Other policy analysis methods

MPA 612: Public Management Economics

April 4, 2018

Fill out your reading report on Learning Suite!

Plan for today

One final CBA trick

Evidence-based public policy and administration

Causality and evaluation

Current events

One final CBA trick

Perpetuity (aka annuity)
Constant stream of money that lasts forever and ever

$$PV_{\text{Perpetuity}} = \frac{X}{r}$$

What happens when the perpetuity doesn't start for a few years?

$$PV_{\text{starting at } t} = \frac{PV_{t-1}}{r} = \frac{\frac{X}{(1-r)^{t-1}}}{r}$$

Evidence-based public policy and administration

What is the role of social scientists in the policy process?

What is the relationship between social science research and public administration?

Evidence-based medicine

Modern evidence-based medicine

Apply evidence to clinical treatment decisions

Move away from clinical judgment and “craft knowledge”

Is this good?

Evidence-based policy

RAND health insurance study

Oregon experiment

HUD's Moving to Opportunity

Tennessee STAR

There’s a whole industry for policy evidence now

Utah’s Evidence-Based Workgroup

Jameel Poverty Action Lab (J-PAL)

Cochrane Collaboration

Campbell Collaboration

Should we have evidence for every policy or program?

No!

Science vs. art/craft

Parachutes

Reducing the drinking age

Causality and evaluation

How do we measure all this evidence?

Does correlation imply causation?

SOMETIMES

David Robinson
@drob

Following

Correlation implies causation, don't @ me

1:12 PM - 22 Jun 2017 from Manhattan, NY

4 Retweets **56** Likes

2 4 56

Tweet your reply

David Robinson @drob · 22 Jun 2017

Replying to @drob

"Correlation implies casuation," the dean whispered as he handed me my PhD.

"But then why-"

"Because if they knew, they wouldn't need us."

5 46 169

Even if it doesn't, it's not a helpful argument

Godwin's Law for statistics

> Not everyone found the news believable. "Facepalm. Correlation doesn't imply causation," wrote one unhappy Internet user. "That's pretty much how I read this too... correlation is NOT causation," agreed a Huffington Post superuser, seemingly distraught. "I was surprised not to find a discussion of correlation vs. causation," cried someone at Hacker News. "Correlation does not mean causation," a reader moaned at Slashdot. "There are so many variables here that it isn't funny."

How do we determine if something is causal?

Figuring out correlation
Math and stats

Figuring out causation
Philosophy. No math.

What does it mean for something (X) to cause something else (Y)?

