Skills, Tasks and Degrees

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Abstract

University graduates have highly differentiated skills, both compared to the general population and other graduates. In recent years, graduates' skills have become central to debates about the value of higher education. While existing research has focused on returns to fields of study, limited work examines the multidimensional nature of skills, their qualitative content and how they relate to the labour market outcomes of university graduates. In this paper, I develop an economic model to estimate the heterogeneous distribution of analytical and interpersonal skills among recent UK graduates across different disciplines between 2001 and 2019. I structurally estimate the model using UK Labour Force Survey data from 2001-2019, to recover the time-varying parameters of the graduate skill distribution. I find rising analytical but stagnant interpersonal skills across most subject areas, diminishing boundaries between fields, and corresponding implications for wages and employment. Specifically, analytical skills have grown fastest among subject areas which had traditionally low levels of analytical skills, suggesting a response to education policy, or increased demand for technical expertise.

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1 Introduction

For about a century, a university degree has been seen as a secure route to wealth and professional success. Especially in recent years the terms "graduate skills" and "graduate jobs" have become commonplace in the language of Higher Education Institutions (HEIs) who try and advertise their ability to give their graduates an important leg up in an ever more competitive labour market.

Judged by the demand for higher education this rhetoric appears to have been highly successful. Over the last 30 years, the UK (and other developed economies) have experienced a rapid expansion of tertiary education participation. Since the passage of the Further and Higher Education Act 1992, university enrolment has roughly doubled to approximately 2 million in recent years. A trend that was sustained in the face of stark tuition fee increases.[1]

In contrast, rising graduate earnings inequality and underemployment (c.f. Altonji et al. (2016), Holmes & Mayhew (2016), Lindley & MacIntosh (2015)) cast some doubt on whether HEIs are delivering on their promises of great skills and good jobs. As of 2019 real wages of young graduates have not recovered to their pre-Financial Crisis levels, and increasing numbers of degree holders fail to secure employment in one of the coveted "graduate jobs". In the UK these developments have meant that the value of a university degree is coming under increased public scrutiny with some questioning the profitability of this expensive investment made by so many young individuals.[2]

The question of whether Higher Education Providers are providing graduates with relevant skills, and what form these "graduate skills" take, is an open one. As technological change accelerates it becomes increasingly relevant for students to be able to acquire the right mix of skills, to remain competitive in the labour market. Yet few studies try to analyse the qualitative dimension of graduate's skills.

In this paper, I develop a model of occupational choice for university graduates to quantify the importance of *qualitatively* different skills for the labour market success of young graduates. Measures of skills are generally unobservable for an econometrician working with individual level survey data. In order to address this issue, I take another approach - framing the question as a latent variable problem: skills are unobserved but related to observable choices and labour market outcomes. Hence, by specifying and estimating a corresponding structural economic model, we can make inferences about the unobserved skill endowments of university graduates only using widely available data sources, such as the UK Labour Force Survey (QLFS) and the Skills and Employment Survey (SES).

The model I develop allows for rich heterogeneity in both skills and preferences. After graduating, graduates differ with regards to their idiosyncratic endowment of two types of general skills: analytical and interpersonal. Skill endowments are modelled as draws from subject specific multivariate distributions and are thus allowed to vary between as well as within university subjects, capturing important dimensions of heterogeneity: Differences between the distributions capture differences in emphasis due to the specific subject, while

[1]The cap on the amount that universities can charge was increased nearly threefold in England in 2012, leading to a large increase in tuition fees with most institutions charging the maximum amount.

[2]Lately, in the UK and the US, the public discourse has revolved around the value of degrees which - according to some - do not provide relevant skills to students, resulting in high dropout rates, or poor labour market outcomes for graduates. As a response the UK government has indicated that funding for such "underperforming" courses might be reduced or cut completely.

each distribution encompasses a further degree of heterogeneity resulting from differences in university quality as well as inherent differences due to individual ability and aptitude conditional on subject choice. Each degree subject is therefore characterised by a time varying, multivariate distribution, and each graduate by the skill endowment which they have drawn from this distribution.

Correspondingly occupations vary in the value they assign to different skills and hence the match between graduate and occupation matters for realised productivity and wages. The production sector follows the standard approach in the task-skill literature (c.f. Autor et al. (2003), Autor & Handel (2013), Sanders & Taber (2015)), and features a multitude of occupations that differ with respect to how intensely they use each type of skill in production. The combination of a worker's skills and the work task requirements of an occupation determine the worker's occupation specific productivity. Upon graduation, graduates choose their preferred occupation taking into account their idiosyncratic skill endowment as well as other preferences.

I use a sample of recent university graduates from 2001-2019 together with occupation level information on the demand for different tasks, to structurally estimate the model using simulated maximum likelihood, and recover the parameters of the underlying latent skill distributions for different subjects and time periods. To ensure robustness of the estimates I control for a variety of potential factors that might affect changes in skill demand. I then use the model estimates to analyse changes in the graduate skill distribution, the changing demand for these skills and their effects on the labour market outcomes of university graduates between 2001 and 2019.

The main finding of the paper is that since the period of 2001-2009 there has been a considerable shift in the skill mix of recent university graduates, with a particular increase in the level of analytical skills. This shift is particularly evident among graduates from fields that traditionally placed less emphasis on analytical skills such as Arts & Humanities. In the wake of this development, analytical skills have become more equally distributed across the distribution and have also become a more relevant factor in determining graduate's earnings. This contrasts with stagnating levels of interpersonal skills, which have become more unequally distributed. A common trend is that skill levels have become less anchored to specific subjects resulting in much higher within-subject variation in skill sets.

This paper adds to a large, and growing literature on the returns to higher education and specifically to a subset of this literature that investigates the return to specific fields of study (see Altonji et al. (2016), Andrews et al. (2022) and Lovenheim & Smith (2022) for extensive surveys). Generally, these studies estimate latent average treatment effects, whilst trying to address the inherent difficulties caused by the existence of selection effects across dimensions of inherent ability and preference using administrative cutoff rules (see for example Kirkeboen et al. (2016), Hastings et al. (2013)); or try to control for observable factors (Hamermesh & Donald (2008)). Given the wide range of possible subjects' students can study, it is natural to assume that differences in subject specific outcomes are -at least partially - due to the different types of skills that are taught in these courses and how these are rewarded in the labour market. My model takes this idea seriously by focussing on the "qualitative" content of different university degrees, and thereby providing a potential mechanism for the observed differences across different degree subjects.

Further, this paper contributes to the literature on how endowments of different types of skills affect labour market outcomes of graduates in an environment where occupations have differentiated skill requirements. This literature tends to focus on the dichotomy between more general (transferable) and more specific skills leading to differences in the risk-return profiles between general and specialised degree subjects (c.f. Leighton & Speer (2020), Onozuka (2019)). Of particular importance here is the paper by Kinsler & Pavan (2015), which estimates a structural model where students acquire mathematical and verbal skills the return of which differ according to their occupation. The modelling approach taken in their paper is necessarily different from my own, but they are related in spirit.

Finally, this paper complements other attempts at eliciting the skill content of different university degrees. Altonji et al. (2014), create measures of the task content of different subject, by mapping task measures from the Dictionary of Occupational Titles to graduate's occupation choices. Similarly, Hemelt et al. (2021) collect information from online job postings, to associate desired skills with different degree subjects. My paper differs in so far as that it uses both occupation choice and wage information for estimation as well as allowing for substantial within subject skill heterogeneity. However, it shares the former's conception of a university degree as a bundle of multidimensional skills that are related to different tasks.

To the best of my knowledge this paper is the first attempt at trying to find quantitative evidence for the actual distribution of skills of university graduates in the UK how it interacts with changes in the demand for these skills. The results suggest that skill heterogeneity plays a large role in explaining the changes in the labour market outcomes of university graduates. Graduates differ in their skill endowments in accordance with the subject that they choose to study and beyond. Furthermore, the distribution of graduate's skills is changing over time meaning that graduates today look very different from those 10-25 years ago. This finding has important implications for educational and more general economic policy going forward.

