technische universität
dortmund

Lecture 1:
Introduction

Michael J. Böhm

Empirical Economics

Wintersemester 2025/26

Labour Economics

The focus of inquiry of labour economics is the labor market, i.e., workers and their jobs and wages:

- Labour force participation, hours worked, jobs, unemployment.
- Wages, skills and productivity, performance pay.
- Job search and matching with employers.
- Demographics, education, human capital.
- Institutions (firms, unions) and policies (minimum wages).
- Impact of international trade and technological change (e.g., on jobs and inequality).

Course details

- **Meeting date**
  - Tuesdays: 8:30am–12pm
  - Location: M127 (Math Tower, TU Dortmund)
  - Starts: 14 October 2025
- **Level**
  - Postgraduate
- **Instructor**
  - Prof. Michael Böhm
  - michael.j.boehm@tu-dortmund.de

Course details

- **Materials**
  - Lecture slides, problem sets, further readings, etc. will be posted on Moodle.
  - No password necessary.
- **Evaluation**
  - Final exam at the end of term.
  - Possibility to improve the grade (20%) by submitting up to four problem sets ...
  - ... & presenting (in teams of 1–3 students) your solutions.
- Active class participation

Course details

Textbooks I recommend as references and background readings:

- Borjas, George. *Labor Economics*. 8th edition. ISE. McGraw-Hill, 2019.
  Online fulltext available at the TU Dortmund library (link).
- Cahuc, Pierre, Stéphane Carcillo and André Zylberberg, *Labor Economics*, MIT Press, 2014.

Prospective topics

1. **Introduction (today)**
2. **Labour supply**
   a. Theory of labour supply.
   b. Estimation of labour supply elasticities.
   c. (Some more notes on regression and IV.)
3. **Firms and labour demand**
   a. Competitive theory of labour demand.
   b. The effects of minimum wages.
   c. Demand and supply with firm heterogeneity.

Prospective topics

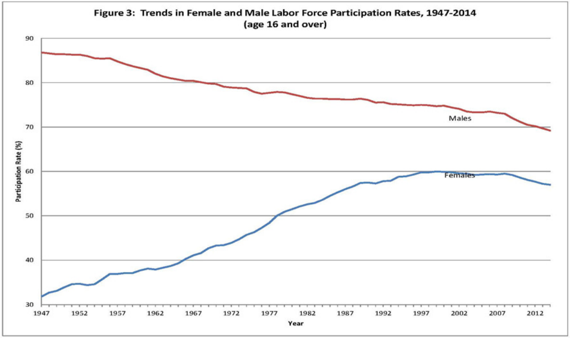
4. **Job Search**
   a. Standard model.
   b. Endogenous effort and empirics of search & matching.
5. **The Role of Human Capital**
   a. Investment in education: Human capital.
   b. Signaling.
6. **Technological Change and Wage Inequality**
   a. Wage inequality.
   b. Regional inequality.

Throughout the course: theory and practice of important econometric methods.

Problem sets

1. 4–5 over the course of the term.
2. Based on influential (applied) research papers.
3. Except one, own empirical analyses (i.e., replication and extension).
   a. The data and (basic) code will be provided.
   b. You can work in teams.
   c. Any software (e.g., Stata, R, Python).
4. Critical for you learning actual data analysis / applied econometrics!
5. "Presentations" very low-key with lots of help.
6. Grading will be generous and improve your final grades.

Labour Supply



Notes: Updated version of Figure from Blau, Ferber and Winkler (2014) based on data from the Current Population Survey available at www.bls.gov and Employment & Earnings, various issues.

Why are levels of Labour Force Participation (LFP=#in LF/total pop) changing? (US-data)

Labour Supply

- Do the levels of labour market participation of women compare to that of men?
- Much progress, but large differences across countries
- Are public policies implicated?