Necessity, sufficiency, redundancy

Causation = Correlation + time ordering + all other factors ruled out

General, easier principle of causality

Challenges

Selection bias

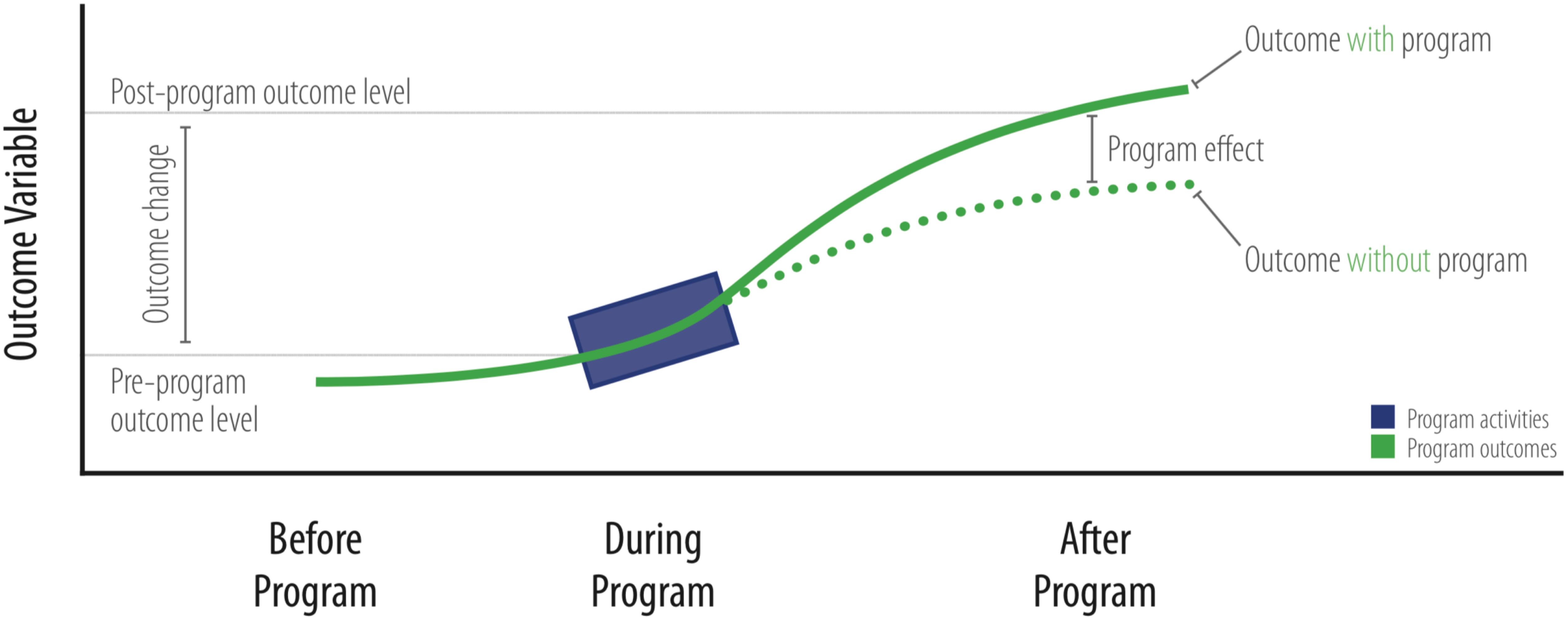
Omitted variable bias

Attrition

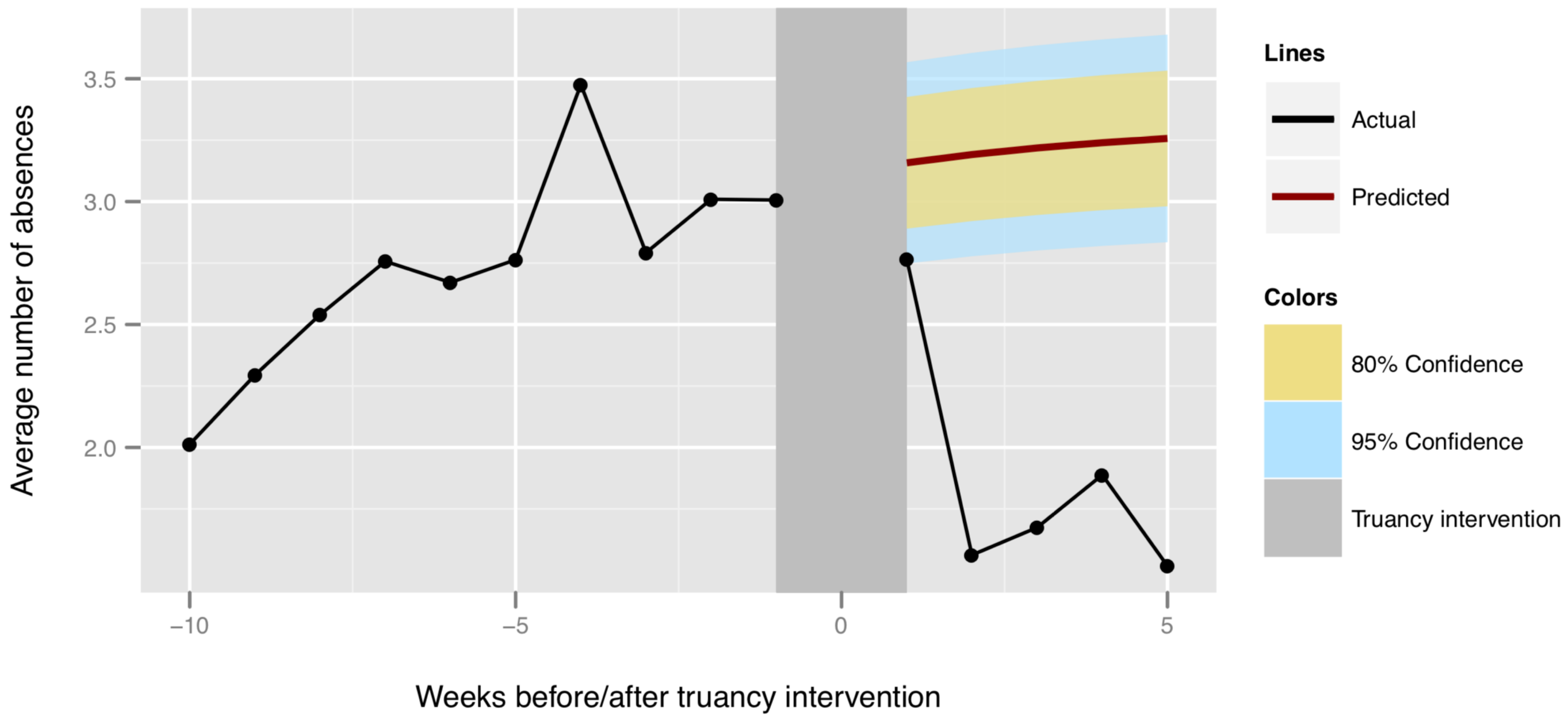
Reverse causality

Treatment effect

$$\text{Average}_{\text{Treatment}} - \text{Average}_{\text{Control}}$$



Outcome Variable
Post-program outcome level
Outcome change
Pre-program
outcome level
Outcome with program
Program effect
Outcome without program
Program activities
Program outcomes
Before
Program
During
Program
After
Program


Lines
Actual
Predicted
Colors
80% Confidence
95% Confidence
Truancy intervention
Average number of absences
