PS200D Quant Methods in Politics IV, Spring 2015

Introduction

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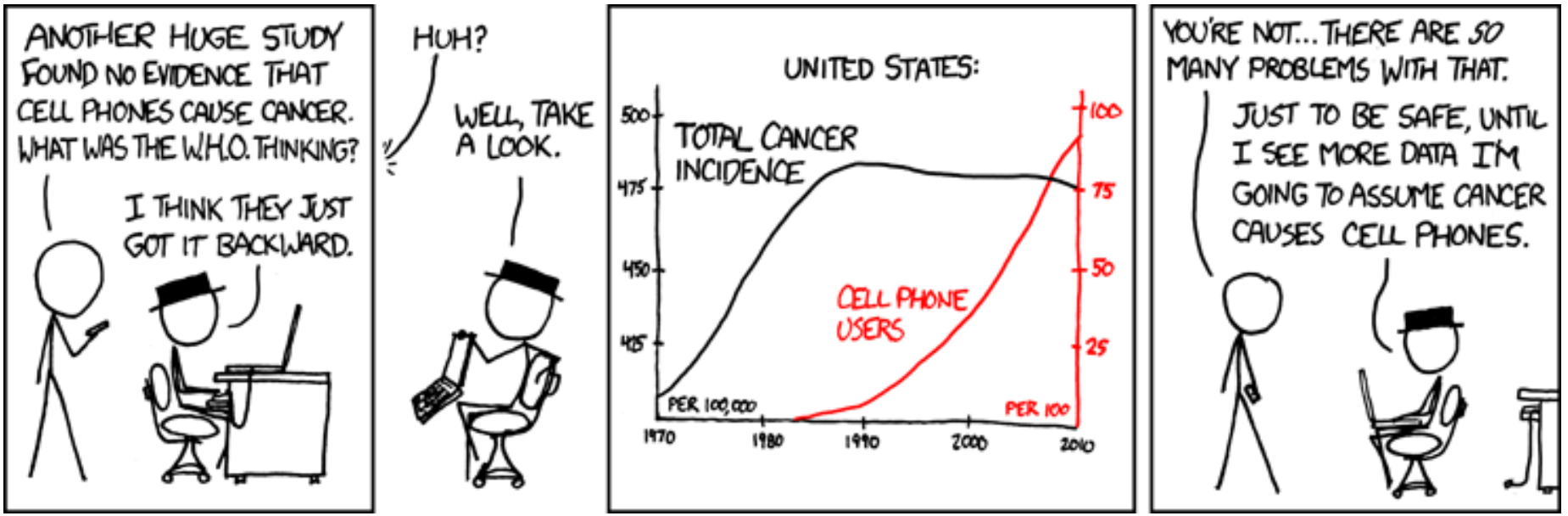
Three Modes of Statistical Inference

1. Descriptive Inference: summarizing and exploring data
   - Inferring "ideal points" from roll-call votes
   - Inferring "topics" from texts and speeches
   - Inferring whether the amount of war has changed over time
2. Predictive Inference: forecasting out-of-sample data points
   - Predicting future state failures from past failures and covariates
   - Estimating population average turnout from a sample of voters
3. Causal Inference: predicting *counterfactuals*
   - Inferring whether incumbency status affects election outcomes
   - Inferring whether the lack of war among democracies can be attributed to regime type
   - Generally, estimating effect of some policy or institution or treatment on some outcome... Policy evaluation.

Causal inference is the most difficult!
(because of the assumptions it requires, not the math)

Correlation $\neq$ Causation



This Matters!
Post-Menopausal Estrogen Replacement Therapy

Numerous observational studies with regression adjustment showed hormone replacement therapy seemed to reduce risk of heart attack.

- Among them, the Nurses Health Study involved tens of thousands of participants, showed a 30% lower risk of heart attack, and was basis for wide scale prescription of estrogen replacement
- Grodstein and Stampfer (1998):

Self-selection: These nurses probably have better living style anyway.
Nurses may not be representative?

*"Consistent evidence from over **40** epidemiologic studies demonstrates that postmenopausal women who use estrogen therapy after the menopause have significantly lower rates of heart disease than women who do not take estrogen. . . the evidence clearly supports a clinically important protection against heart disease for postmenopausal women who use estrogen."*

Not an experiment. No randomized treatment. Only observational.

