Skills, Tasks and Degrees

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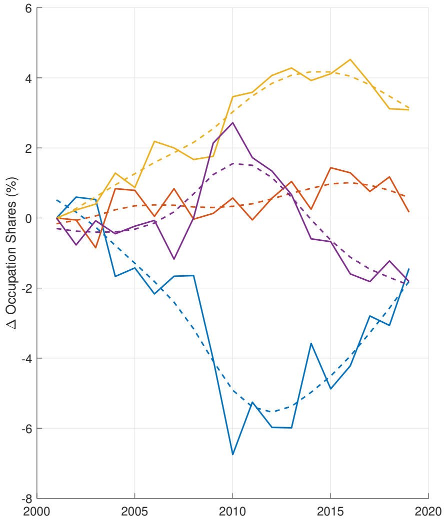
The Benefits of a University Education?

- Recent concerns question the effectiveness of universities in equipping students with the necessary skills for success in the labour market. Press Coverage
- These debates focus on issues like earnings inequality, employability, under-employment, and the cost-effectiveness of higher education.
- In the UK a particular measure of the *success* of graduates is whether they manage to land a *graduate job*.

Changes in the job destinations of young graduates (≤30 y.o.)



Why Are Graduates Joining Non-Typical Occupations?

- **Possible Explanations:**
  - *Skill Mismatch:* Graduates may not possess the skills required for high-skilled jobs prevalent in previous generations. :-(
  - *Occupational Upgrading:* Many non-typical jobs have become more skill-intensive over time, aligning better with graduates' capabilities. :-)
  - *Aggregate Labour Market Shifts:* Changes in job market demand could be influencing the shift towards non-typical occupations. :-/
  - *Preference Changes:* Graduates' own preferences might be evolving, leading them to opt for different career paths. :-?

Disentangling Labour Market Dynamics

- **Significant Changes in the Market for Graduate Skills:**
  - Expansion in higher education and school reforms.
  - Rapid technological advancements.
  - Structural transformation within the labour market.
  - Demographic shifts.
- **Understanding Labour Market Outcomes:**
  - If we want to assess the impact of these changes on the labour market outcomes of young graduates, we should aim to understand the skills acquired by graduates and how these skills align with the evolving requirements of the labour market.

Aim of this paper

- **A model of the labour market for young graduates:**
  - Skill heterogeneity within and between different cohorts of graduates.
  - Changes in the returns to skill in varying occupations.
  - Evolving non-pecuniary amenities.
- **Model Estimation and Application:**
  - 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

- **Occupations and Skill Demand:**
  - There are a finite number of *occupations*, each differing in their demand for a general skill.
- **Skill Heterogeneity:**
  - Graduates, are heterogeneous in their skill sets, which is a the result of pre-existing abilities and skills accumulated throughout university.
- **Match Specific Productivity:**
  - A graduate's productivity is a function of their own skills and the requirements of the occupation they choose.
- **Graduate Career Choices:**
  - Graduates receive utility from monetary and non-pecuniary factors and choose their preferred occupation out of all available options. Model Timeline

- **Graduates:**
  - There is a set of N graduates $i \in N$ which are heterogeneous, wrt. to their skill-sets.
  - Skill is represented by a scalar s_i, distributed log normally: $log(s_i) \sim N(\mu, \sigma^2)$.
- **Occupations:**
  - There is a set O occupations $o \in O$.
  - Occupations vary in the complexity of tasks that they perform and therefore the return λ_o they pay for skill.
- **Market clearing:**
  - Occupations are assumed to be perfectly competitive and pay workers according to their marginal product.

Wage Determination and Log Wage

- The (expected) log wage for worker i in occupation o is given by

$$w_{io} = \eta_o + \lambda_o * s_i + \beta * x_i. \tag{1}$$

- η_o is an occupation-specific fixed effect, capturing factors such as demand or other unobserved influences.
- x_i is a vector of observable characteristics (experience, gender, etc.).

Occupational Choice and Utility Maximization

- **Graduate's Decision Framework:**
  - Utility from occupation o for graduate i is linear in the wage w_{io} plus a random preference component ε_{io}:

$$V_{io} = w_{io} + \varepsilon_{io}. \tag{2}$$

  - A graduate i selects occupation o_i^* that maximizes their utility:[1]

$$o_i^* = \arg\max_{o \in O} \{V_{io}\}. \tag{3}$$

[1] Not working ($o = 0$) is normalised to 0.

