Regression Discontinuity

Han Zhang

Outline

Recommended Readings

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- `https://rdpackages.github.io/`

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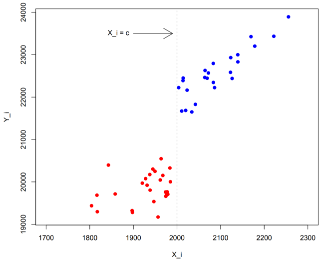
  - Y: future earnings
- Example 2: voting share $>=$ 50% -> win the election

Sharp Regression Discontinuity

- Three core elements

$$D_i = \begin{cases} 1 & \text{if } X_i \geq c \\ 0 & \text{if } X_i < c \end{cases} \tag{1}$$



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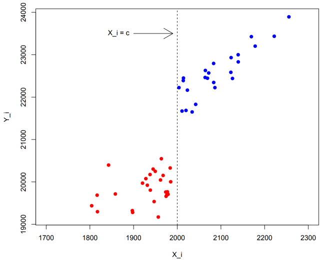

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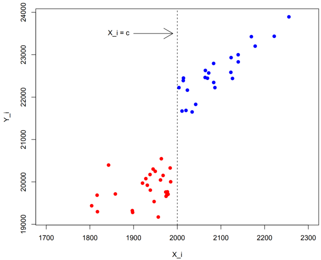

Sharp Regression Discontinuity

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- Running variable, or scores X
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- Treatment assignment D, which is fully determined by X based on cutoff c

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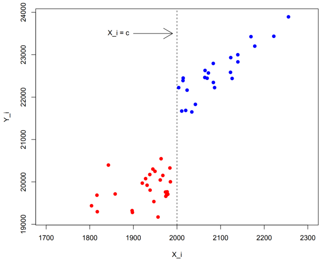
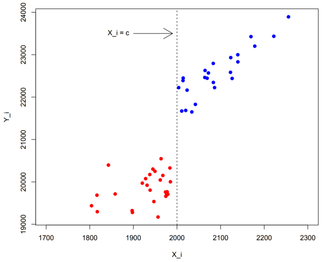


RD Intuition



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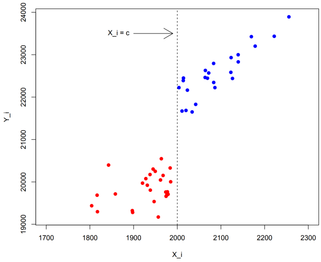

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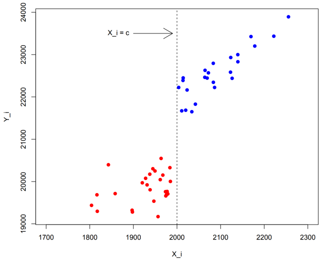

- Positivity assumption is broken: treated and control units do not have overlap on X
- But we can compare Y between points on and just below the cutoff
  - $X = c$ vs. $X = c - \epsilon$,

Sharp RD treatment effect

- If ϵ becomes infinitely small, we obtain the causal effect for $X = c$

$$\tau_{\mathrm{SRD}} \equiv \mathbb{E}\left[Y_i^1 - Y_i^0 | X_i = c\right] = \lim_{x \downarrow c} \mathbb{E}\left[Y_i | X_i = x\right] - \lim_{x \uparrow c} \mathbb{E}\left[Y_i | X_i = x\right] \tag{2}$$

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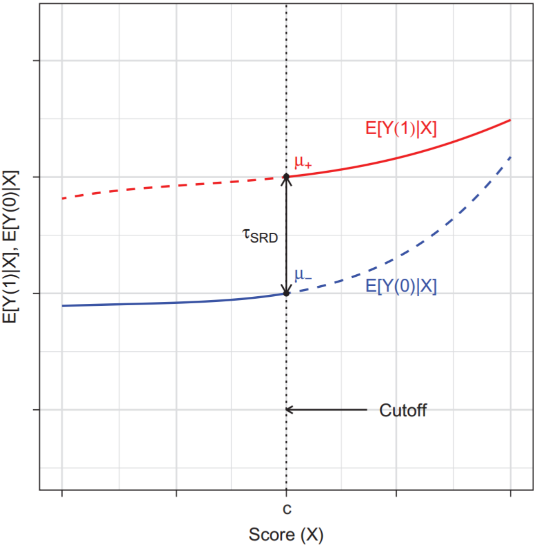
- In contrast to ATT or ATE, Sharp RD identifies a local effect
- The key assumption is that $\mathbb{E}\left[Y_i^1 | X_i = c\right]$ and $\mathbb{E}\left[Y_i^0 | X_i = c\right]$ are continuous