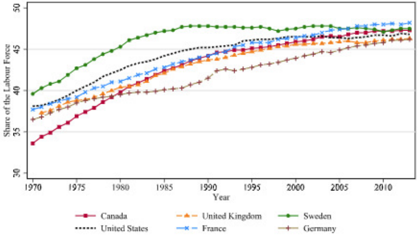
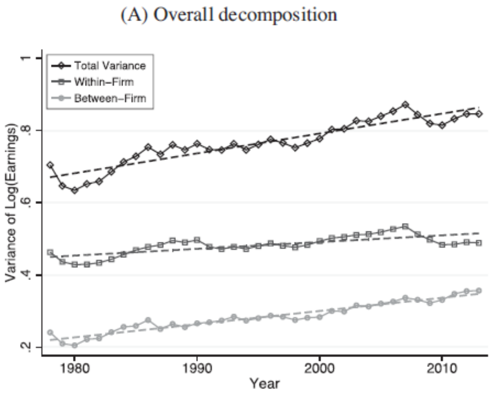


Fig. 1. Women's share of the labour force. Source: BLS and Conference Board, International Labor Statistics, adjusted to US concepts, persons aged 15/16 and over.

Source: Fortin, Bell, Böhm (2017)

Labour Demand

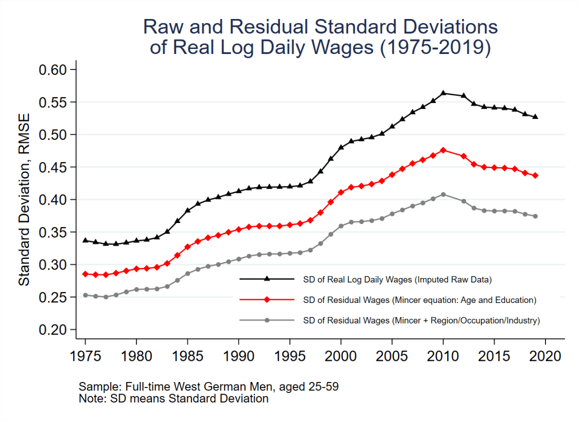
Much of inequality, and most of its increase, is between firms. (US-data)



Source: Song, Price, Guvenen, Bloom, von Wachter, 2019.

Trends in Inequality

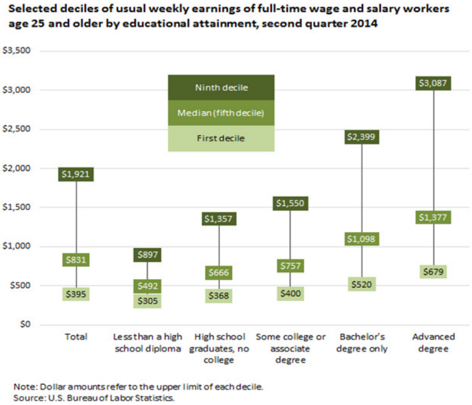
- Wage inequality massively increased,
- but then started to decline after 2010.



Source: Böhm, Etheridge, Irastorza-Fadrique (2024).

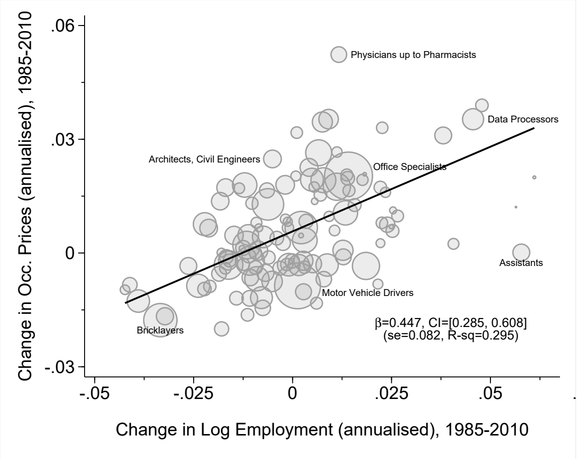
Wage Determination

- How about earnings and wages, does it pay to get a university degree?
- Level but also variance of earnings rises by education level.



