Tasks and Work Force Polarization

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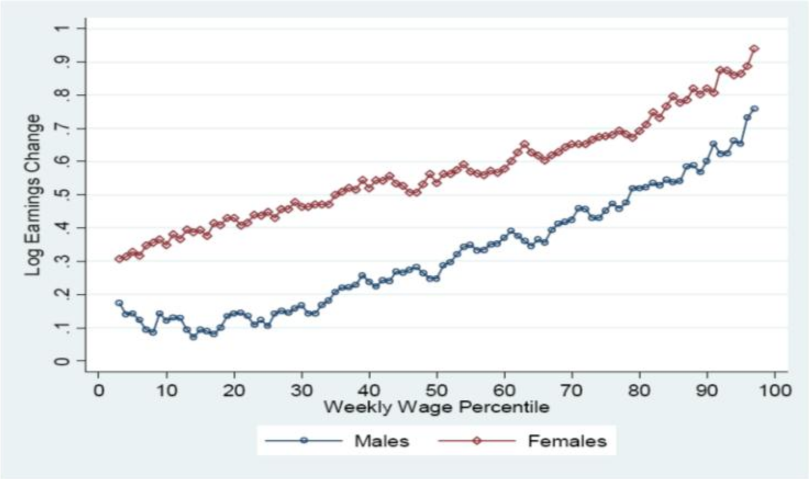
U.S. wage inequality has risen since the 1960s



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

The 'Canonical Model:' Skill-Based Technical Change

- Model features:
  - Two kinds of labor, high-skill (H) and low-skill (L).
  - H and L are different, and imperfect productive substitutes.
  - Technology *factor-augmenting*: raises productivity/wages.
  - Wages set on the demand curve
- Production function representation:

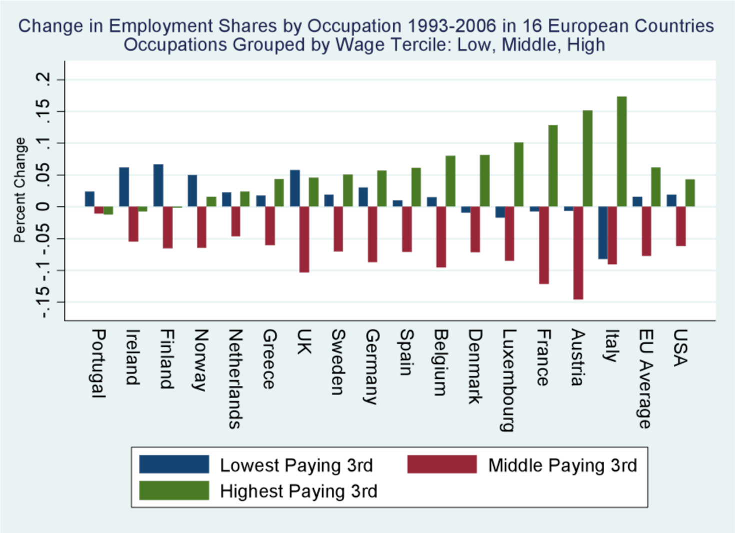
$$F(L,H) = \left[(A_L L)^{\frac{\sigma-1}{\sigma}} + (A_H H)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{(\sigma-1)}}$$

- If $\sigma > 1$, (H, L substitutes), SBTC implies rise in A_H/A_L.

The ‘Canonical Model:’ Skill-Based Technical Change

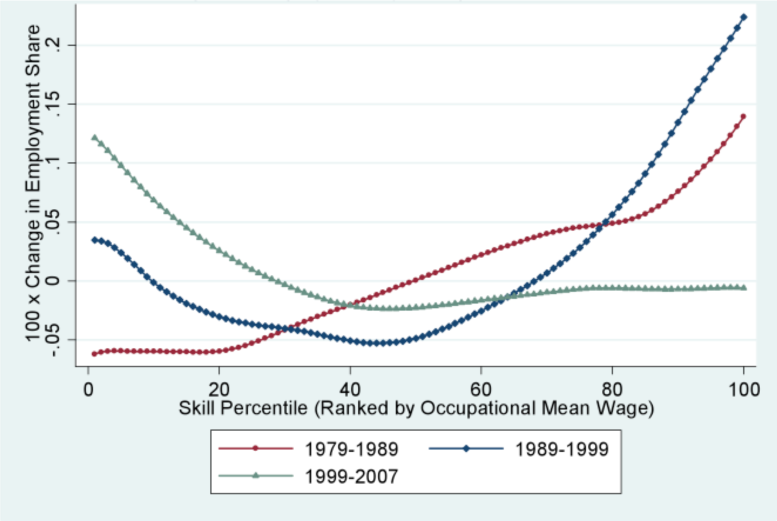
- Predicts
  - Increasing inequality, driven by skill demand.
  - Rising college/education premium.
  - Monotone wage growth in skills.
- Empirically successful, e.g.
  - Katz and Murphy (1992)
  - Card and Lemieux (2001)

