

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

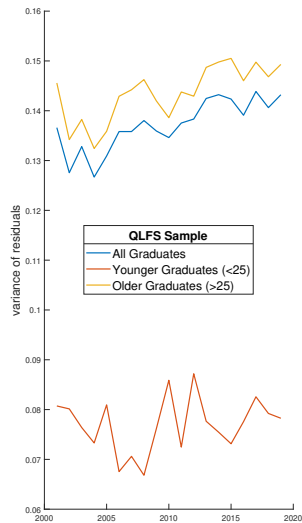
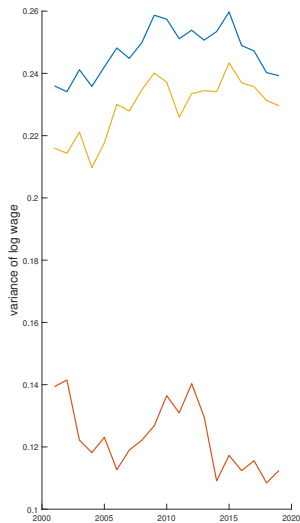
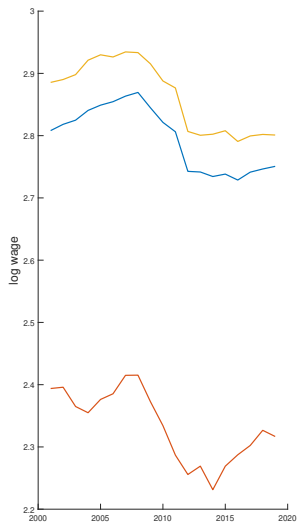
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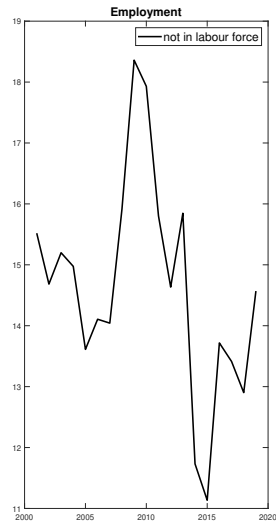
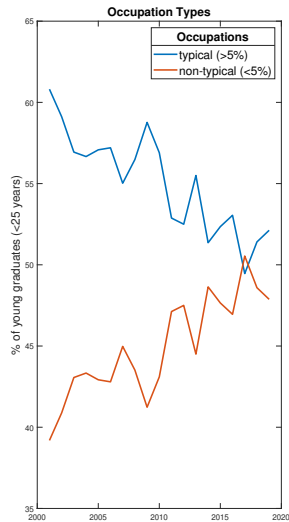
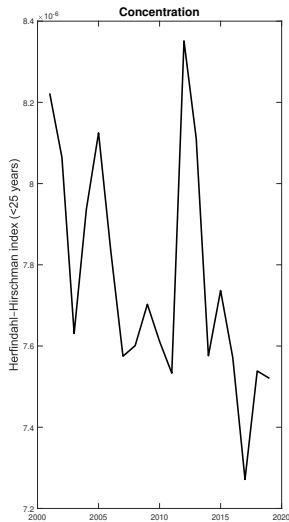
University of Birmingham

3rd of April 2023

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.





- 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 graduate's skills.

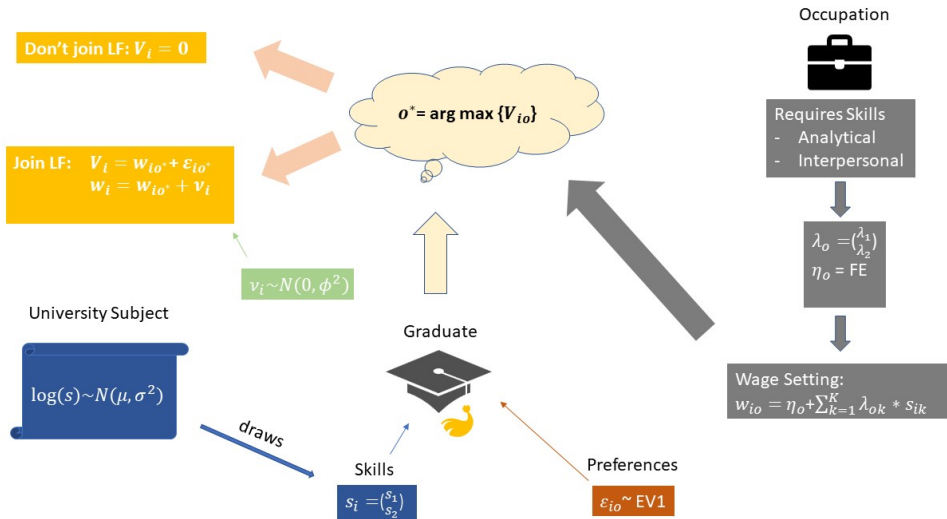
Aim of this paper

- 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](#)

