To what Degree? - Recovering changes in the UK's graduate skill distribution.

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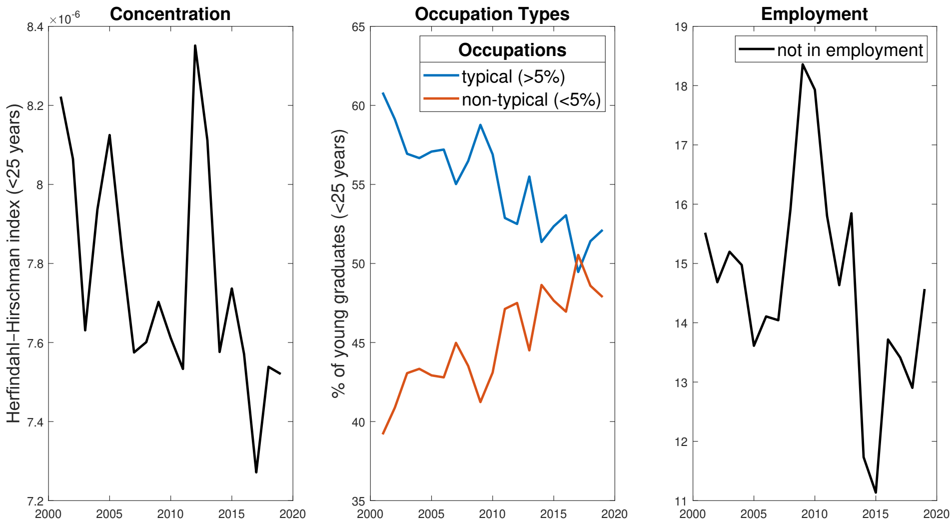
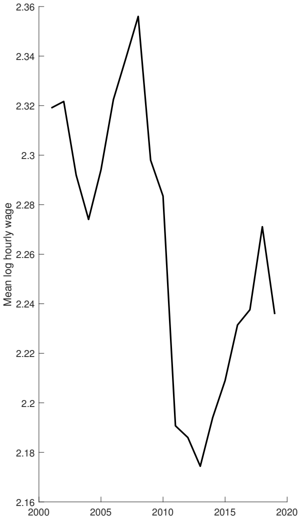
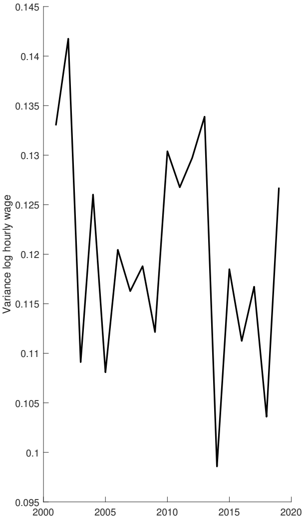
Introduction

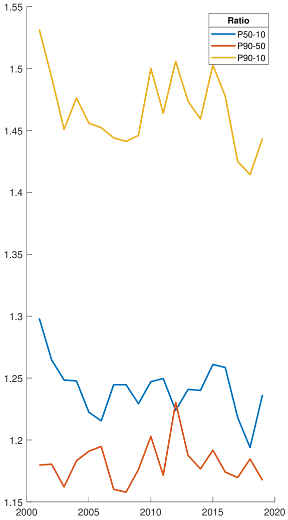
- Generally, we believe a university education is beneficial for the individual, providing skills, good jobs and high earnings. But the HE sector is also crucial in determining the supply of high skilled labour allowing the economy to grow and develop.
- As a result, university education has become an increasingly important fixture of the UK education policy. Over the last 50 years, we have seen a massive increase in enrolment rates and a large increase in the number of HEI's.

- Recently, concerns have been raised about the effectiveness of universities in providing the correct skills to their students, leading to debates about inequality, employability, under-employment and cost-effectiveness.
- These concerns make highlight the importance of understanding the skills that graduates possess when leaving university, and how well these match up with the requirements of a changing labour market.


