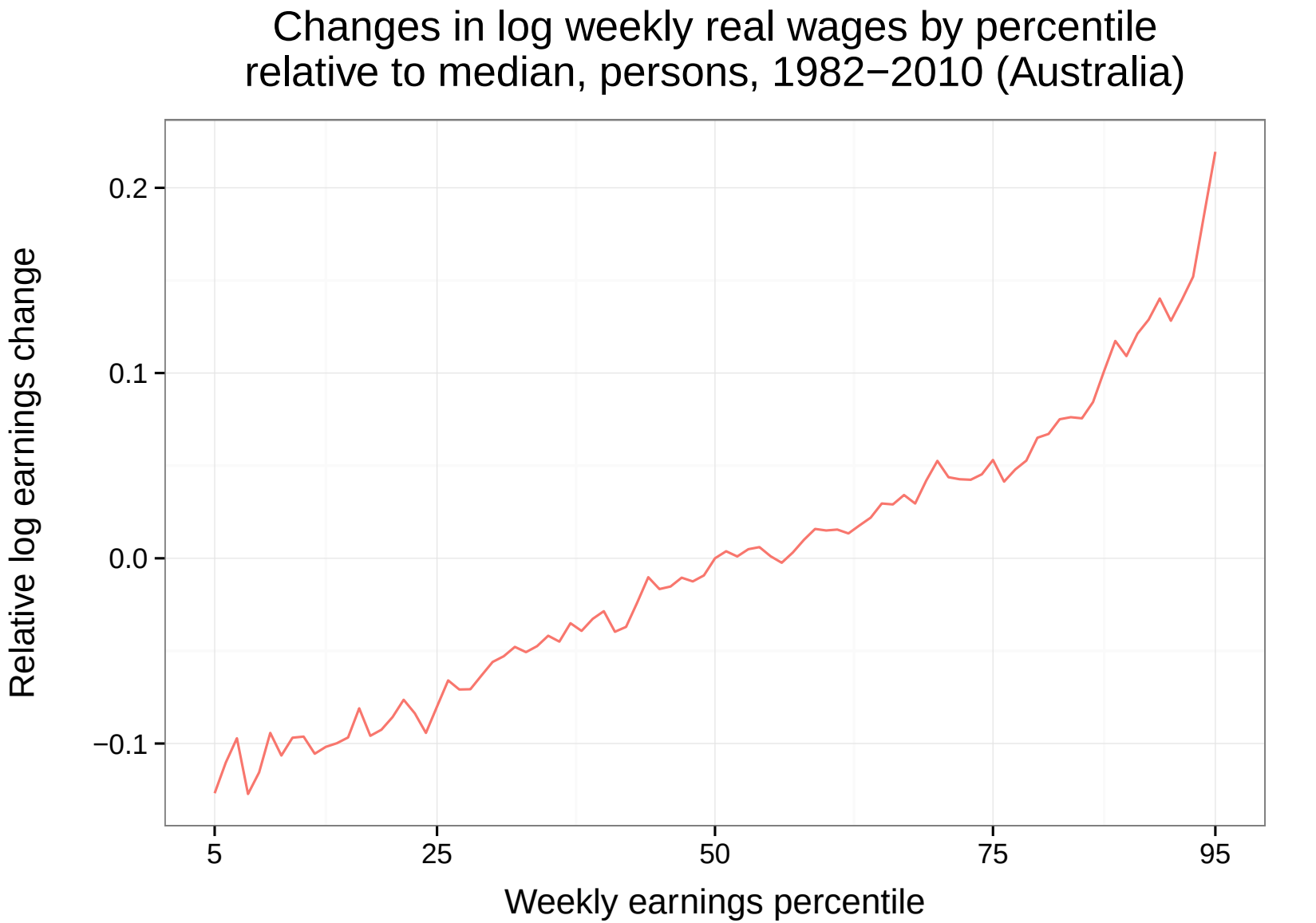
Is Technology Polarising Australia's Work Force?