Econometric Challenges & Strategy

- **Challenges for Estimation:**
  - The primary challenge for the econometrician is that skills are unobserved **and** correlated with observed outcomes.
- **Leveraging Observable Data using an Economic Model:**
  - In this paper, I approach the problem as one of latent variables: Available data on occupation choice and wage can be indicative of underlying skills.
  - I model the joint wage-determination, occupation-choice process that links unobserved skills with observed outcomes. Estimation Strategy

Data

- I use the Quarterly Labour Force Survey (QLFS), providing detailed information on an individual's occupation, hourly pay, demographic covariates, and detailed educational background.
- I estimate the model for young university graduates in the United Kingdom, covering the period from 2001 to 2019. For comparison over time, I split the sample into two cohorts: 2001-10 and 2011-19.
- Identification requires panel data, so I utilise the panel dimension of the QLFS, resulting in a sample of $12,000$ graduates each with 5 quarterly observations.

Estimation

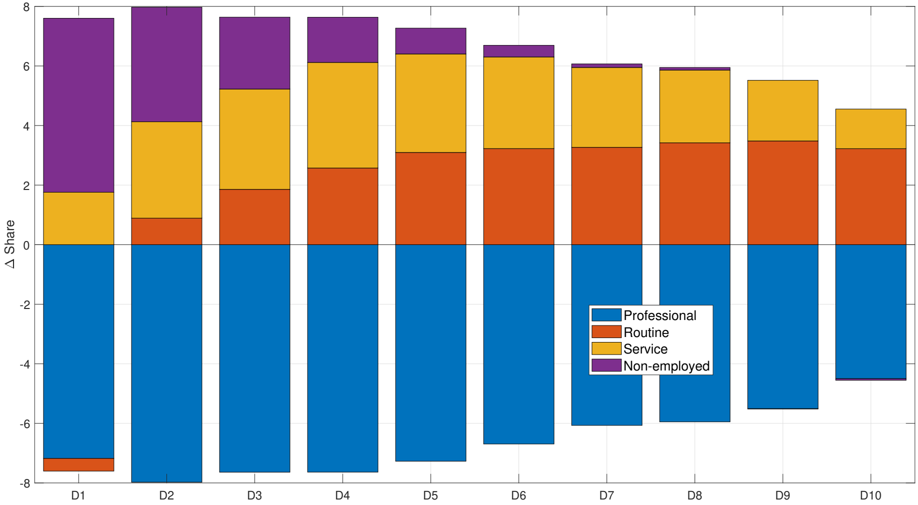
- **Parameters of interest:**
  - The parameters governing the distribution of skills for different cohorts of graduates: μ_c and σ_c, $c \in$ 2001-10,2011-19.
  - The return to skill in the different occupations: $\lambda_{o,t}$.
  - Non-pecuniary occupation preferences: $\omega_{o,t}$
- **Estimation and Simulation:**
  - I estimate the model parameters with Simulated Maximum Likelihood.
  - I simulate the model based on the estimated parameters, to assess model fit, analyse the skill distribution and run counterfactuals. ▸ Model Fit

Key Results

- Between 2001-10 and 2011-19 *average* skill levels have fallen by ∼25% of a standard deviation. Figure
- Increase in the (variable) return to skill across all occupations between 2001 and 2019. Suggesting a shift to more skill-intensive tasks (within occupation upgrading). Figure
- Non-pecuniary utilities increase relative to the outside option - suggesting the value of non-working has gone down. Routine and service occupation appreciated vs professional - potentially indicating improved working conditions or changes in attitude. Figure

Implications for Sorting

- Sorting on skill level is a key feature of the model. *Ceteris paribus* higher-skilled graduates will choose occupations with higher returns to skill.
- These sorting patterns across the distribution imply that when the distribution of skills, or returns changes, this will have non-linear effects on the matching of graduates with jobs.
- Using the model estimates we can pinpoint where in the distribution, graduates are leaving professional occupations, and where they are moving instead.


8
6
4
2
0
-2
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-6
-8
Δ Share
D1
D2
D3
D4
D5
D6
D7
D8
D9
D10
Professional
Routine
Service
Non-employed

Sorting Takeaways

- Nonlinear sorting patterns across the distribution: experience of graduates at the top deciles differs from those at the bottom of the skill distribution.
- The majority of the fall in professional occupations occurs below the median.
- **Bottom deciles**: graduates are more likely to be out of employment.
- **Middle-top deciles**: graduates more likely to be in routine & service occupations.