The rest of the paper is structured as follows: section 2 presents the economic model of wage setting and occupational choice; section 3 presents the econometric strategy, used to estimate the parameters of interest; section 4 presents the data sources used in the analysis; section 5 highlights the estimation procedure; section 6 covers the results including the counterfactual decompositions and section 7concludes.

2 Model

In this section, I present an economic model of occupation choice and wage determination for recent university graduates in order to recover the skills supplied by university degrees. The economic environment in this model closely follows the literature on estimating task returns (c.f. Autor & Handel (2013), Roys & Taber (2016)). Whereas for occupation choice, I follow the methodological approach of the multinominal choice literature, where it is common to estimate unobserved parameters from the observed choices of individuals. In particular I will refer to the class of mixed logit models which seem to be particularly relevant in this context (see Train (2009), Chapter 6). For expositional simplicity, both parts are presented separately, before being combined in the next section.

2.1 Wage Determination

A worker's multidimensional skill-set is summarized by a K dimensional vector $s_i = \{s_{i1}, s_{i2}, .., s_{iK}\}$ where each element $s_{ik} \geq 0$ describes how effective worker i is at performing task k.

On the firm side, the labour market consists of a large number of *occupations* that each use the different skills supplied to them in different proportions. Specifically, every occupation $o \in O$ has an associated vector $\lambda_o = \{\lambda_{o1}, \lambda_{o2}, ...\lambda_{oK}\}$ where each element $\lambda_{ok} \geq 0$ summarizes the productivity of task k in occupation o.

A worker's human capital therefore depends on her skill-set as well as the task-productivity vector of her chosen occupation. Specifically, the human capital of worker i in occupation o is defined as:[3]

$$h_{io} = e^{\sum_{k=1}^{K} \lambda_{ok} s_{ik}} \tag{1}$$

Denote the aggregate amount of human capital in occupation o as

$$H_o = \int_{i \in o} h_{io} d(i). \tag{2}$$

Finally, output is produced by an aggregate production function:

$$Y = F(H_1, ..., H_O) \tag{3}$$

The marginal product of worker i in occupation o is:

$$\frac{\partial Y}{\partial h_{io}} = \frac{\partial F}{\partial H_o} \frac{\partial H_o}{\partial h_{io}} = \frac{\partial F}{\partial H_o} e^{\sum_{k=1}^{K} \lambda_{ok} s_{ik}} \tag{4}$$

Denote $\frac{\partial F}{\partial H_o} = e^{\eta_o}$,[4] and assume that firms pay workers their marginal product, then the log wage of worker i in occupation o can be written as:

$$w_{io} = \eta_o + \sum_{k=1}^{K} \lambda_{ok} s_{ik} \tag{5}$$

This setup is fairly standard in the literature on tasks and skills (c.f. Autor & Handel (2013), Roys & Taber (2016)).

Generally, economies of the type described above are characterized by the sorting of workers according to comparative advantage (see Roy (1951)). This self-selection of workers into different occupations according to their different abilities, poses the main obstacle that is faced by the literature that is concerned with estimating "task prices" (i.e. the set λ). Since there will be a positive correlation between an occupations' task prices λ_o and the skills supplied by workers selecting into this occupation, simply running an OLS regression on equation (5) will not do the trick (see Autor (2013)).

In this paper however, rather than being harmful, self-selection is actually helpful as it allows us to make inferences from a worker's observed occupation to her unobserved skill-set. In order to enable this inference, we will first have to model the discrete choice behaviour of the worker.

[3] For this exposition I am going to ignore any other factors that might influence productivity such as worker specific characteristics. Including these is a trivial extension of the model.

[4] Depending on your preferences, you might want to interpret η_o as a occupation specific demand component, or a occupation fixed effect.

2.2 Occupational Choice

Workers observe their skills, and all potentially relevant characteristics of an occupation and pick whichever occupation provides them with the highest valuation in terms of utility. In this case, suppose that every graduate can observe the set O of all available occupations and attach a personal valuation V_{io} to each of these options. Accordingly, a worker i solves the following (static) occupational choice problem:

$$V_i = \max_{o \in O} \{V_{io}\} \tag{6}$$

Under these circumstances the individual's occupation choice o_i^* will refer to the best available option:

$$o_i^* = \arg\max\{V_{io}\} \tag{7}$$

In the following I will make some assumptions about the different parts affecting the worker's utility V_{io} which allows me to estimate the unobserved characteristics that we are interested in. Let us assume that the utility derived from the occupation is linear in the log wage,[5] leading to the following relationship:

$$V_{io} = w_{io} + \varepsilon_{io} \tag{8}$$

where o is one of the available occupations, w_{io} is the log wage earned by i in occupation o and ε_{io} is an individual-occupation-specific preference shock that is **i.i.d.** across all agents and all occupations.[6] Importantly, the value of V_{io} is perfectly observed by the economic agent, while only o_i^* is observed by the econometrician.

The random component ε_{io} is random in an idiosyncratic sense. Two workers with the same deterministic wage, may have different preferences over the set of occupations. This differentiation in choice behaviour is important since otherwise, the utility maximizing choice would be the same for every worker, leading to unrealistic predictions. Furthermore, the introduction of this random term allows us to capture other factors that influence occupation choice besides the desire to maximize wages, such as other preferences or frictions in the labour market.

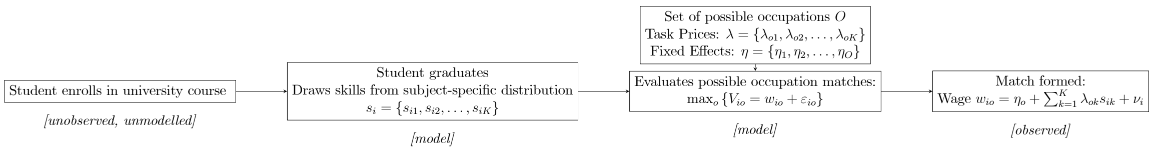


Figure 1: Model Summary

3 Econometric Strategy

The econometric strategy combines the empirical content of the two parts of the economic model described above. The key ingredient is that both, a worker's occupation choice and

[5] This is likely to be the case for an economic agent with a suitably defined utility function (e.g. logarithmic), who is borrowing constrained. I believe it reasonable to assume that this situation applies to the sample population studied in this paper.

[6] Generally, models of this form are known as "random utility models" (RUM), since the worker's valuation of the different options V_{io} can be broken up into a "deterministic" part, w_{io} and a "random" part, ε_{io}.

her realized wage are informative about her skill-set, provided that we also have some information about the occupation task vector λ.

3.1 A mixed logit model of occupational choice

Let us recall the problem our graduate is facing. She knows her own skill set s_i, as well as the the task vectors of all occupations λ, as well as the occupation specific parameters η, and therefore perfectly knows her expected log wage in every occupation o: $w_{io} = \eta_o + \sum_{k=1}^{K} \lambda_{ok} s_{ik}$.

She also perfectly knows her preferences over the non-pecuniary aspects of each occupation ε_i, and is therefore able to assign to each occupation a personal valuation $V_{io} = w_{io} + \varepsilon_{io}$. I include the possibility of not joining the labour force ($o = 0$) as the outside option which is normalised to have a valuation of 0. Finally, given this valuation the graduate chooses her preferred occupation: $o_i^* = \arg\max\{V_{io}\}$.

Making the standard assumption that her idiosyncratic occupation preference shocks ε_i are distributed i.i.d. Type I Extreme Value, we can express the conditional choice probability of her chosen occupation o_i^* as:

$$\Pr(o_i^*|s_i) = \frac{e^{w_{io^*}}}{1 + \sum_{o=1}^{O} e^{w_{io}}} = \frac{e^{\eta_{o^*} + \sum_{k=1}^{K} \lambda_{o^*k} s_{ik}}}{1 + \sum_{o=1}^{O} e^{\eta_o + \sum_{k=1}^{K} \lambda_{ok} s_{ik}}} \tag{9}$$

Assuming that s_i was drawn from a parametric distribution, then it is possible to identify and estimate the parameters of this distribution.[7]

I assume that each skill vector is drawn from a multivariate log-normal distribution with mean μ and variance-covariance matrix Σ:

$$\log(s_i) \sim MVN(\mu, \Sigma). \tag{10}$$

The log-normal is a convenient choice here, as it ensures strictly positive support for the skill-set s, which seems like a reasonable choice for our purposes.