Alex Cooper
Honours Candidate
Macquarie University

August 2013

Wage inequality has risen since the 1980s

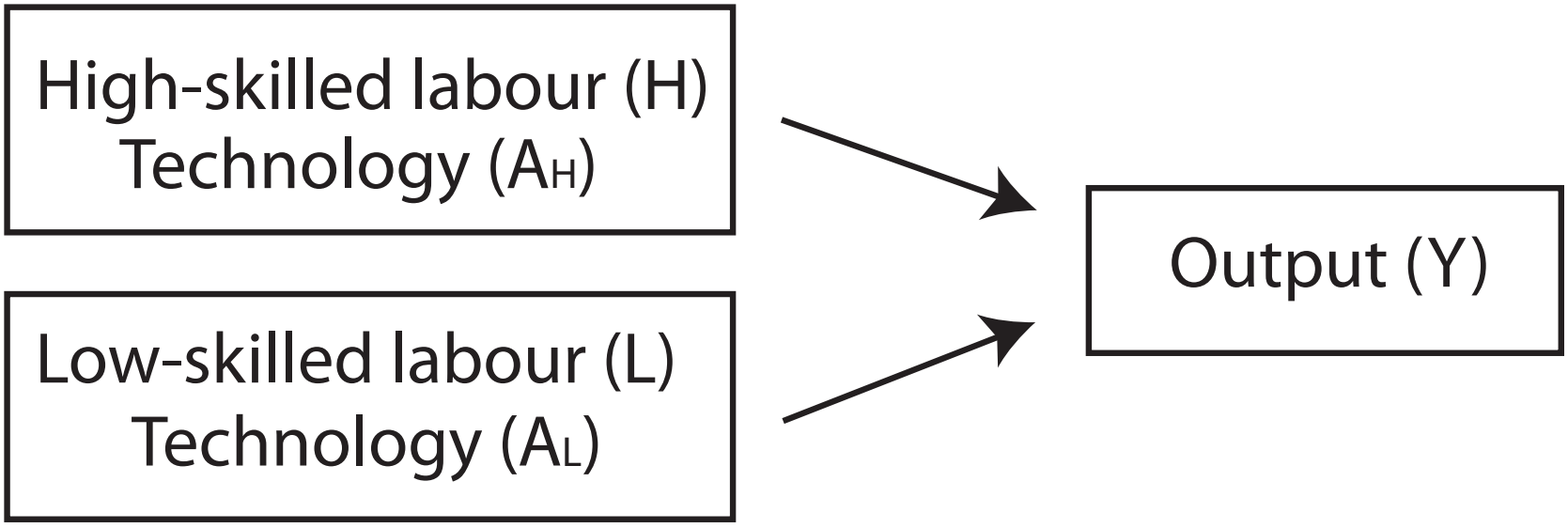


Does technological change explain rising inequality?

Three approaches:

1. The 'canonical' model: skill-biased technical change (SBTC)
2. Are labour and technology substitutes?
3. A new approach: jobs and tasks

The 'canonical model:' skill-biased technical change



Production function:

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

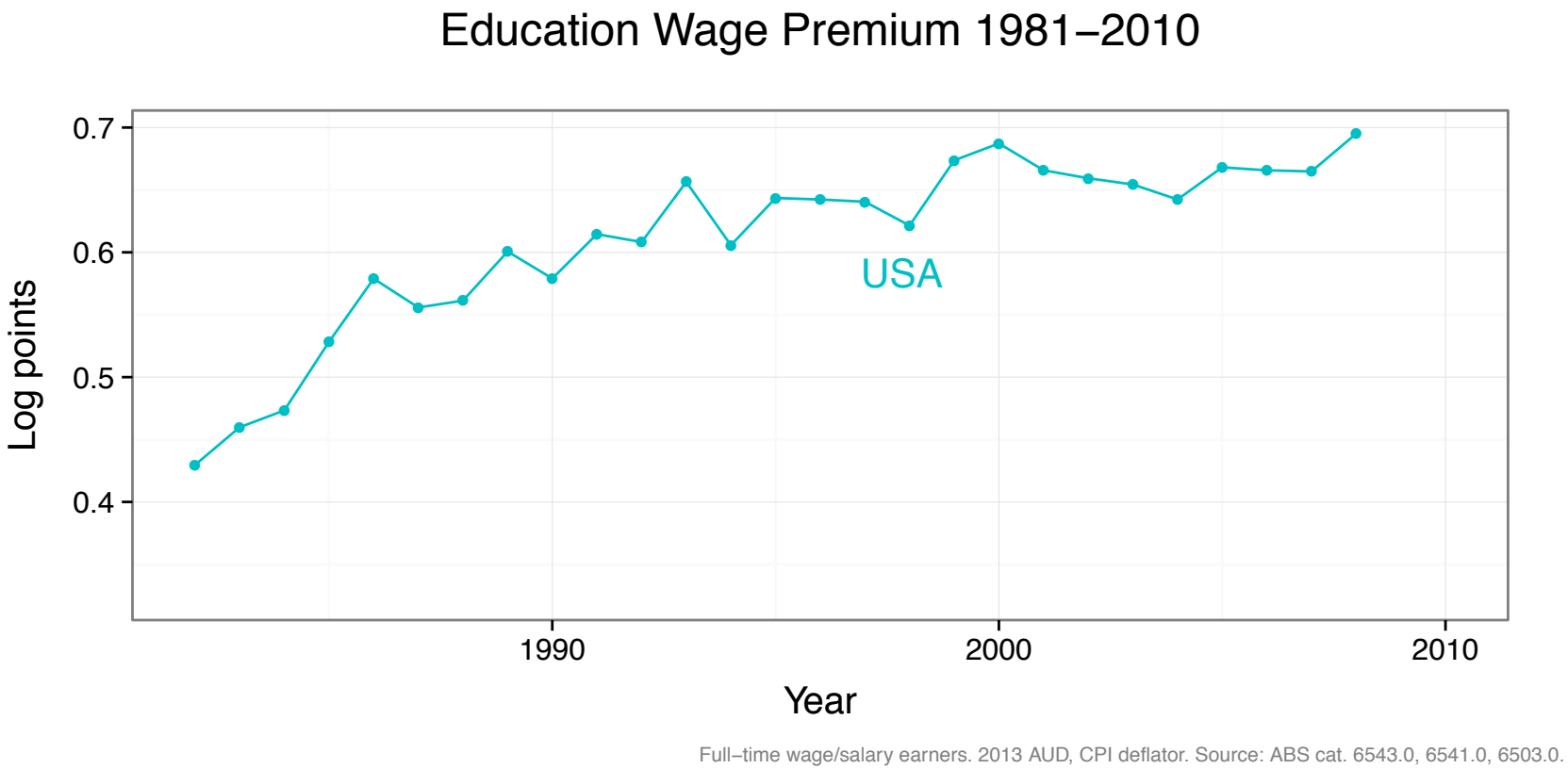
If $\sigma > 1$, SBTC implies rise in the skill premium.

The 'canonical model:' skill-biased technical change

- Predicts
  - Increasing inequality, driven by skill demand.
  - Rising college/education premium.
  - Monotone wage growth in skills.

