =====
##             Point   Robust Inference
##             Estimate      z     P>|z|      [ 95% C.I. ]
## -----
## RD Effect -149.918    -0.190    0.849 [-1205.779 , 992.346]
## =====
## NULL

```



```

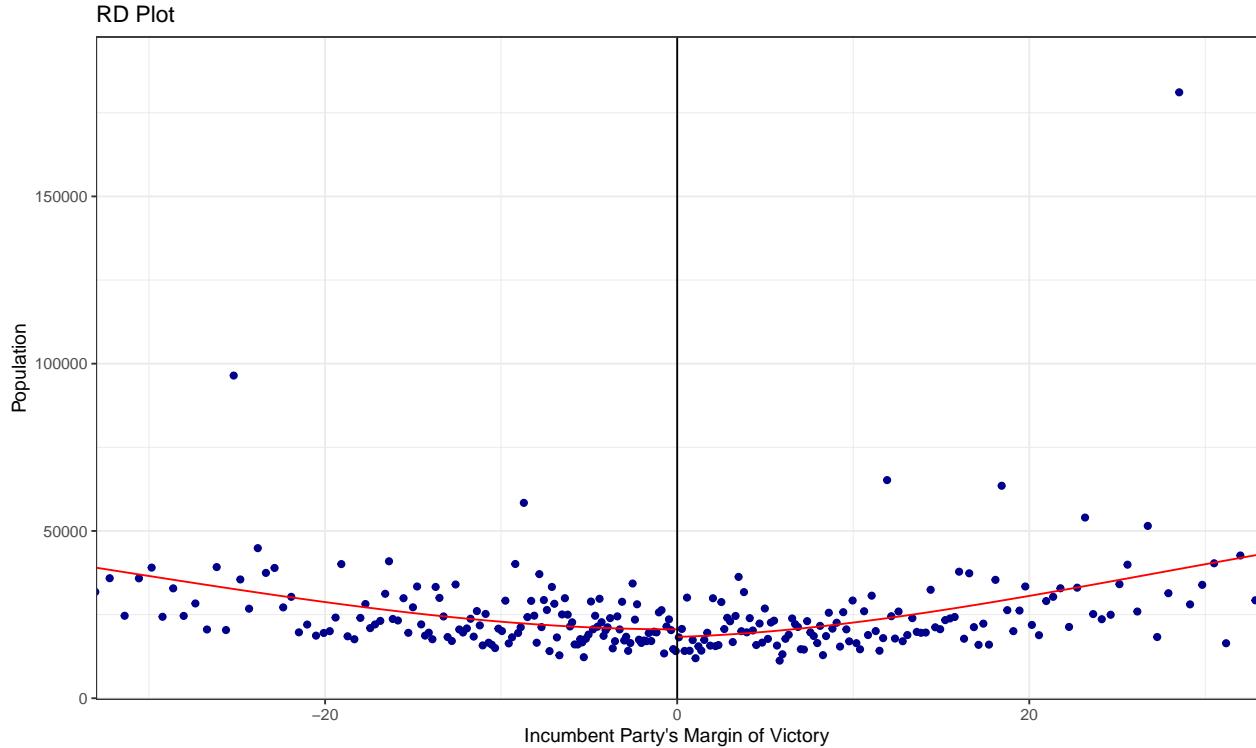
##
## === Testing covariate: Population ===
## Sharp RD estimates using local polynomial regression.
##
## Number of Obs.          13303
## BW type                 mserd
## Kernel                  Triangular
## VCE method               NN
##
## Number of Obs.          6084          7219
## Eff. Number of Obs.     2514          2543
## Order est. (p)          1              1
## Order bias (q)          2              2
## BW est. (h)              8.735         8.735
## BW bias (b)              15.776        15.776

```

```

## rho (h/b)          0.554      0.554
## Unique Obs.       6030       6848
##
## =====
##             Point   Robust Inference
##             Estimate      z    P>|z|      [ 95% C.I. ]
## -----
## RD Effect     -22.559    0.177    0.860 [-3787.982 , 4539.488]
## =====
## NULL

```



```

##
## === Testing covariate: No. Effective Parties ===
## Sharp RD estimates using local polynomial regression.
##
## Number of Obs.           13308
## BW type                  mserd
## Kernel                   Triangular
## VCE method                NN
##
## Number of Obs.           6088      7220
## Eff. Number of Obs.      3312      3409
## Order est. (p)            1         1
## Order bias (q)            2         2
## BW est. (h)              12.440    12.440
## BW bias (b)              20.393    20.393
## rho (h/b)                 0.610    0.610
## Unique Obs.               6033     6849
##
## =====
##             Point   Robust Inference