Counterfactual Decomposition Analysis

- **Counterfactual Decomposition:**
  - I assess the significance of different model components on the evolving labour market outcomes of graduates by decomposing observed changes.
  - The approach involves fixing certain parameters at their 2001-10 values and simulating the model for the 2011-19 period, isolating the effects of specific changes.
  - Then we compare the outcomes in the counterfactual world with those of the baseline model.
- **Modelled Channels:**
  - **Skill Counterfactual:** μ_c and σ_c.
  - **Price Counterfactual:** $\lambda_{o,t}$, and $\eta_{o,t}$.
  - **Preference Counterfactual:** $\omega_{o,t}$

Counterfactual Results

		Counterfactual					
Baseline Model		Skills		Prices		Preferences	
Share	Total Δ	Δ	Explained (%)	Δ	Explained (%)	Δ	Explained (%)
Professional	-6.58	-3.47	52.77	-0.71	10.80	-1.99	30.22
Routine	2.51	0.24	9.44	-0.54	-21.54	3.02	120.60
Service	3.03	0.35	11.71	0.58	19.10	1.61	53.01
Non-employed	1.05	2.88	274.46	0.67	63.97	-2.64	-251.02

Note: Simulations based on a representative sample of 1,000,000 graduates.

- Differences in average skill make it less likely that a graduate is employed in any occupation, but particularly professional occupations.
- Changing preferences make graduates more likely to choose routine and service occupations, drawing from both non-employed and professional groups.
- Relative skill price changes seem to have a small effect on the reallocation of graduates. Counterfactual Sorting Patterns

Concluding Thoughts

- **What have we learned?**
  - Changing skill distributions have played some role in explaining the fall in professional occupations amongst graduates.
  - But this is not the only relevant factor - different preferences matter as well.
- **Open questions?**
  - How has the increased supply of graduates affected the returns to skill?
  - How will the graduate skill distribution shape or be shaped by future technological change (e.g., AI, automation)?

Thank You

- **Thank You for Your Attention!**
- **Questions?** I am happy to answer any questions you may have and hear your suggestions.
- **Contact Information:** max.j.schroeder@durham.ac.uk

Press Coverage

Student finance: How much does university cost and does it increase earnings?

29 August 2023

More students say university not value for money

11 June 2020 · Comments

'Mickey Mouse' university courses could have student loans removed

Press release

Crackdown on rip-off university degrees

University courses that fail to deliver good outcom
high drop-out rates and poor employment prospec
subject to strict controls.

University dropout rates re
high, figures suggest

28 September 2023

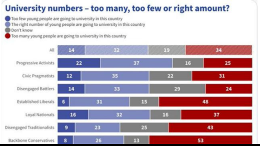
'Dumbed down' courses 'take advantage' of students

1 July 2020

A university education is "not the only way to succeed in life," Rishi Sunak has said as he detailed plans to clamp down on 'low quality' degrees in an exclusive interview with LBC.

University is 'great but not the only way to succeed', PM tells LBC as he outlines crackdown on 'Mickey Mouse' degrees

17 July 2023, 13:02 | Updated: 17 July 2023, 13:41



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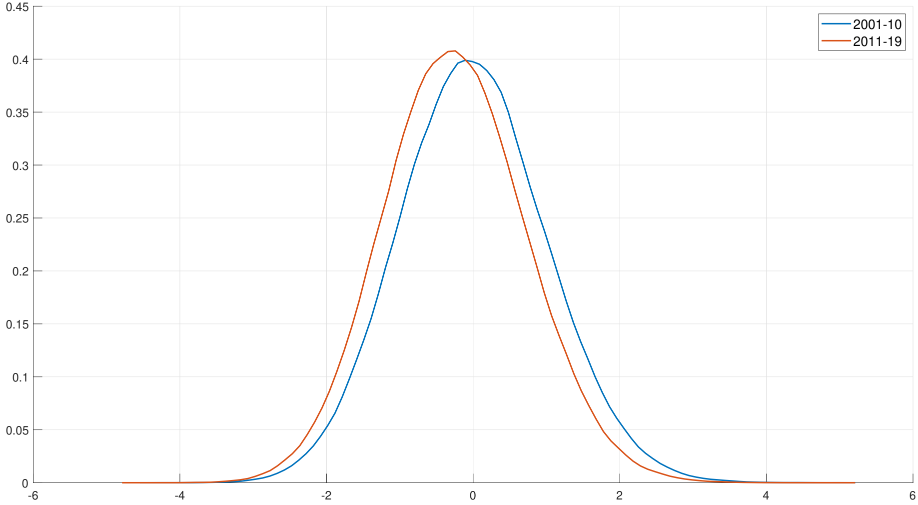
Skill Distributions



