Causal Inference

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March 26th, 2018

Who Take This Class and Why They Take It

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2) Topics: experiments, matching, regression, sensitivity analysis, difference-in-differences, panel methods, instrumental variable estimation, and regression discontinuity designs (and if time, machine learning + causal inference)

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Goal:

Provide you with adequate methodological skills to conduct cutting-edge empirical research

Causal Inference

- Statistics can be used for many purposes:
  - Discovery
  - Measurement
  - Causal inference
    - Relatively new subfield within statistics
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$\boxed{\text{Causal Inference is a Hard Problem}}$

Traditional Approaches

John Stuart Mill's **Method of Difference**:

> *If an instance in which the phenomenon under investigation occurs, and an instance in which it does not occur, have every circumstance in common save one, that one occurring only in the former; the circumstance in which alone the two instances differ is the effect, or the cause, or an indispensable part of the cause, of the phenomenon.*

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More from Mill

If so little can be done by the method to determine conditions of an effect of many combined causes in the case of the medical sciences, still less is the method applicable to a class of phenomena more complicated than even those of physiology, the phenomena of politics and history. There, Plurality of Causes exists in almost boundless excess, and effects are, for the most part, inextricably interwoven with one another. To add to the embarrassment, most of the inquiries in political science relate to the production of effects of a most comprehensive description, such as the public wealth, the public security, public morality, and the like: results liable to be affected directly or indirectly either in plus or minus by nearly every fact which exists, or event which occurs, in human society. The vulgar notion that, the safe methods on political subjects are those of Baconian induction [...] will one day be quoted as among the most unequivocal marks of a low state of the speculative faculties in any age in which it is accredited.

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- Effects of Causes $\rightsquigarrow$ How did a "China Shock" effect support for Trump? (Dawid 2000: I have a headache, will it help if I take aspirin?)

A Case Study in Failed Causal Inference

I Just Ran Two Million Regressions

By XAVIER X. SALA-I-MARTIN*

Empirical Growth Literature

Levine and Ross (1992):

> *There are many econometric specifications in which measures of economic policy are significantly correlated with long-run per capita growth rates.*
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> *The cross-country statistical relationships between long-run average growth rates and almost every particular policy indicator considered by the profession are fragile: small alterations in the "other" explanatory variables overturn past results.*

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Is Causal Inference Possible?

Why We Learn Nothing from Regressing Economic Growth on Policies*

Dani Rodrik*

Why is this a widespread sentiment?

- Important topic
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- Postmenopausal estrogen plus progestin showed large reduced risk in coronary heart disease.
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The New York Times

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April 22, 2003

Hormone Studies: What Went Wrong?

By GINA KOLATA

- Women's Health Initiative (WHI) was a large randomized trial studying the question
- Experiment showed no benefits from the therapy and increased risk from Breast Cancer
- Experiment was halted early and prescription of therapy plummeted immediately thereafter

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- Or:
  "When errors are corrected [in Hajnal, Lajevardi, and Nielson 2017], one can recover positive, negative, or null estimates of the effect of voter ID laws on turnout, precluding firm conclusions" Grimmer, Hersh, Meredith, Mummolo, and Nall (2018)

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- Compensatory campaign spending

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- Misspecified functional form
- Heterogeneous treatment effects

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So talk about it like a causal effect