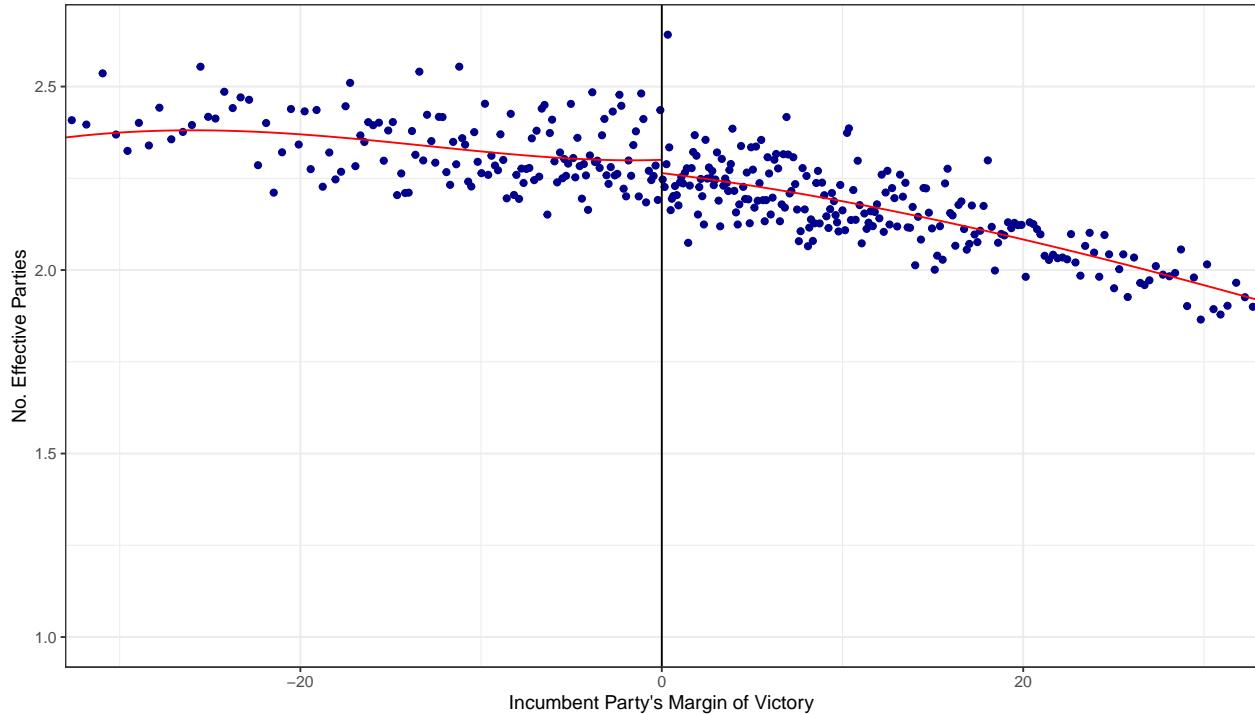
```

```

##                               Estimate      z     P>|z|      [ 95% C.I. ]
## -----
##   RD Effect      -0.036   -1.368    0.171  [-0.100 , 0.018]
## -----
##   NULL

```

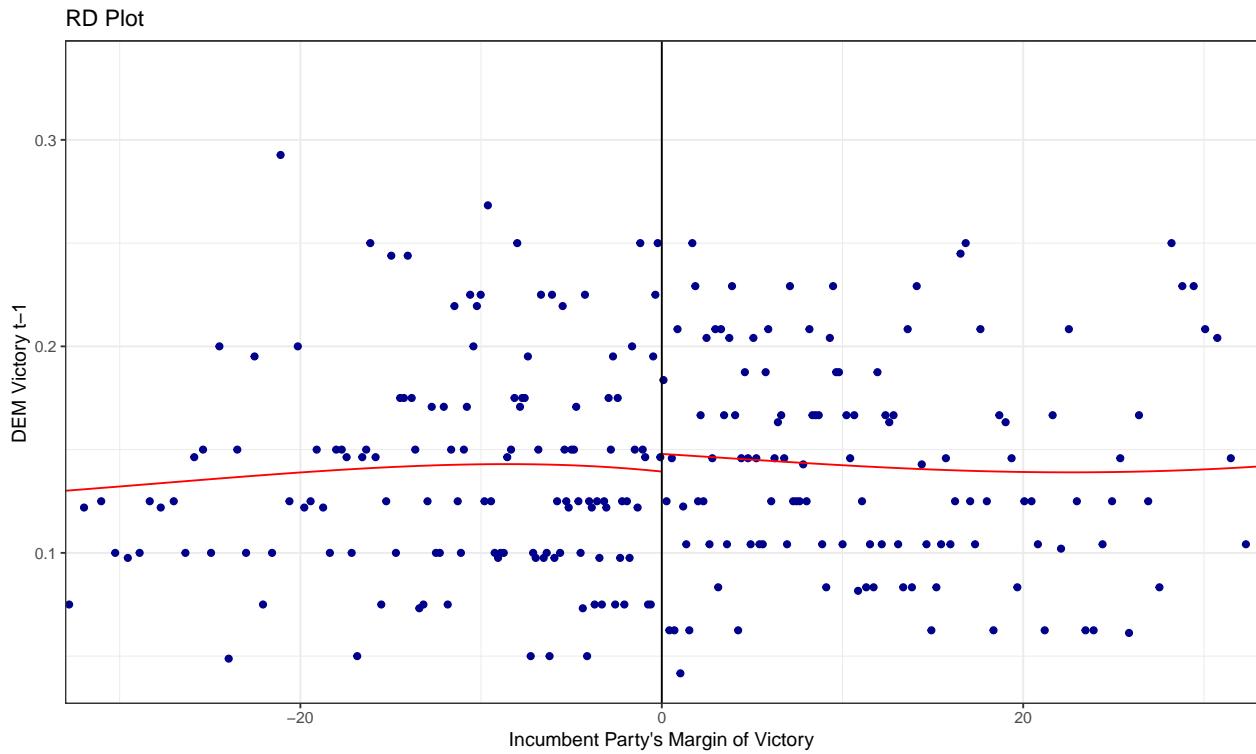
RD Plot



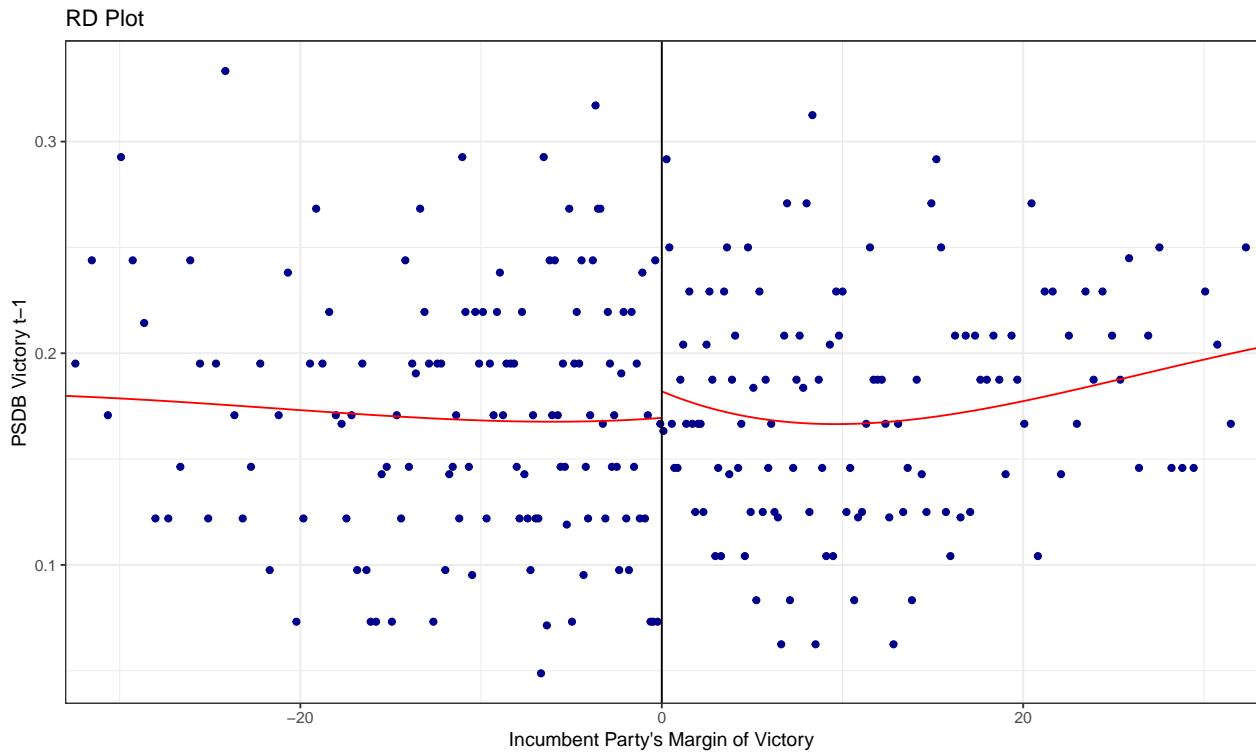
```

##
## === Testing covariate: DEM Victory t-1 ===
## Sharp RD estimates using local polynomial regression.
##
## Number of Obs.          13308
## BW type                 mserd
## Kernel                  Triangular
## VCE method               NN
##
## Number of Obs.          6088      7220
## Eff. Number of Obs.     4026      4183
## Order est. (p)          1         1
## Order bias (q)          2         2
## BW est. (h)              16.654   16.654
## BW bias (b)              29.560   29.560
## rho (h/b)                0.563   0.563
## Unique Obs.             6033     6849
##
## -----
##                               Point      Robust Inference
##                               Estimate      z     P>|z|      [ 95% C.I. ]
## -----
##   RD Effect      0.005   0.119    0.905  [-0.033 , 0.038]
## -----
##   NULL