3.5
3.0
2.5
2.0
−10
−5
0
5
Weeks before/after truancy intervention

Fundamental problem of causation in social science

We can never see individual counterfactuals

Ideally, subject the same person at the same time to treatment and control

But we don't have time machines

Get around this by inventing counterfactuals

Causality continuum

Differences

Pre-post

Multiple regression

Matching

Diff-in-diff

Natural experiments

Regression discontinuity

RCTs

Correlation

Causation

Simple differences

Compare group with treatment with group without treatment

Logical, but what’s wrong?

Pre-post differences

Compare same group before and after the treatment

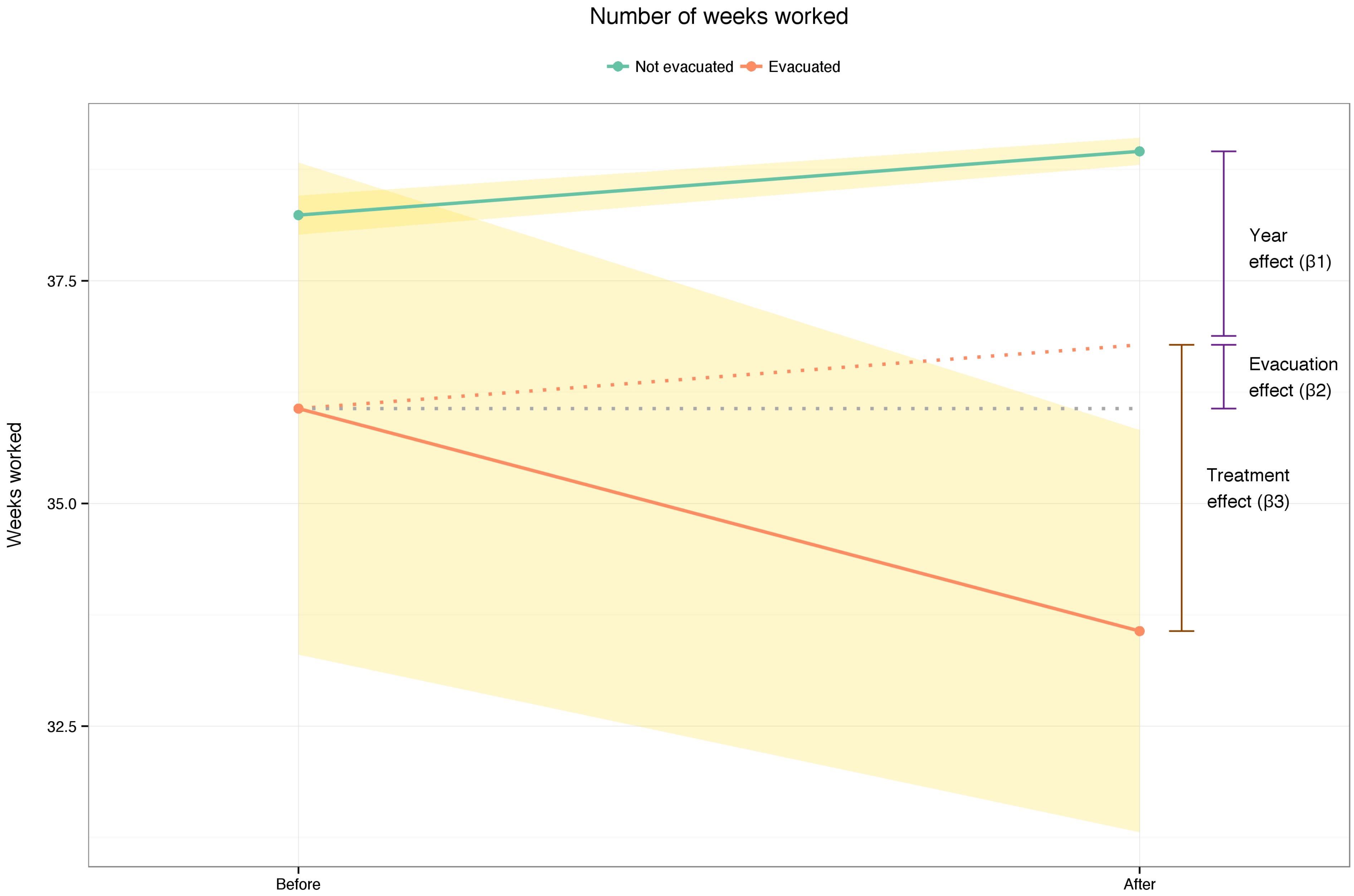
Also logical, but what's wrong?