Using this assumption, we can derive the unconditional choice probability by integrating over the distribution of s:

$$\Pr(o_i^*) = \int \Pr(o_i^*|s_i) f(s) d(s) = \int \frac{e^{\eta_{o^*} + \sum_{k=1}^{K} \lambda_{o^*k} s_{ik}}}{1 + \sum_{o=1}^{O} e^{\eta_o + \sum_{k=1}^{K} \lambda_{ok} s_{ik}}} f(s) d(s) \tag{11}$$

Standard results (c.f. McFadden & Train (2000)) guarantee, that we can use the unconditional choice probability in (11) to get consistent estimates for η, μ and Σ, using simulated maximum likelihood.[8]

However, the model is not complete yet. As of yet there is nothing distinguishing our "skill" interpretation of s from a "taste" interpretation. Indeed, strictly speaking we would have to provide a location normalization for one of our parameters, in order to fix their relative values. In the following I will use the observed wage to address the last two points.

[7] Assuming a parametric distribution for s turns this into a mixed logit model (see Train (2009), Chapter 6), where we are effectively treating skills as random taste parameters over the different tasks. The mixed logit is an extremely flexible choice model that can indeed approximate any random utility model (c.f. McFadden & Train (2000)). Most interesting for researchers is that it naturally generates correlations in choice behaviour across similar alternatives. For example, a worker with a particular large value of some skill is going to prefer all occupations that use this skill with great intensity.

[8] There is no closed form solution for this integral, but integration step can be performed via simulation.

3.2 Adding wage information

So far the model has already made use of the wage setting equation (5), but for any draw of s_i a worker's modeled wage w_i differs from the worker's realized (observed) wage w_i^{obs}, due to the presence of other factors such as individual effort and luck. I capture these elements by adding an additional disturbance term to the wage equation:

$$w_i^{obs} = w_i + \upsilon_i \tag{12}$$

where υ_i is a random, mean zero disturbance, **independent** of the workers occupation choice:

$$\nu_i \sim N(0, \phi^2).$$

Assuming independence this implies that υ_i does not impact the graduate's occupation choice. This would be true if ν_i is only realised after the graduate has made her choice.

Given a specific occupation choice o_i^*, and skill-set s_i, we can calculate the size of ν_i:

$$\nu_i = w_i^{obs} - \left[\eta_{o^*} + \sum_{k=1}^{K} \lambda_{o^*k} s_{ik}\right] \tag{13}$$

Thinking in terms of the estimation strategy, ν_i provides a measure, of how far the wage implied by the model parameters, is from a workers actual observed wage. Jumping ahead a little, we should expect the *true* model to minimize this distance.[9]

As ν_i is normally distributed, we have a closed form expression for the conditional probability of observing the observed wage, conditional on a certain skill set s_i and occupation choice o_i^*:

$$\Pr(w_i^{obs}|s_i, o_i^*) = \frac{e^{(-\frac{\nu_i^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}} \tag{14}$$

Ultimately, I am interested in finding the set of parameters, that maximizes, the unconditional joint probability that a worker chooses the occupation that she is observed choosing and that she earns the wage that she is observed earning: $\Pr(o_i^*, w_i^{obs})$.

To find the correct expression, we first rewrite $\Pr(o_i^*, w_i^{obs})$ as

$$\Pr(o_i^*, w_i^{obs}) = \int \Pr(o_i^*, w_i^{obs}|s_i) f(s) d(s) \tag{15}$$

using the law of conditional probabilities to rewrite:

$$\frac{\Pr(o_i^*, w_i^{obs}|s_i)}{\Pr(o_i^*|s_i)} = \Pr(w_i^{obs}|s_i, o_i^*) \tag{16}$$

$$\Pr(o_i^*, w_i^{obs}|s_i) = \Pr(o_i^*|s_i) * \Pr(w_i^{obs}|s_i, o_i^*) \tag{17}$$

Plugging the expression back in gives us:

$$\Pr(o_i^*, w_i^{obs}) = \int \Pr(o_i^*|s_i) \Pr(w_i^{obs}|s_i, o_i^*) f(s) d(s). \tag{18}$$

[9] For a different interpretation of ϕ see Appendix.

From (9) we know that:

$$\Pr(o_i^*|s_i) = \frac{e^{\eta_{o^*}+\sum_{k=1}^{K}\lambda_{o^*k}s_{ik}}}{1+\sum_{o=1}^{O} e^{\eta_o+\sum_{k=1}^{K}\lambda_{ok}s_{ik}}} \tag{19}$$

and hence we can combine to write:

$$\Pr(o_i^*, w_i^{obs}|s_i) = \left(\frac{e^{\eta_{o^*}+\sum_{k=1}^{K}\lambda_{o^*k}s_{ik}}}{1+\sum_{o=1}^{O} e^{\eta_o+\sum_{k=1}^{K}\lambda_{ok}s_{ik}}}\right)\left(\frac{e^{(-\frac{\nu_i^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}}\right) \tag{20}$$

finally, integrating over the distribution of s leads to the unconditional joint probability:

$$\Pr(o_i^*, w_i^{obs}) = \int\left\{\left(\frac{e^{\eta_{o^*}+\sum_{k=1}^{K}\lambda_{o^*k}s_{ik}}}{1+\sum_{o=1}^{O} e^{\eta_o+\sum_{k=1}^{K}\lambda_{ok}s_{ik}}}\right)\left(\frac{e^{(-\frac{\nu_i^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}}\right)\right\} f(s)d(s) \tag{21}$$

In the appendix I describe a complete algorithm that can be used to estimate the parameters of interest from this model, using the likelihood function implied by (21).

3.3 Model extensions

3.3.1 Other demographic characteristics

For an empirical application, it is necessary to control for a number of observable characteristics, as well as circumstantial factors. However, it is trivial to extend the model to include factors other than the skills considered above. To show this, I extend the log wage equation below:[10]

$$w_{io} = \eta_o + \sum_K \lambda_{ok}s_{ik} + \beta x_i \tag{22}$$

where x_i is a vector of observable characteristics (gender, labour market experience, etc.), β is a vector of coefficients. Clearly this equation can be inserted into the likelihood function (21), and β can be estimated as part of an extended parameter vector θ. Further, as long as neither x_i, nor β, vary across occupations (i.e. the model does not include for example either occupation specific experience (occupational tenure) among the observables, nor occupation specific coefficients in β), the additional terms do not have any impact on the occupational choice probabilities, and can therefore be ignored in the first part of the likelihood calculation.

3.3.2 Systematic occupation preferences

In order to make the model more realistic, I also include systematic non-pecuniary aspects of occupations that might affect the graduate's choice. Specifically, I augment the graduates expected payoff from choosing occupation o by a non-random occupation preference term ω_o, which is constant for all graduates and represents the (dis-) utility of working in a specific occupation. The augmented occupational valuation equation thus reads as follows:

$$V_{io} = w_{io} + \omega_o + \varepsilon_{io} \tag{23}$$

[10] Naturally, this can be understood as an extension of the human capital equation specified above.

Like β, ω can be estimated as part of the extended parameter vector θ. Since ω does only affect the occupational choice probabilities, it can be ignored in the wage equation part of the likelihood function.

3.3.3 Accounting for non-employment and missing wage information

Wage information is only observed conditional on the graduate taking a job that pays a wage. If the analysis is to account for the decisions of the non-trivial share of graduates that do not enter the labour force, we need to modify the model to allow for censored wages in the case of non-employment. For these cases we just ignore the wage part of the likelihood function in the calculation of the likelihood:

$$\Pr(o_i^* = non - employed) = \int \left(\frac{1}{1+\sum_{o=1}^{O} e^{\eta_o + \sum_{k=1}^{K} \lambda_{ok} s_{ik}}} \right) f(s)d(s)$$

This is equivalent to assuming that wages paid to non-employed individuals are equal to 0 and also observed to be 0. The same strategy can be employed to include the information of individuals who are employed but have not reported wages.[11]

4 Data

4.1 Graduates

The main data source used in this paper is the Quarterly Labour Force Survey (QLFS) over the period 2001-2019, which I split into two periods: 2001-2009 and 2010-2019. Since 1994 the QLFS has included reasonably fine grained information on the subject of an individual's first university degree (see Lindley & MacIntosh (2015) for more details).[12] Furthermore, the QLFS also contains information on an individual's current occupation, usual hourly pay and some other demographic covariates. I limit my analysis to this 19 year period for two reasons: Firstly, I use the SOC2000 2-digit occupation classification which is not necessarily compatible with occupation classifications prior to 2001. Secondly, I will be using estimates of the measurement variance of wages based on data from 2009-10, so I try to avoid expanding the analysis beyond 10 years either side.

