(Week 5) Causality and hypothesis testing (Week 6) Quant. analysis: strengths & pitfalls

Research design in comparative political science

9 & 16 November, 2015

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A story about program evaluation

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National Supported Work Demonstration (1975-1979): ex-offenders, drug addicts, etc. receive 12-18 months of subsidized employment in 10 US cities.

MDRC implementing NSW in 1970s

Does it work? Of 6,600 eligible participants, some randomly assigned to **control group** (no subsidized employment).

	Treatment	Control
Avg earnings after program	$4,670	$3,819

Lalonde (1986): "Evaluating the econometric evaluations of training programs with experimental data"

Idea: Ignore the experimental control group; use standard economic surveys instead.

How close to the experimental benchmark do we get with standard econometric approaches? Not very close:

Robert Lalonde, University of Chicago

"Policymakers should be aware that the available non-experimental evaluations of employment and training programs may contain large and unknown biases resulting from specification errors." (p. 617)

Fundamental problem of causal inference

What we want:

Outcome if individual **did participate** in program	minus	Outcome if individual **did not participate** in program
$y_i(1)$	-	$y_i(0)$

Fundamental problem of causal inference is that we never observe both for any individual.

How, then, do we estimate the *counterfactual outcome*?

Fundamental problem of causal inference (2)

What we do:

- Randomly assign units to treatment and control; take difference in averages (RCT)
- Take observational data and use regression, matching, etc to estimate avg outcomes for control group, adjusting for differences in covariates (what **didn't** work in Lalonde)
- Make arguments from theory, existing empirical evidence about what would have happened to a treated unit if it had not been treated (see Fearon 1991)

Credibility revolution (?)

Major change throughout social sciences (though earlier in economics):

- Randomized experiments (RCTs) increasingly common (field, lab, survey)
- Observational studies are increasingly "design-based" & patterned after RCTs ("quasi-experiments")
- Measuring effects of institutions, information, social movements etc. through mere cross-sectional regression is **rarely enough**
- "What's your identification strategy?"

Angrist and Pischke's book

Identification Taliban?

Does obsession with "identification strategy" limit us unnecessarily?

Cleverness over substance?

What can/should we do once we internalize the "credibility revolution"?

Abandon explanation?

Angrist and Pischke

The research formula under the “old regime”

"Impact evaluation" paradigm

A. Identify an unresolved question about the effects of one or more independent variables in some setting (e.g. electoral system, social cleavages and number of parties in Europe)
B. Collect data from that setting
C. Regress outcome on independent variable(s) plus controls; interpret coefficients as "causal effects"

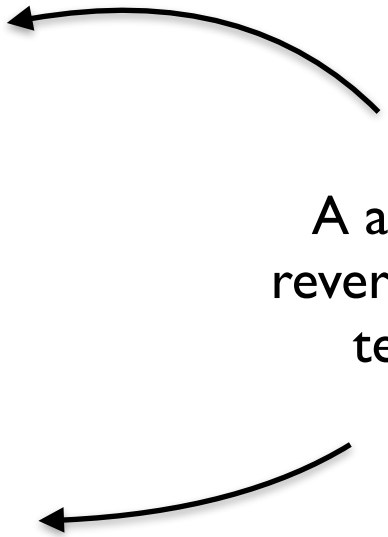
Explanatory paradigm

A. Develop an interest in some outcome (Y, e.g. civil war, turnout, voting for right-wing parties); read the literature about the topic
B. Identify a puzzle (theory vs empirics, empirics vs empirics, etc) and propose a resolution (i.e. theory)
C. Conduct an empirical test of your theory

The research formula for “design-based” research

A. Learn about theoretical debates and empirical questions in a given area

B. Find/create setting where a **hypothesized determinant** differs between otherwise similar units in a favorable way:



A and B can be reversed, but don't tell anyone!

- due to random assignment in your experiment, treatment and control are identical in expectation
- due to draft lottery, some young Americans sent to Vietnam and others not?
- due to arbitrary factors, some candidates elected to House of Commons and others not?
- due to an arbitrary population cutoff, some French villages have PR electoral system and others use plurality?