Differences-in-differences

Compare treatment and control groups before and after the treatment

Table 1. Estimating Difference-in-differences.

	Result before the program	Result after the program	Difference over time
Treated group	24.80	51.22	26.42
Untreated group	36.67	56.27	19.60
Difference-in-differences estimate			6.82



Effect of Katrina on employment

Weeks worked ~ Year + Evacuated + Year × Evacuated

Multiple regression

Control for a bunch of stuff

See effect of individual variables when others are held constant

```
Call:
lm(formula = gktreads ~ gkclasss + gkclasst + st_whiteasian +
    st_girl + freelunch, data = star)

Residuals:
     Min       1Q   Median       3Q      Max
-111.802  -20.083   -3.975   14.392  187.025

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  450.64077    2.50688 179.762  < 2e-16 ***
gkclasss      -0.62043    0.15445  -4.017 5.97e-05 ***
gkclasst       0.05844    0.75544   0.077    0.938
st_whiteasian  4.04922    0.95696   4.231 2.36e-05 ***
st_girl        6.24634    0.79840   7.824 6.06e-15 ***
freelunch    -14.97606    0.89238 -16.782  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 30.3 on 5764 degrees of freedom
  (5831 observations deleted due to missingness)
Multiple R-squared:  0.08895,	Adjusted R-squared:  0.08816
F-statistic: 112.6 on 5 and 5764 DF,  p-value: < 2.2e-16
```

gktreads: reading score in K
gkclass: # of students in class
gkclasst: had a teacher's aid

Table 2: OLS models for four standardized tests

VARIABLES	(1) Reading	(2) Math	(3) Listening	(4) Words
Small class	6.47***	8.84***	3.24**	6.99***
	(1.45)	(2.32)	(1.42)	(1.60)
Regular + aide class	1.00	0.42	-0.58	1.27
	(1.26)	(2.14)	(1.32)	(1.42)
White or Asian	7.85***	16.91***	17.98***	7.08***
	(1.61)	(2.40)	(1.70)	(1.91)
Girl	5.39***	6.46***	2.67***	5.03***
	(0.78)	(1.12)	(0.74)	(0.94)
Free/reduced lunch	-14.69***	-20.08***	-15.23***	-15.97***
	(0.91)	(1.33)	(0.90)	(1.07)
Teacher white or Asian	-0.56	-1.01	-3.68	0.46
	(2.66)	(3.80)	(2.59)	(3.07)
Years of teacher experience	0.30**	0.42**	0.25*	0.30**
	(0.12)	(0.20)	(0.15)	(0.14)
Teacher has MA	-0.75	-2.20	0.50	0.24
	(1.25)	(2.08)	(1.24)	(1.46)
School fixed effects	X	X	X	X
Constant	431.69***	475.52***	531.28***	428.97***
	(3.12)	(4.49)	(2.84)	(3.59)
Observations	5,728	5,809	5,776	5,790
R-squared	0.08	0.07	0.09	0.06
Number of schools	79	79	79	79