I restrict the sample to graduates between the ages of 21 and 24.[13] This age restriction is put in place to make sure that we capture those graduates who are "fresh" out of university, so that their skill-set most accurately reflects their post-university endowment. A small age bracket also reduces contamination by other factors such as age and experience effects as well as on the job skill accumulation.

[11] This is unfortunately true for a nontrivial subset of individuals in the QLFS data. In this case I have to assume that there is no systematic non-reporting bias in the data and that wages are missing at random for these individuals.

[12] I ignore those who have more than one degree, or any further or higher degrees. Postgraduate qualifications take on a more significant role over time, as a higher percentage of graduates pursue these degrees. However, a large fraction of graduates pursues a postgraduate qualification in a subject different from their first degree, making it difficult to assign the skills they exhibit to their first or later degree. I decided to exclude postgraduates in order to keep the relationship between degree subject and skills as clean as possible.

[13] Typically in the UK students finish highschool at 18 and enter 3 year University Courses.

For each graduate in my sample I collect wages measured as usual gross hourly pay, deflated by the CPI;[14] their current occupation (if applicable) as classified by the 2-Digit SOC 2000 Occupational classification schedule; Gender; Subject of first degree; part-time work status; region of usual residence and age, which I use as a proxy for labour market experience.

I split the sample into 5 groups according to broadly defined subject degree categories: 1. Medical and Life Sciences (including Biology & Agriculture); 2. Science, Engineering, Technology & Mathematics (STEM); 3. Business Management & Economics; 4 Arts & Humanities; 5. Other Degrees. In order to avoid complications I drop all those who hold any advanced degrees beyond the undergraduate level.

The total sample includes 46,637 graduates, with around 21,000 individuals in the first and over 25,000 individuals in the second time period.

The labour market outcomes of these recent graduates are summarised in Table 1. Mean real hourly wages decreased for all fields of study, with the largest decrease for Medical and Life Sciences. This suggests that graduates in all fields were earning less in real terms in the later time period than they were in the earlier period (see also Figure 2). The largest decrease in hourly wages for Medical and Life Sciences graduates is particularly noteworthy, as it is a field that is often considered to have high earning potential.

Gini coefficients for hourly wages remained relatively stable for all fields of study, indicating little change in income inequality. Despite the decrease in mean hourly wages for all fields, there was no significant increase in income inequality. This means that while graduates were earning less overall, the distribution of wages remained relatively stable over time.

To measure occupational outcomes, I also report the share of non-typical occupations and the share of graduates not in the labour force. The share of non-typical occupations increased for all fields of study, with the largest increase for Medical and Life Sciences, suggesting a connection with the drop in average wages. This suggests that graduates in all fields were more likely to be employed in jobs that are not typically associated with their field of study in the later time period (see also Figure 2).

The share of non-employed graduates decreased for all fields of study between 2001-2009 and 2010-2019, with the largest decrease for Medical and Life Sciences and Other degrees. This suggests that graduates in all fields were less likely to be unemployed in the later time period than they were in the earlier period. However, there were important differences across different subjects. For example, while STEM graduates saw an actual increase in their non-employed share and Business & Economics and Arts & Humanities saw only small decreases in their non-employed shares. Moreover, those subjects that saw large increases in their share of non-typical occupations experienced a bigger decline in their non-employed share. This may suggest that graduates in those fields who were struggling to find work in traditional jobs were more likely to take non-typical roles in order to gain employment.

4.2 Trends in graduates' labour market outcomes

Figure 2 provides an illustration of the evolution of log hourly wages for young working graduates. Average real wages appear to be trending downwards, even if one makes some allowance for the Great Recession period. At the same time, wage inequality - measured

[14] I also trim the top and bottom 1% of wage values to remove nonsensical values.

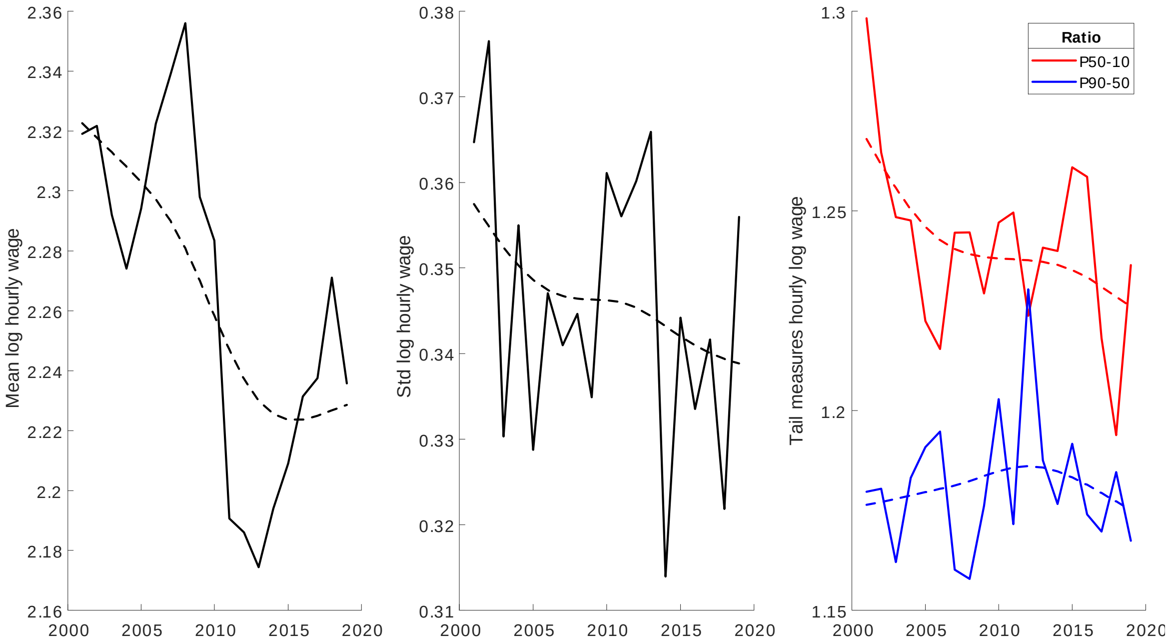
	Mean hourly wage		Gini hourly wage		Share of non-typical occupations		Share of non-employed graduates	
	2001 - 2009	2010 - 2019	2001 - 2009	2010 - 2019	2001 - 2009	2010 - 2019	2001 - 2009	2010 - 2019
Medical and Life Sciences	11.07	9.87	0.19	0.18	67.77	74.04	16.14	13.55
STEM	11.57	10.72	0.19	0.19	46.34	47.28	15.42	18.00
Business & Economics	10.79	9.93	0.19	0.18	39.73	39.42	11.18	10.36
Arts & Humanities	9.79	9.00	0.18	0.18	47.24	51.21	15.88	14.25
Other Degrees	10.45	9.44	0.19	0.19	47.85	53.88	16.94	13.60
All Degrees	10.73	9.77	0.19	0.19	49.98	55.01	15.16	14.08

Note: Wages are CPI deflated (2014 = 100).

Table 1: Summary statistics of QLFS sample - Labour Market Outcomes

by the variance of logarithms - is in a steady decline over the same period. This finding is contrary those of Lindley & MacIntosh (2015), who document rising wage inequality over the period 1994 - 2011, and suggests that recent graduates might have quite different experiences from the general group of graduates.[15] The decline in wage inequality appears to be mainly driven by a contraction of the lower tail of the wage distribution, with the P50-10 ratio falling over the time period and the P90-50 ratio remaining approximately stable.

