ECON 113 DI 02A/B

Dizhi Wang

OH: Thursday 8:30am – 10:30 am E2 403B

About Me

- 4th year PhD candidate in the Economics Department
- Fields: Macroeconomics, International Trade
- Personal Web: https://dizhiwang.github.io/

- Teaching methodology: Active Learning
  - Group discussion
  - Teaching assistant (for a teaching assistant): yogurt
  - If yogurt is with you:
    - Prepare to be the next to answer a question
    - After answering the question toss it to someone else
    - If you don’t feel like answering, toss it to someone else



Econometric + Active Learning

- **Sample**:
- **Sample size**:
- **Data type**: (time series? Cross-sectional? Panel?)
- **Measure of interest**:

- **Population**:
- **Measure of interest (population level)**:

- **What they are trying to do in this research**:

To test the hypothesis that lecturing maximizes learning and course performance, we metaanalyzed 225 studies that reported data on examination scores or failure rates when comparing student performance in undergraduate science, technology, engineering, and mathematics (STEM) courses under traditional lecturing versus active learning. The effect sizes indicate that on average, student performance on examinations and concept inventories increased by 0.47 SDs under active learning (n = 158 studies), and that the odds ratio for failing was 1.95 under traditional lecturing (n = 67 studies). These results indicate that average examination scores improved by about 6% in active learning sections, and that students in classes with traditional lecturing were 1.5 times more likely to fail than were students in classes with active learning.

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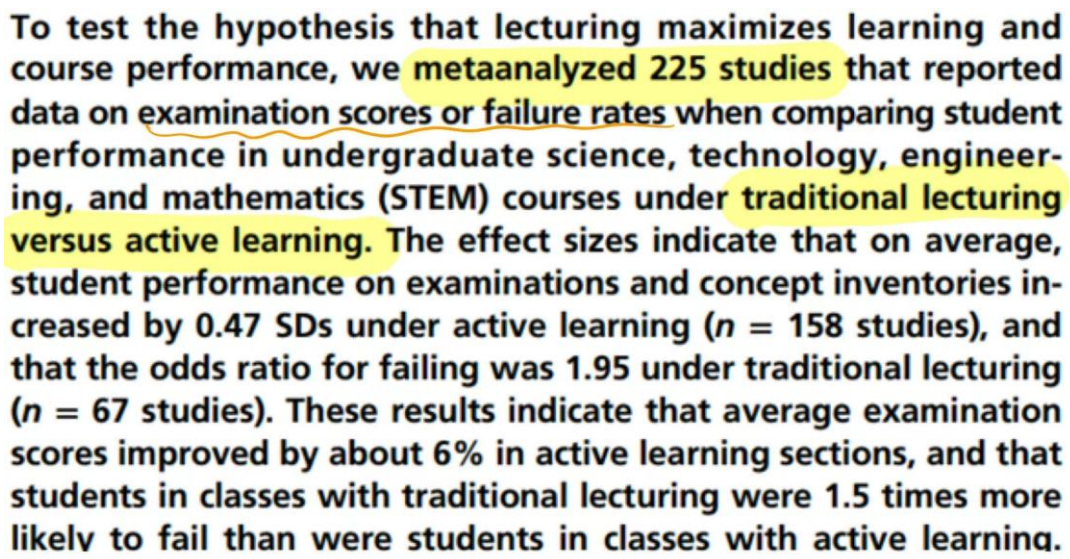
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- They use the sample of observed study results of AL effect (from the 225 studies) to estimate the true average study results of AL effect effect.

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Econometric + Active Learning

- **Measure of interest :average study result of AL effect**
  - **Random Variable: Study result of AL effect**
    - Different study has different “AL effect” result
    - = different observation for the study result
  - **Parameter: Mean/Average**
    - Different study results of AL effect (rv) forms a distribution
    - Human brain needs a “handle” to understand the distribution
    - Handle:
      - Parameter (rv): mean (μ)
      - Statistic (sample): mean ($\bar{x}$)

Retrieve one study out

Suppose one of the studies are using data as follows:

Student ID	Name	Class with AL or not	Exam Score
001	Amy	Yes	91
002	Alex	No	86
003	Cindy	No	77
…	…	…	…

Sample: students who are taking class A
Sample size: 1000
Measure of interest:

What's the difference between this study and the metaanalysis study we just saw before?

Retrieve one study out

Suppose one of the studies are using data as follows:

Student ID	Name	Class with AL or not	Exam Score
001	Amy	Yes	91
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Measure of interest: students exam score difference comparing AL vs. lecture.

What's the difference between this study and the metaanalysis study we just saw before?

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Measure of interest: students exam score difference comparing AL vs. lecture.

What's the difference between this study and the metaanalysis study we just saw before?

Before, we were estimating the population average study result using the sample average study result
Here, we want to see the relationship between exam score and AL treatment.

