Lecture 06: Evaluation of evaluations

PPHA 34600
Prof. Fiona Burlig

Harris School of Public Policy
University of Chicago

From last time: RCTs are the bee's knees

Randomized controlled trials are super powerful:

- Random assignment allows us to solve our selection problem
- We can implement them with tweaks to handle challenges:
  - *Noncompliance:* Dividing τ^{ITT} by share of compliers $\rightarrow \tau^{LATE}$
  - *Spillovers:* Proper design to avoid or measure
- More opportunities than you might imagine for implementation

Moving out of RCT land

We will spend the rest of the course on other research designs:

- Randomized controlled trials (RCTs)
- Trying to control for observable things
- Panel data
- Instrumental variables
- Regression discontinuity
- Big Data and machine learning

Why leave RCT land?

RCTs are the gold standard for a reason, but:

- They can be expensive
- Some programs require evaluation at scale
- RCTs can't always be implemented
- **There's a lot to learn from non-RCTs**

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- "What experiment would I run to answer this question?"
- Useful to nail down your question of interest
- Valuable to think through problems with your non-RCT

The ideal experiment

Even as we move away from RCTs, it's useful to consider the **ideal experiment**

- "What experiment would I run to answer this question?"
- Can be totally feasible (RED for energy efficiency upgrades)...
- ...or totally infeasible (randomly warm one Earth while keeping the other cold)

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This is often referred to as a "LaLonde exercise" after LaLonde (1986)

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Context is really important for this!

Leveraging an RCT we know and love

Blast from the past: We'll use the SMUD pricing RCT

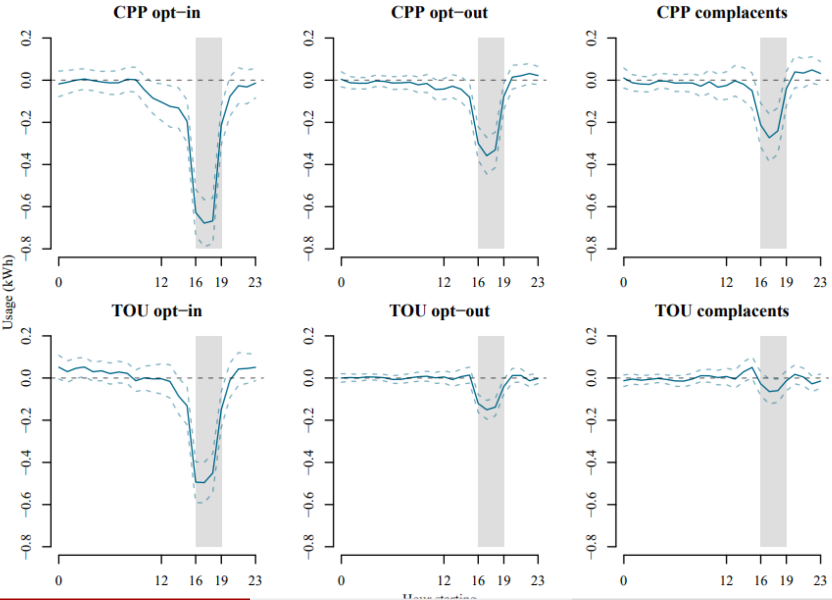
Policy issue:

- The cost of providing electricity is time-varying
- Prices typically aren't
- This causes large welfare losses

Program:

- SMUD (randomly) implemented time-varying pricing
- Experimental run: 2011-2013
- Two flavors: "time-of-use" (TOU) and "critical peak pricing" (CPP)
- Both opt-in and opt-out versions

Fowlie & Wolfram et al results recap



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Potential for selection into treatment on τ_i

- $\rightarrow$ People who choose to get treated may have different price sensitivity
- $\rightarrow$ We know some of this is happening! (two LATEs)

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Why is this problematic for electricity pricing?