Concentration
×10^-6
Herfindahl-Hirschman index (<25 years)
8.4
8.2
8
7.8
7.6
7.4
7.2
2000
2005
2010
2015
2020
Occupation Types
Occupations
typical (>5%)
non-typical (<5%)
% of young graduates (<25 years)
65
60
55
50
45
40
35
Employment
not in employment
19
18
17
16
15
14
13
12
11


Mean log hourly wage
2.36
2.34
2.32
2.3
2.28
2.26
2.24
2.22
2.2
2.18
2.16
2000
2005
2010
2015
2020


Variance log hourly wage
0.145
0.14
0.135
0.13
0.125
0.12
0.115
0.11
0.105
0.1
0.095
2000
2005
2010
2015
2020


Ratio
P50-10
P90-50
P90-10
1.55
1.5
1.45
1.4
1.35
1.3
1.25
1.2
1.15
2000
2005
2010
2015
2020

- The last 20 years saw huge changes in both the demand for and supply of skills:
  - technological change
  - structural transformation of the labour market
  - higher education expansion
  - school reform
  - demographic change
- If we want to understand changes to the labour market outcomes of graduates, we need to take into account both supply and demand factors.

The qualitative margin

- Recent work suggests that subject of study matters a lot for graduate outcomes (e.g. Altonji et al. (2016), Andrews et al. (2022) and Lovenheim & Smith (2022)).
- Further work suggests that task content is an important driver of differences in labour market outcomes (c.f. Autor et al. (2003), Autor & Handel (2013), Sanders & Taber (2015))
- This suggests we should try and study the *qualitative* dimension of graduates' skills i.e. Can we say anything about the types of skills that they have?

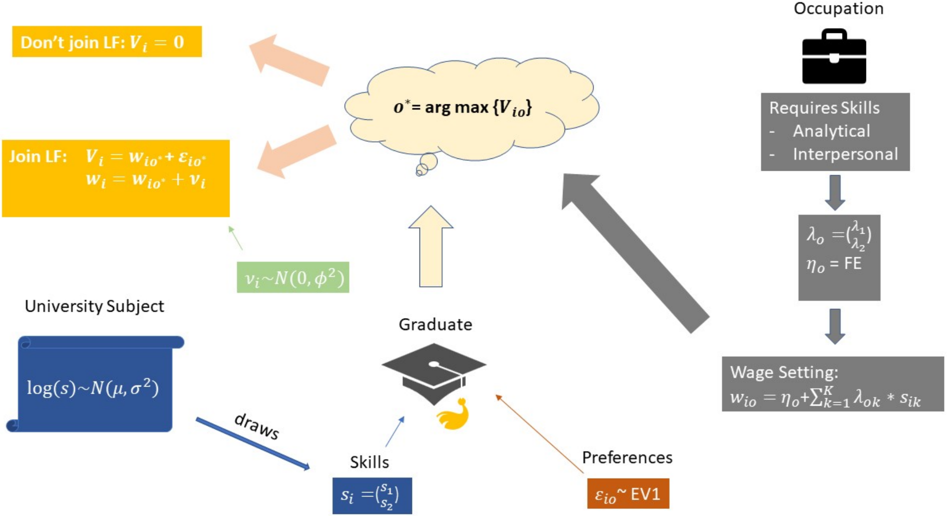
Aim of this paper

- In this paper I develop a model of the labour market for young university graduates. The model features:
  - multidimensional skills
  - skill heterogeneity
  - differences in the return to these skills
  - non-pecuniary preferences
- I estimate the model and use it to decompose the different factors driving changes to the labour market outcomes of young graduates.