Sharp RD



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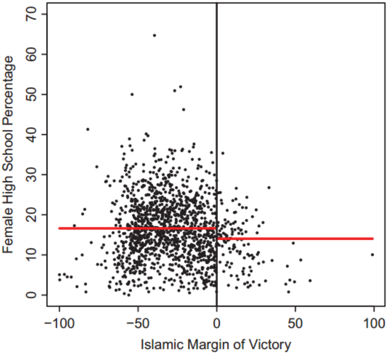
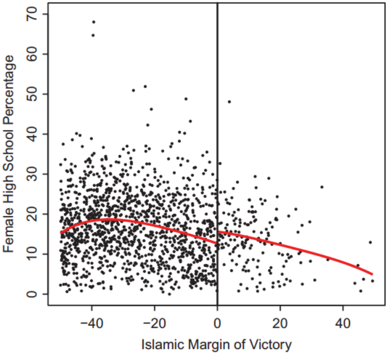
- Question: whether Islamic rules make female less likely to be educated?
- X: vote share margin; vote percentage of an Islamic mayor candidates - vote percentage of a secular candidate, in 1994 Turkish local elections
- c: 0 if Islamic candidate won
- Y: share of local women aged 15 to 20 in 2000 who had competed high school by 2000

RD plot: global vs local

- Globally: negative impact



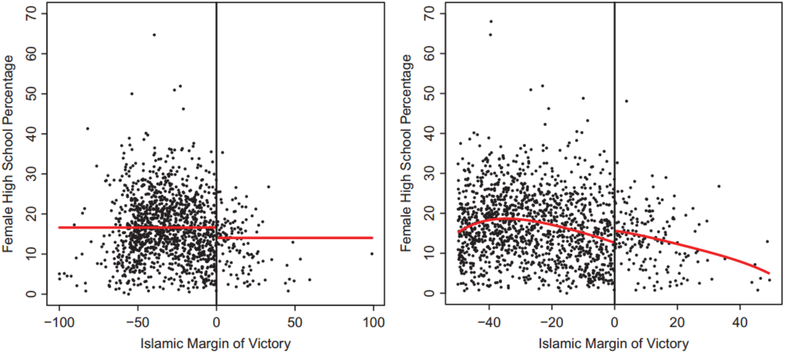
(a) Raw Comparison of Means



(b) Local Comparison of Means

RD plot: global vs local

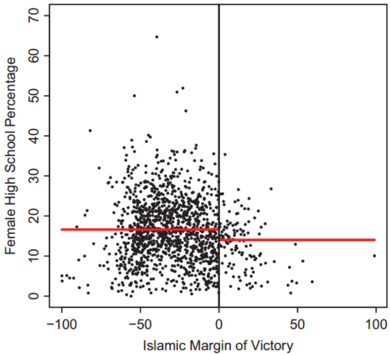
- Globally: negative impact
- Locally: positive impact



(a) Raw Comparison of Means (b) Local Comparison of Means

RD plot: global vs local

- Globally: negative impact
- Locally: positive impact
- Since RD is about local effect, data far away from the cutoff are not useful



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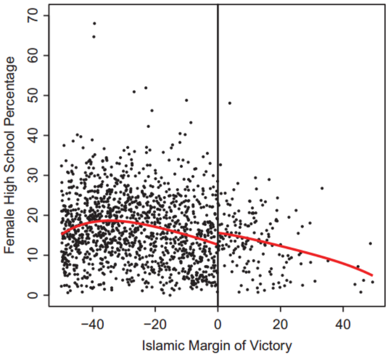
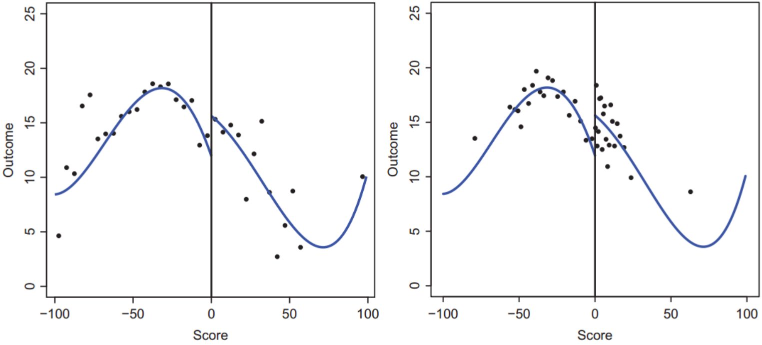


