Occupational polarisation and endogenous task-biased technical change

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Introduction

- Job polarisation: employment has shifted substantially from middle-paying occupations to both the top and the bottom.
  - Observed in many developed countries since the 90s;
  - The most popular explanation is Routine Biased Technical Change (RBTC).
- Complementary explanation: increasing supply of skills and endogenous adoption of technology
  - Exploit the large policy-driven expansion of HE in the UK
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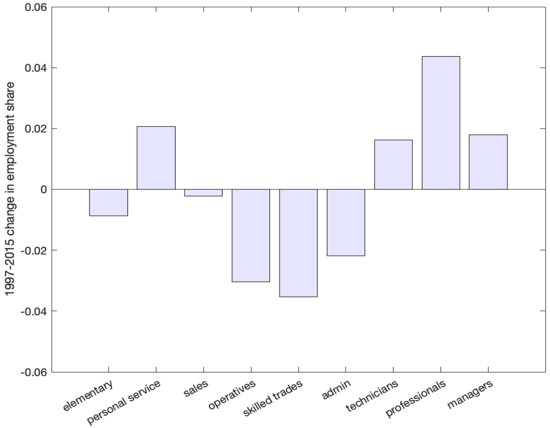

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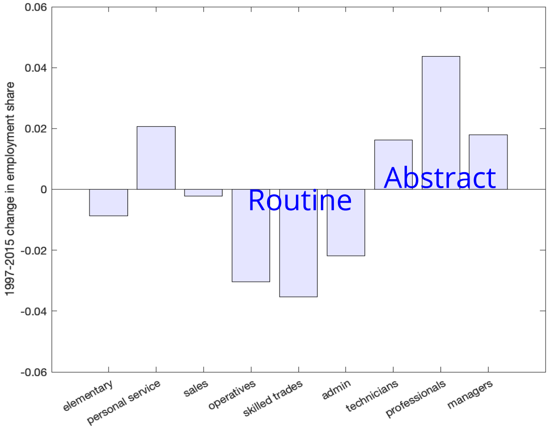

Note: In each year, we regress log wages on gender-age interactions, detailed education, and occupation dummies. The coefficients on occupation dummies form our ’composition-adjusted’ occupational wage data $\log P_{jt}$. We then smoothed over the discontinuities in 2000-1 and 2010-11 by estimating a 5th order polynomial in $\log P_{jt}$ for each j.

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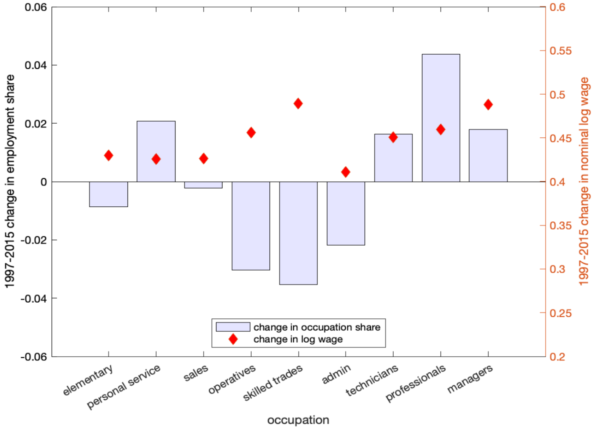
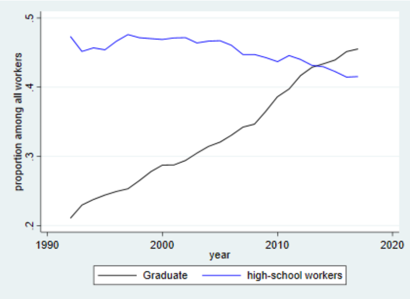


Increasing education and little occupational downgrading



Note: 'graduate' means having at least higher education qualifications (bachelors, NVQ level 4), 'high-school' refers to those with secondary school qualifications such as A-levels, O-Levels, GCSE C+ (NVQ levels 2 and 3). 'abstract' refers to the first three SOC2000 occupation groups: managerial, professional and technicians.
The 'counterfactual' asks if the aggregate share of abstract jobs were to remain constant while the education composition shifted as in reality, how much do the education-specific abstract share need to fall?

