Econometrics 1: Tutorial I

Heikki Korpela

November 6, 2023

Contents

1. Practical matters
2. Why flipped learning?
3. Why self- and peer review?
4. How are the homework and grades related empirically?
5. Estimation and inference
6. Other stages of empirical work

1. Practical matters

- Activities
- Tutorial coverage

Activities

Activity	Covers	Grading
Problem sets	Theory	No
Lectures	Problem sets	No
Tutorials	Any questions	No
Homework	Empirical examples	Yes (40%)
Exercise groups	HW solutions	No
Self-assessment and peer review	Feedback	Yes
Exam	Theory	Yes (60%)

Tutorial coverage

You can ask questions about any part of the course here.

Tutorial	Problem sets	Homework
6.11.	1–5	1–4
13.11.	2–5	1–4
20.11.	3–5	2–4
27.11.	4–5	2–4
4.12.	5	3–4

Elements of a homework submission

Your submission should contain:

- The main numerical results
- A one or two sentence verbal interpretation for each of the results: what did you conclude, and why
- The relevant code used unless you're confident your results are correct; using R is safest

Interpretation of estimates:

- Thinking about structural questions (why is X associated with Y) is usually not required, but may be helpful for your learning
- Safe keywords: 1 unit change in X is <u>associated</u> with a b unit change in Y
- Usually safe: X helps <u>explain</u> or <u>predict</u> Y
- Keywords that need robust justification: X <u>causes</u> Y to change

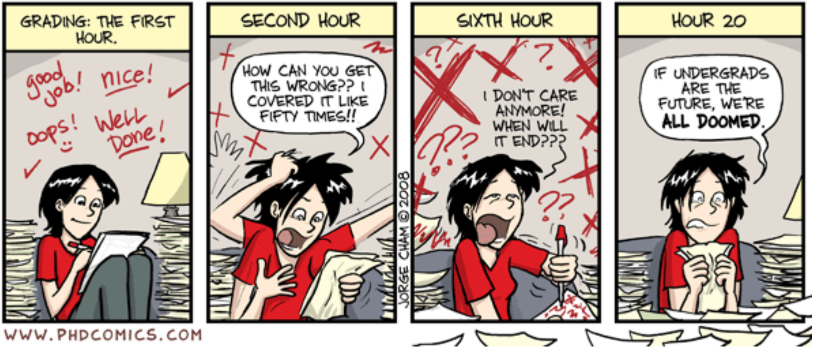
2. Why flipped learning?

- Simply: flipped learning enhances learning
  - e.g. Purba et al 2021: The Flipped Classroom: An Overview of its Impact on Economics Learning, Picault 2021: The Economics Instructor's Toolbox, at least one study by Lombardini on Finland and Economics in particular
- Plausible psychological underpinnings
  - Solving problems and getting feedback instead of passively listening
- For the same reason, students may experience the flipped approach as more cumbersome
- In reality, implementation is likely to matter more than the approach

3. Why self- and peer review?

- The main reason: it can teach valuable skills
- Most real-life expert professions involve giving and receiving feedback and assessing one's progress
- Again, implementation and effort matter
  - The more time you spend giving feedback, the more likely both you and your peer are to learn from the process
- With sufficient guidance, students usually end up assigning the same grades as teachers
- Some literature: Boud and Falchikov 1989: Quantitative studies of student self-assessment in higher education; Topping 2009: Peer Assessment; Falchikov and Goldfinch 2000: Student Peer Assessment in Higher Education: A Meta-Analysis

The harsh truth of grading



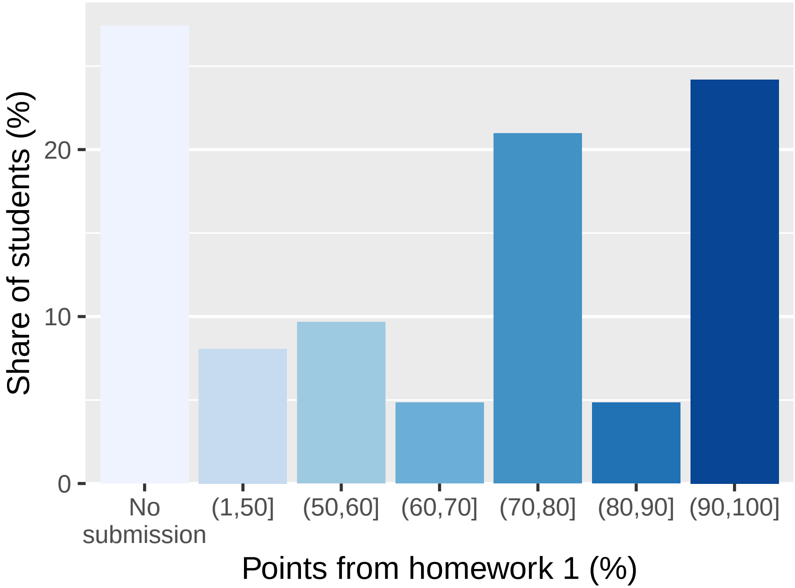
- In my experience, peer review is more likely to resemble ”the first hour” than a TA grading all papers
- Try to give constructive feedback and note both accomplishments and areas for improvement