(b) Local Comparison of Means

RD plot: aggregated individual data



(a) 40 Evenly-Spaced Bins (b) 40 Quantile-Spaced Bins

Figure 7 RD Plots (Meyersson Data)

Estimating Sharp RD Treatment Effect

- Theory: calculate the vertical distance between those on the boundary and those just below the boundary

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- h is called bandwidth
- And the current default choice is local polynomial regression:

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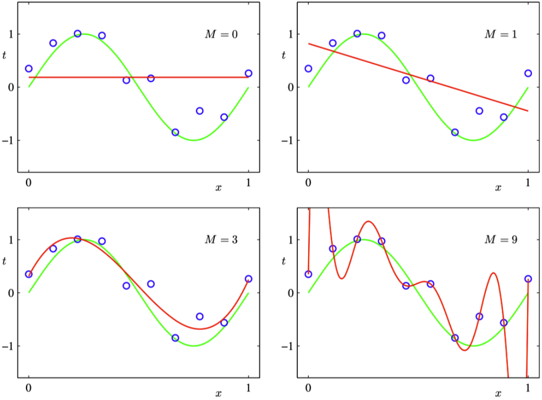
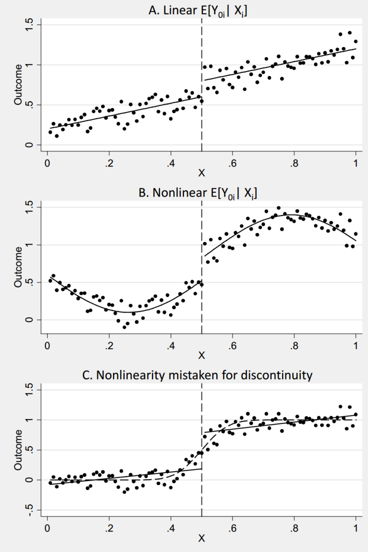
Polynomial example

- here M is p: order of polynomial

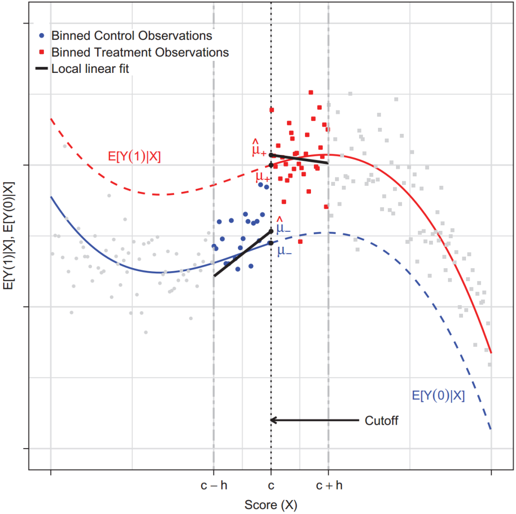


Extrapolation function matters



Using Local Polynomial Regression to predict

- here $p = 1$: linear prediction



Sharp RD procedures

1. Choose a polynomial order p and a kernel function $K()$.
   - Kernel essentially add weights to points according to their distances to c

2. Choose a bandwidth h
3. For $X_i \in [c-h, c)$, Fit a weighted linear regression of Y on $X_i - c, (X_i - c)^2, , (X_i - c)^p$, use weights based on $K(\frac{X_i - c}{h})$. Estimate of $E(Y^0|X = c) = \hat{\mu}_-$

