FLS 6441 - Methods III: Explanation and Causation

Week 12 - Review & Frontiers

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Section 1

Review

Classification of Research Designs

- Correlation is not causation
  - And regresssion is just fancy correlation
- So how do we provide evidence of causation?

Classification of Research Designs

		Independence of Treatment Assignment	Researcher Controls Treatment Assignment?
Controlled Experiments	Field Experiments	✓	✓
	Survey and Lab Experiments	✓	✓
Natural Experiments	Natural Experiments	✓	
	Instrumental Variables	✓	
	Discontinuities	✓	
Observational Studies	Difference-in-Differences		
	Controlling for Confounding		
	Matching		
	Comparative Cases and Process Tracing		

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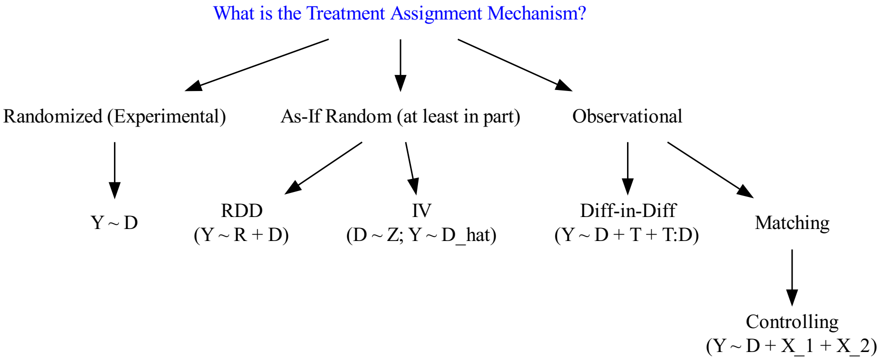
11. SUTVA
12. Overlap in sample characteristics

Choosing a Method



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- For Process Tracing: **Causal Process Observations**

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  - *But*: Aronow and Samii (2016) - simple regression also implicitly weights your sample, so it's not as generalizable as you think

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- Sometimes it's just not possible to show causation. That's OK!
  - We just need to recognize the limits of the evidence we have

Section 2

Frontiers

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- You don't want to publish a paper that someone contradicts next week!

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- Eg. Nunn and Wantchekon (2011) argue that for unmeasured confounders to explain their estimated effect of the slave trade on trust, they would have to be 3 - 11 times larger than measured confounders

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- CRUCIAL: Our **covariate** is not randomly assigned, so the interpretation of heterogeneous effects is **not causal**, just descriptive

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  - Note this does not mean that being a first-term mayor *causes* audits to be more effective

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- More details on this egap page

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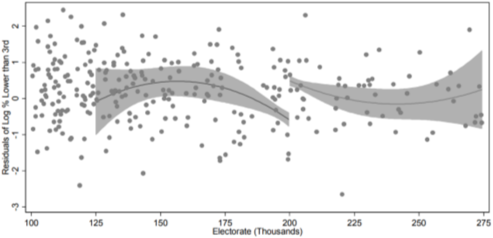
- Common for regression discontinuities (alternative thresholds) and difference-in-differences (alternative times of treatment)

Figure 7. Second-Order Polynomial Estimates for Residuals of the Log of the Combined Vote Share of Third Place or Lower Candidates, weighted by the inverse of distance to the discontinuity point

7A. Estimation in a 75,000 Vicinity of a 200,000 Electorate



7B. Estimation in a 50,000 Vicinity of a 150,000 Electorate (Placebo)

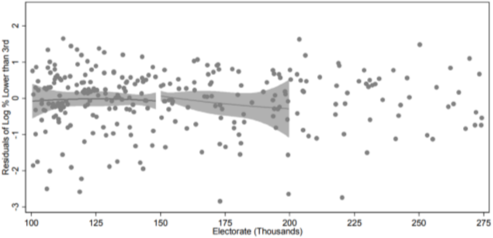


Table 2: **The LPT effect on the PT electoral support in presidential elections (2002-2018)**

	PT (2002)	PT (2006)	PT (2010)	PT (2014)	PT (2018)
LATE	-2.62	6.90***	4.87**	5.97***	5.59**
	(2.12)	(2.68)	(2.32)	(2.46)	(2.62)
BW est (h)	5.28	4.50	5.00	4.31	4.39
BW bias (b)	8.27	7.88	8.24	7.32	7.11
N Left	1711	1711	1711	1711	1711
N Right	3851	3851	3851	3851	3851
Eff N Left	351	303	334	289	295
Eff N Right	491	412	462	389	399
N clusters Left	523	506	521	478	466
N clusters Right	879	826	871	737	697

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. RD local linear estimates using Calonico et al. (2014b) optimal bandwidth triangular kernel selection. Robust standard errors, clustered at the municipal level, in parenthesis. Controls: the expectation of schooling years, and share of households with the mid-school degree. N Left and N Right represent the total number of observation in the left and right sides of the cutoff. Eff N Left and Eff N Right are the number of cases within the bandwidth. BW est (h) is the Bandwidth used to compute the LATE (Local Average Treatment Effect). BW bias (b) is the Bandwidth used to compute the standard errors.

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- The first stage of the IV regression tells us about compliance with treatment
- Relative likelihood that a complier has covariate X equals:

Generalizability

- How ’weird’ are the units we are measuring the Local Average Treatment Effect for?
- We can try to *describe* the characteristics of these compliers
- We don’t know if any single individual is a complier
- But we can describe them **on average**
- The first stage of the IV regression tells us about compliance with treatment
- Relative likelihood that a complier has covariate X equals:

$$\frac{Pr(Complier|X_i = 1)}{Pr(Complier)}$$

TABLE 4.4.3

Complier characteristics ratios for twins and sex composition instruments

		Twins at Second Birth		First Two Children Are Same Sex	
Variable	$P[x_{1i}=1]$ (1)	$P[x_{1i}=1 \mid D_{1i} > D_{0i}]$ (2)	$P[x_{1i}=1 \mid D_{1i} > D_{0i}]/P[x_{1i}=1]$ (3)	$P[x_{1i}=1 \mid D_{1i} > D_{0i}]$ (4)	$P[x_{1i}=1 \mid D_{1i} > D_{0i}]/P[x_{1i}=1]$ (5)
Age 30 or older at first birth	.0029	.004	1.39	.0023	.995
Black or hispanic	.125	.103	.822	.102	.814
High school graduate	.822	.861	1.048	.815	.998
College graduate	.132	.151	1.14	.0904	.704

Notes: The table reports an analysis of complier characteristics for twins and sex composition instruments. The ratios in columns 3 and 5 give the relative likelihood that compliers have the characteristic indicated at left. Data are from the 1980 census 5 percent sample, including married mothers aged 21–35 with at least two children, as in Angrist and Evans (1998). The sample size is 254,654 for all columns.

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  - Replication in different populations
  - Replication of different treatment implementations
- This is how we accumulate knowledge

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Mechanisms

- One practical approach is to run two regressions that recreates our DAG:

$$M_i = \alpha_1 + \beta_1 D_i + \epsilon_1$$

$$Y_i = \alpha_3 + \beta_3 D_i + \beta_4 M_i + \epsilon_3$$

- This implies:

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- It's transparent how far away we have come from the original test of theory