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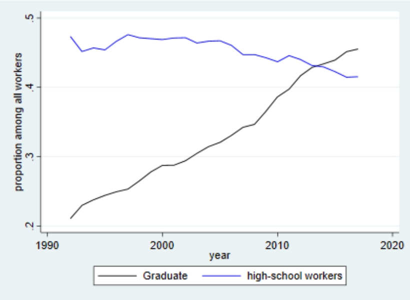

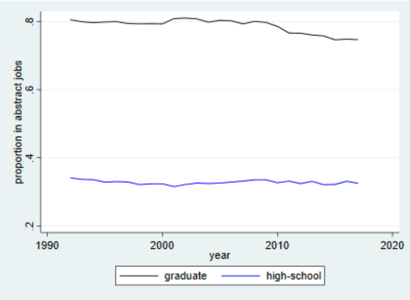

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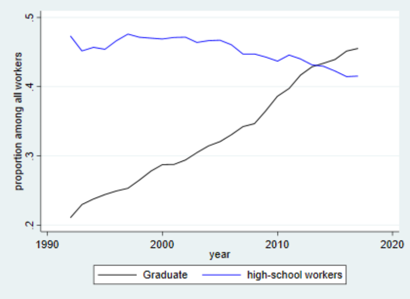

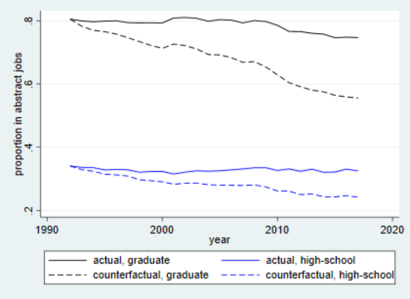

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2. Quantify the contributions of three factors to job polarisation:
1) Skill supply shifts, 2) between-industry demand shifts, 3) RBTC within industries

Related literatures

- Polarisation:
  - attributes job polarisation to RBTC
    Autor et al. (2003), Acemoglu and Autor (2011), Autor and Dorn (2013),Goos et al. (2014), Goos and Manning (2007),...
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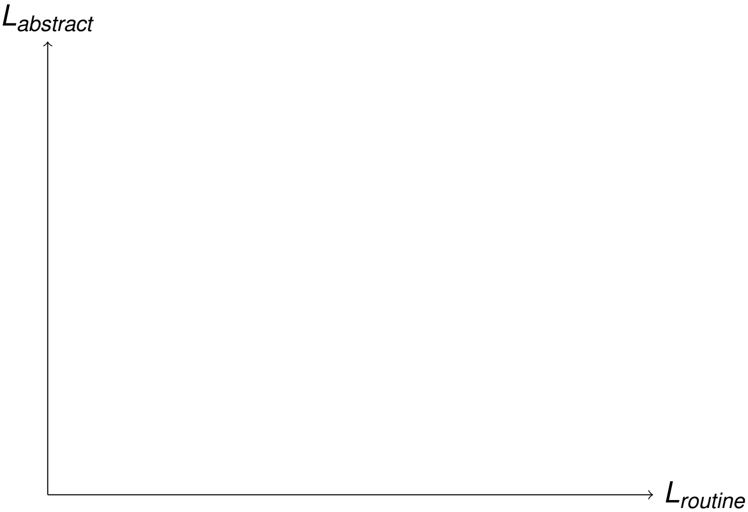
- Endogenous technical change:
  - directed innovations: Acemoglu (1998, 2002)... Acemoglu and Restrepo (2018),
  - adoption of technologies: Beaudry et al. (2010), Lewis (2011), Akerman et al. (2015),... Carneiro et al. (2018), Blundell et al. (2022) link