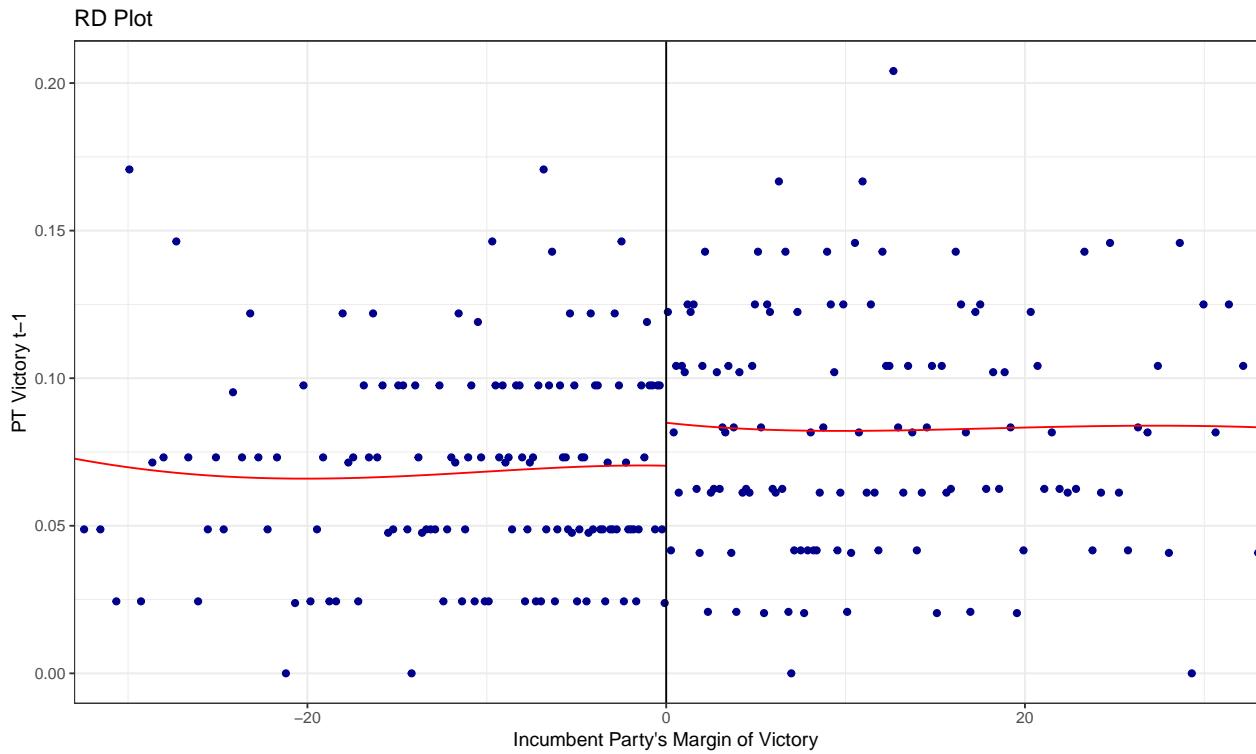
```



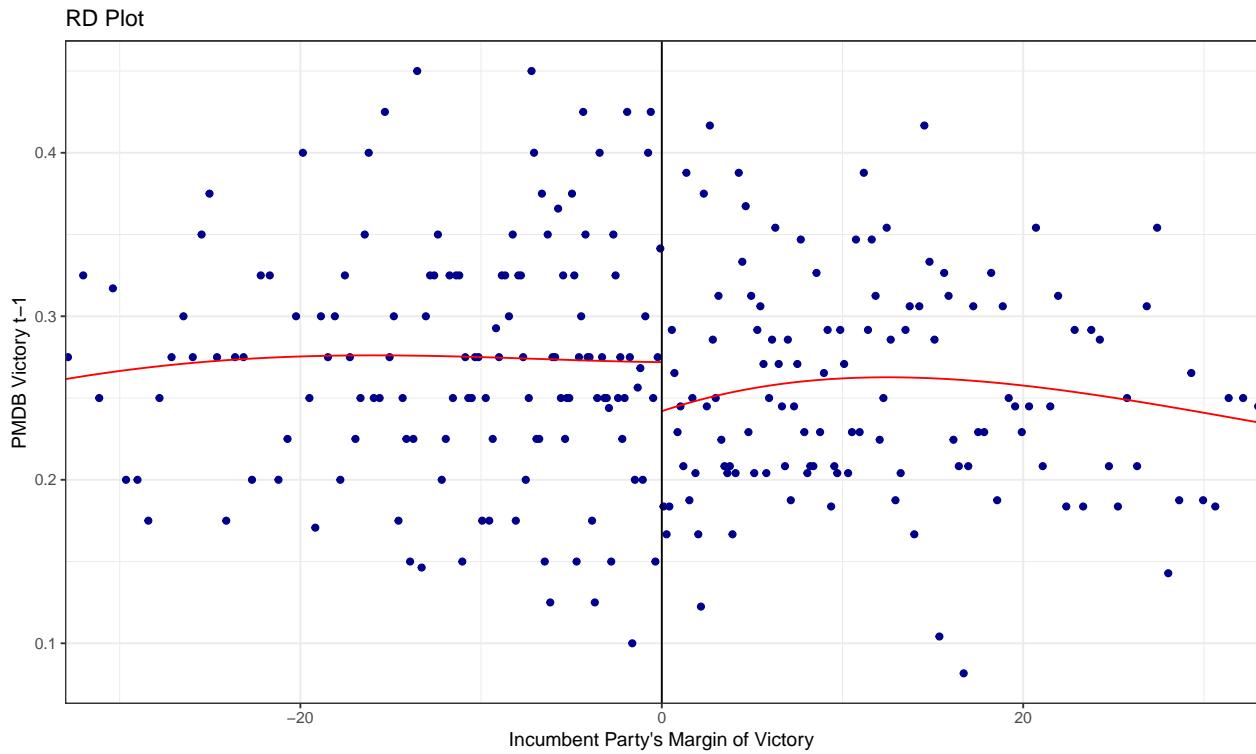
```
##
## === Testing covariate: PSDB Victory t-1 ===
## Sharp RD estimates using local polynomial regression.
##
## Number of Obs.          13308
## BW type                 mserd
## Kernel                  Triangular
## VCE method               NN
##
## Number of Obs.          6088      7220
## Eff. Number of Obs.    3800      3914
## Order est. (p)          1         1
## Order bias (q)          2         2
## BW est. (h)              15.152   15.152
## BW bias (b)              30.475   30.475
## rho (h/b)                0.497   0.497
## Unique Obs.             6033     6849
##
## =====
##           Point   Robust Inference
##           Estimate      z      P>|z|      [ 95% C.I. ]
## -----
## RD Effect    0.023    1.439    0.150  [-0.010 , 0.068]
## =====
## NULL
```