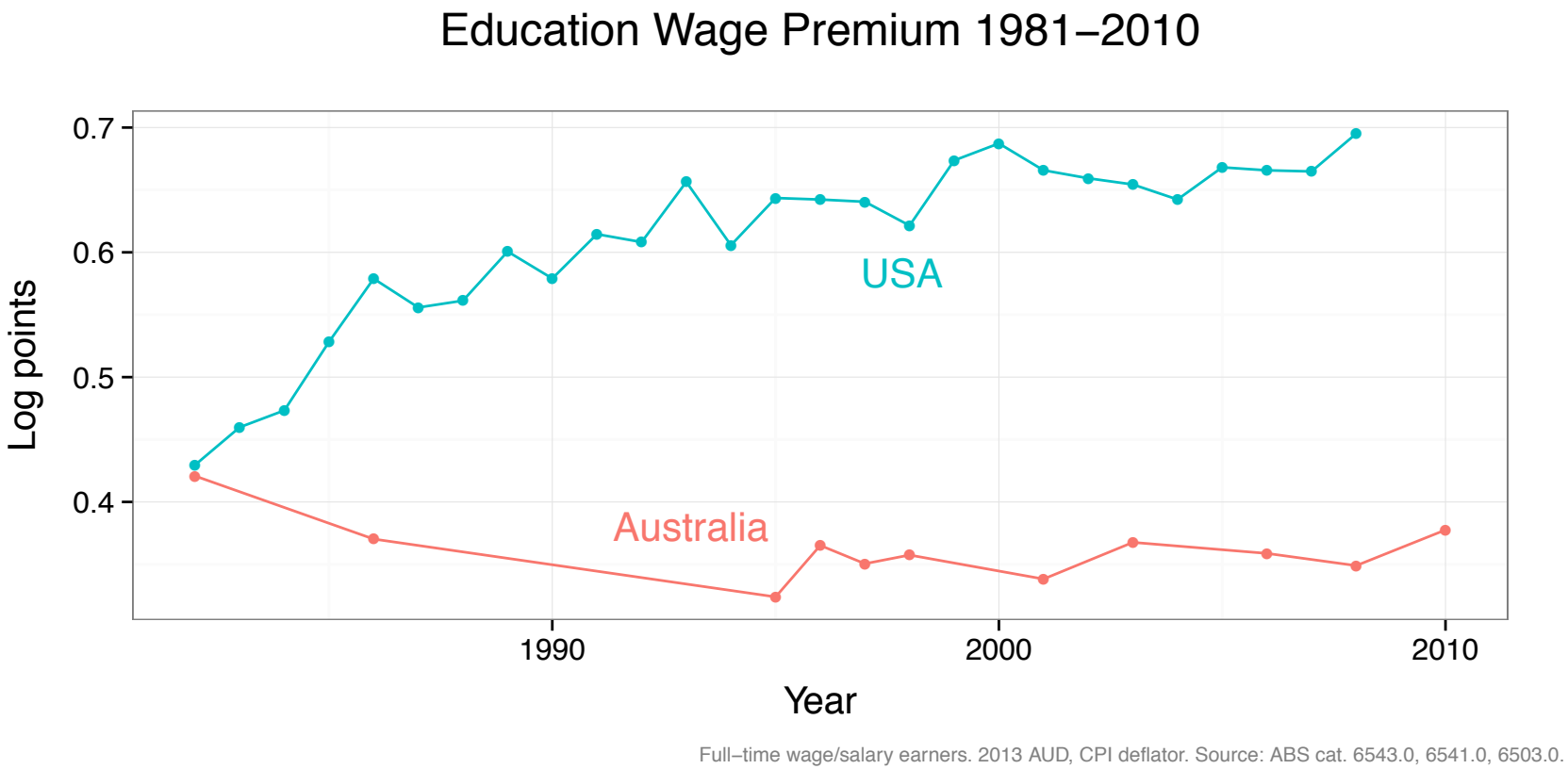
- Empirically successful, e.g.
  - **Katz1992**
  - **Card2001**

College wage premium



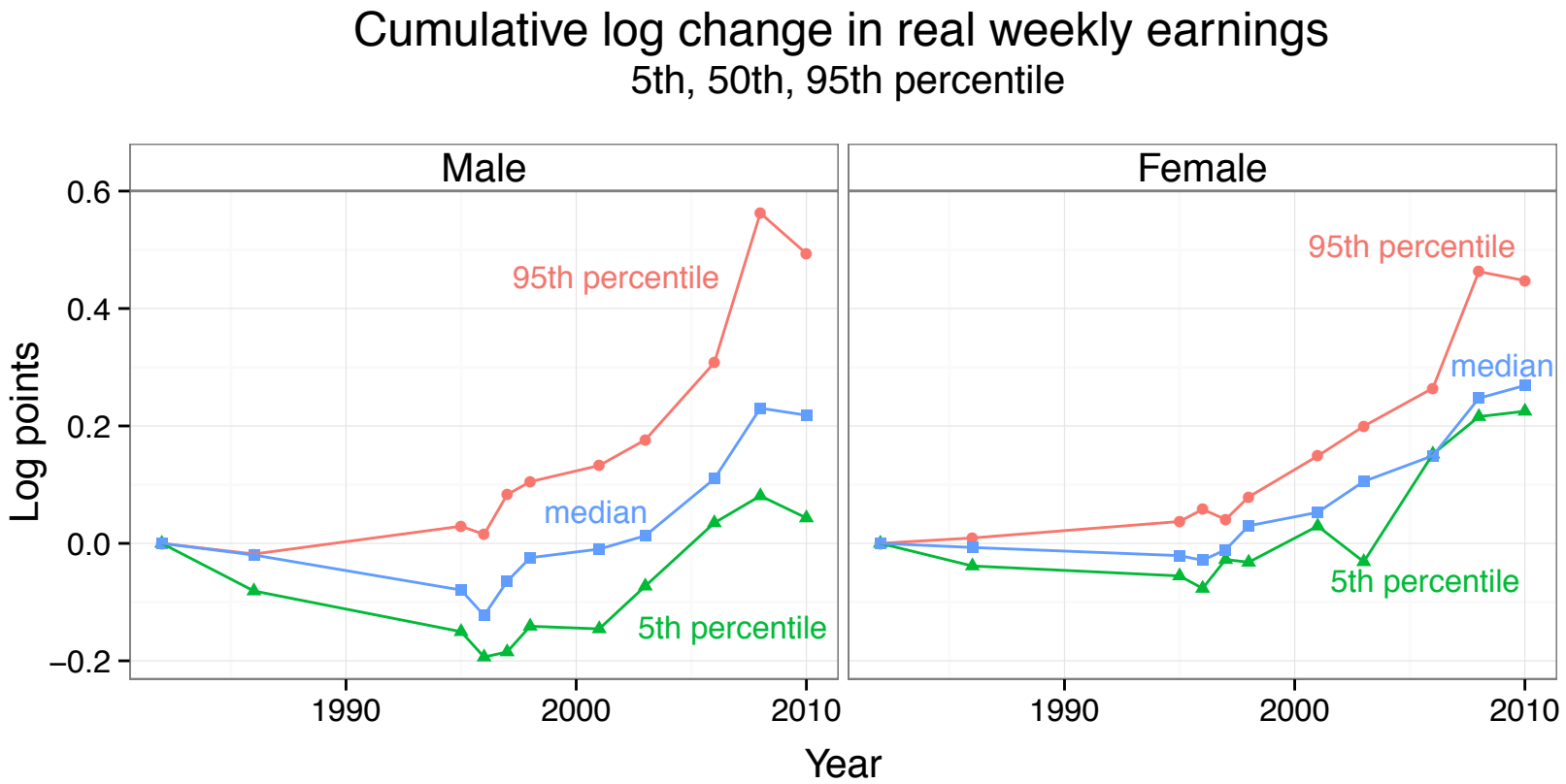
USA Data: Acemoglu & Autor (2011)