Comparison – More rigorously

- Before, we were estimating the population mean using the sample mean
  - 1 random var: result from research
  - Parameter: mean;
  - Estimation (statistic): sample mean

- Here, we want to see the relationship between exam score and AL treatment.
  - 2 random vars: students' score and their AL treatment;
  - Parameter: conditional mean; (relationship ⇔ conditional mean???)
  - Estimation (statistic): sample conditional mean

Relationship vs Conditional Mean

- My model:

$$Exam\ Score = \beta_0 + \beta_1 AL_{dummy} + u$$

- Where u is the idiosyncratic error
  - Which is also a random variable!
- Conditional mean: $E\left[ExamScore \middle| AL_{dummy}\right] = E[Y|X]$
- From this point suppose the ideal situation where
  - My model is 100000% true
  - We have population data for Y and X
- Calculate Parameter $E[Y|X]$:
  - $E[Y|X] = E[\beta_0 + \beta_1 X + u|X]$
    $= E[\beta_0|X] + E[\beta_1 X|X] + E[u|X]$
    - **What would be a convenient characteristic for u?**

Relationship vs Conditional Mean

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    $= E[\beta_0|X] + E[\beta_1 X|X] + E[u|X]$
  - $Assume\ E[u|X] = 0$ (Example?)

Relationship vs Conditional Mean

- My model:

$$Exam\ Score = \beta_0 + \beta_1 AL_{dummy} + u$$

- Ideal situation:
  - My model is 100000% true
  - We have population data for Y and X
  - $E[u|X] = 0$
- Conditional Mean: $E\left[ExamScore\middle|AL_{dummy}\right] = E[Y|X]$
  - $E[Y|X] = E[\beta_0 + \beta_1 X + u|X]$
    $= E[\beta_0|X] + E[\beta_1 X|X] + E[u|X]$
  - $E[Y|X] = \beta_0 + \beta_1 X$ ⇔ Relationship we care about

Relationship!

- $E[Y|X] = \beta_0 + \beta_1 X$ => Relationship we care about
- We want to calculate β_0, β_1 from random variables
  - random variables => population data for Y and X
- Start from β_0
  - Intuition: β_0 is constant no matter the change of X
  - $E[Y] = E[\beta_0 + \beta_1 X + u] = \beta_0 + \beta_1 E[X] + E[u]$
  - $E[u] =$? Given $E[u|X] = 0$

Relationship

- $E[Y|X] = \beta_0 + \beta_1 X$ => Relationship we care about => regression!
- We want to calculate β_0, β_1 from random variables
  - random variables => population data for Y and X
- Start from β_0
  - Intuition: β_0 is constant no matter the change of X
  - $E[Y] = E[\beta_0 + \beta_1 X + u] = \beta_0 + \beta_1 E[X] + E[u]$
  - $E[u] = E\big[E[u|X]\big] = \mathrm{E}[0] = 0$
  - $E[Y] = \beta_0 + \beta_1 E[X]$
  - $\beta_0 = E[Y] - \beta_1 E[X]$

Relationship

- $E[Y|X] = \beta_0 + \beta_1 X$ => Relationship we care about
- We want to calculate β_0, β_1 from random variables
  - random variables => population data for Y and X
- Come to β_1
  - Intuition: β_1 is how Y and X inter-winded
  - $E[XY] = E[X(\beta_0 + \beta_1 X + u)] = \beta_0 E[X] + \beta_1 E[X^2] + E[uX]$
  - What is $E[ux]$? What does $E[u|X] = 0$ mean?

Relationship

- $E[Y|X] = \beta_0 + \beta_1 X$ => Relationship we care about => regression!
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  - What is $E[ux]$? What does $E[u|X] = 0$ mean?
    - X and u are independent
    - $E[uX] = E[u]E[X] = 0$
  - $E[XY] = E[X(\beta_0 + \beta_1 X + u)] = \beta_0 E[X] + \beta_1 E[X^2]$
  - Sub $\beta_0 = E[Y] - \beta_1 E[X]$

Relationship

- $E[Y|X] = \beta_0 + \beta_1 X$ => Relationship we care about => regression!
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  - random variables => population data for Y and X
- Come to β_1
  - $E[XY] = E[X(\beta_0 + \beta_1 X + u)] = \beta_0 E[X] + \beta_1 E[X^2]$
  - Sub $\beta_0 = E[Y] - \beta_1 E[X]$
  - $E[XY] = (E[Y] - \beta_1 E[X])E[X] + \beta_1 E[X^2]$
    $= E[Y]E[X] - \beta_1 E[X]^2 + \beta_1 E[X^2]$
  - $\beta_1(E[X]^2 - E[X^2]) = E[Y]E[X] - E[XY]$
  - $\beta_1 = \frac{E[Y]E[X] - E[XY]}{E[X]^2 - E[X^2]} = \frac{COV(X,Y)}{V(X)}$