```
##
## === Testing covariate: PT Victory t-1 ===
## Sharp RD estimates using local polynomial regression.
##
## Number of Obs.          13308
## BW type                 mserd
## Kernel                  Triangular
## VCE method               NN
##
## Number of Obs.          6088      7220
## Eff. Number of Obs.     4407      4645
## Order est. (p)          1          1
## Order bias (q)          2          2
## BW est. (h)              19.699    19.699
## BW bias (b)              34.080    34.080
## rho (h/b)                0.578    0.578
## Unique Obs.             6033      6849
##
## =====
##           Point   Robust Inference
##           Estimate      z      P>|z|      [ 95% C.I. ]
## -----
## RD Effect      0.013    1.000    0.317    [-0.013 , 0.040]
## =====
## NULL
```



```
##
## === Testing covariate: PMDB Victory t-1 ===
## Sharp RD estimates using local polynomial regression.
##
## Number of Obs.          13308
## BW type                 mserd
## Kernel                  Triangular
## VCE method               NN
##
## Number of Obs.          6088      7220
## Eff. Number of Obs.    3837      3962
## Order est. (p)          1          1
## Order bias (q)          2          2
## BW est. (h)              15.415    15.415
## BW bias (b)              28.415   28.415
## rho (h/b)                0.542    0.542
## Unique Obs.             6033     6849
##
## =====
##           Point Robust Inference
##           Estimate       z     P>|z|      [ 95% C.I. ]
## -----
## RD Effect    -0.035   -1.707    0.088  [-0.086 , 0.006]
## =====
## NULL
```



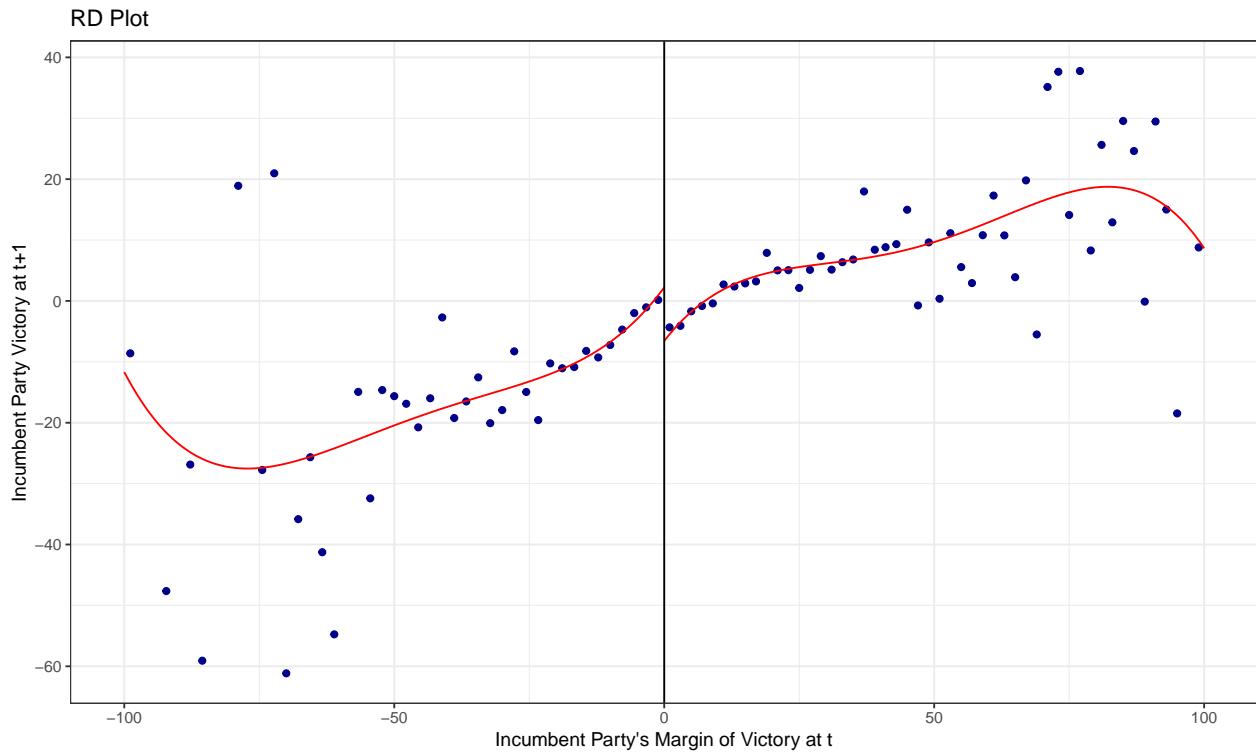
#### Interpretation:

Covariate balance tests check whether pre-treatment characteristics are continuous at the threshold. If covariates jump discontinuously at the cutoff, this suggests the treatment is not “as-if” randomly assigned, which would undermine the validity of the RD design.

### 4.3 Part C - Outcome Analysis

#### 4.3.1 RD Plot