Sources: Bureau of Labor Statistics, U.S. Department of Labor.

Demand and supply for different types of work



Source: Böhm, Etheridge, Irastorza-Fadrique (2024).

Emergence of new work

TABLE I

EXAMPLES OF NEW TITLES ADDED TO THE CENSUS ALPHABETICAL INDEX OF OCCUPATIONS BY VOLUME, 1940–2018

Year	Example titles added	
1940	Automatic welding machine operator	Acrobatic dancer
1950	Airplane designer	Tattooer
1960	Textile chemist	Pageants director
1970	Engineer computer application	Mental-health counselor
1980	Controller, remotely piloted vehicle	Hypnotherapist
1990	Circuit layout designer	Conference planner
2000	Artificial intelligence specialist	Amusement park worker
2010	Technician, wind turbine	Sommelier
2018	Cybersecurity analyst	Drama therapist

Notes. The table reports examples of new titles added to the census Alphabetical Index of Occupations volume of year Y corresponding to titles recognized by census coders between the start of the prior decade and the year preceding the volume's release, for example, the 1950 CAI volume includes new titles incorporated between 1940 and 1949.

Source: Autor, Chin, Salomons, Seegmiller (2024).

Emergence of new work

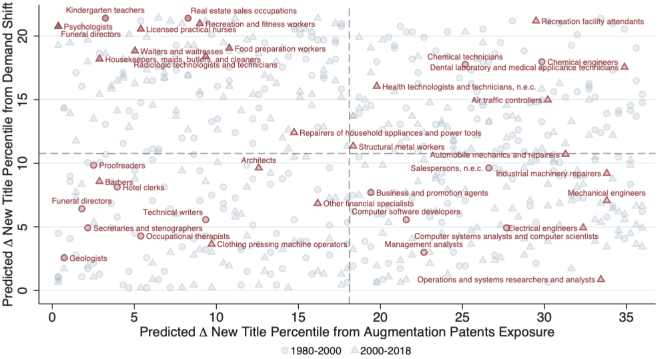


FIGURE VIII

Predicted Δ Occupational New-Title Share Percentile from Exposure to Augmentation versus Exposure to Demand Shifts, 1980–2000 and 2000–2018

Source: Autor, Chin, Salomons, Seegmiller (2024).

Research Design

So far we have seen interesting facts (or descriptive statistics).

- We can develop models that try to explain them (and we will).
- But we don't know if a particular model is correct.

One way to deal with this is to estimate "causal effects" from experiments:

- When an intervention (called "treatment") is randomly assigned, the simple difference between groups with different exposure levels is due to the exposure itself and not to other uncontrolled factors.
- If the treatment corresponds to the mechanism in the model, we are up to something...

Research Design

- More formally, let Y_i^1 denote an outcome of interest if the observation unit i is treated. If unit i is not treated, we cannot observe this counterfactual or potential outcome.
- Let Y_i^0 denote the outcome if the observation unit i is not treated.
- Randomized trials form the conceptual benchmark for assessing the success or failure of studies based on quasi-natural experiments.

Research Design

Letting $D_i = 1$ when an observation unit is treated and equal 0 when it is not, the observed outcome, Y_i, can be written in terms of potential outcomes as

$$\begin{aligned} Y_i &= \begin{cases} Y_i^1 & \text{if } D_i = 1 \\ Y_i^0 & \text{if } D_i = 0 \end{cases} \\ &= Y_i^0 + (Y_i^1 - Y_i^0)D_i. \end{aligned}$$

We only observe either Y_i^1 or Y_i^0 for a single individual!