The Economic Environment

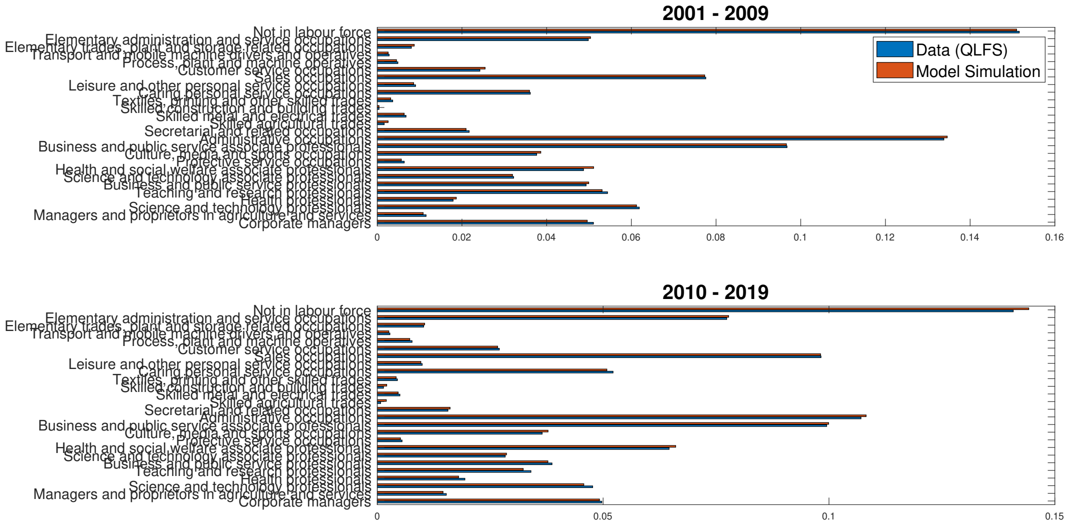
- There is a finite number of *Occupations*, that differ in their demand for a finite number of general skills according to the tasks that are required to produce their output in each case.
- Similarly, workers are heterogeneous with respect to the multidimensional set of skills that they have.
- Workers choose which occupation they want to enter and workers are paid their marginal product ▸ Derivation

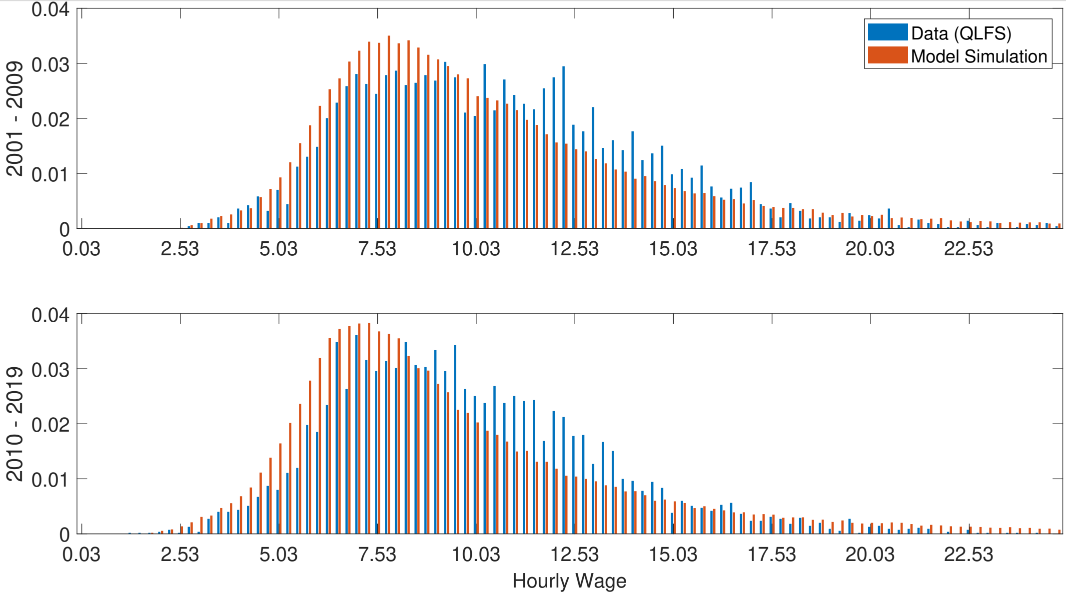
A picture says more than e^6.90775527898 words