Case Study: Post-Menopausal Estrogen

April 22, 2003

Hormone Studies: What Went Wrong?

By GINA KOLATA

- Women's Health Initiative (WHI, 2002) was a large randomized trial studying `Prempro` for estrogen+progesterone replacement.
- Experiment showed 40% *increase* in risk of heart attack; also increased risk of breast cancer, and dementia.
- Had to halt experiment, issue new advice to physicians
- Why do you think the results were so different?
- Later randomized trials:
  - reaffirmed the WHI result, showed it holds for estrogen-only replacement
  - showed the risk depends on age and other factors. Heterogeneous effect.

A Traditional Approach

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.*

This could work, but we rarely have such comparisons in the social sciences...and worse, data cannot in general tell us when this holds.

We need a way to know when the data we have will allow us to estimate a causal effect: **identification**.

A Theme of the Course: Identification

In this course we will often need to discuss whether a (causal) quantity is **identifiable** before we can proceed.

Something is **identifiable** if you can get it from the joint distribution of observable random variables.

Causal Identification (Manski 1995)

> *...it is useful to separate the inferential problem into statistical and identification components. Studies of **identification** seek to characterize the conclusions that could be drawn if one could...obtain an unlimited number of observations. Identification problems cannot be solved by gathering more [data].*

Manski continues,

> *"The study of identification logically comes first. Negative identification findings imply that statistical inference is fruitless... positive identification findings imply that one should go on to study the feasibility of statistical inference."*

Causal Identification Requires Assumptions

In reality, identification of causal quantities without an experiment requires assumptions; the question is how weak we can make these.

We are interested in causal identification: the combination of assumptions and data needed to make a causal conclusion.

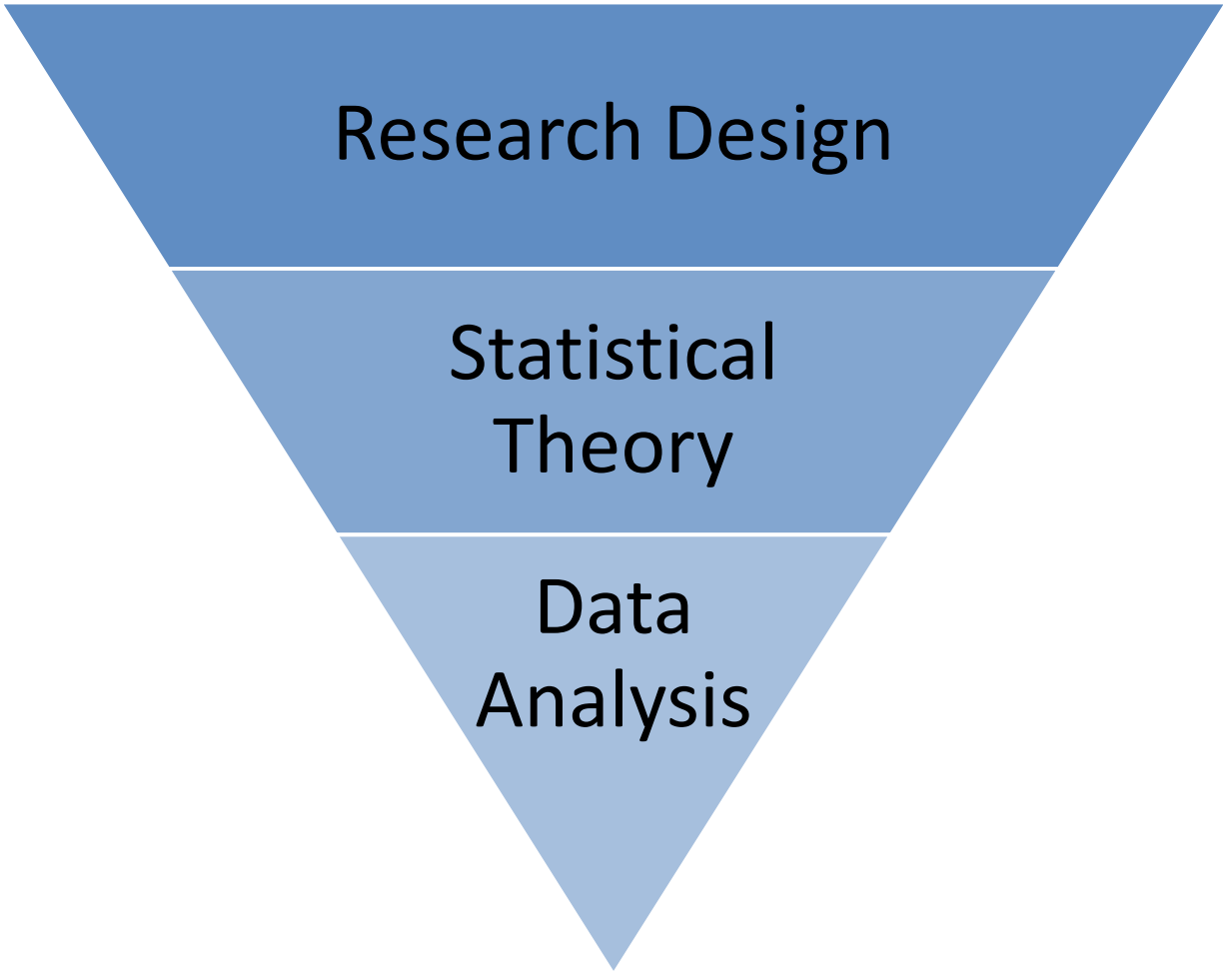
$$\text{Assumptions} + \text{Data} \rightarrow \text{Causal Conclusions}$$