Roadmap

- Three Facts
- Model (Intuition, full model)
- Data sources and model identification
- Corroborative evidence
- Estimation methods
- Results and Counterfactual analysis
- Summary

Intuition

Simplified Model: Two tasks and Two Technologies



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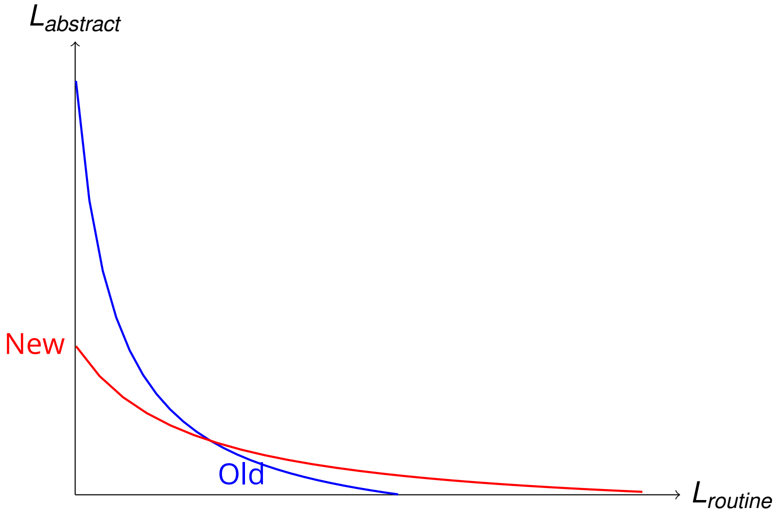

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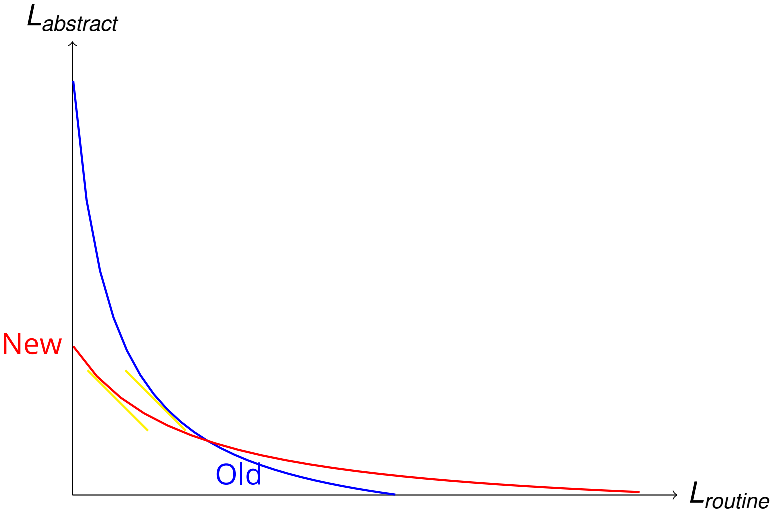

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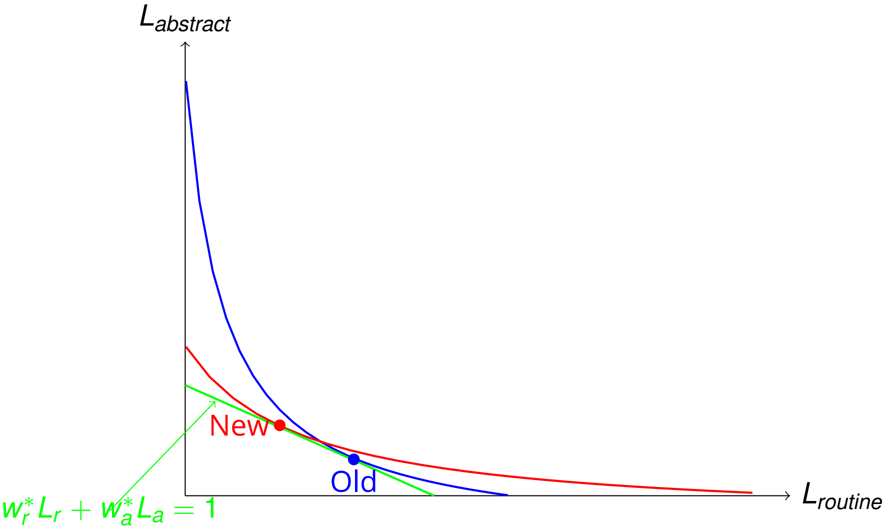