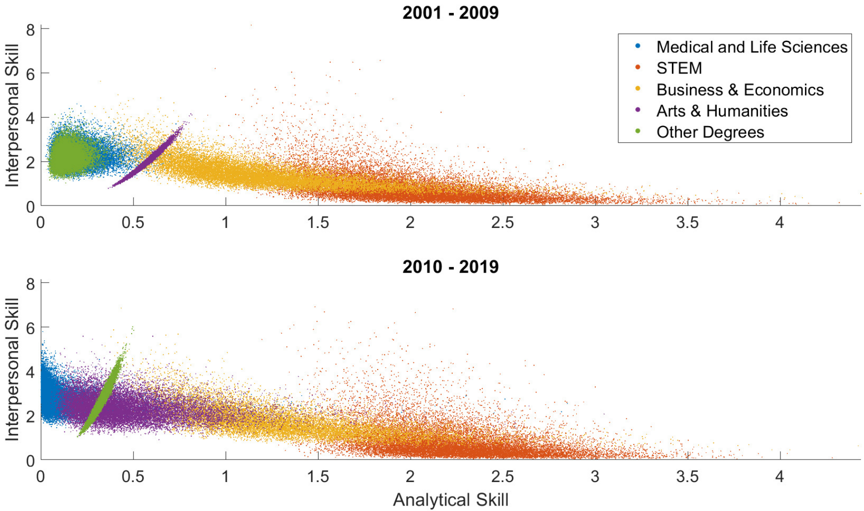
Taking the model to the data

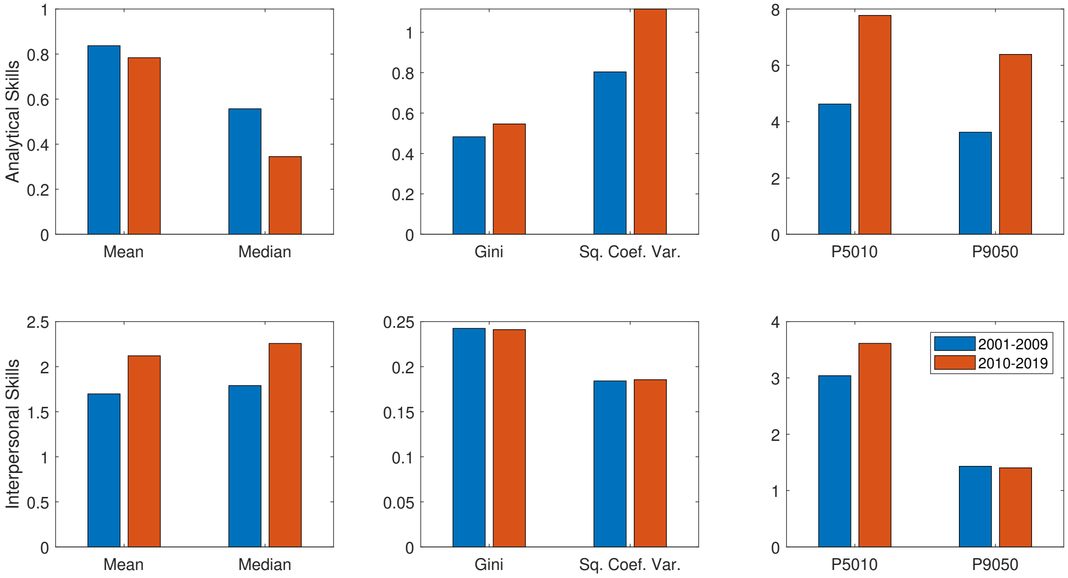
- Split sample into 2 periods: 2001 - 2009, 2010 - 2019. ▸ Sample details
- Aggregate degree subjects: Medical & Life Sciences, STEM, Business & Economics, Arts & Humanities, Other
- Two types of skill: **abstract** & **interpersonal**. Skill prices are estimated from SES. ▸ Skill Prices ▸ Task Examples
- Ask the computer (nicely) to maximize the LL given the observables while integrating out the distribution of unobservable skills. ▸ Estimation


2001 - 2009
2010 - 2019
Data (QLFS)
Model Simulation
Not in labour force
Elementary administration and service occupations
Elementary trades, plant and storage related occupations
Transport and mobile machine drivers and operatives
Process, plant and machine operatives
Customer service occupations
Sales occupations
Leisure and other personal service occupations
Caring personal service occupations
Textiles, printing and other skilled trades
Skilled construction and building trades
Skilled metal and electrical trades
Skilled agricultural trades
Secretarial and related occupations
Administrative occupations
Business and public service associate professionals
Culture, media and sports occupations
Protective service occupations
Health and social welfare associate professionals
Science and technology associate professionals
Business and public service professionals
Teaching and research professionals
Health professionals
Science and technology professionals
Managers and proprietors in agriculture and services
Corporate managers
0
0.02
0.04
0.06
0.08
0.1
0.12
0.14
0.16
0.05
0.15



Data (QLFS)
Model Simulation
2001 - 2009
2010 - 2019
0.04
0.03
0.02
0.01
0
0.03
2.53
5.03
7.53
10.03
12.53
15.03
17.53
20.03
22.53
Hourly Wage