Figure 2: Trends in wages and wage inequality among young graduates in the UK (2001 - 2019)



Note: Wages are hourly wages, deflated by 2014 CPI Index. Working graduates aged between 21 and 24 years.

Broken lines represent HP-filtered trends with a smoothing parameter of 100.

Source: Quarterly Labour Force Survey

Another important measure of graduate's success is the type of jobs that graduates enter upon graduation. Traditionally university graduates were closely associated with high skilled white collar occupations such as professional and managerial jobs. However, at least for new entrants into the labour market this distinction appears to have weakened over the last couple of years. Figure 3 provides some evidence as to the changing patterns of the destinations of young graduates. The first subplot shows the evolution of the

[15] Lindley & MacIntosh (2015) do consider a much wider age range in their analysis. Indeed if I extend the analysis to graduates aged 21 to 55 years I also find increasing wage inequality over the time period.

Herfindahl-Hirschman index of occupation concentration amongst young graduates for the sample period. The graph shows a clear downward trend in occupation concentration over the last 20 years. This is mirrored by the second subplot, which shows the share of graduates entering "typical" versus "nontypical" occupations. I define these categories as the group of 2-digit SOC (2000) occupations that in 2001 had more (less) than 5% of graduates. Again there is a clear trend towards less concentration, with increasing numbers of young graduates entering occupations that would have been unusual for graduates to choose 10-15 years ago. The final subplot shows the share of young graduates not in employment. It is a bit difficult to spot a clear pattern here as the great recession causes a huge spike in graduate non-employment, but there appears to be a somewhat small downward trend.

Figure 3: Trends in employment of young graduates in the UK (2001 - 2019)

Note: UK graduates aged 21-24 years. 2-digit SOC 2000 occupations.

Typical occupations are those SOC codes that in 2001 contained at least 5% of graduates.

Source: Quarterly Labour Force Survey

4.3 Occupations & Tasks

The 2-digit SOC 2000 schedule provides me with 25 occupation groups. For the task dimension I choose two broad groupings: 1. Analytical; 2. Interpersonal Tasks. I choose these groups since I believe that these kind of tasks are of particular relevance to university graduates.[16]

To obtain an estimate of the occupation task requirements, I use four waves of the UK Skills and Employment Survey (SES). The years of these surveys, 2001, 2006 & 2012 and 2017 map neatly into our sample periods. Since the beginning of the task literature

[16] For example I do not include manual or routine tasks, as I do not believe that these are particularly interesting in the context of higher education.

there have been many different approaches that try to approximate the task requirement vector λ using survey data (c.f. Autor (2013), Autor et al. (2003), Autor & Handel (2013), Rohrbach-Schmidt & Tieman (2013)). Here I loosely follow the approach of Bisello (2013) who also works with the SES.

In the SES, respondents answer questions related to their job and score the importance of performing certain tasks on a Likert scale. I restrict the sample to prime aged workers aged between 21 and 55 years. I then proceed as follows to obtain the occupation task requirements:

As a first step, I select a number of survey items that relate to the task dimensions that I chose above.[17] Since these survey questions are coded on an ordinal scale, I rescale them so that the Likert scale points are equidistant between 0 and 1. I then run a principal component analysis retaining the first two principal components. Whilst there is considerable differentiation between jobs in terms of the required analytical and interpersonal skills, there is likely also an element of correlation as generally more complex jobs will require both high levels of analytical and interpersonal skills. In order to avoid such a general "complexity" factor, I rotate the factor loadings matrix using an orthogonal rotation (see Appendix for details). I then average the obtained principal components across 2-digit SOC 2000 occupations for each year in the SES. I interpolate the missing years using linear interpolation. Finally, I scale the obtained values between 0 and 1.

5 Estimation

Let's recall that we are interested in estimating the parameters of the subject-specific graduate skill distribution, which had been specified as: $\log(s_i) \sim MVN(\mu_t, \Sigma_t)$.

I want to recover changes of the skill distribution over time, so both μ_t and Σ_t are specified as time varying. I have specified two task dimensions and correspondingly the skill distribution also has two dimensions $k = \{1, 2\}$. Furthermore, there are 5 degree subjects, $m = \{1, .., 5\}$ and two time periods $t = \{1, 2\}$, leading to $M * T = 10$, subject-period specific multivariate skill distributions.

For each multivariate skill distribution I estimate a vector $\mu_{mt} = \begin{pmatrix} \mu_{mt}^{analytical} \\ \mu_{mt}^{interpersonal} \end{pmatrix}$ and a variance covariance matrix $\Sigma_{mt} = \begin{bmatrix} \sigma^2_{analytical,mt} & \sigma^2_{corr,mt} \\ \sigma^2_{corr,mt} & \sigma^2_{interpersonal,mt} \end{bmatrix}$, where $\sigma^2_{corr,mt}$ is the subject, time specific correlation between both skills.

Occupation fixed effects (η_{ot}) are also allowed to vary between the two periods, in order to capture structural changes in the demand for their output. Across the two periods, the sample spans 19 years, and I allow for year specific aggregate conditions in the labour market, by including year and geographic region fixed effects. I also include a linear term for experience, part-time status and gender, both of which are allowed to vary across periods.

To summarize, we have to estimate 50 parameters (μ_{kmt} & σ^2_{kmt}) for the 10 different lognormal distributions, 50 for the occupation fixed effects η_{ot}, 50 for the occupation specific preference terms ω_{ot} , 17 year fixed effects, 38 geographic region fixed effects and 2 each for gender, part-time and experience controls - a total of 211 parameters.

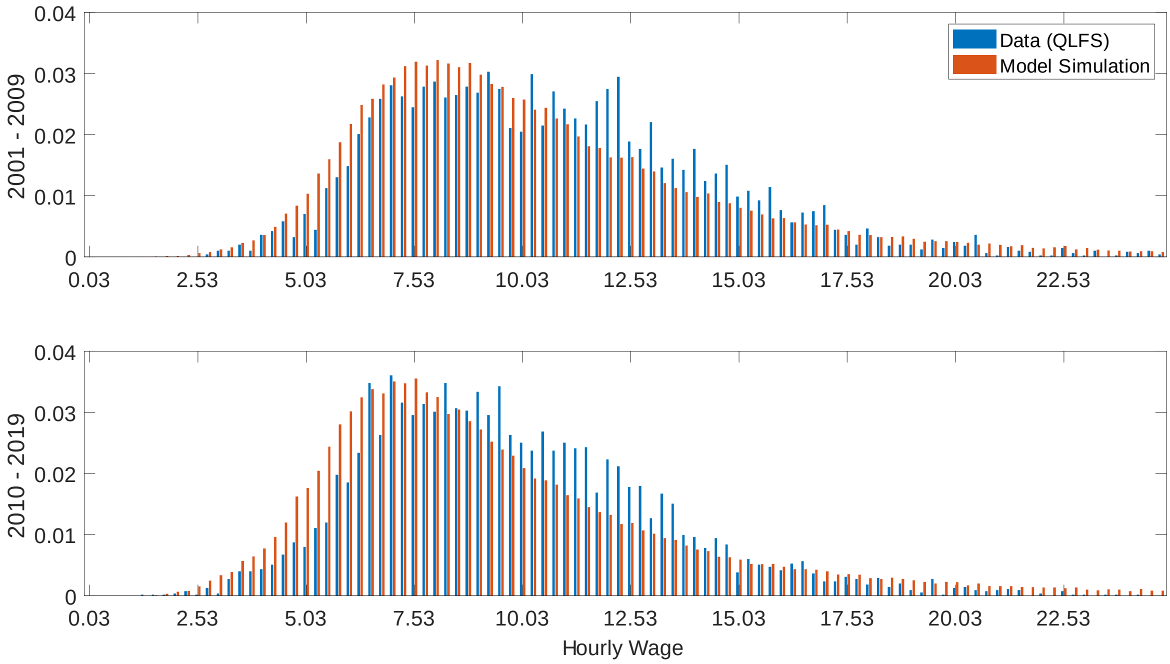
[17] For a full list of the selected survey questions see Appendix.