```
# Create RD plot of outcome variable
rdplot(Y, X,
       y.label = "Incumbent Party Victory at t+1",
       x.label = "Incumbent Party's Margin of Victory at t")
```



#### 4.3.2 Continuity-Based RDD Analysis

```
# Main RDD estimate without covariates
rdr <- rdrobust(Y, X)
summary(rdr)

## Sharp RD estimates using local polynomial regression.

##
## Number of Obs.          5463
## BW type                mserd
## Kernel                 Triangular
## VCE method              NN
##
## Number of Obs.          2220      3243
## Eff. Number of Obs.    1533      1740
## Order est. (p)          1          1
## Order bias (q)          2          2
## BW est. (h)             15.291    15.291
## BW bias (b)             27.509    27.509
## rho (h/b)               0.556     0.556
## Unique Obs.             2213      3119
##
## =====
##           Point   Robust Inference
##           Estimate      z      P>|z|      [ 95% C.I. ]
## -----
## RD Effect     -6.281   -3.545     0.000  [-10.223 , -2.944]
## =====
```

```

cat("\n==== RDD ESTIMATE (without covariates) ====\n")

##
## === RDD ESTIMATE (without covariates) ===
cat("Point estimate:", rdr$coef[1], "\n")

## Point estimate: -6.281309
cat("Robust p-value:", rdr$pv[3], "\n")

## Robust p-value: 0.000392509
cat("95% CI: [", rdr$ci[3,1], ", ", rdr$ci[3,2], "] \n")

## 95% CI: [ -10.22321 , -2.943645 ]
cat("\nBandwidth (left):", rdr$bws[1], "\n")

##
## Bandwidth (left): 15.29111
cat("Bandwidth (right):", rdr$bws[2], "\n")

## Bandwidth (right): 27.50885
cat("Effective N (left):", rdr$N_h[1], "\n")

## Effective N (left): 1533
cat("Effective N (right):", rdr$N_h[2], "\n")

## Effective N (right): 1740

```

#### 4.3.3 RDD Analysis with Covariates

```

# RDD estimate with covariates
rdrcovs <- rdrobust(Y, X, covs = covs)
summary(rdrcovs)

## Covariate-adjusted Sharp RD estimates using local polynomial regression.
##
## Number of Obs.          5460
## BW type                mserd
## Kernel                 Triangular
## VCE method              NN
##
## Number of Obs.          2218      3242
## Eff. Number of Obs.    1481      1672
## Order est. (p)          1         1
## Order bias (q)          2         2
## BW est. (h)             14.451   14.451
## BW bias (b)             25.248   25.248
## rho (h/b)               0.572    0.572
## Unique Obs.             2211     3118
##
## =====
##           Point  Robust Inference
##           Estimate       z     P>|z|      [ 95% C.I. ]

```

```

## -----
##      RD Effect     -6.106    -3.401     0.001    [-9.881 , -2.655]
## -----
cat("\n==== RDD ESTIMATE (with covariates) ===\n")