4. How are the homework and grades related empirically?

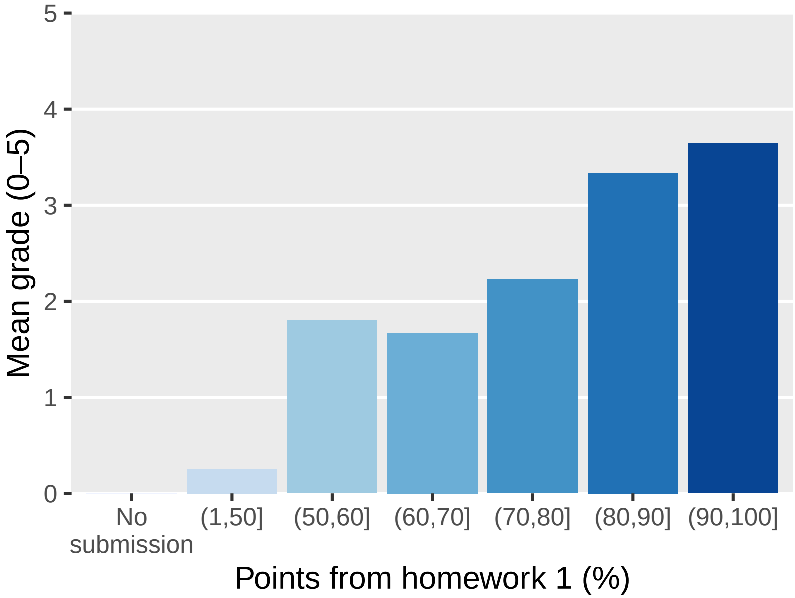
From a previous course:

- Distribution of points from homework 1
- Homework 1 grade and overall grade
- Homework 1 and exam
- What does it mean?

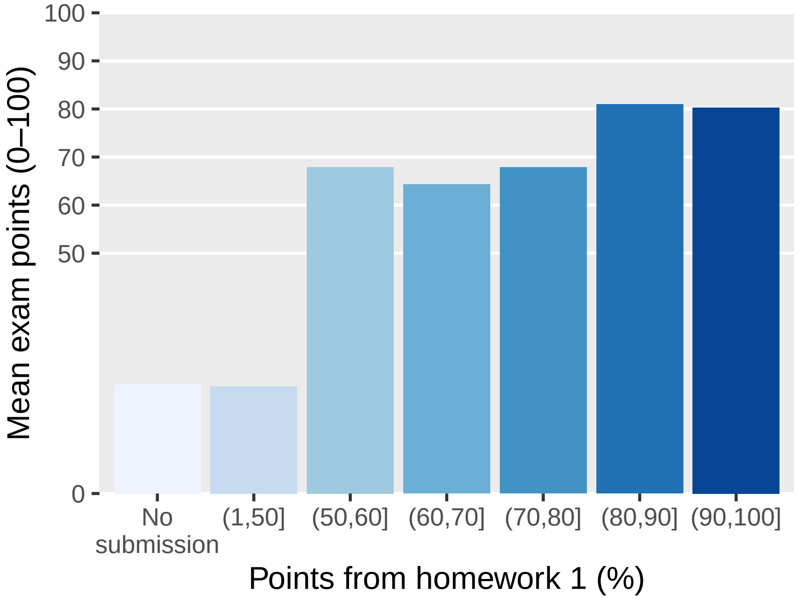
Previous course: HW 1 distribution



Homework 1 grade and course grade



Homework 1 grade and exam points



Does homework cause better grades?

- Scoring 1% higher on homework 1 was associated with scoring 0.68% (0.10) more points on the exam.
- Scoring 1% higher on homework overall was associated with scoring 0.66% (0.08) more points on the exam.
- Doing the homework probably has a causal effect on your grade (and hopefully your learning), but this OLS won't tell that. (Why?)

5. Estimation and inference

- Empirical work, and where does this course fit in
- The estimator and the estimate
- The estimator and the sample counterparts
- Uncertainty
- Why do bias and accuracy matter?
- What is a ”better” model?

Stages of actual empirical work

A. The question to be asked
B. The identification strategy
C. Acquiring and processing the data
D. Estimation and inference
E. Sensitivity
F. Writing

The highlighted parts are the main focus of this course, in the context of the linear model. We will start with questions related to estimation and inference.