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

4. The same thing for $X_i \in [c, c+h]$; obtain estimate of $E(Y^1|X = c) = \hat{\mu}_+$
5. Sharp RD treatment effect is simply the difference in means:

$$\hat{\tau}_{\mathrm{SRD}} = \hat{\mu}_+ - \hat{\mu}_- \tag{3}$$

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Different kernels

- in practice, kernal choices are less sensitive

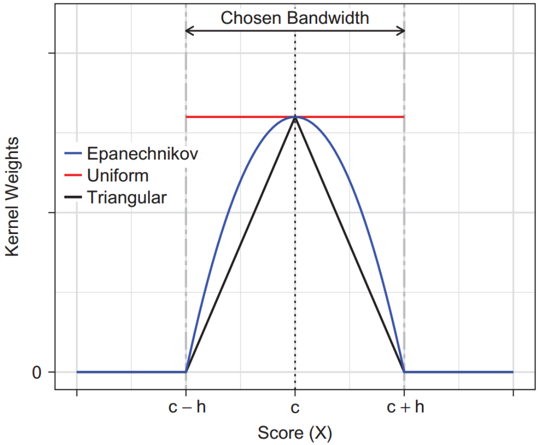
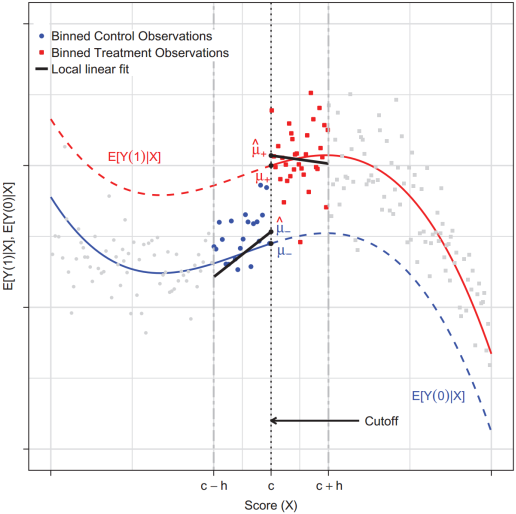


Figure 13 Different Kernel Weights for RD Estimation

Bandwidth matters



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- Bias-variance trade-off again

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Bandwidth selection

- Key idea: bias-variance trade-off

$$\text{MSE}\left(\hat{\tau}_{\text{SRD}}\right) = \text{Bias}^2\left(\hat{\tau}_{\text{SRD}}\right) + \text{Variance}\left(\hat{\tau}_{\text{SRD}}\right) \tag{4}$$

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- Total bias is the sum of bias for $X < c$ and bias for $X > c$

Bandwidth selection

- With Taylor Expansion, we can also write $E(Y^0|X = X_i)$ as:

$$E(Y^0|X = X_i) = \sum_{p=0}^{\infty} \left(\frac{d^p E(Y^0|X)}{dX} (X_i - c)^p \right) \tag{6}$$

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- And we also discard all terms from $p + 2$ (since $X_i - c$ is already small)
- And assume we have infinite amount of data (so called asymptotic analysis), and take the limits

$$\text{Bias}\left(\hat{\tau}_{\text{SRD}}\right) \approx \lim_{x_i \to c} E(Y^0|X = X_i) - E(Y^0|X = c) \approx h^{p+1} B, \tag{7}$$

Bandwidth selection

- With Taylor Expansion, we can also write $E(Y^0|X = X_i)$ as:

$$E(Y^0|X = X_i) = \sum_{p=0}^{\infty} \left(\frac{d^p E(Y^0|X)}{dX} (X_i - c)^p \right) \tag{6}$$

- So substititing the Taylor expansion into Equation (3), terms up to p-th order will be cancelled out
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- Where h is bandwidth and B is asymptotic bias (those cannot be removed by taking limits)

Bandwidth selection

- Using similar idea, variance can be roughly expressed as

$$\text{Variance}\left(\hat{\tau}_{\text{SRD}}\right) = \frac{1}{nh}V, \tag{8}$$

$$\begin{aligned}\text{MSE}\left(\hat{\tau}_{\text{SRD}}\right) &= \text{Bias}^2\left(\hat{\tau}_{\text{SRD}}\right) + \text{Variance}\left(\hat{\tau}_{\text{SRD}}\right) \\ &\approx h^{2(p+1)}B^2 + \frac{1}{nh}V\end{aligned}$$