C. Collect data, estimate treatment effects using simple comparisons, show (in)sensitivity of results to specification

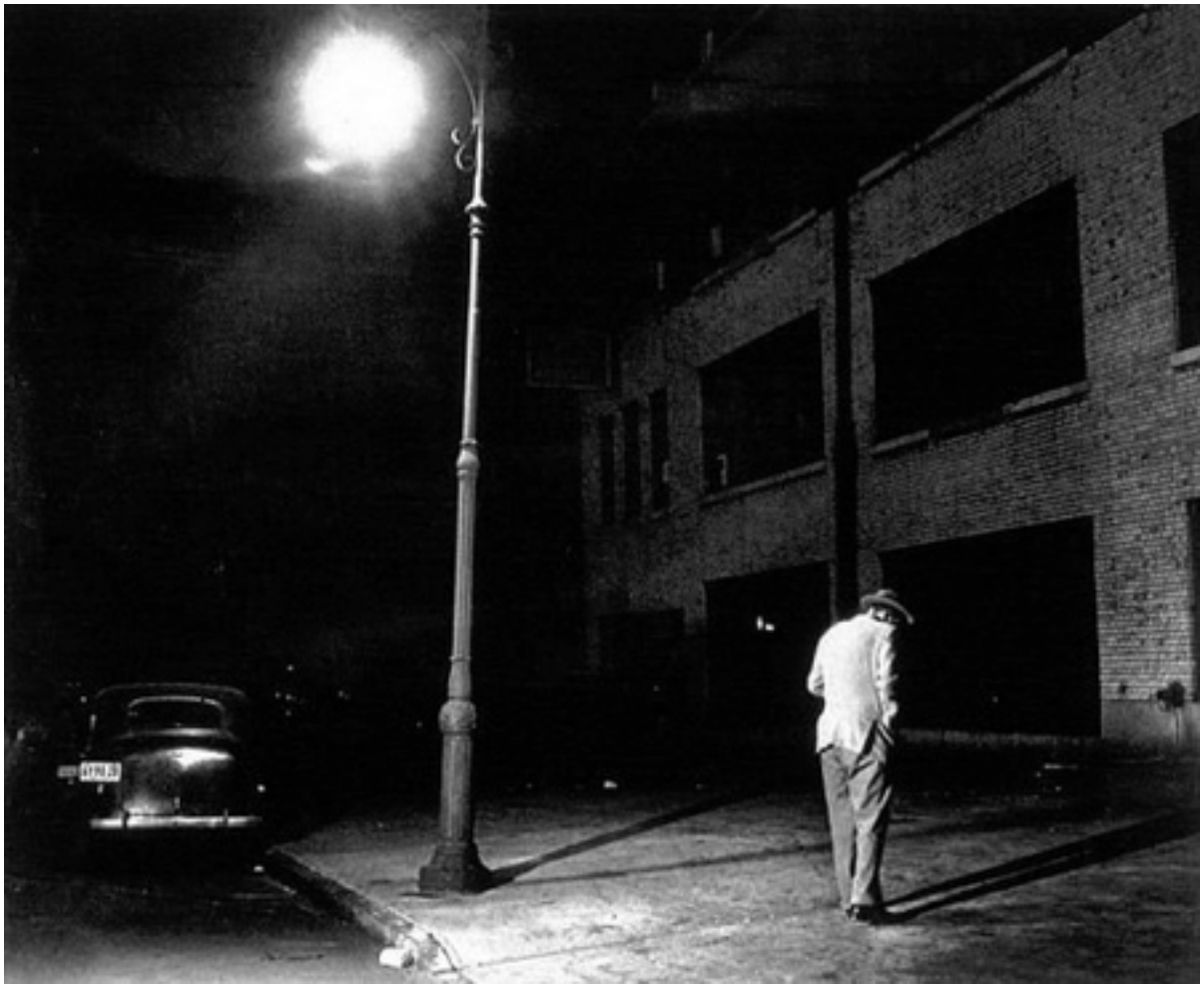
Design vs statistical control

Key feature of design-based approach: choosing settings where statistical control is less necessary.