International evidence of non-monotone wage growth



Wage growth by occupational wage tercile, 16 European countries (Acemoglu & Autor, 2011).

Non-monotone employment growth (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.

- 'Canonical' approach: factors produce output:

$$K, L \xrightarrow{F(\cdot)} Y.$$

- ALM: factors produce tasks, which produce output:

$$K, L \longrightarrow \text{tasks} \longrightarrow Y.$$

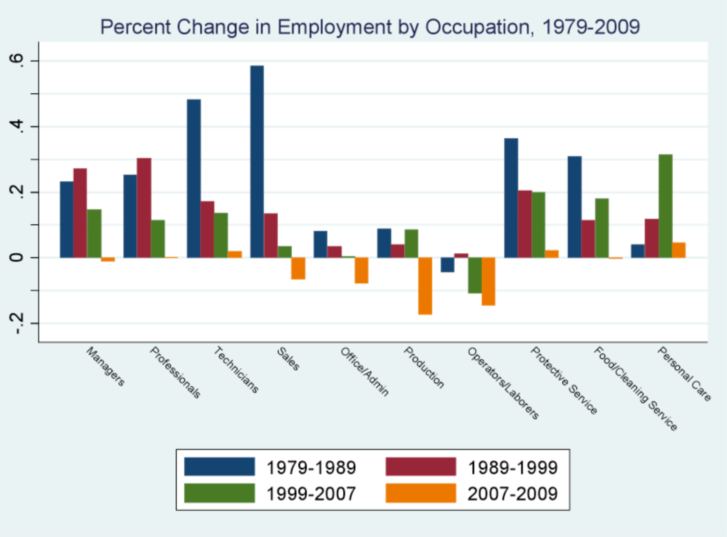
The Task Approach

- Jobs have different *task content*, so technology can be factor-augmenting or a substitute.
- Real cost of computing capital and machinery dramatically falling.
- Capital can substitute for only certain 'routine' tasks.
- Model:
  - Two kinds of tasks: routine (L_R), and non-routine (L_N). Capital C and L_R perfectly substitutable:

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

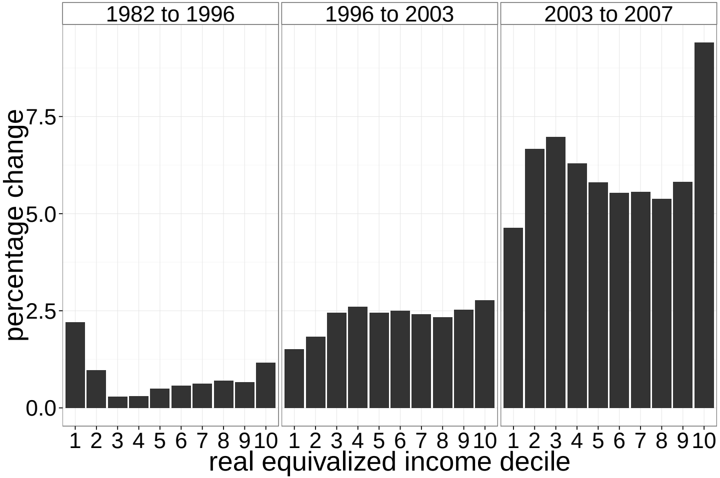
  - Workers are endowed with a fixed 'skills'
  - Workers choose tasks they will supply endogenously
- Predictions: non-routine employment and wage growth exceeds that of routine employment

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: Questions

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 explain this trend?