Robust standard errors in parentheses.
Standard errors corrected with Huber-White clustering by kindergarten teacher ID
*** p<0.01, ** p<0.05, * p<0.1

	con_proced		con_days	
	(1)	(2)	(3)	(4)
con_proced_lag	0.708***	0.780***		
	(0.023)	(0.032)		
con_days_lag			0.903***	0.971***
			(0.015)	(0.008)
ranked_lag	-1.279***	0.348	-67.357***	-1.605
	(0.258)	(0.506)	(5.427)	(3.386)
gdpcap_ln_lag	-0.383***	-0.167	-5.263	-3.550**
	(0.145)	(0.104)	(3.237)	(1.559)
gdpgrowth_lag	-0.038	-0.016	-2.627***	-1.292***
	(0.024)	(0.025)	(0.676)	(0.463)
polity_lag	-0.112***	-0.083**	1.219**	0.573
	(0.039)	(0.032)	(0.525)	(0.376)
pop_ln_lag	0.023	0.124	2.358	3.673**
	(0.109)	(0.087)	(2.561)	(1.839)
civtot_lag	0.208**		9.935**	
	(0.101)		(4.295)	
inttot_lag	0.292		-2.168	
	(0.393)		(3.915)	
loan_bin_lag	-0.371		3.842	
	(0.487)		(11.148)	
Constant	15.702***	4.800***	124.001***	17.250
	(2.421)	(1.757)	(42.007)	(35.766)
Year fixed effects	No	Yes	No	Yes
Observations	1,634	1,635	1,633	1,634
R^2	0.725	0.836	0.868	0.923
Adjusted R^2	0.723	0.834	0.867	0.922

Note: *p<0.1; **p<0.05; ***p<0.01
OLS models. Robust standard errors clustered by country.

Warning!

This doesn't usually get us all the way to causality

Don’t say that smaller class sizes cause increases in test scores

Also don’t say “Ceteris paribus”

You’re not paribusing all the ceteri

Do say “Smaller class sizes predict an increase in test scores, controlling for X, Y, and Z”

Randomized Controlled Trials (RCTs)

Gold standard of causality kind of

People can't select into treatment, there are no omitted variables, and reverse causation is addressed

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Childhood Skill Development and Adult Political Participation

JOHN B. HOLBEIN [a1]

https://doi.org/10.1017/S0003055417000119 Published online: 19 June 2017

Abstract

Recent child development research shows that the psychosocial or noncognitive skills that children develop—including the ability to self-regulate and integrate in social settings—are important for success in school and beyond. Are these skills learned in childhood also important for adult political behaviors like voting? In this article, I use a unique school-based 20-year field experiment to explore whether children who develop psychosocial skills early on are more likely to vote in adulthood than those who do not. Matching subjects to voter files, I show that this intervention had a noticeable long-run impact on political participation. These results highlight the need to better understand how childhood experiences shape civic behaviors later in life. During this critical period, children can be taught the not explicitly political, but still vital, skills that set them on a path toward political participation in adulthood.

Reducing Intimate Partner Violence through Informal Social Control: A mass media experiment in rural Uganda

Research Method

Blocked and clustered field experiment with 6,449 respondents in 112 villages.

Country

Uganda

Co-Authors

Donald Green, Anna Wilke

Partners

Innovations for Poverty Action (IPA Uganda), Peripheral Vision International (PVI)

Research Question

Can mass media shore up informal channels for reducing intimate partner violence?

Abstract

We assess a mass media campaign designed to reduce intimate partner violence (IPV). A placebo-controlled experiment conducted in 2016 exposed over 10,000 Ugandans in 112 rural villages to a sequence of three short video dramatizations of IPV. A seemingly unrelated opinion survey conducted eight months later indicates that villages in which IPV videos were aired experienced substantially less IPV in the preceding six months than villages that were shown videos on other topics. A closer look at mechanisms reveals that the IPV videos had little effect on attitudes about the legitimacy of IPV. Nor did the videos increase empathy with IPV victims or change perceptions about whether domestic violence must be stopped before it escalates. The most plausible causal channel appears to be a change in norms: women in the treatment group became less likely to believe that they would be criticized for meddling in the affairs of others if they were to report IPV to local leaders, and their personal willingness to intervene increased substantially. These results suggest that education-entertainment has the potential to markedly reduce the incidence of IPV in an enduring and cost-effective manner.