College wage premium



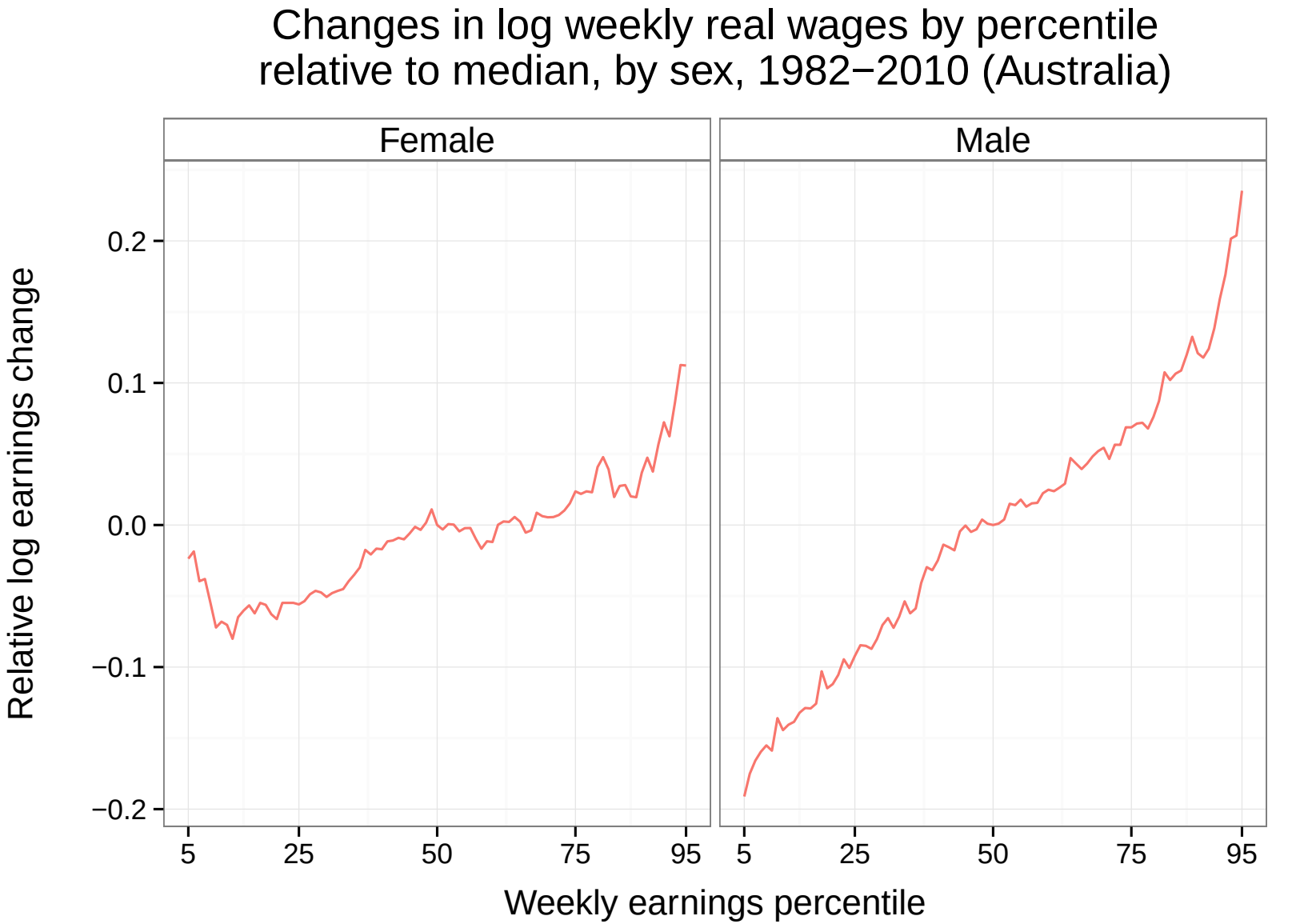
USA Data: Acemoglu & Autor (2011)

Non-monotone wage growth in time



Full–time wage/salary earners. 2013 AUD, CPI deflator. Source: ABS cat. 6543.0, 6541.0, 6503.0.