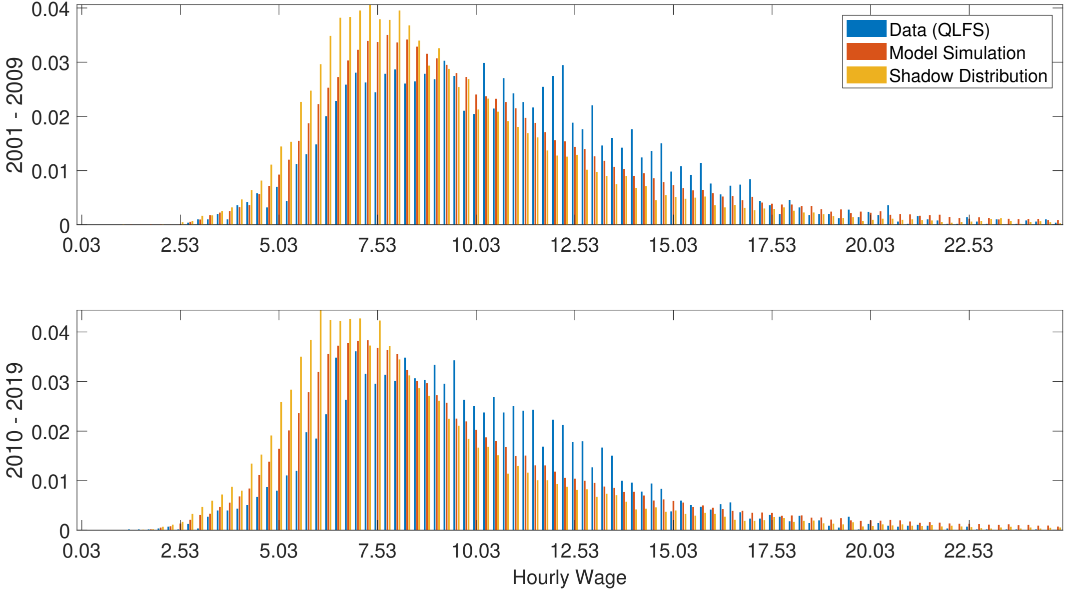

2001 - 2009
Interpersonal Skill
8
6
4
2
0
0
0.5
1
1.5
2
2.5
3
3.5
4
Medical and Life Sciences
STEM
Business & Economics
Arts & Humanities
Other Degrees
2010 - 2019
Interpersonal Skill
Analytical Skill

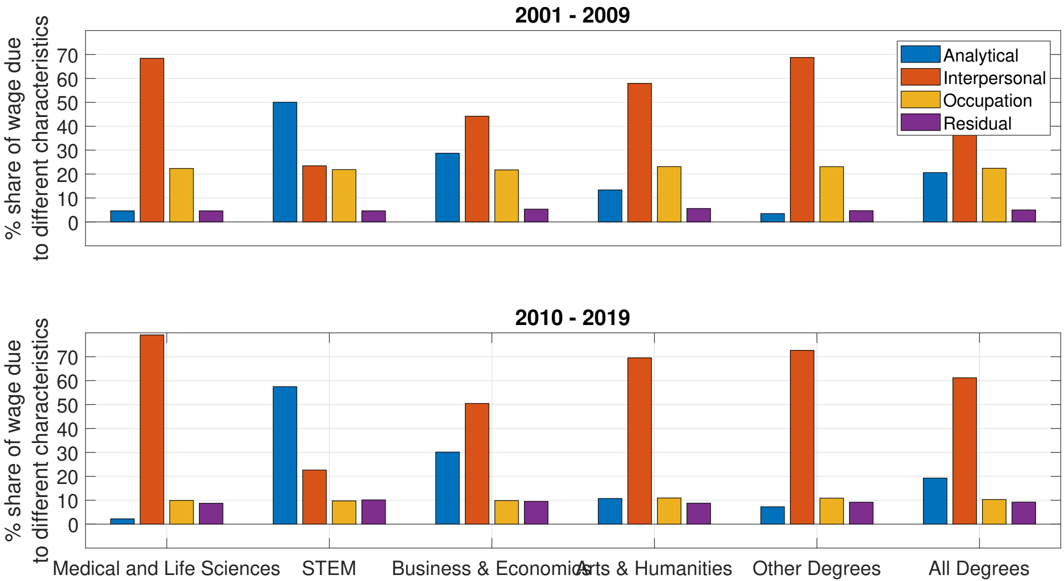


Analytical Skills
Interpersonal Skills
Mean
Median
Gini
Sq. Coef. Var.
P5010
P9050
2001-2009
2010-2019