##
## === RDD ESTIMATE (with covariates) ===
cat("Point estimate:", rdrcovs$coef[1], "\n")

## Point estimate: -6.10612
cat("Robust p-value:", rdrcovs$pv[3], "\n")

## Robust p-value: 0.0006725427
cat("95% CI: [", rdrcovs$ci[3,1], ", ", rdrcovs$ci[3,2], "]\n")

## 95% CI: [ -9.880999 , -2.655401 ]
cat("\nBandwidth (left):", rdrcovs$bws[1], "\n")

##
## Bandwidth (left): 14.4507
cat("Bandwidth (right):", rdrcovs$bws[2], "\n")

## Bandwidth (right): 25.24774
cat("Effective N (left):", rdrcovs$N_h[1], "\n")

## Effective N (left): 1481
cat("Effective N (right):", rdrcovs$N_h[2], "\n")

## Effective N (right): 1672

```

#### Interpretation:

The RDD estimates show the causal effect of barely winning an election (vs. barely losing) on the probability of the incumbent party winning the next election. This tests the “incumbency curse” hypothesis - that winning may actually hurt a party’s chances in the next election due to weak parties and term limits in Brazilian municipalities.

Compare the estimates with and without covariates. If they are similar, this provides additional evidence that the RD design is valid (covariates should not matter much if treatment is as-if random near the threshold).

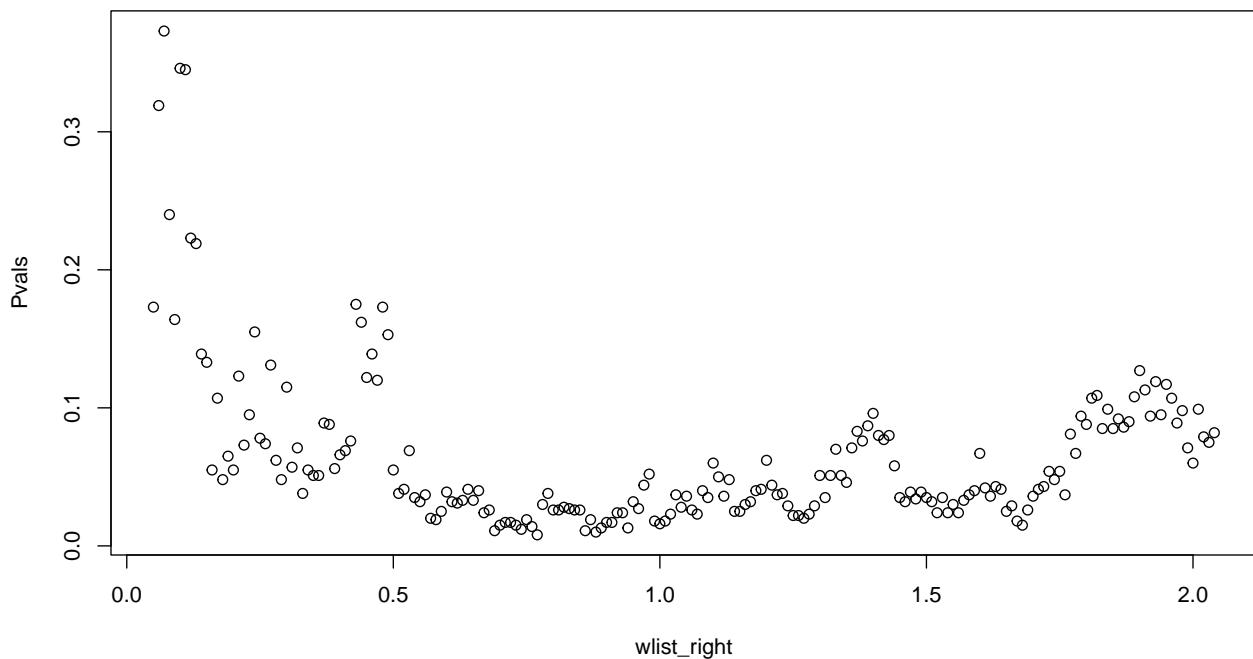
## 4.4 Part D - Local Randomization Approach

```

# Window selection for local randomization
rdwin <- rdwinselect(X, covs, wmin = 0.05, wstep = 0.01, nwindows = 200,
                      seed = 765, plot = TRUE, quietly = TRUE)

## Mass points detected in running variable
## You may use wmasspoints option for constructing windows at each mass point

```



```

# Use selected window (or manually choose)
w <- 0.15

# Randomization inference
rdrand <- rdrandinf(Y, X, wl = -w, wr = w, reps = 1000, seed = 765)

##
## Selected window = [-0.15;0.15]
##
## Running randomization-based test...
## Randomization-based test complete.
##
##
## Number of obs      =      5463
## Order of poly      =          0
## Kernel type        =    uniform
## Reps               =      1000
## Window             = set by user
## H0:                 tau =      0.000
## Randomization      = fixed margins
##
## Cutoff c = 0.000  Left of c  Right of c
##       Number of obs   2220      3243
##   Eff. number of obs   19       20
##   Mean of outcome     0.631     -9.361
##   S.d. of outcome     17.733    16.610
##   Window             -0.150      0.150
##
## =====
##                                     Finite sample           Large sample
##                                     -----
## Statistic          T      P>|T|      P>|T|      Power vs d =  8.867
## =====

```

