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# Microeconometrics

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## Logistics

### Schedule

**Lectures:** Tue 9:30-11:00, 11:30 - 13:00;

**Exercises:** Mon 9:30-11:00;

**Office hours:** By appointment

**TA:** Wisse Rutgers

### Home assignments

Home assignments will include theoretical, computational, and empirical exercises. I strongly encourage you to use R for the coding problems. Home assignments should be done in groups with a minimal size of two and a maximal size of three students.

### Grading

Grades will be based on group home assignments (10%), presentations (10%), and a final exam (80%). The final exam will consist of two equally weighted parts: a replication project and a take-home exam.

## Course Objectives

The primary goal of this course is to guarantee that students can (a) understand, (b) implement, and (c) discuss possible improvements of any empirical paper in economics/finance (from the econometric perspective). We will develop the necessary theory and will illustrate it with empirical exercises. A secondary goal is to introduce modern statistical techniques (ML and high-dimensional statistics) and show how they can be used to improve standard estimation procedures.

## Prerequisites

Satisfactory performance in the first-year statistical and econometric courses (including Applied Microeconometrics, if applicable).

## Plan

1. Prediction: Empirical Risk Minimization and Regularization;
2. Basic Toolkit: Experiments, Weak Instruments, Unconfoundedness, RDD, Two-Way Models;
3. Beyond MHE: Selection Models, Marginal Treatment Effects;
4. General view: GMM and Related Problems;
5. Topics: Bipartite Networks, Quantile Methods, Shift-Share Designs;
6. Uncertainty Quantification: Design-Based vs. Model-Based Inference;

## Literature

### Textbooks

Lecture notes will be uploaded weakly on the course website. There is no textbook for the course, but the references below can be useful:

- Econometrics textbook by Bruce Hansen (old version available online);
- “Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction”, by Guido W. Imbens and Donald B. Rubin;
- Manuel Arellano’s lecture notes (available on his website);
- Stefan Wager’s lecture notes for STATS 361 (available on his website)
- “Mostly Harmless Econometrics” by Joshua D. Angrist & Jorn-Steffen Pischke;
- “Elements of Statistical Learning” by Hastie, Tibshirani, Friedman (available online).
- “Computer Age Statistical Inference” by Hastie and Efron (available online);

### Papers

Lecture notes will be partially based on the papers below (the list will be updated throughout the course). I do not expect you to read all or any of them (some are very technical), but I will let you know the most useful ones.

## References

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- S. Bonhomme and E. Manresa. Grouped patterns of heterogeneity in panel data. *Econometrica*, 83(3):1147–1184, 2015.
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