Setting ϕ^2, i.e. the variance of the measurement error, is a difficult task in this model, that requires some additional steps. The error term υ_i does not only capture traditional measurement error, but also any other productivity differentials that materialize over the course of the graduate's early career, such as health episodes or promotions. The standard approach to setting ϕ^2 would be to run a regression of wages on a number of observables and use the variance of the residuals as an estimate. For this model, this requires controls for mathematical, verbal abilities. Luckily, I can resort to an auxiliary data set (Understanding Society, Wave 3), providing me with an estimate for $\phi = 0.103$.The details of the estimation algorithm are provided in the Appendix.

5.1 Model Fit

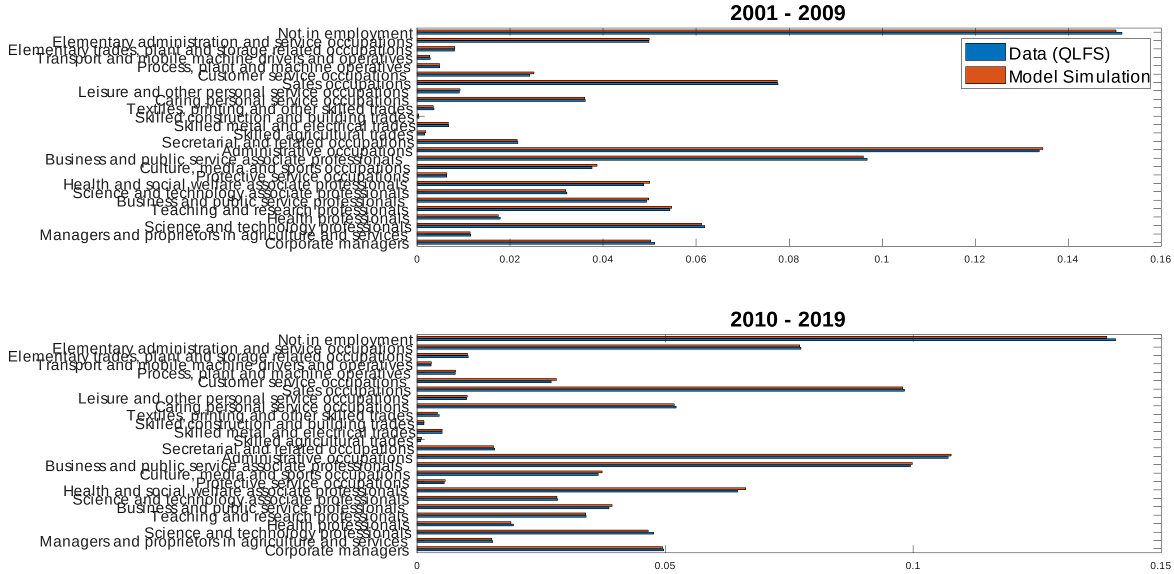
After I estimate the model, I evaluate the ability of the model to capture both the occupation choices of graduates as well as their wage outcomes. For this purpose I simulate a random, representative sample of 100,000 graduates in each time period. Figure 4 below show the histogram of the hourly wage across all time periods, while Figure 5 highlights the model fit with respect to the occupation choices of graduates in each time period.

Figure 4: Histogram of Hourly Wages.



Notes: Histogram of hourly wages. QLFS Data and Simulation. Wages in the data are deflated by the 2014 CPI Index.

Figure 5: Occupation Distribution - QLFS Data and Model Simulation.



Notes: 2-Digit SOC 2000.

To complement the visual with some statistical evidence the table below compares the model and the data with respect to the mean and median log wage, the upper and lower tail inequality measures of the hourly log wage and the occupation concentration index, as well as the share of non-typical occupations. The model fit is quite good, with the overall model predictions matching their empirical counterparts closely.

The model generally performs quite well in estimating both mean and median log wages across a variety of fields, with most discrepancies being quite small. Specifically, for mean log wages, the model's estimates are largely within a 2% difference from the actual data for all fields except for "STEM." This high level of accuracy is evident in sectors like "Medical and Life Sciences" and "Arts and Humanities" where the model estimates are exceptionally close to the real-world figures. When it comes to median log wages, the model maintains a reasonable level of accuracy, staying within a 4% difference for most fields. Again, the "STEM" field emerges as a slight outlier, where the model underestimates the median wages by as much as -7.17% for the years 2010-2019.[18] Overall, the model exhibits a strong fit for both mean and median log wages across multiple fields, with the "STEM" field being a notable, albeit slight, exception. This suggests that the model is largely successful in capturing the central tendencies of wage distributions across various sectors, with some room for improvement in the "STEM" field.

For the lower tail inequality, represented by P5010 log wages, the model performs quite well when looking at the aggregated data across all fields. The percentage differences between the model's estimates and the actual data are relatively low, with a slight overestimation of 0.90% for 2001-2009 and a modest overestimation of 3.01% for 2010-2019. This suggests that the model is fairly accurate in capturing the lower end of the wage distribution for all graduates. When it comes to upper tail inequality, represented by P9050 log wages, the model's fit is less precise. The model consistently overestimates

[18]This suggests that theer might be a substantial "STEM" premium paid to graduates in this field which is not captured by the model.

this metric, with a difference of 5.56% for the years 2001-2009 and a more significant difference of 9.42% for 2010-2019. While the fit is not dramatically off, it does indicate that the model tends to generate a higher level of wage inequality at the upper end of the distribution than what is observed in the actual data.[19]

When examining the aggregated data for all graduates irrespective of field of study, the model demonstrates a high level of accuracy for both the Herfindahl-Hirschman Index (HHI) and the share of non-typical occupations. For the HHI, the model's estimates are within a 1.22% difference for both time periods, suggesting a very good fit in capturing overall occupational concentration. Likewise, for the share of non-typical occupations, the model estimates are also closely aligned with the actual data, showing a minimal difference of less than 0.5% for both time periods.

However, when breaking down the data by specific fields, the model's performance appears to be less consistent. Specifically, the model significantly underestimates the HHI across all subjects. These field-specific discrepancies in model fit could be attributed to the absence of field-specific occupation preferences in the model.[20] Correspondingly, the model tends to overestimate the share of non-typical occupations amongst all subjects except for Medical and Life Sciences, where it underestimates the share of graduates pursuing non-typical occupations. Overall, the model performs quite well in capturing the broader trends in occupational concentration (HHI) and share of non-typical occupations, as evidenced by the close fit in the aggregated category. In the following analysis I will therefore put an emphasis on the aggregate level when discussing related results.

[19] This might be a result of the choice of skill distribution which can generate high right tails, or be an artifact of artificial wage ceilings in the real world data.

[20] For example, if the occupations of medical doctor and engineer have similar task weight vectors, then the model would predict that a graduate should be approximately indifferent in choosing either occupation, nonwithstanding that in reality there are obvious additional factors that determine whether one chooses to become one rather than the other.

