Tasks and Work Force Polarization

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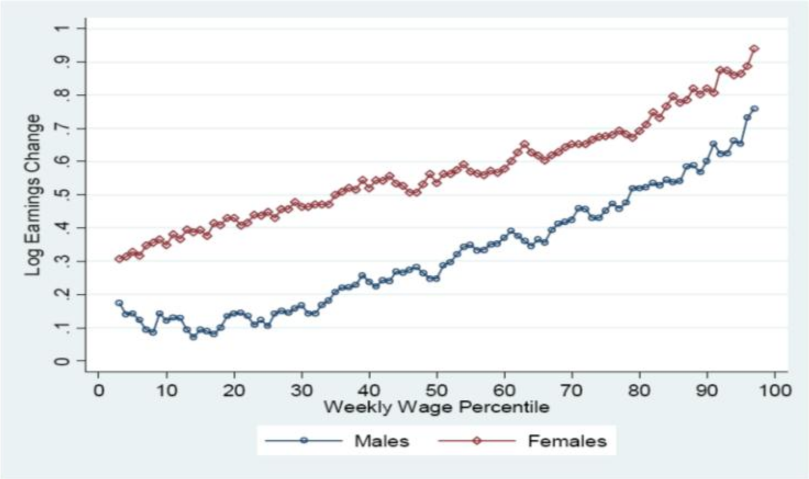
U.S. wage inequality has risen since the 1960s



Change in Log Real Weekly Wage by Perecntile, Full-Time Workers, 1963-2005. (Autor, L. F. Katz, & Kearney, 2008)

Skill-Based Technical Change (SBTC)

- Model features:
  - Two skills, high (H) and low (L).
  - H and L are different, and imperfect productive substitutes: $\sigma > 0$.
  - Technology *factor-augmenting*: always raises productivity/wages.
  - Wages set on the demand curve
- Empirically successful. e.g.
  - Katz and Murphy (1992)
  - Card and Lemieux (2001)

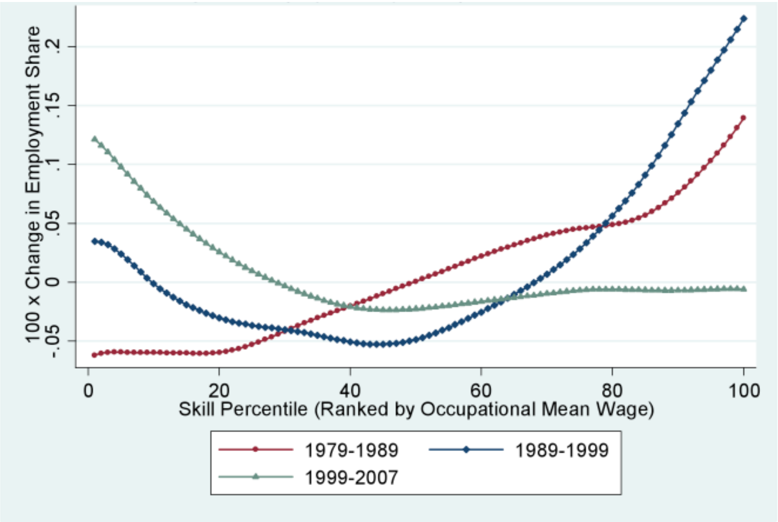
The 'Canonical Model' of Skill-Based Technical Change

- Production function representation:

$$F(L,H) = \left[(A_L L)^{\frac{\sigma-1}{\sigma}} + (A_H H)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{(\sigma-1)}} \tag{1}$$

- Empirical implications depend on σ. SBTC implies
  - Rise in A_H/A_L if H and L are gross substitutes ($\sigma > 1$)
  - Fall in A_H/A_L if H and L are gross complements ($\sigma > 1$)
- Predicts
  - Increasing inequality, driven by skill demand.
  - Rising college/education premium.
  - Monotone wage growth in skills.

Non-monotone increases in wage by skill percentile (USA)



Smoothed changes in employment by occupational skill percentile, 1979-2007 (Acemoglu & Autor, 2011)

Autor, Levy, and Murnane, 2003

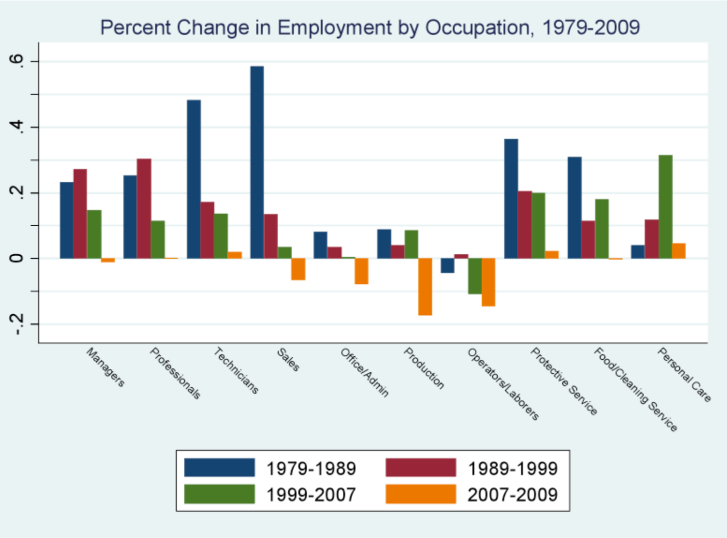
"The skill content of recent technological change: An empirical exploration." *The Quarterly Journal of Economics*, 118(4), 1279–1333.