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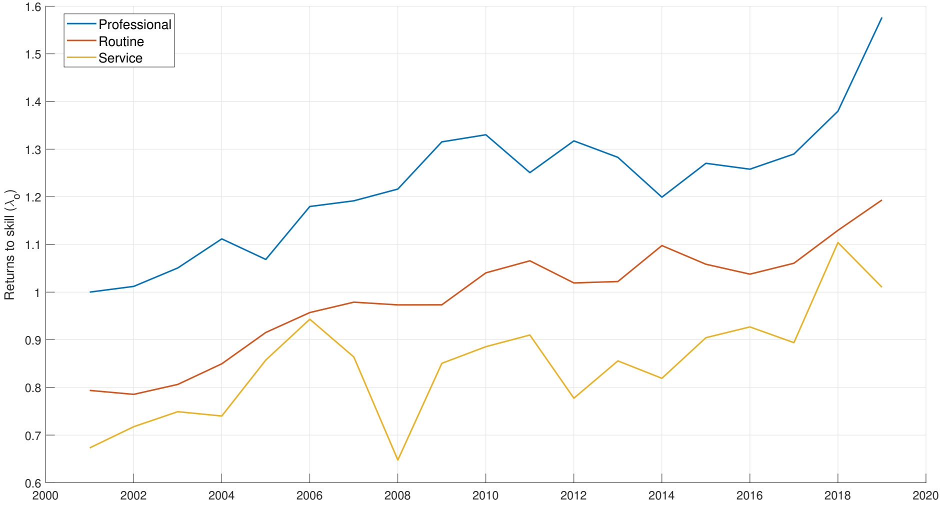
Skill Prices



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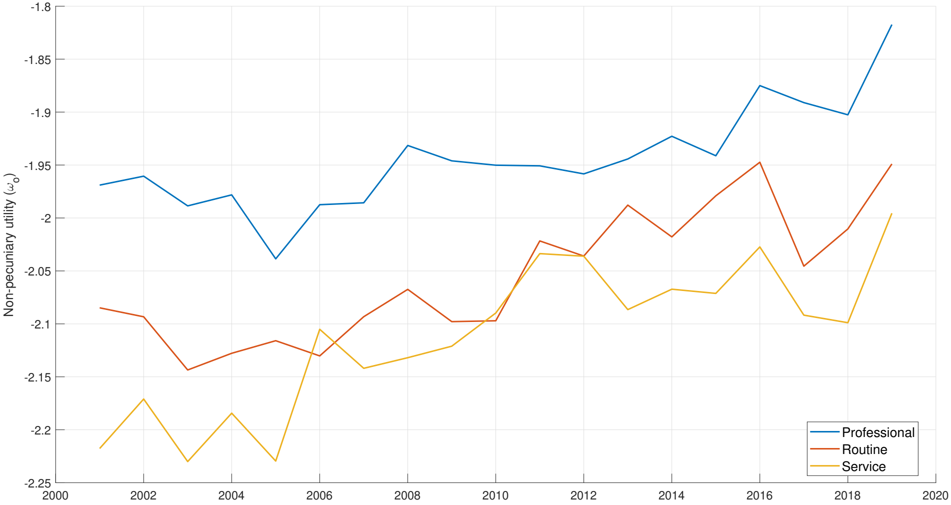
Amenities



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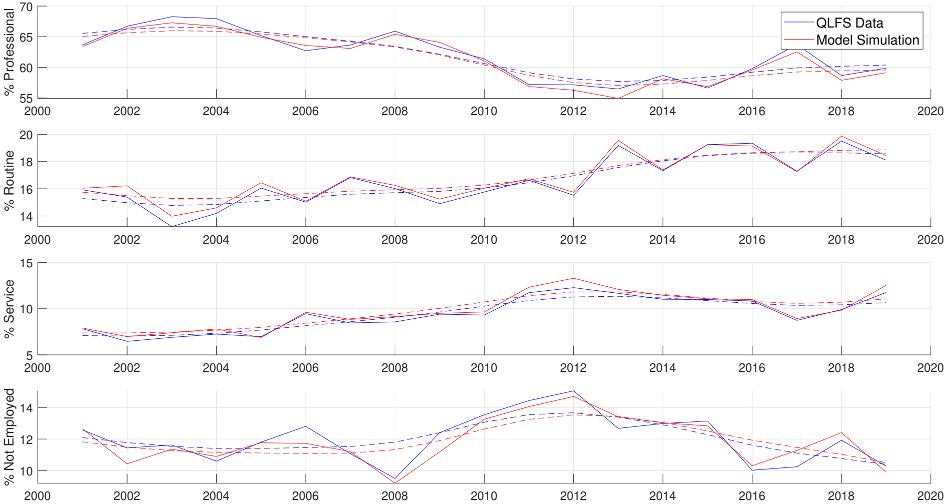
Model Fit