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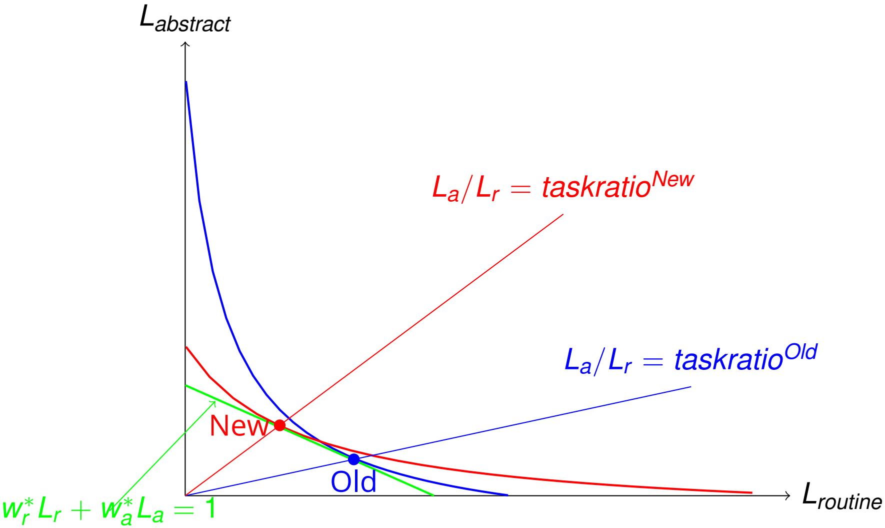

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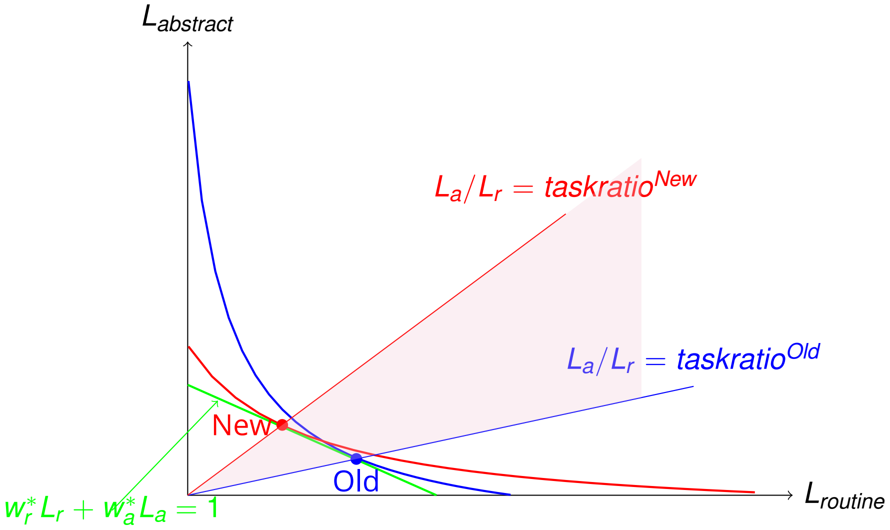