	Mean log wages						Median log wages					
	2001-2009			2010-2019			2001-2009			2010-2019		
	Data	Model	% diff.	Data	Model	% diff.	Data	Model	% diff.	Data	Model	% diff.
Medical and Life Sciences	2.34	2.32	-1.00	2.24	2.24	0.22	2.39	2.28	-4.40	2.27	2.19	-3.54
STEM	2.39	2.29	-4.02	2.31	2.22	-3.88	2.43	2.28	-6.41	2.36	2.19	-7.17
Business & Economics	2.32	2.28	-1.68	2.24	2.21	-1.37	2.32	2.27	-2.17	2.24	2.19	-2.05
Arts & Humanities	2.23	2.23	0.04	2.14	2.12	-1.22	2.23	2.19	-1.58	2.15	2.06	-4.08
Other Degrees	2.29	2.25	-1.83	2.18	2.17	-0.33	2.29	2.21	-3.51	2.18	2.11	-3.10
All	2.31	2.27	-1.71	2.22	2.20	-1.15	2.33	2.25	-3.66	2.23	2.15	-3.89
	$\frac{P50}{P10}$ log wages						$\frac{P90}{P50}$ log wages					
	2001-2009			2010-2019			2001-2009			2010-2019		
	Data	Model	% diff.	Data	Model	% diff.	Data	Model	% diff.	Data	Model	% diff.
Medical and Life Sciences	1.27	1.21	-4.78	1.26	1.23	-2.65	1.15	1.24	7.20	1.15	1.27	10.08
STEM	1.27	1.31	3.33	1.27	1.43	12.96	1.15	1.26	9.40	1.16	1.36	17.48
Business & Economics	1.22	1.27	3.76	1.23	1.33	8.40	1.18	1.21	2.47	1.19	1.27	6.52
Arts & Humanities	1.21	1.24	2.57	1.22	1.25	1.93	1.19	1.26	5.91	1.19	1.29	9.00
Other Degrees	1.24	1.23	-0.69	1.24	1.25	0.87	1.19	1.24	3.62	1.21	1.30	7.69
All	1.24	1.25	0.90	1.24	1.28	3.01	1.18	1.24	5.56	1.18	1.29	9.42
	HH-index						Non-typical share					
	2001-2009			2010-2019			2001-2009			2010-2019		
	Data	Model	% diff.	Data	Model	% diff.	Data	Model	% diff.	Data	Model	% diff.
Medical and Life Sciences	0.09	0.08	-20.44	0.10	0.07	-30.44	56.84	44.41	-21.87	64.01	51.28	-19.89
STEM	0.10	0.08	-19.51	0.10	0.07	-26.40	39.19	39.33	0.36	38.77	44.19	13.97
Business & Economics	0.13	0.08	-37.73	0.12	0.08	-38.77	35.29	41.69	18.13	35.33	45.64	29.18
Arts & Humanities	0.10	0.08	-18.01	0.09	0.08	-13.39	39.74	43.69	9.94	43.92	47.46	8.07
Other Degrees	0.10	0.07	-22.07	0.08	0.08	-4.73	39.75	46.22	16.29	46.55	47.50	2.02
All	0.08	0.08	-1.14	0.08	0.07	-1.22	42.40	42.94	1.28	47.27	47.49	0.48

Note: Wages are CPI deflated (2014 = 100).

Table 2: Model Fit

6 Results

This section presents the results of the estimated model. I first present an evaluation of the model's fit to the data. Then I discuss the changes in the underlying unobserved skill distributions and their implications for the observed wage dynamics. Finally, I present the results of some counterfactual experiments in the next section.

6.1 Graduate Skills

Unfortunately, the shape parameters of a log normal distribution are not particularly intuitive, and so I have presented the effective median and mean skill levels and changes in the next table. Since the lognormal is not symmetric there is a difference between the median and the mean outcome. Overall the trends and results are very similar if we take the mean instead (reported in the same table). For this part I will focus the discussion on the median, as it provides the convenient interpretation of the skills of a "typical" graduate.

Looking at the provided values we can see that there is clear differentiation with respect to the different types of skills. Analytical skills, which include critical thinking, problem-solving, and data analysis, tend to be stronger in STEM and Business & Economics degrees. This is likely because these fields require a high degree of quantitative and analytical thinking. On the other hand, Interpersonal skills, which include communication, teamwork, and leadership, tend to be stronger in Medical and Life Sciences and

Arts & Humanities degrees. This is because these fields require a high degree of social and emotional intelligence, as well as the ability to work well with others. Specialisation however is not perfect, and both Business and Economics and Arts and Humanities graduates show both analytic and interpersonal skills to some degree.

When considering median analytical skills, the data still manifests distinct disparities between various academic disciplines. Specifically, STEM and Business & Economics appear to be outliers compared to other fields. For example, STEM had a median analytical skill level of 1.62 in 2001-2009, which further increased to 2.78 in 2010-2019. Business & Economics also saw a substantial increase from 0.98 to 2.14 over the same periods. In contrast, fields like Medical and Life Sciences, Arts & Humanities, and Other Degrees started from a significantly lower baseline and, although they showed some increase, did not approach the levels of STEM and Business & Economics. This differentiation suggests that students in STEM and Business & Economics either acquire or are required to have more advanced analytical skills, possibly due to the specific emphasis of the curriculum or selection of more analytically minded students that enter these fields.

Between the periods, an increase in the level of median analytical skills is evident across all disciplines, not just those traditionally considered analytical. For instance, Medical and Life Sciences saw an increase from 0.03 to 0.65, and Arts & Humanities from 0.38 to 1.33. This steady rise over the two decades under consideration suggests that the supply of analytical skills is becoming more pervasive, irrespective of the academic field. The observed increase in median analytical skills could have multiple underlying causes. It may be indicative of a broader shift in educational priorities, with curricula being updated to include more analytical course-work even in disciplines where this was not traditionally the focus.[21] Another contributing factor could be the changing landscape of the job market, where data-driven decision-making has become crucial, thereby increasing the demand for analytical skills, which elicits a corresponding response from the higher education providers.[22]

When it comes to median interpersonal skills, the simulations suggests less dramatic differences between fields compared to analytical skills. STEM is on the lower end of the spectrum, with median interpersonal skills decreasing slightly from 1.94 in 2001-2009 to 1.77 in 2010-2019. Fields like Medical and Life Sciences and Arts & Humanities, on the other hand, have higher interpersonal skills levels, ranging from 3.42 to 3.83 and 3.00 to 3.10, respectively, across the two time periods. Business & Economics falls somewhere in between, with slight changes from 2.57 to 2.51. This spread suggests that certain fields may naturally attract or cultivate individuals with higher interpersonal capabilities, or perhaps that the education in these fields places a greater emphasis on such skills.

Contrary to the trend in analytical skills, median interpersonal skills have remained relatively stable over time across all fields. There are minor fluctuations, but these are not as pronounced as those observed in analytical skills. For instance, Medical and Life Sciences saw a minor increase from 3.42 to 3.83, while STEM experienced a small drop from 1.94 to 1.77. This stability could indicate that interpersonal skills are either less affected by changing educational or job market demands, or that they are inherently less variable over time.

Overall, the model points to a relative increase in the supply of analytical skills across

[21] Indeed, focussing on more mathematical and technical skills was one of the education priorities of the New Labour government in the early 2000's.

[22] The increasing demand for analytical skills has been well documented in the literature.

all academic fields, which is a highly encouraging trend. This universal uptick could signify that educational systems are adapting to the demands of a more complex, data-driven world, thereby equipping graduates with the skills they need to navigate modern professional landscapes. The rise in analytical skills holds the promise of creating a workforce that is better prepared to engage with the complexities of contemporary roles, from data analysis and strategic planning to problem-solving in various sectors. It suggests that graduates are not only more qualified for existing analytical roles but also more adaptable to new challenges in a fast-evolving job market.

However, the model also reveals a stagnation in the development of interpersonal skills, which merits cautious attention. This stability could indicate that while there is a concerted effort to bolster analytical skills, perhaps the same level of focus is not being accorded to interpersonal capabilities. In a world where automation and artificial intelligence are on the rise, the human-centric skills of communication, teamwork, and emotional intelligence remain irreplaceable (see Deming (2017)). The lack of growth in these skills could lead to a workforce that, while analytically competent, may fall short in roles requiring strong interpersonal interactions, such as leadership, negotiation, or client relations. Therefore, while the increase in analytical skills is a positive development, the stagnant levels of interpersonal skills suggest that a more balanced skill set continues to be crucial for comprehensive career preparedness.