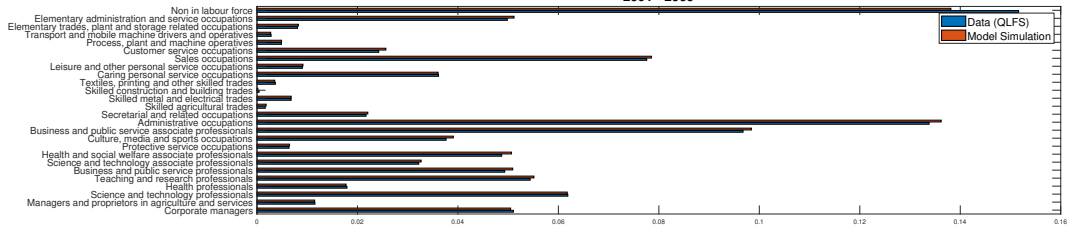
A picture says more than $e^{6.90775527898}$ words



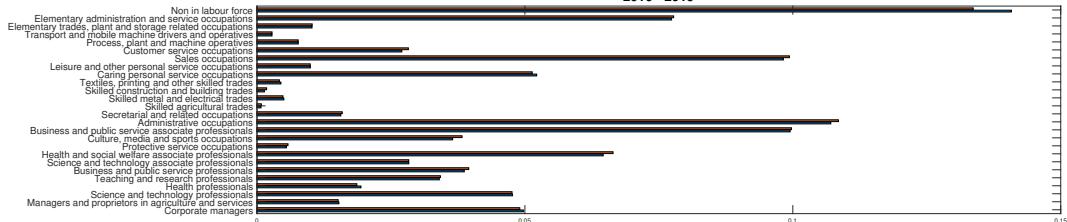
Taking the model to the data

- 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](#)

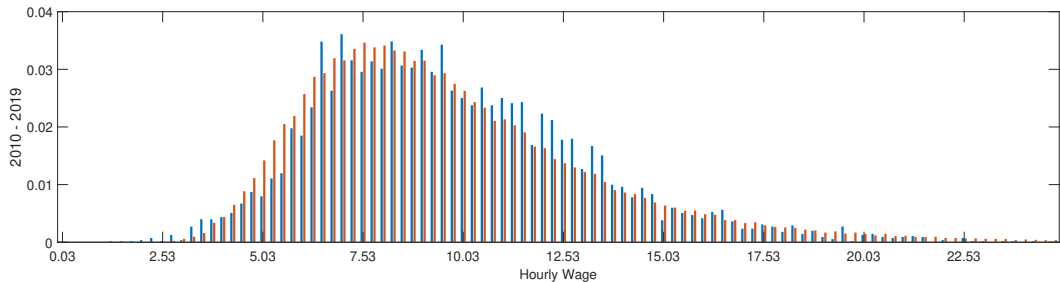
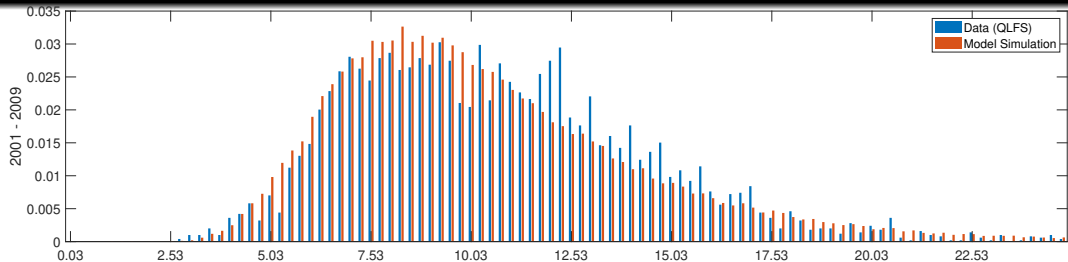
2001 - 2009