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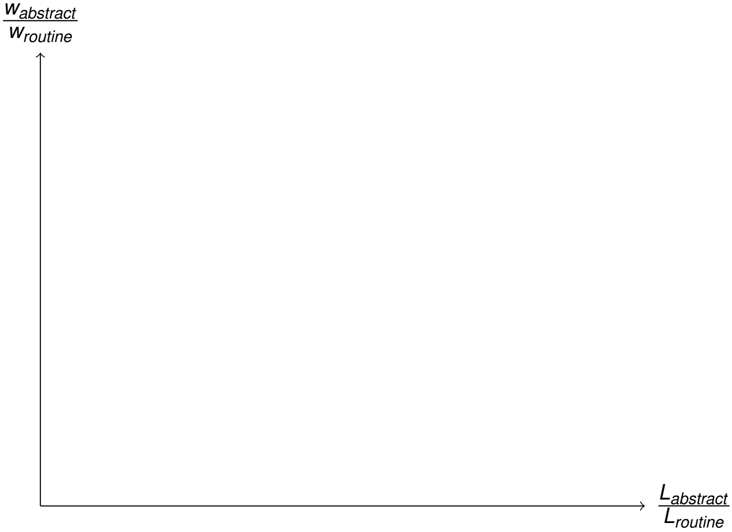
Simplified Model: demand curve



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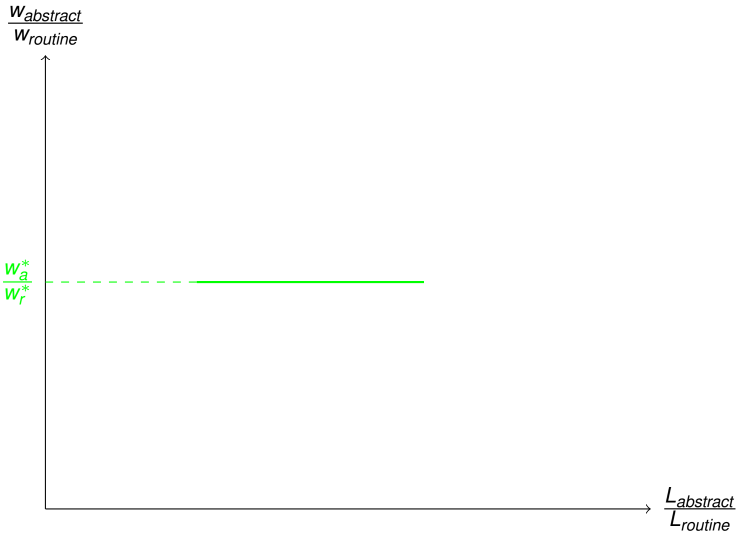

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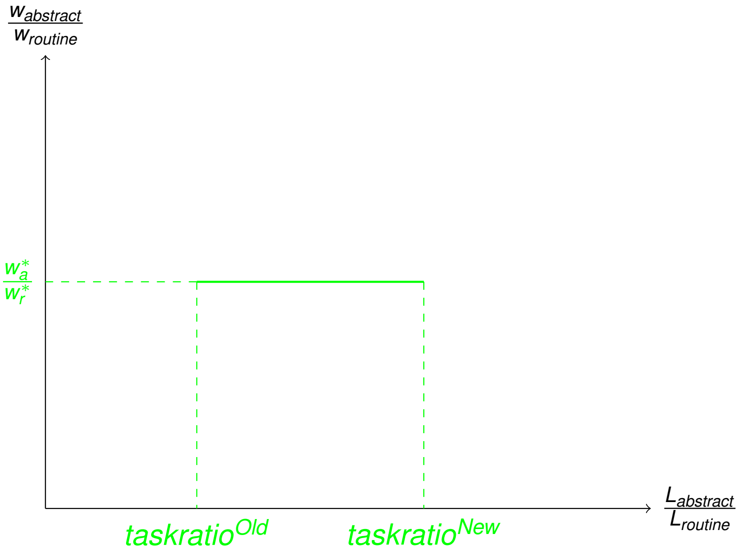