Estimation and inference: the DGP

- Key estimation questions (bias, efficiency) are defined for the hypothetical scenario where we ”repeat” the research many times
  - Example: suppose that you give me 1000 random samples of the Finnish unemployed, and ask me to answer a research question, <u>one sample at a time</u>
- It is useful to think that there is an underlying data generating process (DGP); for example, some process that determines unemployment
- Each observed sample (no matter how big) is a ”draw” from the DGP
  - e.g., the unemployed between 1999 and 2023
  - The unemployed in 2024 would be a different draw
- The only case where we <u>know</u> the DGP is a computer simulation; c.f. the problem 4 in each assignment.

Estimator and estimate

- The estimator is always a random variable (a function of other random variables) that ”lives” within the DGP
- The estimator properties are established by the theory, given some assumptions about the DGP (the model)
- The estimates are draws of the estimator
- Bias and efficiency are properties of the estimator

Estimator and sample

Target	Purpose	DGP	Sample
The parameter	The DGP, e.g. by how much does duration of benefits change unemployment	Estimator b	Estimate $\hat{\beta}$
The error	The statistical uncertainty; in OLS, the part not explained by the model variables	Error term ε_i	Residual errors e_i
The test	How likely would this sample be under a null hypothesis	$\mathbb{P}(\lvert t\rvert > t_c)$	p-value

Estimation and uncertainty

- Any numerical uncertainty (e.g. *p*-value) reported is based on the properties of the estimator, and thus rely on the assumptions. This is usually an <u>underestimate</u>, because it ignores the uncertainty related to the assumptions.
- Some assumptions can themselves be tested for, but many cannot. You still need to justify them (with as much data as you can).
- In the non-instrumental baseline OLS, the fundamentally untestable assumption is that the error term is uncorrelated with the observables.
- This assumption is often <u>unrealistic</u> in practical applications.
- Instrumental variables use (arguably) more realistic assumptions, but the crucial assumption remains untestable.

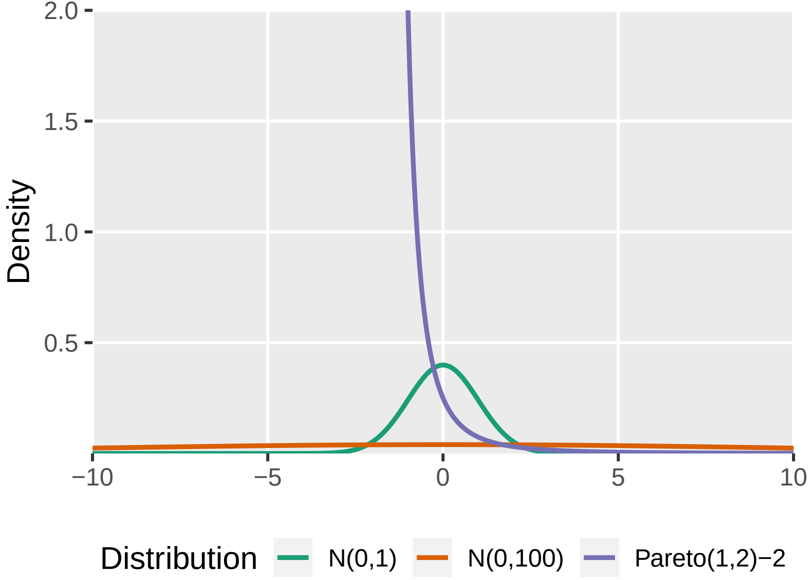
Estimation and uncertainty

- Every single estimator you use will have some bias, because assumptions don't hold exactly and because pretty much all variables you use will have some measurement error
- The key question is how much bias you have
- Can you, for example, plausibly rule out the hypothesis that benefit duration has a near-zero effect (or has a large effect) on unemployment?
- This involves looking at both the nominal or statistical uncertainty and your assumptions critically (sensitivity analysis)
- Put differently, rejecting the null hypothesis should usually be read as "probably either the null hypothesis <u>or</u> the assumptions are wrong"

Bias and efficiency/precision

- Bias tells us, under repeated sampling, the average difference between the estimate and the true parameter. It is about the mean of the estimator.
- Efficiency informs us about the general noisiness of the estimate. It is about the variance of the estimator.
- A (point) estimate without some measure of the noise is basically useless even if it is on average unbiased.
- Most commonly, point estimates are presented with either standard errors or confidence intervals in parentheses, e.g. "5 (1.5)".
    - As a rule of thumb, multiply the number in parentheses by two to get the 95% confidence interval.

Distributions with the same mean



What is a ”better” model?