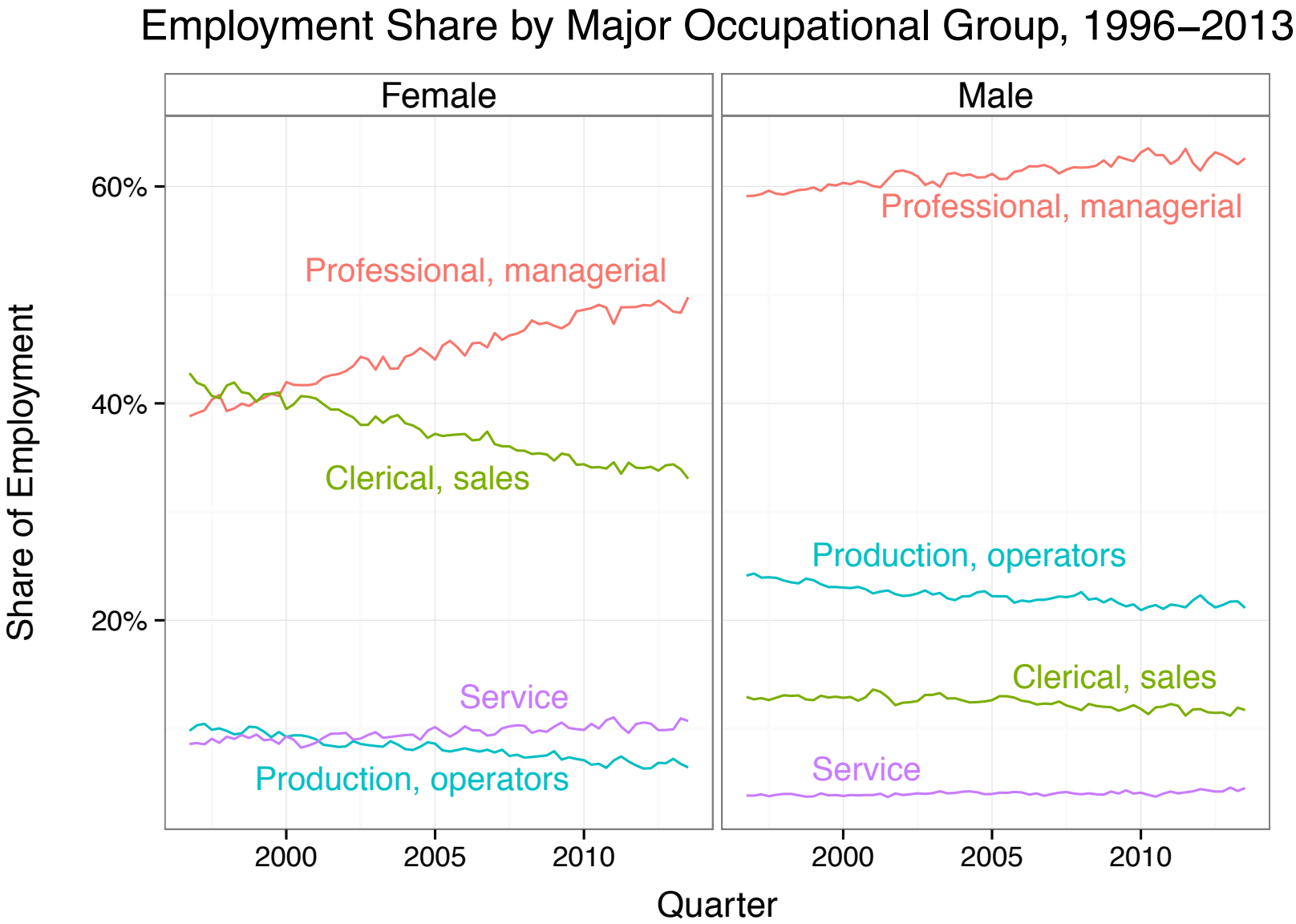
Wage growth by wage percentile and sex



Failure of the SBTC model: summary

- No clear 'college premium' in Australia (see Coelli 2007)
  - Education a poor proxy for skills ('credentialism')?
  - Expanding supply of college-educated workers?
  - Does not appear to be driving inequality trend
- Wage growth is non-monotone
- Non-monotone wage growth across earnings spectrum
- Despite composition adjustment, male and female wage profiles differ

Could job polarisation explain the trend?



The 'task approach'

Autor, Levy, and Murnane (QJE 2003)

- Recall 'canonical' approach: factors produce output via production function F

$$\text{capital, labour} \xrightarrow{F} \text{output.}$$

  - Technology is factor-augmenting (labour and capital complements)

- ALM: factors produce tasks, which produce output:

$$\text{capital, labour} \longrightarrow \text{tasks} \xrightarrow{F} \text{output.}$$

  - Technology can be complementary or a substitute

The 'task approach'

- Jobs have different task content
- Capital can substitute for only certain 'routine' tasks.
  - Typically 'middle-skill,' like clerical work
- Michaels *et al* (2013) expand the canonical model with 'middle-skilled' labour
  - Three kinds of labour: H, M, L, and ICT capital C.
  - Capital C and M are perfect substitutes
  - Middle-skilled workers compete with ICT capital