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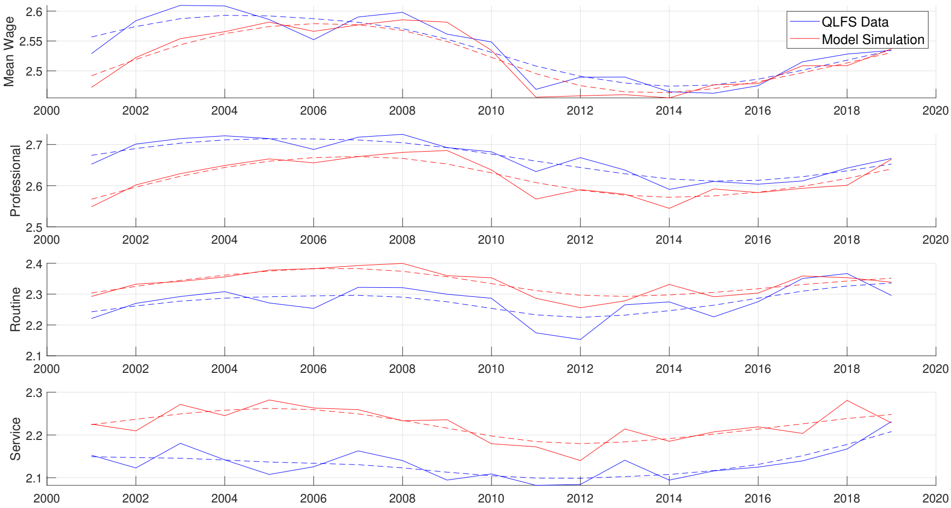
Mean Wage
Professional
Routine
Service
QLFS Data
Model Simulation
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020

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Model Timeline

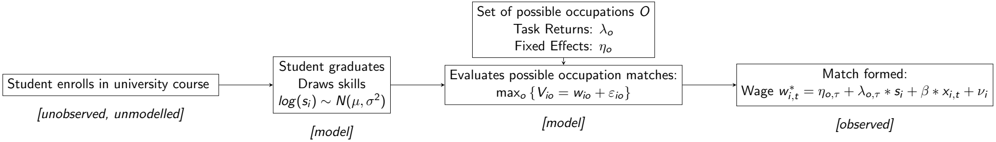

Figure: Model Timeline

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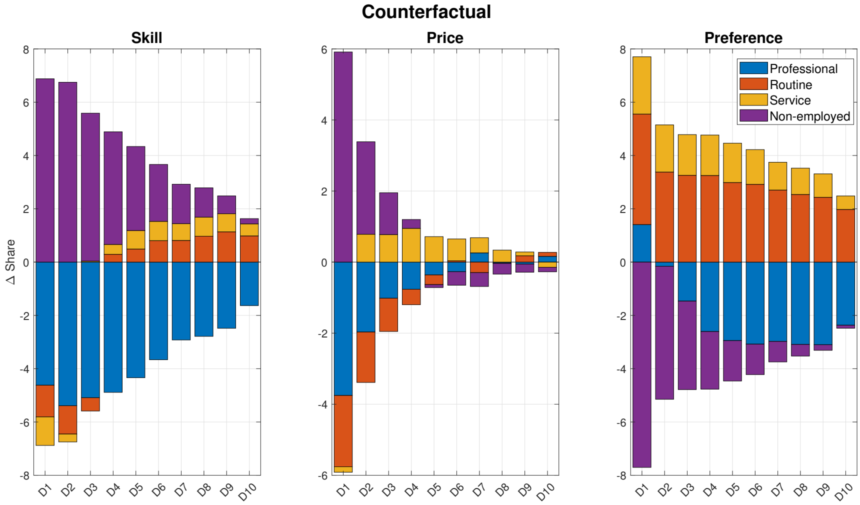
Counterfactual Sorting



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Likelihood Function and Estimation