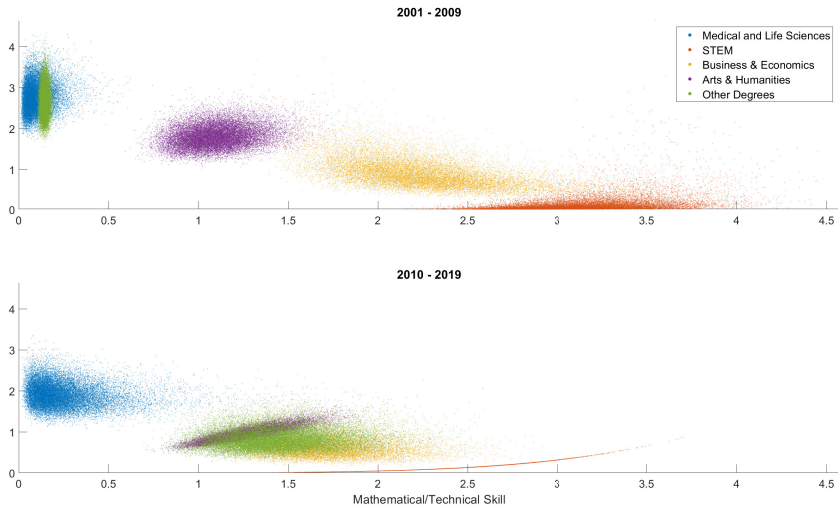


2010 - 2019

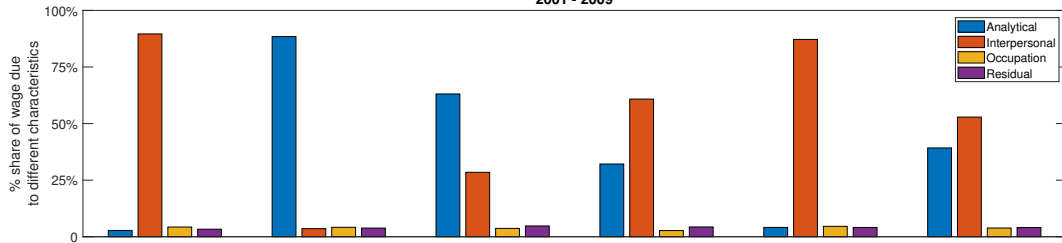


Source: QLFS and Model Simulation

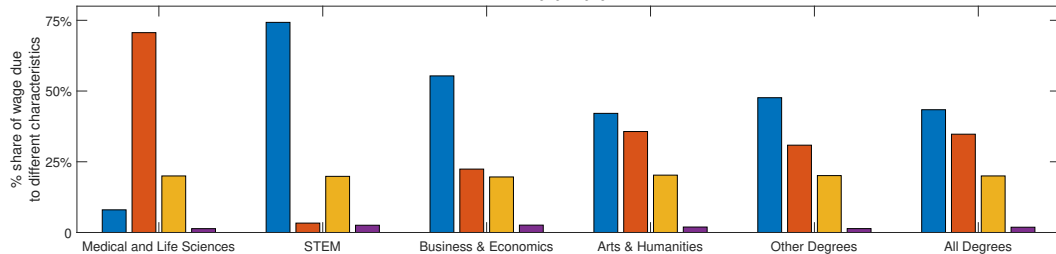




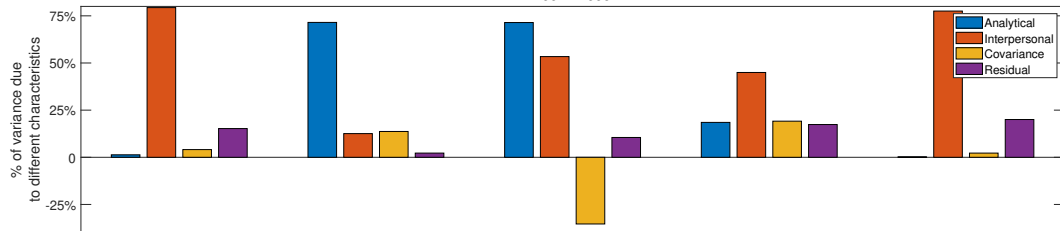
2001 - 2009



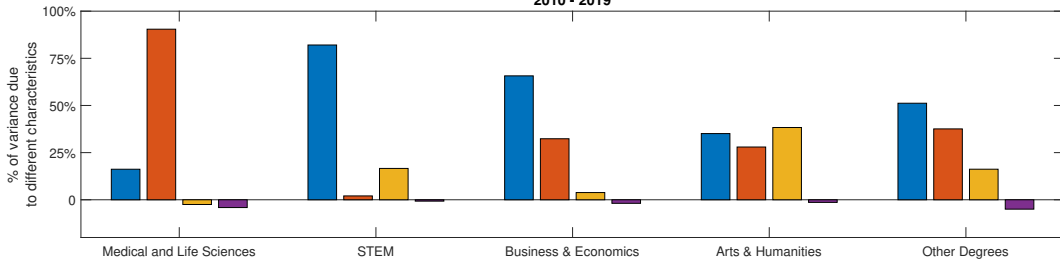
2010 - 2019



2001 - 2009

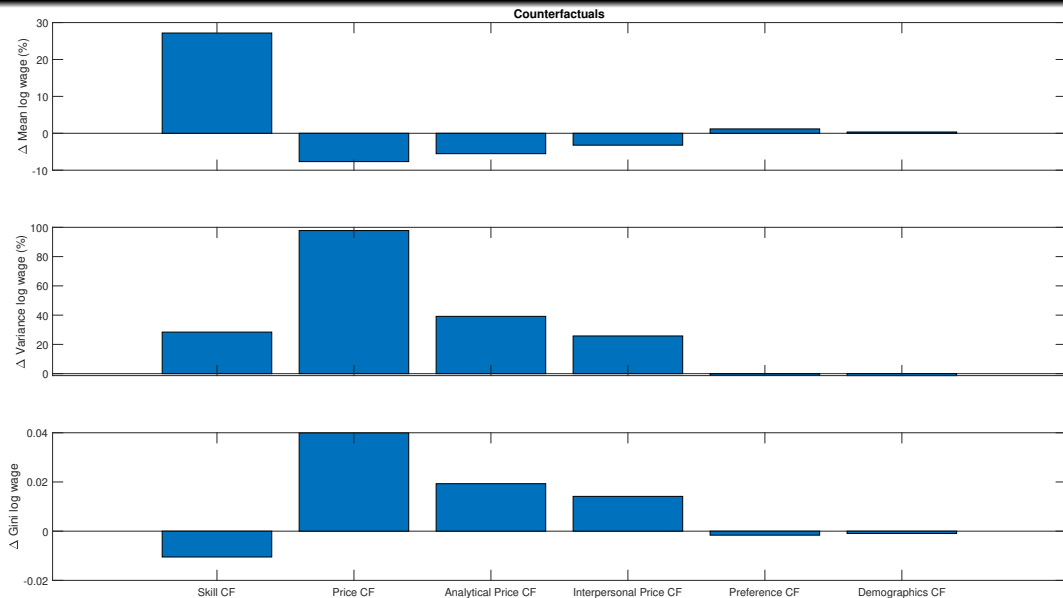


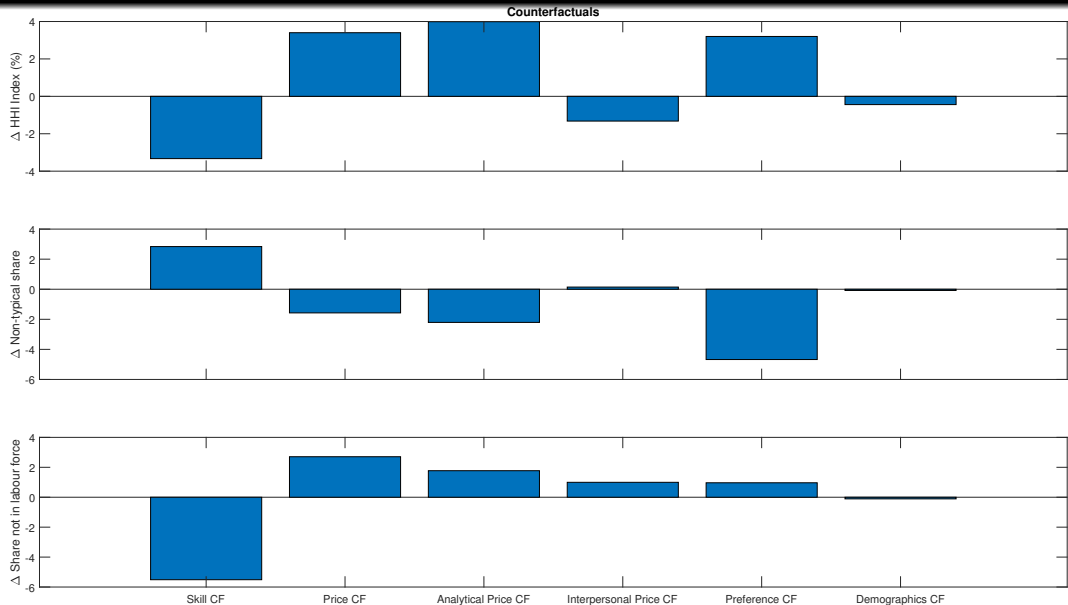
2010 - 2019



Counterfactuals

- Having estimated the parameters of the economy, I perform some counterfactual analyses by keeping different parts of the parameter space fixed at the period 1 values. Specifically consider:
 - ① Keeping the skill distribution fixed.
 - ② Keeping the skill prices fixed at 2001 values (abstract, interpersonal & both).
 - ③ Keeping demographic composition fixed.
 - ④ Keeping non-monetary preferences fixed.