- In the first homework, we are mostly worried about rather specific threats to identification.
- You can think of the main task as trying to predict a phenomenon, instead of causal questions.
- A model is ”better” than another if it has a better AIC (or, if specifically asked for, the $\bar{R}^2$).
- i.e., it yields a good prediction (less noise left unexplained by the model) while being relatively parsimonious (fewer explanatory variables).
- In applied work, good models often have poor $\bar{R}^2$'s, and will even discard covariates that would improve it!
- Example: number of days in part-time unemployment helps predict the duration of unemployment, but is usually a terrible covariate. (Why?)

6. Other stages of empirical work

A. The question to be asked
B. The identification strategy
C. Acquiring and processing the data
D. Estimation and inference
E. Sensitivity
F. Writing

The question

- Empirical questions usually revolve around either <u>prediction</u> or <u>causality</u>
- Examples:
  - If we change the maximum duration of unemployment benefits, how does the average duration of unemployment change?
  - Given what we know about individual X, how long are they going to stay unemployed (without intervention)?
- ”What explains unemployment” or ”how could we lower unmeployment” are valid questions, but rarely considered a single empirical project

The identification strategy

- In this course, ”identification” is considered in rather technical terms
- Identification strategy is a strategy that yields the elusive identification
  - In causal settings: how do we know that we are estimating the causal effect of X on Y?
  - Unemployment (Y) is affected by many factors
  - How do we squeeze out the causal impact of changing the maximum benefit duration (X)?
- Some popular strategies:
  - Differences-in-differences (DiD or DD)
  - Regression discontinuity (RD)
  - Instrumental variables (IV)
  - Randomized controlled trials (RCT)
  - Adjustment/unconfoundedness (see also: matching and weighting)

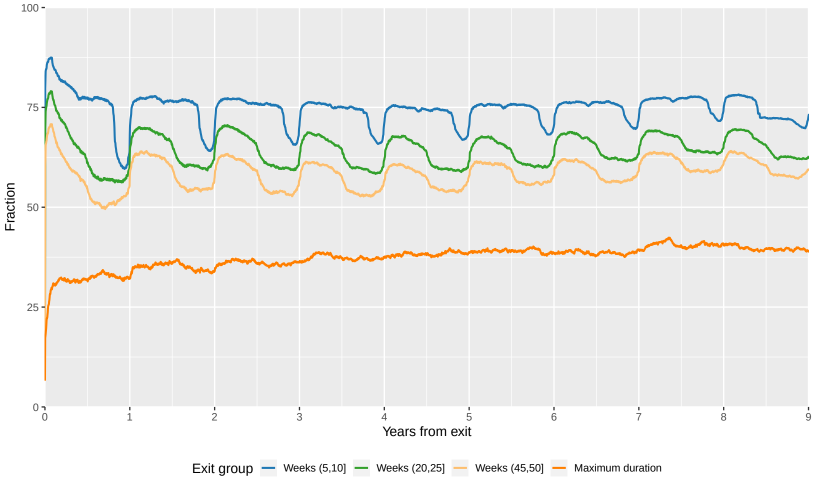
Causality

- The books: Angrist and Pischke: Mostly Harmless Econometrics, or Mastering Metrics (less technical)
- Complementary reading
  - Pearl: The Book of Why
  - Imbens 2020: Potential Outcome and Directed Acyclic Graph Approaches to Causality: Relevance for Empirical Practice in Economics
- Courses
  - Applied Microeconometrics I and II (Aalto University) cover empirical research using micro-level data
  - Applied Macroeconometrics I and II (UoH) cover time series using macroeconomic data
  - Applied courses are very helpful if you want to do or cite empirics in your thesis (you probably will)

Acquiring and processing data

- Rarely taught in courses
- It can take the majority of the time in an actual research project
- In applications, privacy and computational efficiency often become pressing concerns
- Let's quickly look at an example
- Suppose you observe, for each unemployed person, roughly 100 demographic variables for 40 years and their full unemployment and employment histories
- The task is to predict whether the duration of an individual's unemployment is "short" given observables. Which variables do you pick?

Example with data



The figure illustrates post-unemployment outcomes for the Finnish unemployed. The curves indicate the share (%) employed for each day after an exit from unemployment.

Employment data

Person ID	Start	End	Wage	Employer ID
1	2010-03-01	2010-05-31	5000	1
1	2010-02-15	2010-03-15	500	2
⋮	⋮	⋮	⋮	⋮

- Best predictor (xgbTree, RMSE) for ”short” unemployment duration that I found was the number of previous distinct employment spells
- All indicators for the prior duration in unemployment are only second best. (Why?)
- Those with more employment spells have shorter but more frequent spells of unemployment