

Causal Inference

MIXTAPE SESSION

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Roadmap

Hidden curriculum

- Background

- Empirical workflow

- Hierarchical folder structure

- Naming conventions

- Version control

- Soft skills

What this course is about

- This course will cover topics in “causal inference”, a field within statistics and the quantitative social sciences
- I will use lectures, simulations, replications, discussion of papers, and coding together to teach this material
- My goal is to help you become competent so that you feel confident enough to apply this material in your own research

Foundations of scientific knowledge

- Scientific methodologies are the epistemological foundation of **scientific knowledge**, which is a particular kind of knowledge
- Science **does not** collect evidence in order to “prove” what people already believe or want others to believe.
- Science is **process oriented**, not **outcome oriented**.
- Good science allows us to accept unexpected and sometimes even undesirable answers.
- Causal inference is one of science’s cornerstones

What is causal inference

- Don't think of causal inference as a synonym for statistics or even econometrics
- Causal inference is a sub-field within statistics and econometrics that focuses on *estimation of causal effects* using either experimental or non-experimental data
- Causal effects are the consequences of actions and interventions like government policy (e.g., Medicaid), firm marketing (e.g., Black Friday sales) and other actions (e.g., raising prices), or even personal choices (e.g., marriage; having a child; going to college)
- Awarded the Nobel Prize in economics in 2021 (David Card, Joshua Angrist and Guido Imbens)

Causal inference is necessary

- Causal inference is not a substitute for good sense or theoretical knowledge
- Causal inference provides *a priori* information to decision makers about what to expect with policy changes
- Policy makers are everywhere – in households, firms, government agencies
- Policies are actions chosen; causal effects are the outcomes of those actions
- The task of causal inference is to separate the causal effects from spurious accidents that often happen with but which are technically not the result of the actions chosen
- Failure to distinguish between causality and correlation can lead to fatal mistakes

School of thought

- I will tend to focus on a specific school of thought within the broader stream of work in statistics and econometrics focused on causal inference associated with the 1970s and 1980s labor group at Princeton
- Key architects include Orley Ashenfelter, David Card (2021 Nobel Prize winner), Josh Angrist (2021 Nobel Prize winner), Guido Imbens (2021 Nobel Prize Winner), Bob LaLonde, Alan Krueger, Don Rubin, Alberto Abadie and many more
- Usually associated with the “potential outcomes” model, randomization and natural experiment methodologies

Gaps in coverage

- Because it tended to come from the Princeton group, it followed as a body of work *applied micro* researchers, and less so econometrics, and even less so data science
- Incorporation into traditional econometrics curriculum, including textbooks, lagged its adoption in applied social sciences
- Adoption tended to follow academic job placements, empirically oriented field classes (labor, public, health, development), editorial positions at high ranked journals
- My goal with this course is to “fill in” the spots it hasn’t moved into with “explainer” style workshops, books and other writings

Biographical sketch

- Scott Cunningham, Professor of economics at Baylor (Waco Texas)
- Graduated from University of Georgia in 2007 with fields in econometrics, industrial organization, public and labor
- Research focus on sex work, mental healthcare, drug policy, abortion policy and crime
- Author of one book, co-editor of another, 19 peer reviewed articles, 4 book chapters
- Co-editor at the Journal of Human Resources

Mission: “to democratize causal inference”

- **Book:** Causal Inference: the Mixtape (Yale University Press) at <https://mixtape.scunning.com>
- **Substack:** Causal Inference: the Remix at <https://causalinf.substack.com>
- **Mixtape Sessions:** Platform hosting on-site and online workshops on causal inference at <https://www.mixtapesessions.io>
- **Mixtape Tracks:** Self-paced courses at <https://mixtape.thinkific.com>
- **Twitter:** @causalinf
- **Universities:** Baylor University, UT-Austin, University of Oxford, Universidad Catolica del Uruguay and more

My journey into causal inference

- In grad school, I knew I was going to be an empiricist, so I made econometrics my main field – passed field exam on second attempt
- Research topics have included risky sex, drug policy, abortion, mental healthcare and health topics more generally
- I developed courses on causal inference, as well as wrote a book on the subject, because many students do not know it even if they have studied econometrics
- This is because causal inference isn't taught historically in traditional econometrics

My pedagogy

- I am not an econometrician, although it was my field in grad school and I still love the field
- I am a consumer of econometrics – I use these designs in my work when I need to, and don't when I don't need to
- If I can understand this material well enough to teach it, anyone can learn it
- I want researchers to feel empowered and knowledgeable enough to implement these methods profitably
- Tend to emphasize the art as well as the science as well as the coding

Some reading resources

1. Causal Inference: the Mixtape. Cunningham. Free online version at mixtape.scunning.com. Introductory to intermediate
2. Mostly Harmless Econometrics. Angrist and Pischke. Classic, advanced
3. Mastering Metrics. Angrist and Pischke. Classic, introductory
4. The Effect. Nick Huntington-Klein. Excellent, introductory
5. Counterfactuals and Causal Inference. Morgan and Winship. Excellent, introductory to intermediate
6. Causal Inference for Statistics, Social and Biomedical Sciences. Imbens and Rubin. Advanced
7. Book of Why. MacKenzie and Pearl. Introduction to graphs.