Counterfactuals

- ① Skill Counterfactual: **higher mean wages, moderately higher variance (lower tail), less unemployment** → **Interpersonal skills matter for young graduates wages**
- ② Price Counterfactual(s): **small wage effect, large increase in variance (analytic > interpersonal), more concentration, less non-typical (analytical!) → Changing demand for analytical skill drew graduates into non-typical occupations.**

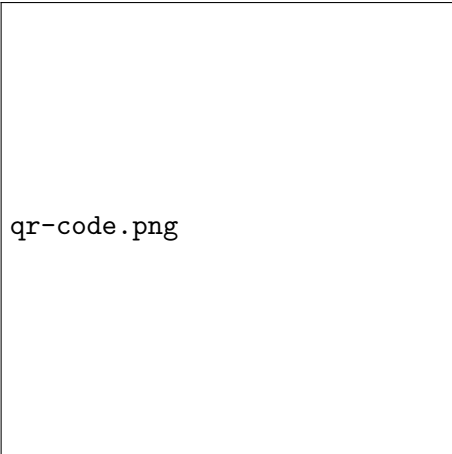
Counterfactuals

- ④ Demographic Counterfactual: **very little effect on either outcome**
- ⑤ Preference Counterfactual: **some impact on occupation concentration → non-typical occupations have become more attractive**

Conclusion - what have we learned?

- This paper has provided novel quantitative evidence on the changing distribution of graduate's skills in the UK. There are clear differences of skill endowments for students from different subject areas over time.
- On average, graduates tend to have more mathematical skills today, but less verbal skills. Inequality has also been falling somewhat. (But be mindful of heterogeneity and selection!)
- Overall, the skill supply appears to have evolved to take advantage of opportunities in the labour market, providing an inequality reducing thrust. So if large disparities exist and persist, we should probably look for complementary explanations.

The end.



qr-code.png

Derivation of marginal product

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

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

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

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

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

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

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

- 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:

$$ll(\theta) = \sum_{i=1}^N \log(\Pr_i(o^*, w_i^{obs} | \theta))$$

[▶ back](#)

Derivation of Likelihood

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

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

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

$$\Pr(o_i^*, w_i^{obs}) = \int \Pr(o_i^* | s_i) \Pr(w_i^{obs} | s_i, o_i^*) f(s) d(s) \quad (\text{Integrate over skill distribution})$$

Derivation of Likelihood cont.

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

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

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

[▶ back](#)

Tasks (with Examples)

① Abstract Tasks

- Specialist knowledge and understanding
- Complexity level of computer use
- Advanced Mathematics/Statistics

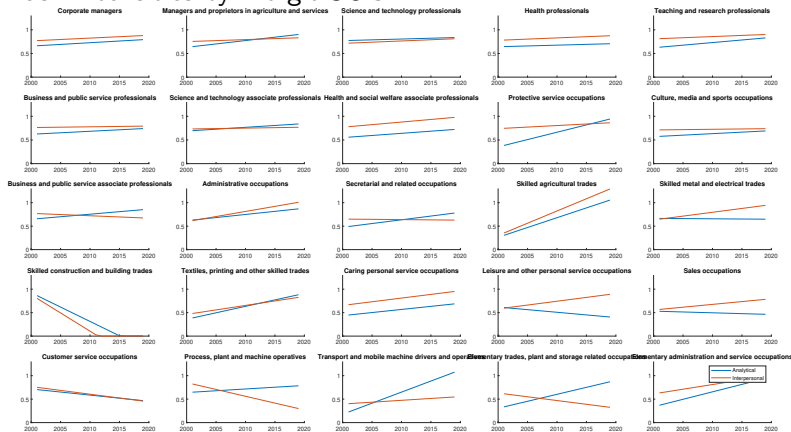
② Interpersonal

- Making Speeches/Presentations
- Persuading or influencing others
- Cooperating with colleagues

▶ back

Skill Prices

Task intensities by 2 digit SOC



Source: SES, authors own calculations

[▶ back](#)