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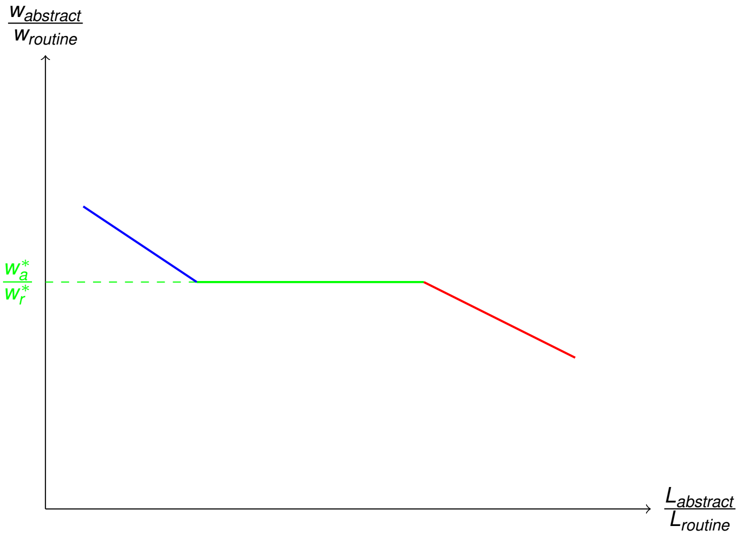

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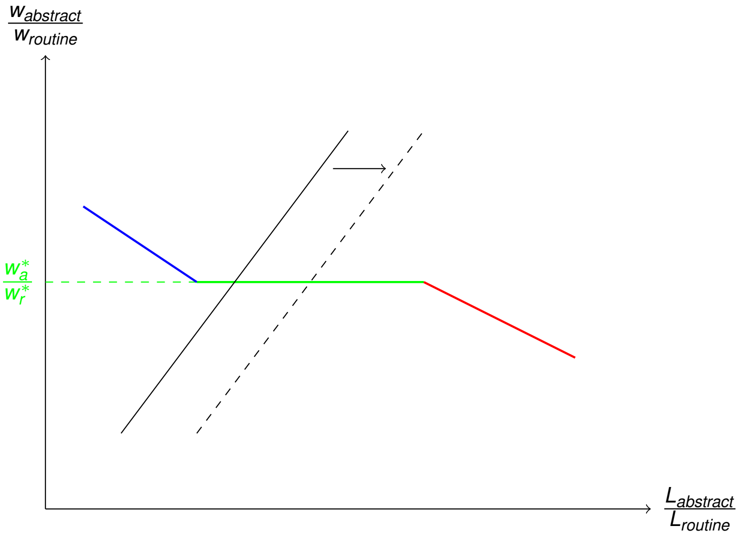
$\frac{w_{abstract}}{w_{routine}}$
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The Full Model - overview

- There are 9 tasks $j = 1, 2...9$ and 7 industries $g = 1, 2...7$. In each industry, firms choose between 2 technologies.
- Many points of relative task prices will be consistent with both technologies being adopted in all industries.

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- Static, Frictionless, Competitive markets

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- Between-industry demand shifts are exogenous.

Model prediction

Firms' F.O.C. $\Rightarrow$

$$\log\left(\frac{p_{jt}}{p_{1t}}\right) = (\rho - 1)\log\frac{EMP_{gjt}}{EMP_{g1t}} + (1-\rho)\log\left[(1-w_{gt})\left(\frac{\alpha^{O}_{gj}}{\alpha^{O}_{g1}}\right)^{\frac{1}{1-\rho}} + w_{gt}\left(\frac{\alpha^{N}_{gj}}{\alpha^{N}_{g1}}\right)^{\frac{1}{1-\rho}}\right] \tag{3}$$

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- w_{gt} is the share of new technology in industry g at time t.

w_{gt} moves endogenously. The movement in the 2nd term attenuates the impact of labour supply shift on relative wages. details

jump to identification

The Model - Supply side

Worker i in occupation j produces task output

$$y(i,j) = k_j e^{\beta_{aj} a_i + \beta_{sj} s_i + \mu_i} \tag{4}$$

where a_i, s_i are two observable skills that determine comparative advantage, μ_i is unobserved general ability.