Paper

See here for latest working paper.

Replication Archive

Replication by JPAL underway, data forthcoming.

Charity During Crackdown: Analyzing the Impact of State Repression of NGOs on Philanthropy*

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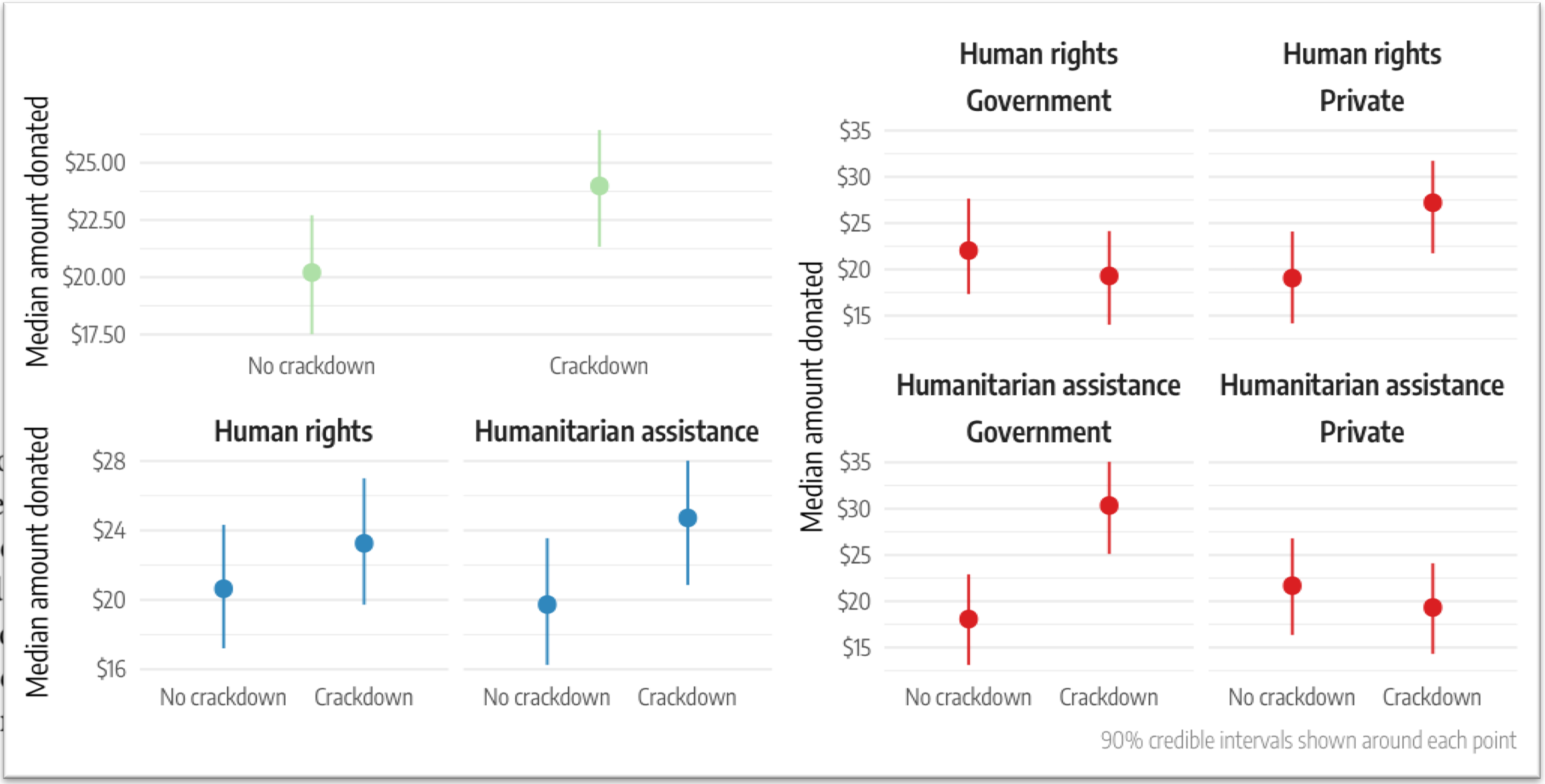