Research question	Statistical control approach	(Non-experimental) design approach
What is effect of job training program?	Gather data on a bunch of people including participants and non-participants. Regress wages on participation indicator and controls.	Compare barely-eligible participants with barely-ineligible non-participants.
What is effect of PR (compared to plurality) on turnout?	Gather data on turnout from various countries. Regress turnout on electoral system indicator and controls.	Compare French cities just above and below population cutoff that determines electoral system.

Design vs statistical control

Key feature of design-based approach: choosing settings where statistical control is less necessary.

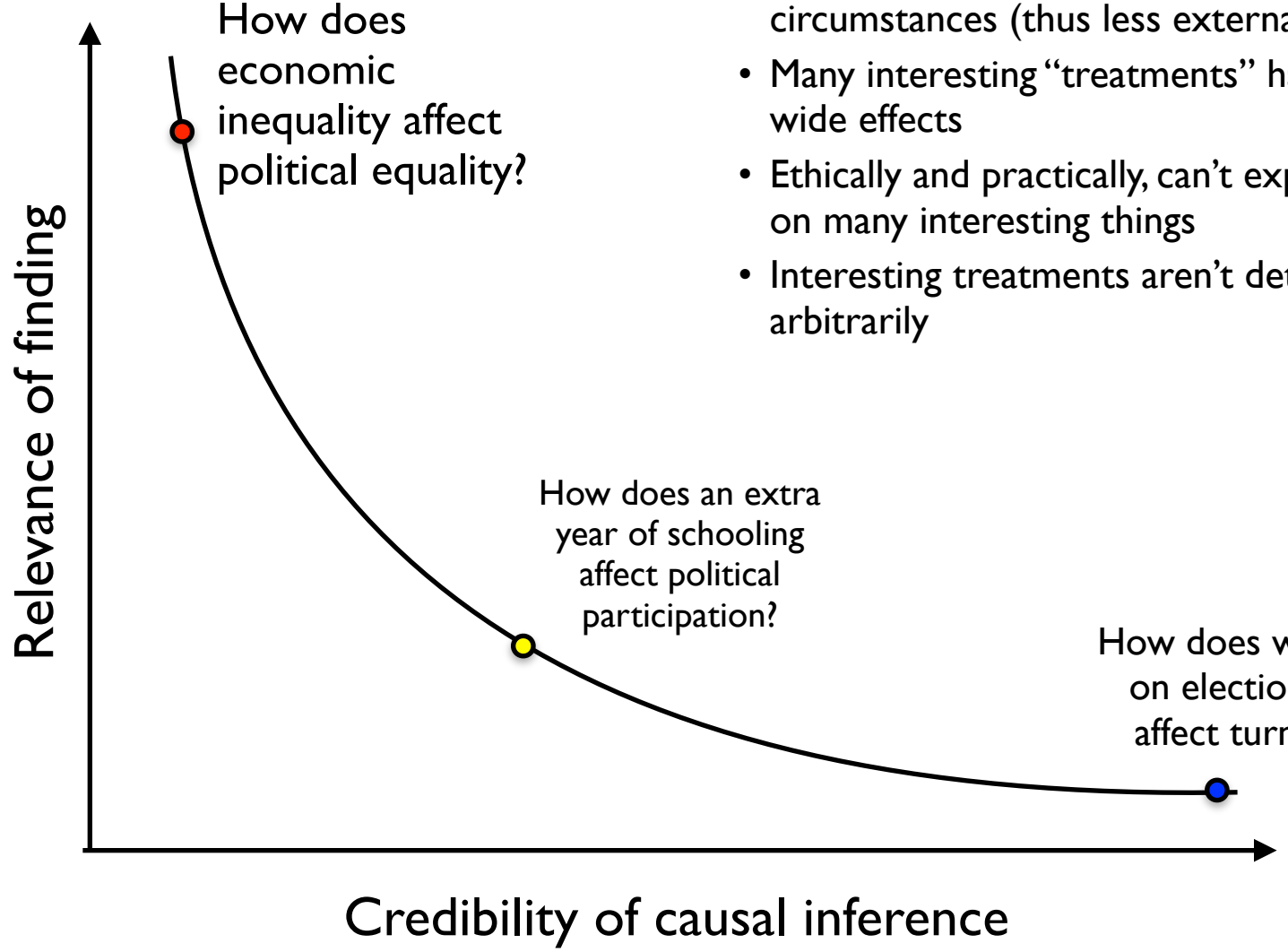


What questions are amenable to the "design-based" approach?