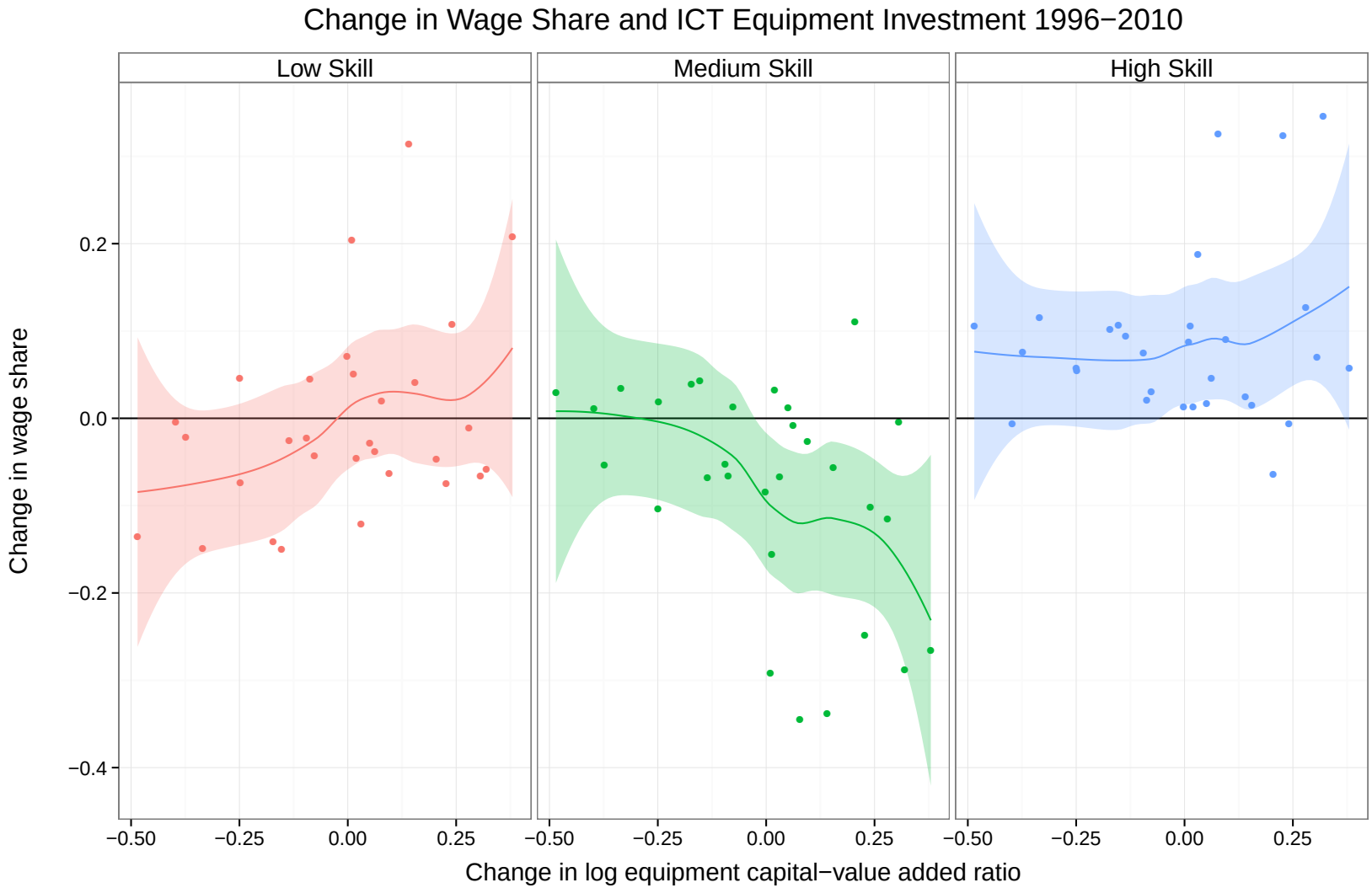
A simple test (Michaels *et al.* 2013)

Production function with three types of labour and ICT capital C:

$$Y = \left[\underbrace{(A_L L)^{\frac{\sigma-1}{\sigma}}}_{\text{low}} + \underbrace{(A_M M + C)^{\frac{\sigma-1}{\sigma}}}_{\text{medium}} + \underbrace{\left((A_H H)^{\mu} + C^{\mu}\right)^{\frac{\sigma-1}{\mu\sigma}}}_{\text{high}} \right]^{\frac{1}{\sigma-1}}$$

- Comparative statics: if C increases exogenously, then:
  - high wage share should increase, and
  - medium wage share should decrease.
- We form three groups of occupations:
  - High-skilled—managers and professionals
  - Middle-skilled—clerical and sales workers
  - Low-skilled—labourers, tradespersons, transport workers
- For each industry we compute:
  - Skill group wage share (Survey of Income and Housing)
  - ICT capital stock/value added ratio (National Accounts)

ICT capital (equipment) and wage shares by group



Problems with this result

- Model gives only *wage share*, not *wage*
- ICT investment endogenous, with no obvious instruments
- Tests have low power
  - few industry groups
  - occupational groupings too simplistic
- Conflicting results with other ICT capital measures (software, computer peripherals)
- No obvious way to deflate ICT capital for consistent comparison

A more sophisticated approach

Following Firpo, Fortin, & Lemieux (2011),

- Labour market as Roy model
  - Self-selection into occupations by comparative advantage
- Assume that ICT investment reduces demand for 'routine' and 'off-shoreable' occupations
- For these occupations, we predict:
  - high-quality workers self-select out of these occupations
  - a wage compression in these occupations at higher quantiles

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'
   - Manually mapped to ANZSCO categories
3. Australian Bureau of Statistics
   - Census of Population and Housing for wages and occupations

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)

Summary

- Skill-biased technical change does not appear to explain widening inequality in Australia
- Changes in occupational composition seem important
- Correlation between 'polarisation' and ICT capital
- Further work will focus on changes in wage structure and 'task content' of jobs

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. 10431171). Elsevier

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), 12791333.

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), 705746

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, 3578.