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The utility worker i gets from occupation j is

$$U_{ij} = \ln(y(i,j)p_j) + \eta_j + e_{ij}, \quad j = 1, ...J \tag{5}$$

where e_{ij} follows iid Type-1 extreme value distribution, with location parameter at 0 and scale parameter ζ. η_j is job amenity in occupation j.

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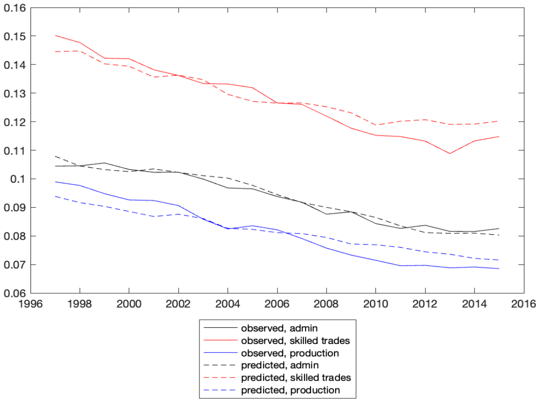
$\Rightarrow$ The probability of worker i choosing any occupation is simply a function of (a_i, s_i) and task prices. details

jump to identification

Model fit

Figure: routine occupations employment shares



We achieve a good fit for EMP_{jt}, $\log P_{jt}$, w_{gt}, $\log P_{gt}$, $\forall g, \forall j$ over $1997 \leq t \leq 2015$. more figures

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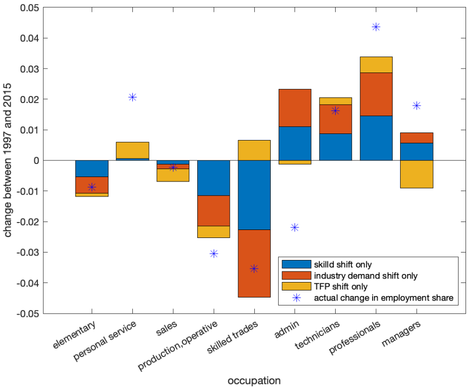
- In future, we can model changes to the skill distribution due to further increase in education and immigration policies.

Counterfactual effects on occupation employment

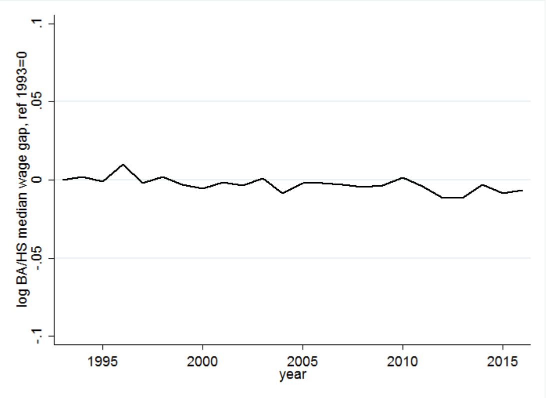


Note: There are 3 time-varying exogenous factors: skills distribution, industry demand, and TFP. For each counterfactual, we hold 2 factors constant and allow one factor to vary according to baseline estimates. Occupational wage change are normalized to be zero on average.

Summary

- I build a task-based model with endogenous adoption of technology. It can simultaneously explain:
  - job polarisation and the absence of wage polarisation
  - limited occupational downgrading within education groups when education increases
- Occupational demand is very elastic within the cone of diversification $\Rightarrow$ different implication for any policy that shifts the distribution of skills.
- Skill supply shift and between-industry demand shift can each explain about a third to two thirds of the decline in routine manual employment, and a third to half of the increase in abstract employment.

Graduate wage premium has been completely flat



Note: Figure 2 in Blundell, Green and Jin 2022 ”The U.K. as a Technological Follower: Higher Education Expansion and the College Wage Premium”, The Review of Economic Studies back

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