- **Effects of causes:** "what is effect of X", not "what explains Y"
- Effects of causes that have **local effects**: e.g. "exposure to Fox News", "PR vs plurality in municipal elections", not "unipolar international system"
- Effects of causes that **vary in sizable populations** (e.g. "across individuals", "across municipalities", not "across hemispheres")
- Effects of causes that are **binary** (not strictly necessary but helps!)

Most important question: What is the control group?

The credibility/relevance tradeoff



Some underlying reasons:

- Internal validity requires special circumstances (thus less external validity)
- Many interesting "treatments" have very wide effects
- Ethically and practically, can't experiment on many interesting things
- Interesting treatments aren't determined arbitrarily

The research design check-list

Research design	Important?	Well-identified?	Data collection feasible?
Time-series cross-sectional regression to measure effect of economic development on democratization	Yes	No	Yes
Exploit randomized candidate order on California ballots to measure effect of ballot order on vote outcomes	No?	Yes!	Yes
Compare attitudes toward gov't just before French revolution in similar areas with different governing arrangements	Yes	Maybe?	Maybe

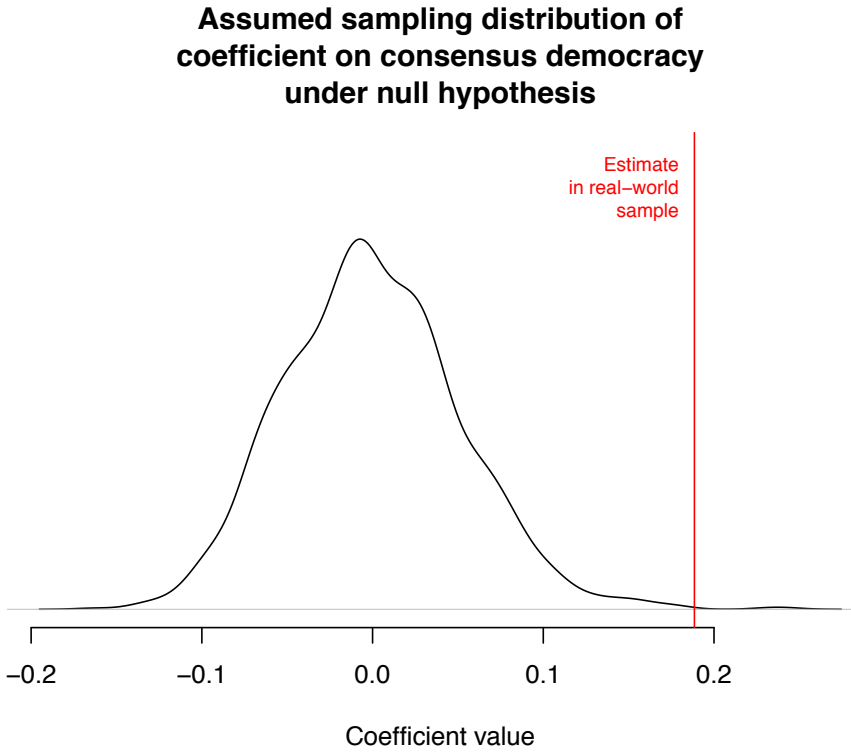
The big questions about design-based inference and the "credibility revolution"

- Does a study on elections in French villages tell us anything about national elections? (external validity)
- What about explanation? What does the study in French villages tell us about why turnout is higher in PR countries (the puzzle to be explained)?
- What about "theory-testing"? What theory is tested when the setting for our analysis was carefully chosen?
- What about "effects of causes" questions that can't be answered this way: what is the effect of globalization?