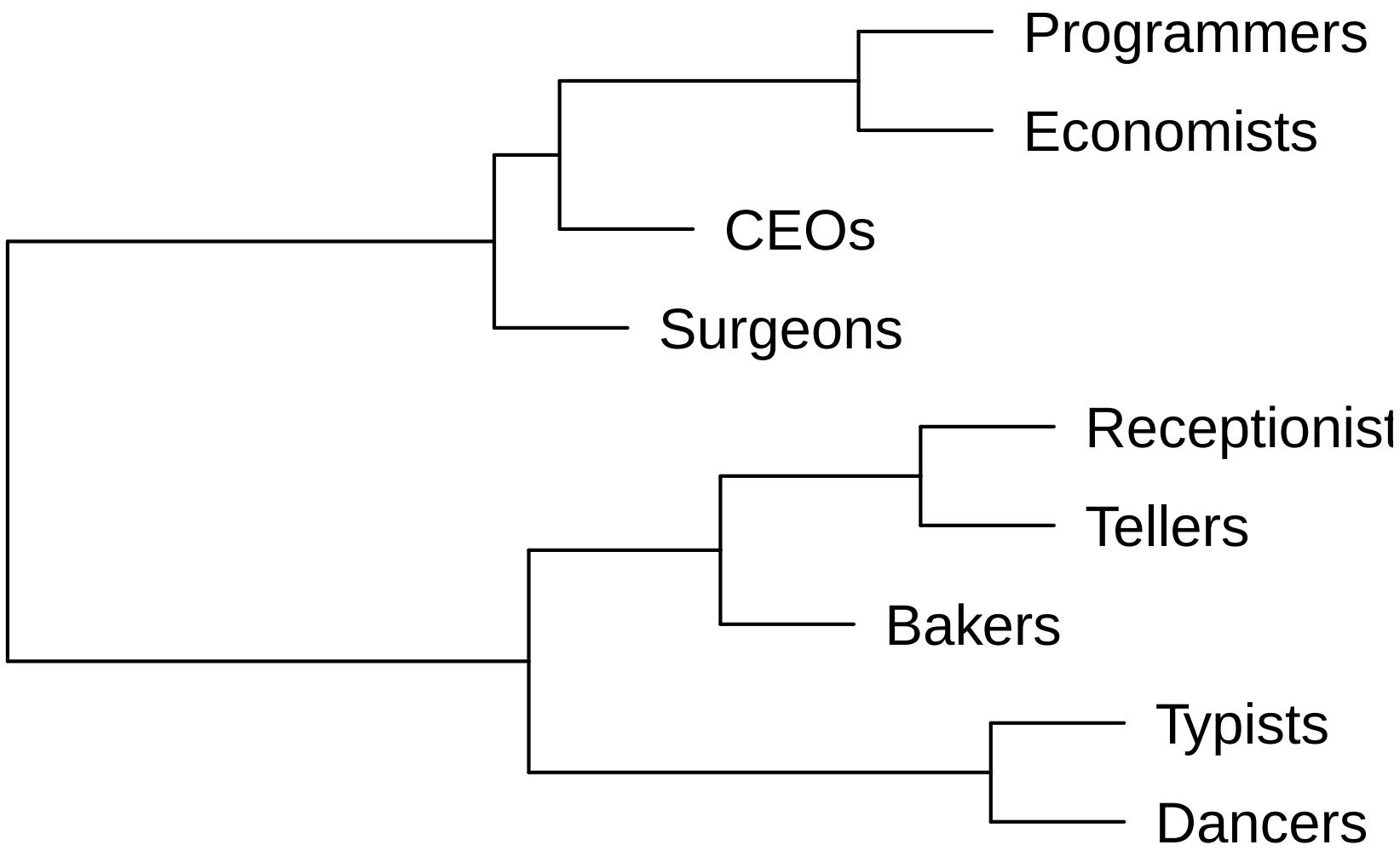
Spare Slides

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

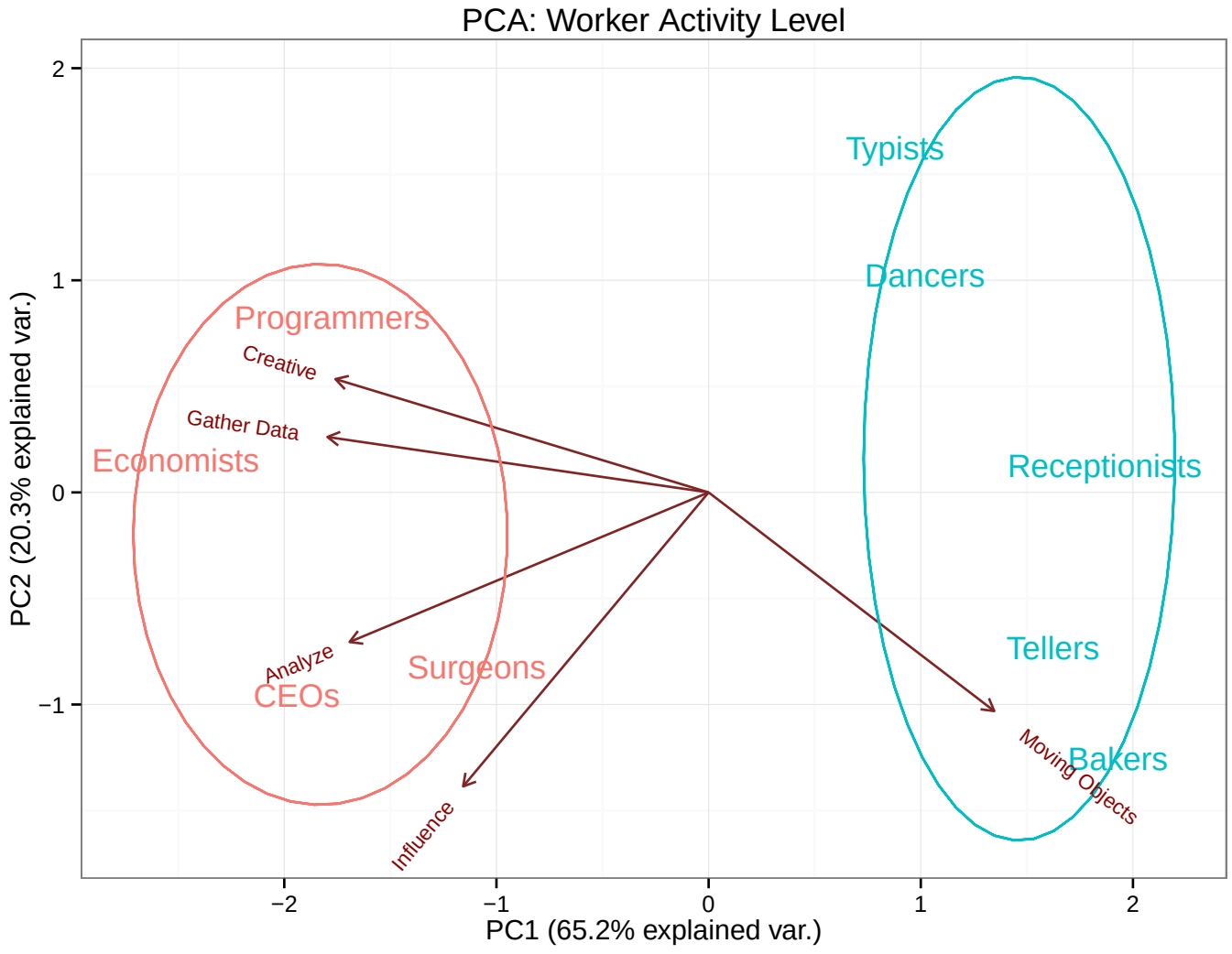
Table : O*NET Work Activity Example (Levels, Scale 0–7)