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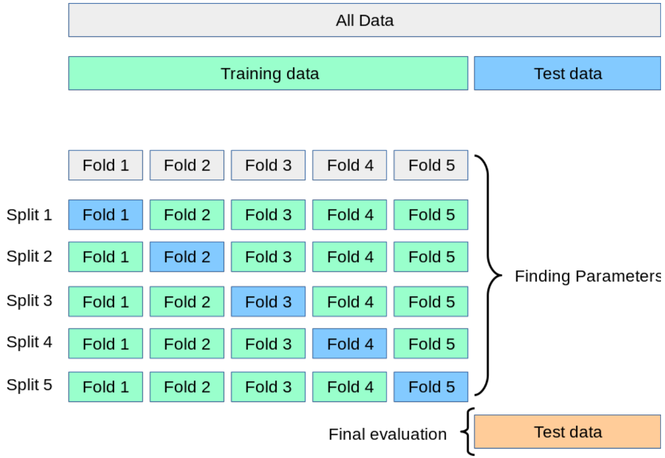
- Predict data in $[c - h, c)$ (test data)
- And the best choice of h should make this prediction MSE the smallest

Cross-validation

- K-fold cross validation (below example shows $K = 5$)



Cross-validation example

- Lee and Lemieux, 2010, *Journal of Economic Literature*

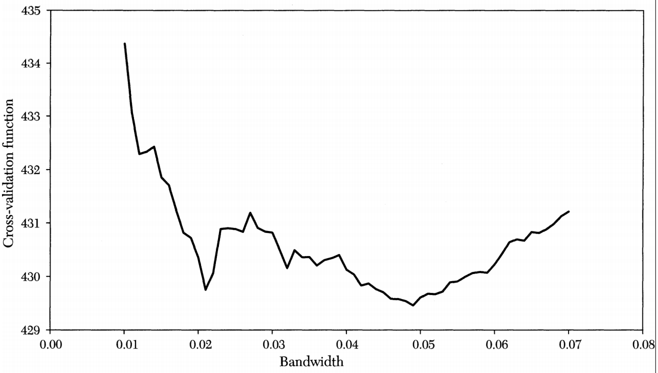


Figure 12. Cross-Validation Function for Choosing the Bandwidth in a RD Graph: Winning the Next Election

RD assumption Clarification

- The key assumption is that $\mathbb{E}\left[Y_i^1 | X_i = c\right]$ and $\mathbb{E}\left[Y_i^0 | X_i = c\right]$ are continuous

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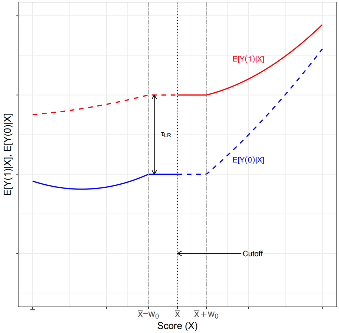
  - with a small boundary $[c-h, c+h]$,
- The local randomness assumption is not necessary! It is more demanding than the continuity assumption
- E.g., in voting example, it's hard to argue that districts in which parties has a narrow win share is due to randomness.

Local randomness assumption in figures

- Local randomness assumption essentially means that the counterfactual outcome is independent of the treatment within $[c-h, c+h]$



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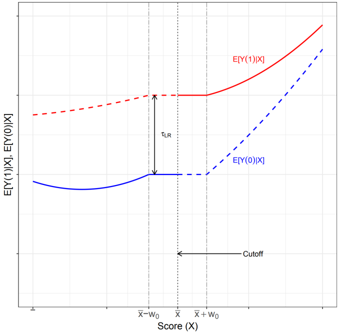

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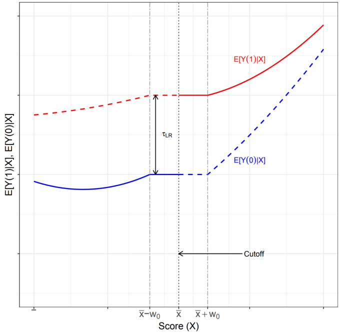
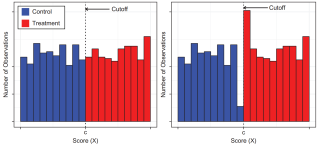
- And independence implies straight lines of $E(Y^1|X=c)$ and $E(Y^1|X=c)$
- This is a stronger assumption than local continuity