Data

1. O*NET: Occupational task database
   - Developed by US Department of Labor
   - Details work activities by occupation
2. David Autor's work type data categories
   - Routine/non-routine and 'off-shoreable'
3. Australian Bureau of Statistics: Employment, Wages, Capital Investment
   - 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

ABS data: N Australian occupations and M industries.
O*NET: K occupations, L activities.

1. Employment by occupations and industry, is $\underset{M\times N}{\mathbf{\Omega}_t}$.
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:

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

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

Questions

and

I'd love your feedback.

References

Acemoglu, D., & Autor, D. H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In D. Card & O. Ashenfelter (Eds.), *Handbook of labor economics, volume 4, part b* (Chap. 12, Vol. Volume 4, pp. 1043–1171). Elsevier

Autor, D. H., Katz, L. F., & Kearney, M. S. (2008). "Trends in US wage inequality: Revising the revisionists." *The Review of Economics and Statistics*, *90*(2), 300–323.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). "The skill content of recent technological change: An empirical exploration." *The Quarterly Journal of Economics*, *118*(4), 1279–1333.

Card, D., & Lemieux, T. (2001, May). "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis." *The Quarterly Journal of Economics*, *116*(2), 705–746

Firpo, S., Fortin, N., & Lemieux, T. (2011). *Occupational tasks and changes in the wage structure*. Institute for the Study of Labor.

Katz, & Murphy, K. J. (1992). "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." *Quarterly Journal of Economics*, *107*, 35–78.

Roy, A. D. (1951, June). "Some Thoughts on the Distribution of Earnings." *Oxford Economic Papers*. New Series, *3*(2),

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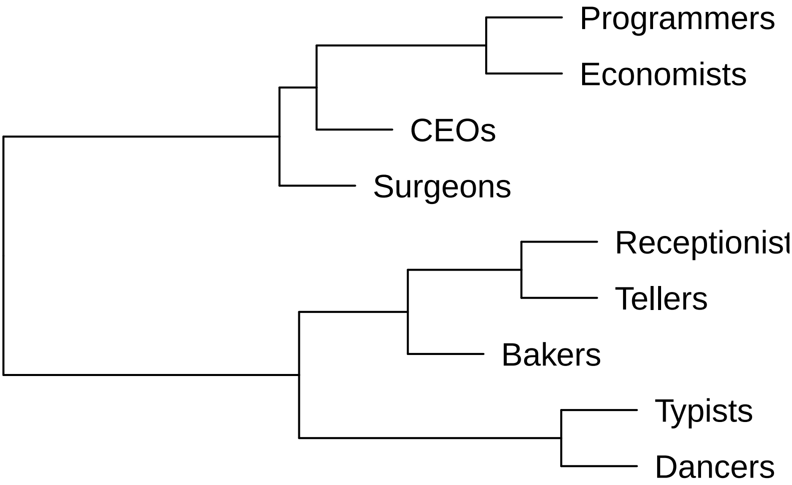
O*NET Data Example

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

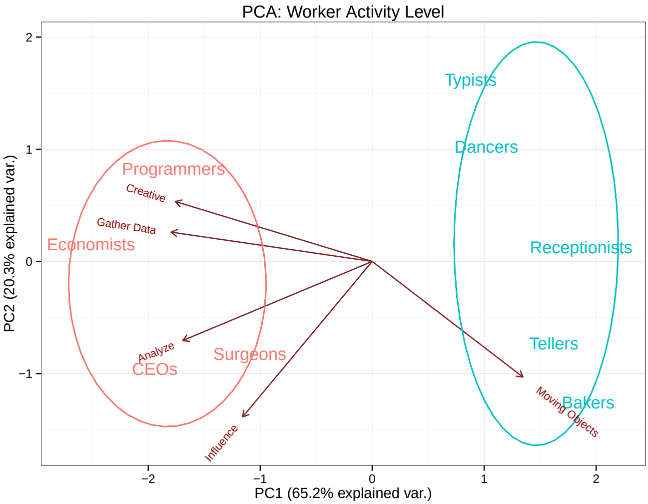
Table : O*NET Work Activity Example (Levels, Scale 0–7)

O*NET Data Example: Dendrogram



Hierarchical cluster analysis, work activity (Eucledian distance)

O*NET Data Example: PCA



Groups identified with k-means cluster analysis (k=2).

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.