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A research design:

- Tries to solve the selection problem without randomization
- Invokes stronger assumptions than the RCT
- Allows us to make progress without randomization
- Best-case scenario: mimics an RCT

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3. **Regression discontinuity**
   - Essentially compares just-treated units to just-untreated units
   - Leverages cutoffs in policy

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   $\rightarrow$ Control for common shocks to everyone
3. Subtract difference (1) from difference (2):

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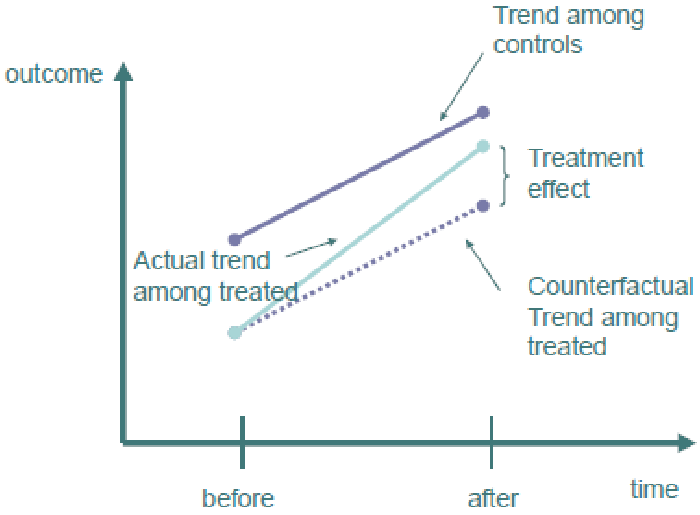
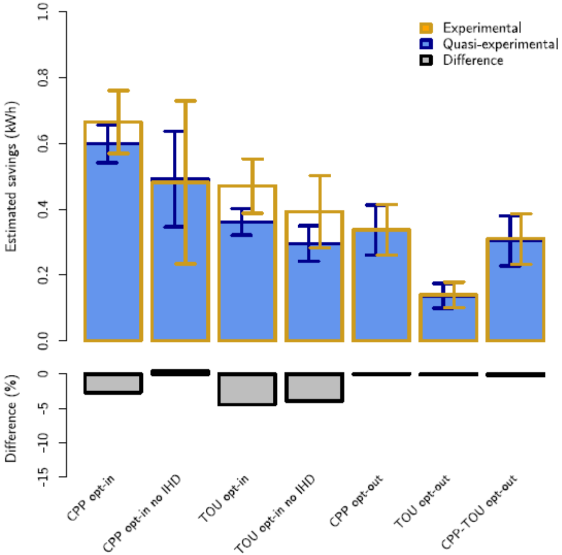
Note: Spurlock et al drop encouraged-but-untreated units

→ Was this necessary?

Difference in difference intuition



Comparing experimental and diff-in-diff results



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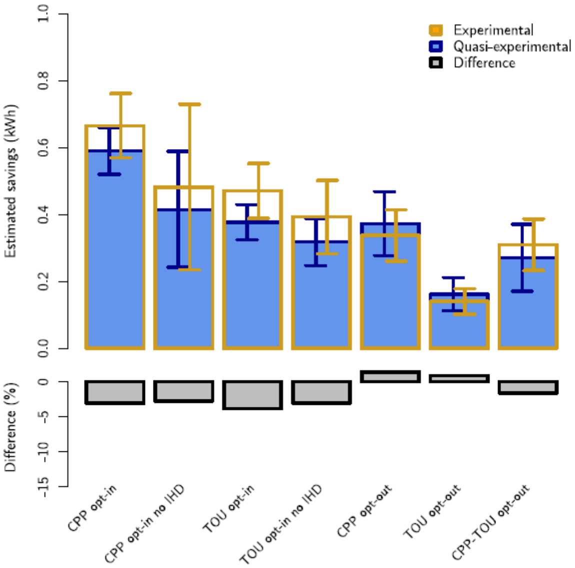
For this to work, we require:

- Our selection control soaks up everything that matters!