State repression of civil society c
uitous in recent decades. Beside
states have also increasingly use
riers to their entry, funding, and
NGOs to engage in advocacy an
NGOs impact patterns of privat
making? With decreasing fundi

BUT

Compliance

Treatment spillovers

Generalizability

Power

Cost

Ethics

Politics

Hawthorne effects

John Henry effects

Causality continuum

Differences

Pre-post

Multiple regression

Matching

Diff-in-diff

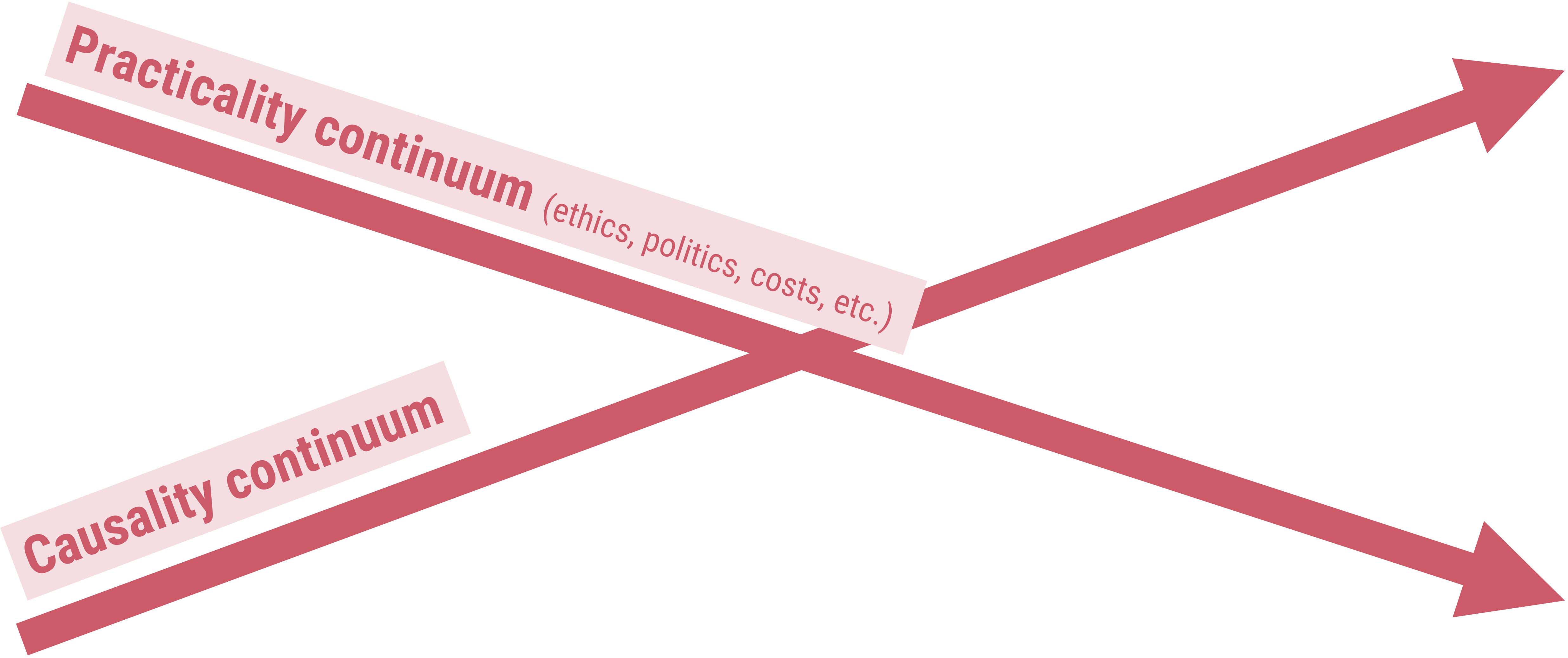
Natural experiments

Regression discontinuity

RCTs

Correlation

Causation


Practicality continuum (ethics, politics, costs, etc.)
Causality continuum

Moral of the story…

Evidence-based policy and administration IS HARD AND COMPLEX