Design-based research and hypothesis testing

The basic hypothesis testing framework

- Generate a hypothesis and a test statistic (e.g. regression coefficient)
- Derive sampling distribution for test statistic under the null hypothesis (e.g. if true regression coefficient is zero)
- p-value indicates probability of getting a test statistic as extreme as observed estimate if null hypothesis actually true
- Convention: reject null hypothesis if p-value < .05



$$\alpha \equiv \Pr(\text{Reject null} | \text{Null is true}) = .05$$

Should we believe empirical claims in published research? (1)

What's the probability that the null hypothesis is *actually* false, given that the author rejects the null hypothesis in a statistical test?

Remember Bayes Theorem?

$$\Pr(a|b) = \frac{\Pr(b|a)\Pr(a)}{\Pr(b)}$$

$$\Pr(\text{Null is false}|\text{Reject null}) = \frac{\Pr(\text{Reject null}|\text{Null is false})\Pr(\text{Null is false})}{\Pr(\text{Reject null})}$$

Should we believe empirical claims in published research? (2)

What's the probability that the null hypothesis is *actually* false, given that the author rejects the null hypothesis in a statistical test?

$$\Pr(\text{Null is false}|\text{Reject null}) = \frac{\text{Power} \times \Pr(\text{Null is false})}{\text{Power} \times \Pr(\text{Null is false}) + \alpha(1 - \Pr(\text{Null is false}))}$$

Power: probability of **correctly** rejecting null

alpha: probability of **incorrectly** rejecting null

Implication: we should believe claims when

- alpha is low (goal is .05)
- Pr(Null is false) is high (i.e. the rejection is not surprising)

Should we believe empirical claims in published research? (3)

First challenge: Editors and reviewers require surprising results.

- *This gene causes turnout!*
- *The outcome of football games affects incumbent vote share!*
- *The disease environment during colonization affects current economic development (through institutions)!*

This makes published results (especially in top journals) less believable.

What can we do?

Should we believe empirical claims in published research? (4)

Second challenge: What is true value of alpha (probability of incorrectly rejecting the null hypothesis)?

We reject the null when the p-value is below .05. Is this the same as alpha = .05?

Consider:

- You run 20 regressions to pick your "preferred specification" (specification search)
- You don't pursue projects with null results (file-drawer problem)

In practice, alpha might be much higher than .05!

Four kinds of "search" to worry about

Specification search: Having chosen an X and Y of interest and a setting, try various control variables, functional forms, etc until you find a significant relationship between X and Y

Outcome search: Having found a setting where X is quasi-randomly assigned, try various outcome variables Y until find a significant relationship

Treatment search: Having chosen a Y of interest and a setting, run a regression and choose your hypotheses based on what coefficients turn out to be significant/interesting

Subgroup search: Having found a setting where X is quasi-randomly assigned, try various subgroups (e.g. young Asian men) until find a significant relationship

Which of these is better with "credibility revolution"?
Which is worse?

Replication movement and DA-RT

http://www.dartstatement.org/

Petition to delay DA-RT implementation

Petition to Delay DA-RT Implementation

November 3, 2015 [list includes those who signed of November 8 5:15 pm EST]]

Dear Colleagues,

We write as concerned members of the American Political Science Association to urge an important amendment to the statement, "Data Access and Research Transparency (DA-RT): A Joint Statement by Political Science Journal Editors." In the joint statement, dated October 6, 2014, journal editors committed their respective journals to a set of principles, to be implemented by January 15, 2016.

DA-RT organizers have made many efforts over the past five years to reach out to members of the profession through various symposia and meetings. However, these issues began to gain widespread attention only when the journal editors signed the statement of October 6, 2014 and panels at the 2015 annual meeting of the American Political Science Association brought the issue to the attention of many scholars who had not realized the possible implications of that statement for their own research, despite the previous outreach activities. Conversations at the panels, roundtables, section business meetings, and other venues at the recent annual meeting demonstrated that members of the Association have only just begun to grapple with the

Pre-registration movement and EGAP