Credibility of RD assumptions

- Density test is popularized by McCrary, 2008, *Journal of Econometrics*



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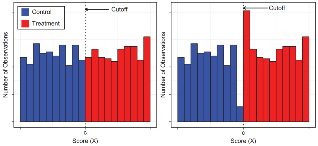

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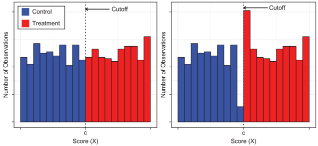

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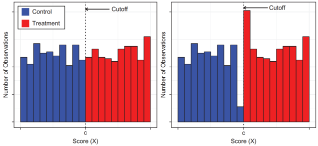

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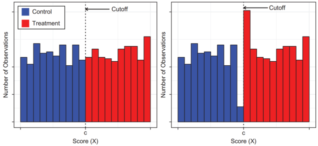
    - note that RD plot is X against Y



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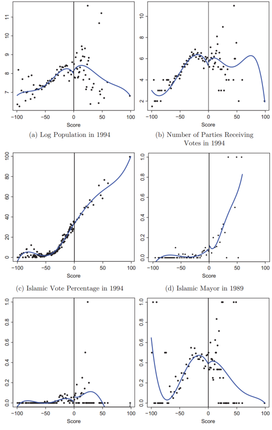
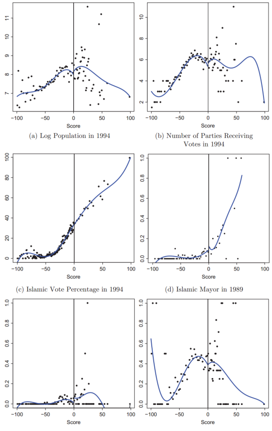


(a) Log Population in 1994 (b) Number of Parties Receiving Votes in 1994 (c) Islamic Vote Percentage in 1994 (d) Islamic Mayor in 1989 (e) Province Center Indicator (e) District Center Indicator

Figure 16 RD Plots for Predetermined Covariates (Meyersson Application)

Credibility of RD assumptions

- We can again use placebo test to falsify RD assumptions
- X determines D, but it should not determine other controls



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RD as a linear regression

- Some older literature write RD as a linear regression (e.g., MHE)

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- Regression estimator provides the equivalent point estimate to the difference-in-mean estimator
- But the standard error estimates from raw regression are usually wrong; they have not considered the variances in the bandwidth selection process
- Modern RD packages ('rdrobust' in R and Stata) generally does not use regression under the hood.

Covariates in RD

- We have discussed how to estimate RD by comparing means at the cutoff

Analogously to the case of randomized experiments, the generally valid justification for including covariates in RD analysis is the potential for efficiency gains, not the promise to fix implausible identification assumptions.

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- Cattaneo et al., 2019, p. 71:

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- Z_i should have been balanced (use placebo test in the previous slides)
- And if Z_i is balanced, it can be proven that τ_{SRD} estimated with and without Z should be similar

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  - The only practical difference is that you need to select bandwidth

Fuzzy RD

- And the causal effect under can again be obtained from Wald estimator:

$$\tau_{FRD} = \frac{\hat{E}(Y^1|X = c) - \hat{E}(Y^0|X = c)}{\hat{E}(D^1|X = c) - \hat{E}(D^0|X = c)} \tag{13}$$

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- Numerator: effect of treatment assignment X on outcome Y, at the cutoff c (ITT)
- Denominator: effect of treatment assignment X on treatment take-up D, also at the cutoff
- τ_{FRD} again estimates local treatment effect for compliers (those who actually follows the assignment of the running variable)

p-hacking

- Abel Brodeur, Nikolai Cook, and Anthony Heyes, *Methods Matter: P-Hacking and Publication Bias in Causal Analysis in Economics*, American Economic Review **110** (2020), no. 11, 3634–3660

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  - DiD
  - IV
  - RD

p-hacking

- Transform p-values or t-statistics into z-statistics (for larger sample sizes)