O*NET Data Example: Dendrogram



Hierarchical cluster analysis, work activity (Euclidean distance)

O*NET Data Example: PCA



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

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

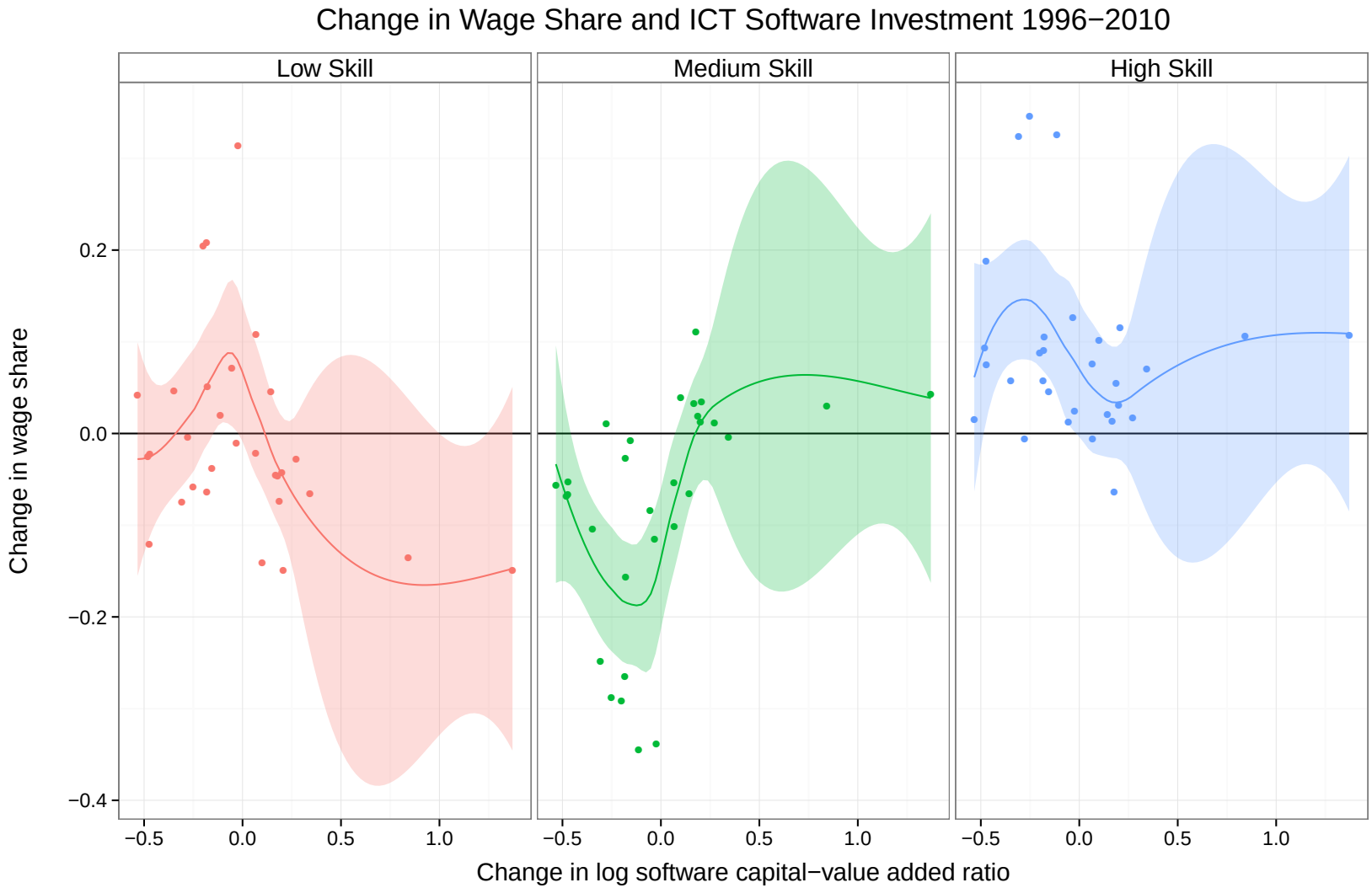
$$z_{n,k} = \begin{cases} 1 & \text{if US occupation } n \text{ is equivalent to } k \\ 0 & \text{otherwise.} \end{cases}$$

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-shoreable labour.

ICT capital (software) and wage shares



ICT capital (computers and peripherals) and wage shares