- The probability of observing the occupation outcome $o^*_{i,t}$ and wages $w^*_{i,t}$ given the latent variables s_i is defined as: Derrivation

$$\Pr(o^*_{i,t}, w^*_{i,t}|s_i) = \left(\frac{e^{\rho(w_{i,o^*,t}+\omega_{o^*,\tau})}}{1+\sum_{o=1}^{O} e^{\rho(w_{i,o,t}+\omega_{o,\tau})}}\right)\left(\frac{e^{-\frac{\nu^2_{i,t}}{2\phi^2}}}{\sqrt{2\pi\phi^2}}\right)$$

- The L-QLFS contains 5 quarterly observations on each individual:

$$L(\theta) = \prod_{i\in N}\int\prod_{t=1}^{5}\Pr(o^*_{i,t}, w^*_{i,t}|s_i)f(s)\,d(s)$$

- The integral is solved by simulation, and the parameters $\hat{\theta}$ are estimated using a global optimization algorithm.

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Algorithm to Maximize the Likelihood

- **Step-by-Step Algorithm:**
  1. Initialize with a guess for $\hat{\theta}$, specify a tolerance criterion ϵ, and set the number of draws R to 1,000.
  2. For each individual i, draw skill vectors s_i R times, denoting each draw as s_i^r.
  3. For each draw $r = 1$ to R:
     1. Calculate the discrepancy ν_i^r
     2. Calculate the probability $\Pr^r(o_i^*, w_i^{obs})$ for the given pair (s_i^r, ν_i^r).
  4. Average over all R values of $\Pr^r(o_i^*, w_i^{obs})$ to obtain $\Pr^{sim}(o_i^*, w_i^{obs})$.
  5. Repeat steps 2-4 for all N individuals and calculate the simulated log likelihood ll^{sim}.
  6. Update $\hat{\theta}$ iteratively until $|ll_{new}^{sim} - ll_{old}^{sim}| < \epsilon$.

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Cluster Refinement Global Optimization Algorithm

- **Addressing Non-Convex Optimization Challenges:**
  - The likelihood function in discrete choice models, especially with high-dimensional parameters, is often non-convex, leading to multiple local maxima.
  - Standard gradient-based optimization routines may converge to these local maxima, failing to find the global maximum.
- **Implementing Cluster Refinement Algorithm:**
  - I develop a Cluster Refinement Global Optimization algorithm to navigate the complex parameter space effectively.
  - It uses machine learning techniques to identify regions in the parameter space that are likely to contain the global maximum.
- **Advantages:**
  - The algorithm efficiently navigates the parameter space while being highly parallelizable.

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Occupation Choice Probabilities and Logit Model

- **Taste Shocks:**
  - Taste shocks (ε_i) are assumed to be independently and identically distributed according to the Extreme Value Type I distribution.
  - This assumption leads to a convenient closed-form expression for the choice probabilities.
- **Conditional Choice Probability:**
  - The probability of graduate i choosing occupation o^*, given their skill-set s_i, is expressed as:

$$\Pr(o_i^* | s_i) = \frac{e^{w_{io^*}}}{1 + \sum_{o=1}^{O} e^{w_{io}}} \tag{4}$$

  - This represents the classic logit choice probability, where w_{io} is the deterministic part of the utility from occupation o for graduate i.

Incorporating Skill Distribution into the Model

- **Specifying Skill Distribution:**
  - Skills are assumed to follow a log-normal distribution:

$$\log(s_i) \sim MVN(\mu, \sigma) \tag{5}$$

- **Unconditional Choice Probability:**
  - The unconditional choice probability, is obtained by integrating the conditional choice probability over the skill distribution:

$$\Pr(o_i^*) = \int \Pr(o_i^* | s_i) f(s) d(s) \tag{6}$$

Incorporating Wage Information

- **Refining the Wage Equation:**
  - The wage equation is augmented with an additional error term ν_i to account for discrepancies between the modelled wage (w_i) and the observed wage (w_i^*):

$$w_i^{obs} = w_i + \nu_i \tag{7}$$

  - This term $\nu_i \sim N(0, \phi^2)$ captures unobserved factors (like individual effort and luck) affecting wages, assumed to be independent of the graduate's occupation choice.
- **Probability of Observing w_i^*:**
  - Given the variance of the error term ϕ^2, the probability of observing a specific w_i^*, given the occupation choice o_i^* and skill set s_i, is:

$$\Pr(w_i^* | s_i, o_i^*) = \frac{e^{\left(-\frac{\nu_i^2}{2\phi^2}\right)}}{\sqrt{2\pi\phi^2}} \tag{8}$$

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