Skill results

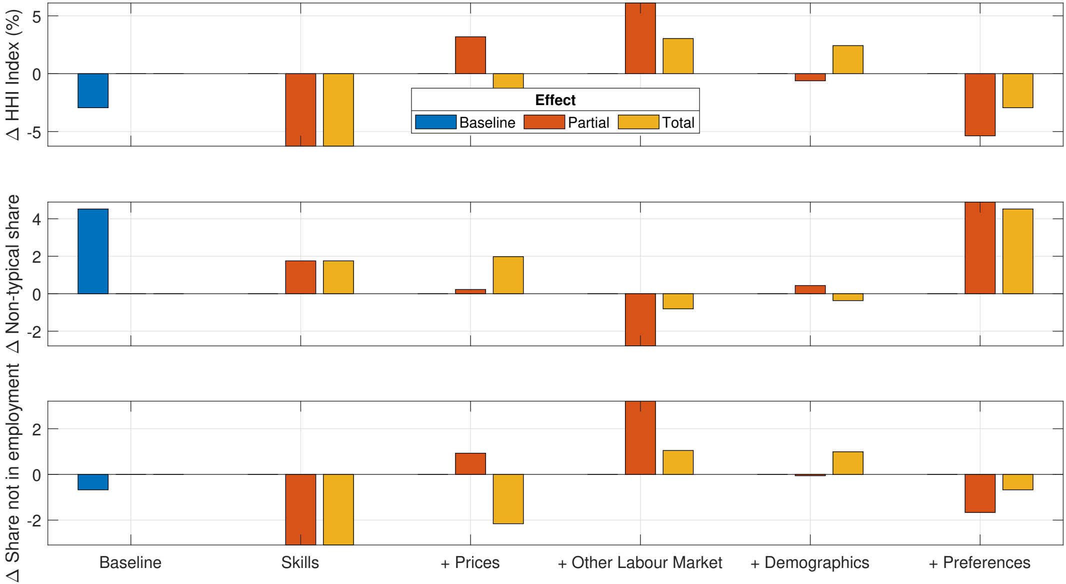
- Fall in median analytical skill, compounded by increase in inequality.
- Offset by fairly uniform increase in interpersonal skills.


Data (QLFS)
Model Simulation
Shadow Distribution
2001 - 2009
2010 - 2019
0
0.01
0.02
0.03
0.04
0.03
2.53
5.03
7.53
10.03
12.53
15.03
17.53
20.03
22.53
Hourly Wage