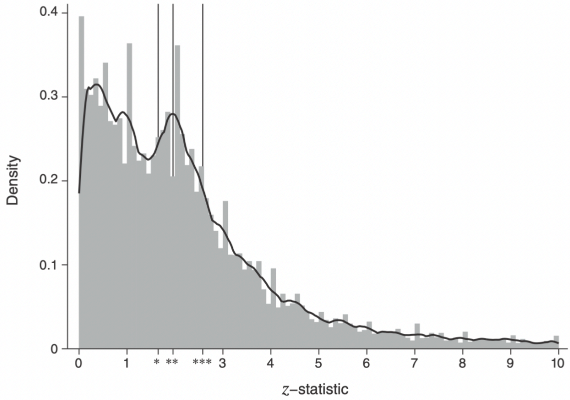
z	p
1.65	< 0.1
1.96	< 0.05
2.58	< 0.01

p-hacking

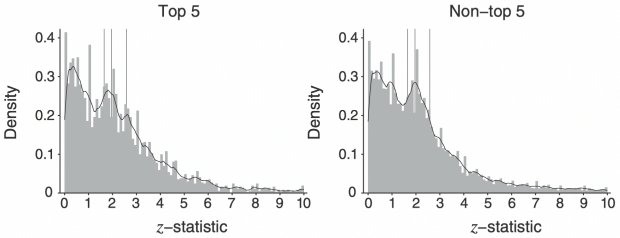
- Transform p-values or t-statistics into z-statistics (for larger sample sizes)
- If there were no p-hacking, we would expect that the probability density distribution around the below cutoffs would be smooth

z	p
1.65	< 0.1
1.96	< 0.05
2.58	< 0.01

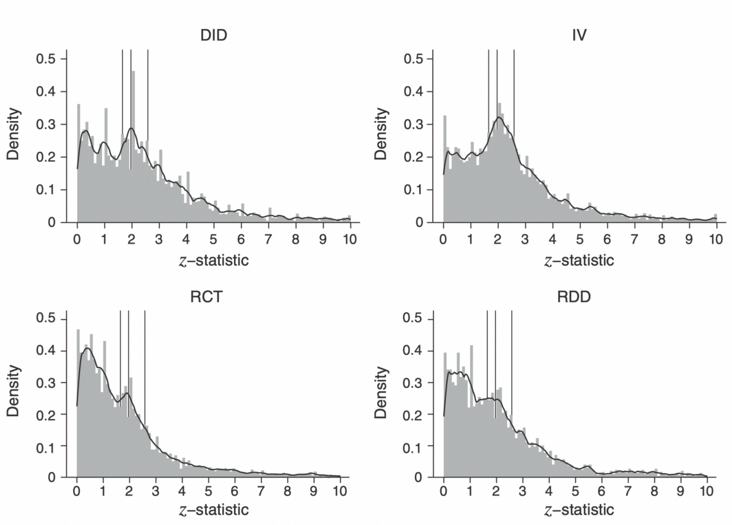
p-hacking



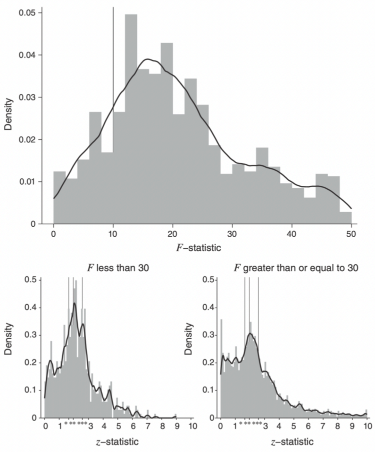
p-hacking by journals



p-hacking by methods

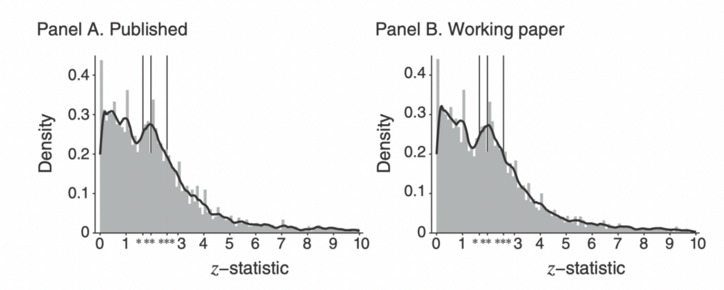


p-hacking and weak instruments



p-hacking and review process

-do people hack because they want their working papers to be published?



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- IV is particularly subject to p-hacking
- DiD also suffers from p-hacking, but at a lesser extent than IV
    - But we know that two-way fixed effect needs special attention because you don't know what you get from coefficients
- Randomized controlled experiments and RD are relatively better