Research Design

- We cannot hope to observe $Y_i^1 - Y_i^0$ for a particular unit i, which is the true causal effect.
- In an experimental setting, we may however observe the average difference in the potential outcomes as the average causal effect or Average Treatment Effect:

$$ATE = E[Y_i^1 - Y_i^0] = E[Y_i^1] - [Y_i^0]$$

Research Design

We can write the observed difference in outcomes for the treated and untreated as the sum of two terms:

$$
\begin{aligned}
\underbrace{E\left[Y_i|D_i=1\right]-E[Y_i|D_i=0]}_{\text{Observed difference}} &= E\left[Y_i^1|D_i=1\right]-E[Y_i^0|D_i=0\right] \\
&= E\left[Y_i^1|D_i=1\right]-E[Y_i^0|D_i=1\right] \\
&+ E\left[Y_i^0|D_i=1\right]-E\left[Y_i^0|D_i=0\right] \\
&= \underbrace{E\left[Y_i^1-Y_i^0|D_i=1\right]}_{\text{average treatment effect on the treated}} \\
&\quad + \underbrace{E\left[Y_i^0|D_i=1\right]-E\left[Y_i^0|D_i=0\right]}_{\text{selection bias}}
\end{aligned}
$$

Research Design

If D_i is randomly assigned it is (statistically) independent of potential outcomes. As a result

$$
\begin{aligned}
E\left[Y_i|D_i=1\right]-E[Y_i|D_i=0] &= E\left[Y_i^1|D_i=1]-E[Y_i^0|D_i=0\right] \\
&= E[Y_i^1|D_i=1]-E[Y_i^0|D_i=1],
\end{aligned}
$$

where the independence of Y_i^0 and D_i allows us to swap $E[Y_i^0|D_i=1]$ for $E[Y_i^0|D_i=0]$ in the second line. In fact,

$$
\begin{aligned}
E\left[Y_i^1|D_i=1\right]-E\left[Y_i^0|D_i=1\right] &= E\left[Y_i^1-Y_i^0|D_i=1\right] \\
&= E\left[Y_i^1-Y_i^0\right].
\end{aligned}
$$

Research Design

- If the treatment is randomly assigned, the assignment to treatment is independent of potential outcomes $Y_i^1, Y_i^0 \perp D_i$, the assignment is also said to be ignorable.
- The selection bias will vanish and the treatment-control difference provides an unbiased estimate of the average treatment effect.

Research Design

- The quasi-experimental methods we will see (and apply) devise ways to correct for this bias, i.e., approximate the random experiment:
  - Fixed effects absorb all time-invariant differences across subjects.
  - Difference-in-Differences use a common trend assumption to control for changes over time not due to treatment.
  - (Event studies exploit the timing of the assignment to study the differing trends of treatment and controls.)
  - IV uses an instrument to make treatment close to random.
  - (Regression Discontinuity Designs use units around a cut-off to mimic random assignment.)

Research Design

- Decomposition methods usually do not aim at causality but aim to quantify relationships:
  - Oaxaca-Blinder decomposes the mean differences between groups into price effects and differences in groups' observable characteristics.
  - DiNardo-Fortin-Lemieux (DFL) reweighing decomposes the whole distribution (e.g., of wages) into these components.
  - (Unconditional) quantile regressions study the contribution of an explanatory variable to specific quantiles of the outcome variable.

Review Questions

1. In the average treatment effect versus selection bias decomposition, which terms in last expression are observed?
   a. $E\left[Y_i^1 | D_i = 1\right]$
   b. $E\left[Y_i^0 | D_i = 1\right]$
   c. $E\left[Y_i^0 | D_i = 0\right]$

2. Suppose D_i is statistically independent of potential outcomes Y_i^1 and Y_i^0. Does this mean it is independent of observed Y_i?

3. If X_i are covariates, why might we want to look at

   $E\left[X_i | D_i = 1\right] - E[X_i | D_i = 0]$?

Basic Readings

- Angrist, Joshua D., and Jörn-Steffen Pischke. Mostly harmless econometrics: An empiricist's companion. Princeton university press, 2009.