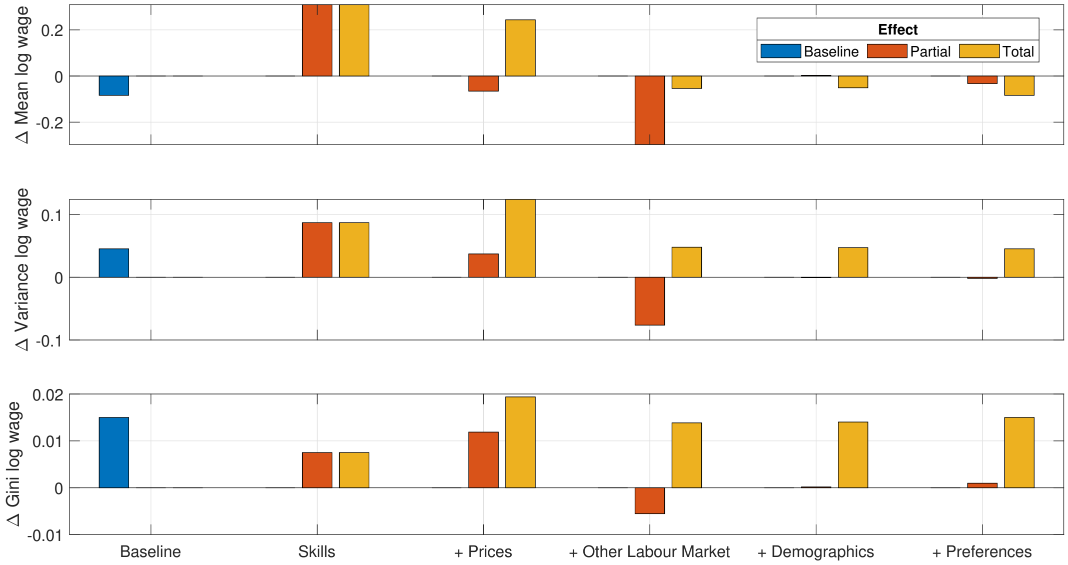

2001 - 2009
2010 - 2019
% share of wage due to different characteristics
Analytical
Interpersonal
Occupation
Residual
0
10
20
30
40
50
60
70
Medical and Life Sciences
STEM
Business & Economics
Arts & Humanities
Other Degrees
All Degrees

Counterfactual Decompositions

- Having estimated the parameters of the economy, I perform a decomposition analysis by starting the parameter space fixed at the period 1 values and then turning on different parts of the model. Specifically consider:
  1. Subject specific skill distributions.
  2. Skill prices.
  3. Other labour market factors.
  4. Demographic composition of graduate cohort.
  5. Changes in non-monetary preferences.



Δ HHI Index (%)
5
0
-5
Effect
Baseline
Partial
Total
Δ Non-typical share
4
2
0
-2
Δ Share not in employment
2
0
-2
Baseline
Skills
+ Prices
+ Other Labour Market
+ Demographics
+ Preferences


Effect
Baseline
Partial
Total
∆ Mean log wage
0.2
0
-0.2
∆ Variance log wage
0.1
0
-0.1
∆ Gini log wage
0.02
0.01
0
-0.01
Baseline
Skills
+ Prices
+ Other Labour Market
+ Demographics
+ Preferences

Counterfactual Decompositions

1. Changes in skills tend to be offset by changes in prices $\Rightarrow$ Price Mechanism in action?
2. Changes in preferences play large role in explaining move to non-typical occupations.

Conclusion - what have we learned?

- The qualitative dimension of labour matters. Both for graduates and for the jobs that they go into. Just looking at high level descriptors (degree subjects, occupation classifications) obscures large changes within these categories.
- Skill distributions do change over time. Analytical skills have become a bit rarer and more unevenly distributed, but interpersonal skills compensate somewhat for this decline.
- But skills and skill prices are never the full story. Other factors (particularly) preferences are an important part of the story.

The end.

Derivation of marginal product

$$h_{io} = e^{\sum_K \lambda_{ok} s_{ik}} \qquad \text{(Workers HC)}$$

$$Y = F(H_1, ..., H_O) \qquad \text{(Aggregate Production Function)}$$

$$\frac{\partial Y}{\partial h_{io}} = \frac{\partial F}{\partial H_o}\frac{\partial H_o}{\partial h_{io}} = \frac{\partial F}{\partial H_o} e^{\sum_K \lambda_{ok} s_{ik}} \qquad \text{(Take derivative)}$$

$$\frac{\partial F}{\partial H_o} = \eta_o$$

$$w_{io} = \eta_o + \sum_K \lambda_{ok} s_{ik} \qquad \text{(Log Wage Equation)}$$

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Data Sources

- Quarterly Labour Force Survey (2001 - 2019)
  - Degree Subject
  - Gross hourly wages (CPI deflated)
  - Occupation (2 Digit SOC)
  - Age
  - Gender
  - Geographic location
- Skills and Employment Survey (2001, 2006, 2012, 2017)

  Examples
- Focus on *fresh* graduates (≤ 24 years). Resulting in a sample of $46,637$ individuals. Go back

Simulated Maximum Likelihood

- By combining the elements of the model, we can form the likelihood function:

Derivation

Likelihood Function

$$\Pr(o_i^*, w_i^{obs}) = \int \left(\underbrace{\left(\frac{e^{\eta_{o^*} + \sum_K \lambda_{o^* k} s_{ik}}}{\sum_{o=1}^{O} e^{\eta_o + \sum_K \lambda_{ok} s_{ik}}} \right)}_{Occupation} \underbrace{\left(\frac{e^{\left(-\frac{\nu_i^2}{2\phi^2}\right)}}{\sqrt{2\pi\phi^2}} \right)}_{Wage} \right) f(s)d(s)$$

- The estimation procedure works via *simulated maximum likelihood* - we find the vector of economic parameters θ, that maximizes the probability of observing the actual outcomes.
- Use $1,000$ *quasi-random* Halton draws to approximate the integral.
- Additional controls: Year and geography Fixed Effects, experience, part-time status and gender. As well as occupation specific non-pecuniary benefits.