We thus relax the requirements by including data as part of identification strategy. As a result, we are interested in "design-based" causal inference in contrast to model-based causal inference.

Design-based inference

Many assumptions are best made reasonable by *design*.

Hence, “design-based inference”:



Questions Answered in This Course

- Why do we accept results from randomized experiments as causal? What makes experiments so special?
- In social sciences we often cannot run randomized experiments. Can we still make a causal inference?
- Can observational studies ever produce causal conclusions? If so, when?
- Some have said statistics is only useful for analyzing association, not causation. Is that not true?
- *How can I publish a paper in a top social science journal?*

WBER editors Alain de Janvry and Elisabeth Sadoulet:

World Bank Eco Review

Question: Any pet peeves with submissions or with referees that it would be good for people to avoid?

> *Unfortunately yes. Our main two criteria in selecting papers for publication are rigorous identification and policy relevance. The two go together as we cannot have credible policy recommendations without strong causal inference. Too many of the submitted papers offer simple "determinants" that are partial correlates with no causal value, and yet are the basis for bold policy recommendations... This includes a large number of cross-country panel regressions with only mechanical, and hence not credible, identification, and yet eventually huge claims of policy implications.*

Who Takes This Class

- Anyone who plans to practice quantitative empirical research involving causal inference

- Regardless of your specialty, the goal is to:
  - know what assumptions are required to make causal claims
  - design your research to maximize the credibility of causal claims
  - know where a study falls on the credibility spectrum
  - know tools for testing, maximizing the credibility of causal claims.
  - goal is NOT to tell you you cannot study certain topics, rather to let you answer questions of interest in the best way possible.

Is This Class Right for You?

Appropriate for anyone who plans to do quantitative empirical research involving causal questions, but some technical requirements:

Should have solid handle on the basics of:

1. probability theory
2. multivariate calculus (test: recognize $\frac{\partial y}{\partial x}$, $\frac{\partial^2 y}{\partial x x'}$))
3. statistics up through linear regression (test: $(\boldsymbol{X}^\top \boldsymbol{X})^{-1}(\boldsymbol{X}^\top \boldsymbol{y})$)
4. linear algebra (test: $\boldsymbol{X}\beta$, $x_i^\top \beta$, derive β_{OLS})
5. familiarity with statistical software R and hopefully LaTeX

If you have taken PS200B & C and are comfortable with the material, great.

Students from other departments welcome if qualified.

Problem Set 0 will give sense of background needed

Roadmap for the Course

- Introduction and review
- Potential outcome model
- Randomized experiments, natural experiments
- Causal inference under "selection on observables"
  - matching
  - weighting
  - propensity scores
  - regression
  - extensions: effect heterogeneity, mediation, mechanism

Obs are somewhat randomly assigned within stratified X's.

Whether effect goes through some variables.

- Sensitivity analyses

How sensitive our results to the violation of different assumptions.