Note: Same approach as DD, but now controlling for more

Comparing experimental and propensity score results



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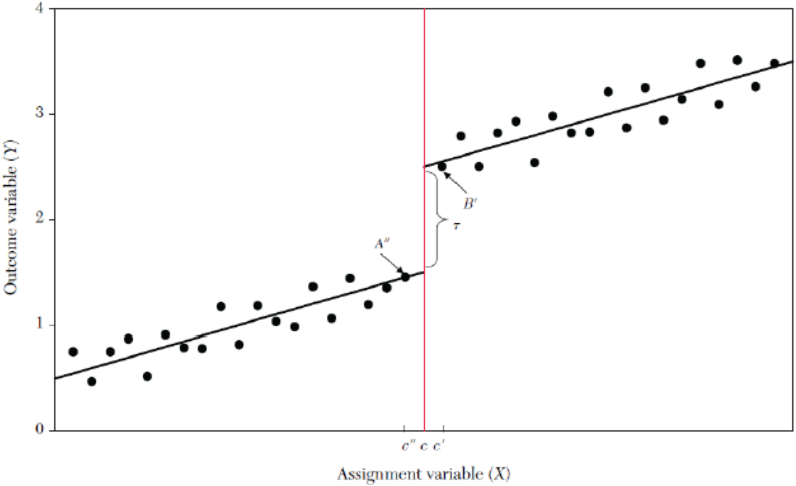
Note: Spurlock et al construct fake cutoffs

- They stitch together control group units with treatment group units
- The stitching point is their artificial cutoff

Regression discontinuity intuition



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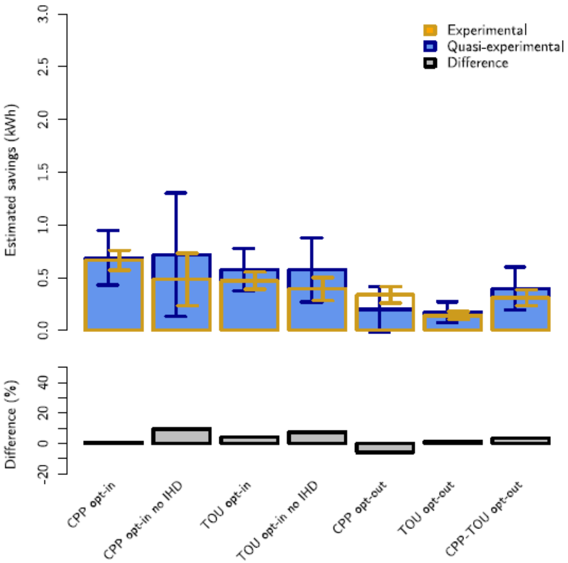

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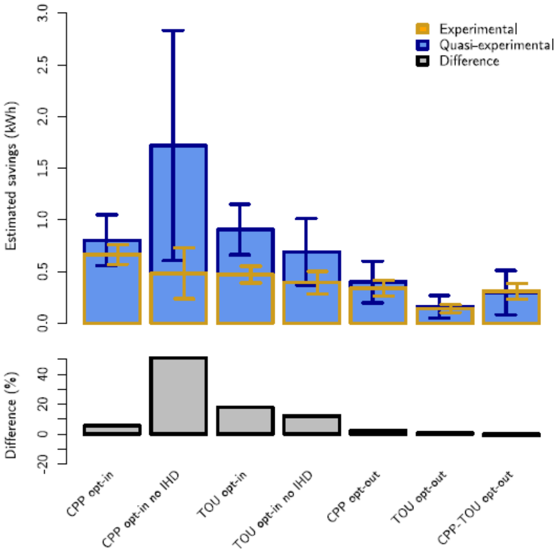

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- Regression discontinuity estimates *overstate* treatment effects
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  - OR estimating a different LATE
- Opt-out treatments are less biased than opt-in treatments
  - Intuition: We do better with a less-selected treatment

Exercise caution with non-experimental results

"Even though I was unable to evaluate all non-experimental methods, this evidence suggests that policymakers should be aware that the available non-experimental evaluations...may contain large and unknown biases resulting from specification errors." – LaLonde (1986)

Recap

TL;DR:

1. RCTs are (still) great!

2. Quasi-experimental methods can get things wrong

3. We don't usually have a good experimental benchmark (☠)