1. Find $\Pr(o^*, w_i^{obs}|s_i;\theta)$ using the structure of the economic model.
2. Integrate over the unobserved skill distribution $f(s|\theta))$:
$\Pr(o^*, w_i^{obs}|\theta)) = \int \Pr(o^*, w_i^{obs}|s_i;\theta))f(s|\theta))ds$.
3. Find vector of parameters $\hat{\theta}$ that maximizes the Log Likelihood function:
$$ll(\theta) = \sum_{i=1}^{N} \log(\Pr_i(o^*, w_i^{obs}|\theta)))$$

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Derivation of Likelihood

$$\Pr(o_i^*, w_i^{obs}) = \int \Pr(o_i^*, w_i^{obs}|s_i) f(s) d(s) \qquad \text{(Rewrite unconditional probability)}$$

$$\frac{\Pr(o_i^*, w_i^{obs}|s_i)}{\Pr(o_i^*|s_i)} = \Pr(w_i^{obs}|s_i, o_i^*) \qquad \text{(Bayes Rule)}$$

$$\Pr(o_i^*, w_i^{obs}|s_i) = \Pr(o_i^*|s_i) * \Pr(w_i^{obs}|s_i, o_i^*) \qquad \text{(rearange)}$$

$$\Pr(o_i^*, w_i^{obs}) = \int \Pr(o_i^*|s_i) \Pr(w_i^{obs}|s_i, o_i^*) f(s) d(s)$$

(Integrate over skill distribution)

Derivation of Likelihood cont.

$$\Pr(o_i^*|s_i) = \frac{e^{\eta_{o^*} + \sum_K \lambda_{o^*k} s_{ik}}}{\sum_{o=1}^{O} e^{\eta_o + \sum_K \lambda_{ok} s_{ik}}} \qquad \text{(Logit Choice Probability)}$$

$$\Pr(w_i^{obs}|s_i, o_i^*) = \frac{e^{(-\frac{\nu_i^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}} \qquad \text{(Normal PDF)}$$

$$\Pr(o_i^*, w_i^{obs}) = \int \left(\left(\frac{e^{\eta_{o^*} + \sum_K \lambda_{o^*k} s_{ik}}}{\sum_{o=1}^{O} e^{\eta_o + \sum_K \lambda_{ok} s_{ik}}} \right) \left(\frac{e^{(-\frac{\nu_i^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}} \right) \right) f(s) d(s) \qquad \text{(insert)}$$

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Tasks (with Examples)

1. Abstract Tasks
   - Specialist knowledge and understanding
   - Complexity level of computer use
   - Advanced Mathematics/Statistics
2. Interpersonal
   - Making Speeches/Presentations
   - Persuading or influencing others
   - Cooperating with colleagues

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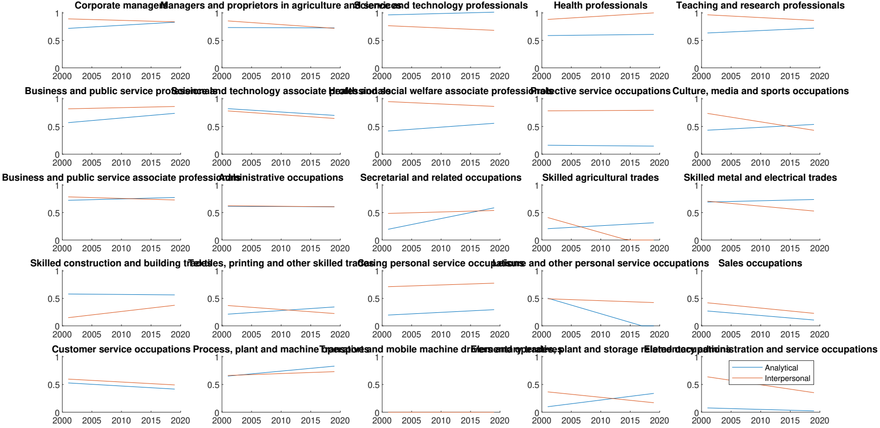
Skill Prices

Task intensities by 2 digit SOC



Source: SES, authors own calculations

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