```

##      Diff. in means     -9.992      0.076      0.070      0.363
## -----
summary(rdrand)

##          Length Class  Mode
## sumstats     10   -none- numeric
## obs.stat      1   -none- numeric
## p.value       1   -none- numeric
## asy.pvalue    1   -none- numeric
## window        2   -none- numeric

cat("\n==== LOCAL RANDOMIZATION INFERENCE ===\n")

##
## === LOCAL RANDOMIZATION INFERENCE ===
cat("Window: [", -w, ", ", w, "] \n")

## Window: [ -0.15 , 0.15 ]
cat("Treatment effect:", rdrand$obs.stat, "\n")

## Treatment effect: -9.992264
cat("P-value:", rdrand$p.value, "\n")

## P-value: 0.076

```

#### Interpretation:

The local randomization approach assumes that units very close to the threshold (within a narrow window) are essentially randomly assigned to treatment. This provides an alternative inference method that doesn't rely on asymptotic approximations and may be more appropriate with discrete running variables.

## 4.5 Part E - Assessment

#### Key Findings:

1. **Density Test:** [Interpret whether there is evidence of manipulation]
2. **Covariate Balance:** [Summarize whether covariates are balanced]
3. **RDD Estimates:** [State the main findings about the incumbency effect]
4. **Robustness:** [Assess whether estimates are stable across specifications]

#### Overall Validity:

[Your assessment of whether the RDD design is credible in this context and whether the findings support the "incumbency curse" hypothesis]

## 5 References

Acemoglu, D., Johnson, S., & Robinson, J. A. (2001). The Colonial Origins of Comparative Development: An Empirical Investigation. *American Economic Review*, 91(5), 1369–1401.

Albouy, D. (2012). The Colonial Origins of Comparative Development: An Investigation of the Settler Mortality Data. *American Economic Review*, 102(6), 3059–3076.

Klašnja, M., & Titiunik, R. (2017). The Incumbency Curse: Weak Parties, Term Limits, and Unfulfilled Accountability. *American Political Science Review*, 111(1), 129-148.

## 6 Session Information

```
sessionInfo()

## R version 4.5.1 (2025-06-13)
## Platform: aarch64-apple-darwin20
## Running under: macOS Tahoe 26.0.1
##
## Matrix products: default
## BLAS:    /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/lib/libRblas.0.dylib
## LAPACK:  /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/lib/libRlapack.dylib;  LAPACK v
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## time zone: Europe/Berlin
## tzcode source: internal
##
## attached base packages:
## [1] stats      graphics   grDevices utils      datasets   methods    base
##
## other attached packages:
## [1] rdlocrand_1.1    rddensity_2.6     rdrobust_3.0.0   kableExtra_1.4.0
## [5] knitr_1.50       boot_1.3-31      stargazer_5.2.3  ggplot2_4.0.0
## [9] dplyr_1.1.4      haven_2.5.5     AER_1.2-15      survival_3.8-3
## [13] sandwich_3.1-1   lmtest_0.9-40   zoo_1.8-14     car_3.1-3
## [17] carData_3.0-5
##
## loaded via a namespace (and not attached):
## [1] generics_0.1.4      xml2_1.4.0        lpdensity_2.5    stringi_1.8.7
## [5] lattice_0.22-7     hms_1.1.3         digest_0.6.37    magrittr_2.0.4
## [9] evaluate_1.0.5     grid_4.5.1        RColorBrewer_1.1-3 fastmap_1.2.0
## [13] Matrix_1.7-3      Formula_1.2-5    tinytex_0.57     viridisLite_0.4.2
## [17] scales_1.4.0       textshaping_1.0.3 abind_1.4-8      cli_3.6.5
## [21] rlang_1.1.6        splines_4.5.1    withr_3.0.2      yaml_2.3.10
## [25] tools_4.5.1       tzdb_0.5.0      forcats_1.0.0    vctrs_0.6.5
## [29] R6_2.6.1          lifecycle_1.0.4  stringr_1.5.2    MASS_7.3-65
## [33] pkgconfig_2.0.3    pillar_1.11.1    gtable_0.3.6     glue_1.8.0
## [37] systemfonts_1.2.3  xfun_0.53       tibble_3.3.0     tidyselect_1.2.1
## [41] rstudioapi_0.17.1 farver_2.1.2     htmltools_0.5.8.1 labeling_0.4.3
## [45] svglite_2.2.1     rmarkdown_2.29   readr_2.1.5      compiler_4.5.1
## [49] S7_0.2.0
```