- Jobs have different *task content*, so technology can be factor-augmenting or a substitute.
- Two kinds of labor: routine (L_R), and non-routine (L_N). Capital is perfectly substitutable for non-routine tasks:

$$F(R, N) = (L_R + C)^{1-\beta} L_N^{\beta}, \quad \beta \in (0, 1)$$

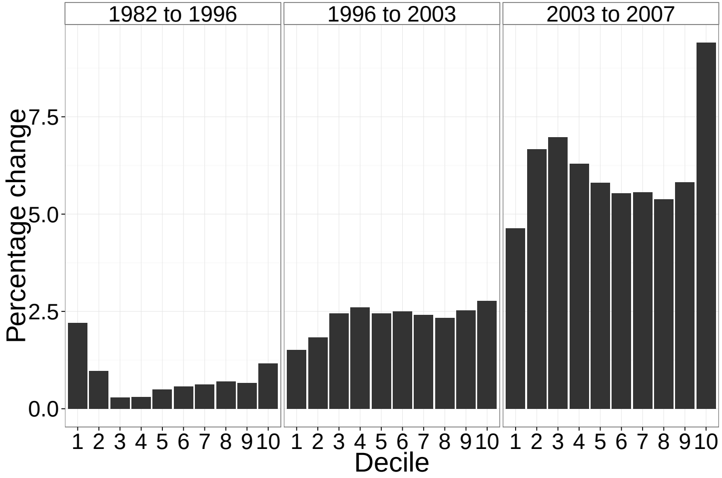
- Workers are endowed with a fixed set of skills, inelastically supply 1 unit of labor.
- 'Ricardian' model: assignment of workers to tasks is endogenous (as in Roy, 1951).

Job Polarization: United States



Percentage change in employment level, by occupation group, USA, 1979-2009 (Acemoglu & Autor, 2011)

Income growth, Australia, 1981-82 to 2007-08



Average annual percentage change in real equivalent income unit income, working age (Whiteford, 2012)

This Project

1. Has employment in Australia polarized in terms of routine and non-routine tasks as it has overseas?
    - If not, why is Australia special?
2. Does ICT capital investment or off-shoring explain this trend?

Data

1. O*NET: Occupational task database
    - Developed by US Department of Labor
    - Detailed break-down of work activities by occupation
2. David Autor's work type data categories
    - Mapping to O*NET tasks
    - "Routine" and "Non-routine"
    - "Off-shorable"
3. Australian Bureau of Statistics
    - Labor Force Survey (LFS)
    - Survey of Income and Housing
    - Census of Population and Housing
    - National accounts: ICT and Machinery investment, capital stock

Imputing Worker Activities from O*NET

Assume we have N Australian occupations and M industries. In the O*NET dataset, we have K occupations, and L activities.

1. Employment by occupations and industry, is $\underset{M\times N}{\mathbf{\Omega}}$.
2. Define an occupation equivalence matrix, $\underset{N\times K}{\mathbf{Z}}$, where

$$z_{n,k} = \begin{cases} 1 & \text{if US occupation } n \text{ is equivalent to } k \\ 0 & \text{otherwise.} \end{cases}$$

3. O*NET activity weights by US occupation are $\underset{K\times L}{\mathbf{\Psi}}$.
4. Then employment of worker activities is:

$$\underset{M\times L}{\mathbf{Q}} = \mathbf{\Omega}\ \mathbf{Z}\ \mathbf{\Psi}$$

5. $\mathbf{Q}$ can be further weighted for routine, non-routine and off-shorable labor.

Identification Challenge

- Employment is an outcome of supply and demand.
- But supply and demand curves are unobservable.
- However, wage quantiles *are* observable.
- Firpo, Fortin, and Lemieux (2011) exploit quantile regression to analyze changes in labor demand.

Questions?

References

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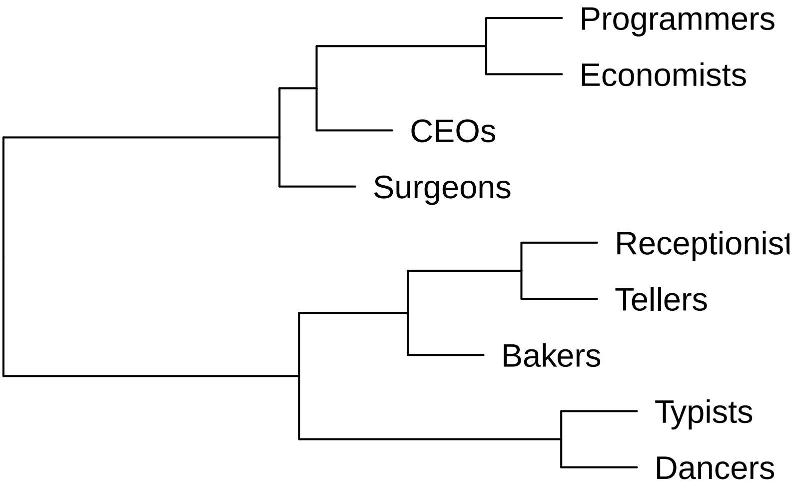
O*NET Data Example

Job Title	Gather Data	Analyze Data	Think Creatively	Handle Moving Objects
CEOs	5.03	4.82	5.1	1.1
Economists	5.88	6.58	5.38	0.54
Dancers	3.88	1.96	4.37	2.63
Programmers	4.91	5.05	5.96	0.44
Tellers	2.91	2.65	2.21	2.74
Surgeons	5.72	5.49	4.67	3.62
Bakers	2.8	3.29	2.93	5.06
Receptionists	3.1	2.45	2.54	2.88
Typists	4.35	1.52	3.9	1.43

Table : O*NET Work Activity Example (Levels, Scale 0–7)

O*NET Data Example



Hierarchical cluster analysis by work activity Eucledian distance.