- Parallel-trend related approaches

Searching for counterfactuals for causal identification.

  - difference in difference
  - panel methods
  - synthetic controls
- Instrumental variables
- Discontinuity designs

Course Requirements and Grades

- Required readings (*before* lecture)
  - 2–3 chapters/articles per week
  - Read slowly, do not skip equations
  - Read multiple times if you don't get it first time
- Attendance and participation (5%)
- Psets (50%): about 5 of them,
  - working in groups encouraged, but must produce your own complete solutions (see syllabus), list people you worked with.
- Project (45%) (see below)
- Pass/fail option: no project.

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. 2007. *Counterfactuals and Causal Inference: Methods and Principles for Social Research*. Cambridge University Press.

Other assigned articles and chapters: most linked from syllabus, a few will be posted on course website

Project

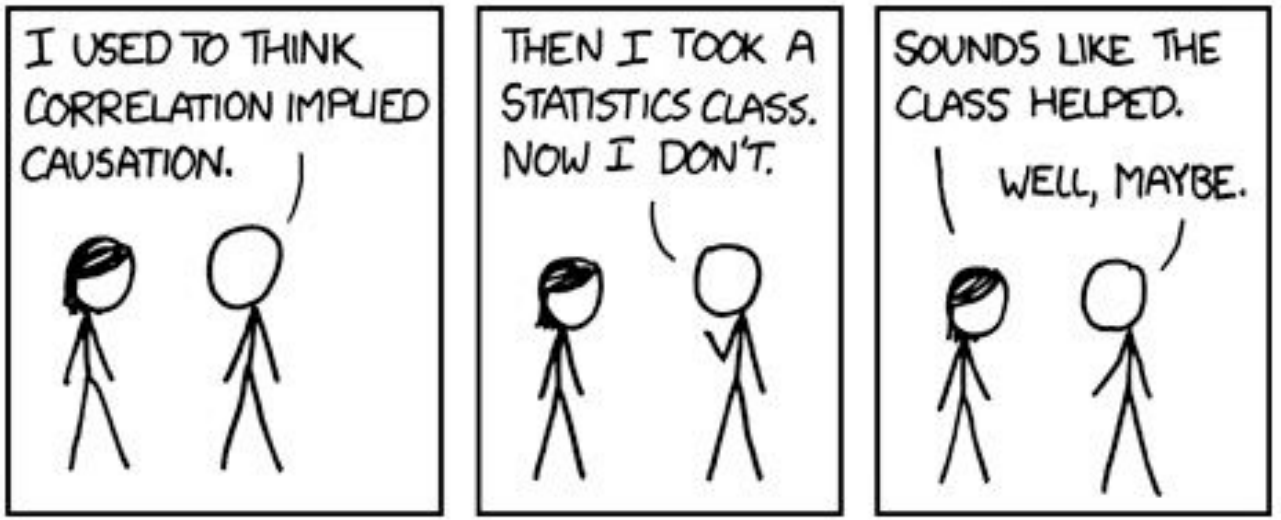
- A short research paper, typically applying a method learned in this course to an empirical problem of substantive interest.
- Focus on research question, data, empirical strategy, results and conclusions; omit lengthy literature reviews, theoretical background, etc.
- Key attribute: *follow the guidelines of the course in terms of maximizing and characterizing the credibility of causal claims*
- Coauthoring strongly encouraged!
- Could write an `R` package & vignette instead of a paper in special cases; talk to me.
- We will likely have class presentations, but depends on size

Paper Milestones

- April 13: submit teams and (if possible) a notional topic or title for your project
- April 27: submit a brief description of your project
- May 13: submit a two-page progress report on your project
- June 10, submit final project by email

Housekeeping

- Course website (moodle/CCLE): Slides and code, psets, data sets
- Interrupt any time if you have a question! If something is unclear to you it is probably unclear to others.
- Problem set submissions: give hard copy of write-up to Lauren, including code snippets; post code on course website.
- Office hours: open-door and by appointment
- Surveys: room/time change; LaTeXworkshop


I USED TO THINK CORRELATION IMPLIED CAUSATION.
THEN I TOOK A STATISTICS CLASS. NOW I DON'T.
SOUNDS LIKE THE CLASS HELPED.
WELL, MAYBE.

Questions?