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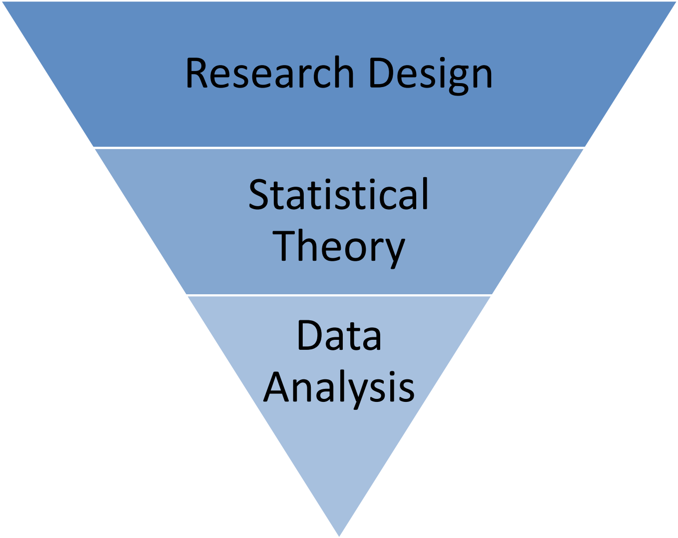
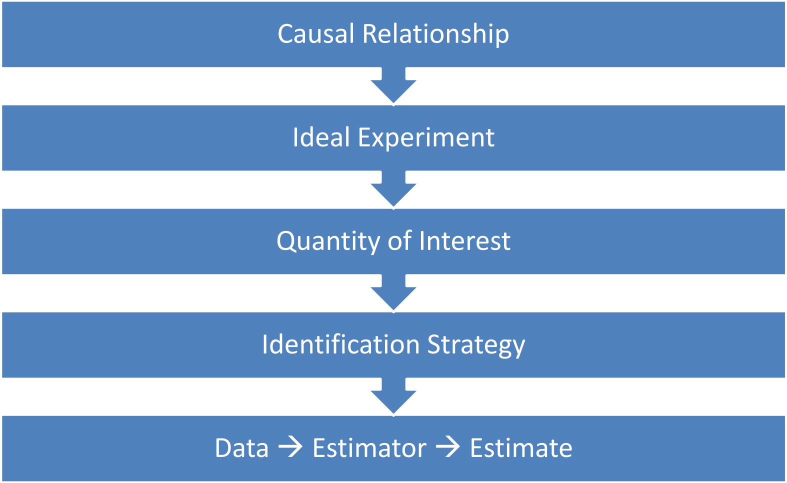
How can we conduct causal inference?



Causal Inference Workflow



Roadmap for the Course

- Potential Outcomes Model
- Random Assignment
  - Design and Analysis of Experiments
- Selection on Observables
  - Matching, Regression
  - Sensitivity Analyses
- Selection on Unobservables
  - Longitudinal Research Designs: Difference-in-Differences, Panel Methods, and related methods
  - Cross-Sectional Designs: Instrumental Variables, Regression Discontinuity Design

If there is time...

Machine Learning + Causal Inference

- Heterogeneous Treatment Effects, Extrapolation of Effects
- Text + Causal Inference.

Prerequisites

- This course assumes a graduate level knowledge of linear regression, probability, and statistical computing in `R` .
- A willingness to work hard on possibly unfamiliar material
- A correlate of whether you have the background:
  - $\beta = (X'X)^{-1}X'Y$
  - $Var[X + Y] = Var[X] + Var[X] + Cov[X + Y]$
- Computing: `R`

Requirements

- Readings (best read before lecture)
  - Read slow, some material should be read multiple times, and do not skip equations.
  - Read at least one application of every technique.
- Homework assignments (35% of the final grade)
  - Posted on Wednesday, due following Wednesday before class.
  - Can work in groups, but solo attempt first.
  - Provide your own printed write-up and submit code files.
- Midterm exam (30% of the final grade). Date is April 30th.
- Final exam (30% of the final grade).
- Participation and presentation (5% of the final grade).

Housekeeping

- Piazza course website will have slides, homework, data sets, and some additional readings:
  `piazza.com/uchicago/spring2018/plsc30600/home`

- You can sign up on the Piazza course page directly from the above address. There are also free Piazza apps for mobile devices.

- The course github is at `https://github.com/justingrimmer/CausalInf` . There you'll find all the content that I post here, homeworks, code, etc.
- Use OHs and Piazza site to ask questions about the course and homework. Do not email your questions directly to the instructor or TAs.

- Office hours:
  - Justin: Open Door

Readings

- Books:
  - Angrist, Joshua D. and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.
  - Morgan, Stephen L. and Christopher Winship. 2015. *Counterfactuals and Causal Inference: Methods and Principles for Social Research*, **Second Edition**. Cambridge University Press.
- Assigned articles
  - Most linked from syllabus, a few will be posted on course website

Scheduling to Keep in Mind

1) No class on 5/28
2) I'll be absent on 4/2 and 4/4. I'll hold make up sessions on 3/30 and 4/6. Time and location TBA
3) Last day of Class is 5/30
4) Midterm is 4/30. you must be here
5) Final exam is 6/4 - 6/7. You can take it remotely.