	Mean Skills				Median Skills			
	Analytical		Interpersonal		Analytical		Interpersonal	
	2001-2009	2010-2019	2001-2010	2010-2019	2001-2009	2010-2019	2001-2009	2010-2019
Medical and Life Sciences	0.03	0.74	3.44	3.87	0.03	0.65	3.42	3.83
STEM	1.68	2.88	2.05	1.97	1.62	2.78	1.94	1.77
Business & Economics	1.03	2.21	2.59	2.60	0.98	2.14	2.57	2.51
Arts & Humanities	0.38	1.41	3.02	3.17	0.38	1.33	3.00	3.10
Other Degrees	0.00	1.33	3.35	3.30	0.00	1.24	3.34	3.24
All Degrees	0.65	1.62	2.87	3.06	0.38	1.43	2.98	3.13
	Sq. Coeff. Var. Skills				Gini Skills			
	Analytical		Interpersonal		Analytical		Interpersonal	
	2001-2009	2010-2019	2001-2010	2010-2019	2001-2009	2010-2019	2001-2010	2010-2019
Medical and Life Sciences	0.05	0.31	0.01	0.02	0.12	0.28	0.06	0.08
STEM	0.09	0.07	0.10	0.23	0.16	0.14	0.18	0.25
Business & Economics	0.12	0.07	0.04	0.08	0.19	0.15	0.11	0.16
Arts & Humanities	0.00	0.11	0.02	0.04	0.03	0.18	0.08	0.11
Other Degrees	0.00	0.14	0.01	0.04	0.00	0.20	0.06	0.11
All Degrees	1.20	0.33	0.06	0.10	0.58	0.32	0.14	0.18
Between	84.69	64.45	52.71	44.61				
Within	15.31	35.55	47.29	55.39				
	P5010 Skills				P9050 Skills			
	Analytical		Interpersonal		Analytical		Interpersonal	
	2001-2009	2010-2019	2001-2010	2010-2019	2001-2009	2010-2019	2001-2010	2010-2019
Medical and Life Sciences	1.31	1.93	1.15	1.20	1.32	1.93	1.15	1.20
STEM	1.48	1.39	1.48	1.76	1.43	1.40	1.52	1.80
Business & Economics	1.58	1.41	1.31	1.46	1.54	1.42	1.28	1.45
Arts & Humanities	1.07	1.51	1.19	1.29	1.07	1.52	1.19	1.30
Other Degrees	1.01	1.59	1.17	1.29	1.01	1.60	1.16	1.29
All Degrees	173.99	2.44	1.64	1.84	4.54	2.06	1.24	1.36

Table 3: Skill results

The simulations indicates a high level of inequality in analytical skills during the earlier period (2001-2009), primarily driven by substantial skills in STEM and Business

& Economics relative to other subjects. The Square Coefficient of Variation for all degrees was at 1.20, and the Gini coefficient was at 0.58. Over time, however, both metrics show a decrease, with the Square Coefficient falling to 0.33 and the Gini coefficient to 0.32 by 2010-2019. This decline in inequality coincides with an overall increase in the level of analytical skills across all fields. While the increase in the level of analytical skills across all subjects acts to reduce analytical skill inequality overall, it tends to increase the disparities among students within specific fields that are newly adapting to this analytical focus. This is particularly evident in the increase in inequality among Medical and Life Sciences, Arts & Humanities and Other degrees. This suggests that this transition is not happening uniformly for all individuals within these disciplines. It could be that students at more resource-rich institutions within these fields are gaining analytical skills more rapidly, or that certain sub-disciplines are adopting these skills more quickly than others. As a result, while these fields are collectively becoming more analytically skilled, they are also becoming more internally diverse in terms of those skills.

When it comes to interpersonal skills, the overall level of inequality, as measured by both the Square Coefficient of Variation and the Gini coefficient, is notably lower than in analytical skills. While the Square Coefficient of Variation for all degrees was at 0.06 in 2001-2009 and increased to 0.10 in 2010-2019, the Gini coefficient rose from 0.14 to 0.18. Despite being lower, the inequality in interpersonal skills displays a different trend compared to analytical skills—it's increasing rather than decreasing over time.

Both STEM and Business & Economics show higher levels of inequality in interpersonal skills compared to other fields. STEM saw an increase in the Square Coefficient of Variation from 0.10 to 0.23, and Business & Economics saw it increase from 0.04 to 0.08. This suggests that these fields, traditionally strong in analytical skills have higher internal disparities when it comes to interpersonal skills. Unlike the case of analytical skills, where inequality decreased in certain fields, interpersonal skill inequality increased in all subjects, irrespective of trends in mean or median interpersonal skill levels. This suggests a generalized trend of increasing disparities in interpersonal skills across the board, irrespective of the subject. The increasing inequality in interpersonal skills could have various ramifications. For one, the uptick in interpersonal skill inequality, especially in fields like STEM and Business & Economics, could indicate a growing polarization within these subjects. Some roles might increasingly require strong interpersonal skills, like client-facing or managerial positions, while others continue to focus more on technical expertise. This divergence could make the career paths within these fields more bifurcated and could also affect wage structures, with positions requiring a blend of high analytical and interpersonal skills potentially commanding premium compensation.

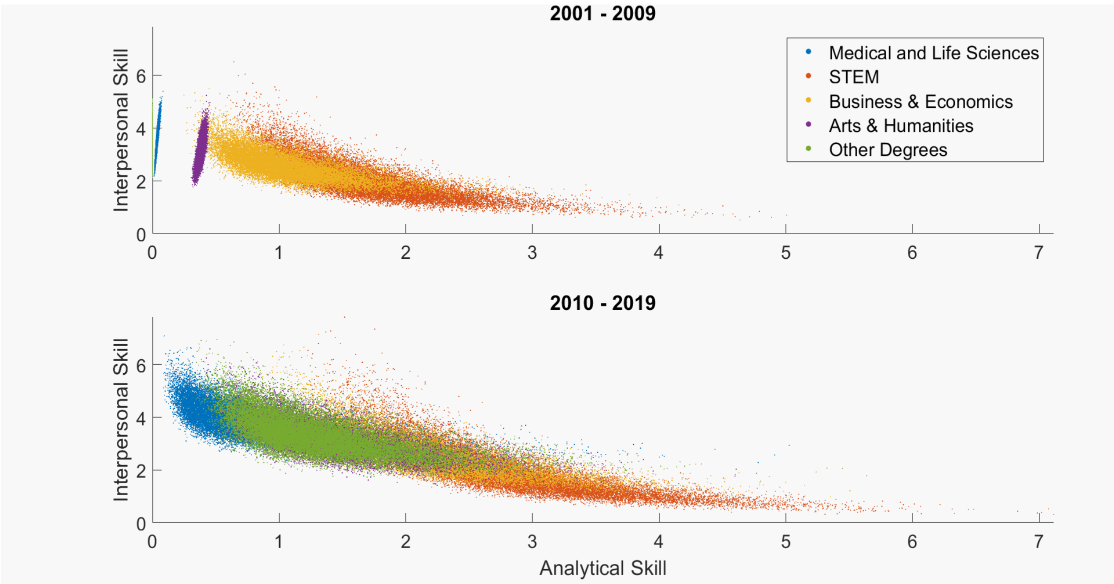
When considering the trends in skill inequality skills together, we see a common trend: the traditional boundaries that defined skill sets associated with specific fields are becoming increasingly porous. This suggests a general 'leveling' of skill sets across fields for both analytical and interpersonal skills, making each field more heterogeneous internally. For analytical skills, the 'between' variation dropped significantly from 84.69% to 64.45%, indicating that the distinction between fields in terms of analytical skills is diminishing. On the flip side, the 'within' variation increased from 15.31% to 35.55%, suggesting that the range of analytical skills within each field is widening. For interpersonal skills, the 'between' variation decreased from 52.71% to 44.61%, and the 'within' variation increased from 47.29% to 55.39%. Although the shifts are less drastic than those for analytical skills, they follow the same general trend: less differentiation between fields and more differentiation within fields.

For the labour market, this joint increase in 'within' variation and decrease in 'between' variation for both skill sets significantly complicates the hiring landscape. Employers can no longer rely on the field of study as a reliable indicator for either analytical or interpersonal skills. This makes the recruitment process more challenging and resource-intensive, necessitating more comprehensive skill assessments for different types of skills. Moreover, the training and development component for new hires may need to be more customized and ongoing to cater to the increasing variation in skill levels within each field. From a research perspective, these changes in 'within' and 'between' variation highlight the diminishing utility of using field of study as a straightforward control variable in analyses related to skill sets, career outcomes, or educational paths. Future research may need to employ more complex models that account for the increasingly multidimensional nature of skill sets, both within and across traditional academic boundaries.

6.2 Specialists or Generalists?

Understanding the multidimensional nature of skills is not merely about acknowledging their individual importance but also about grasping how different types of skills comove. By examining the comovement of skills, we can better conceptualize university degrees as either generalist or specialist in nature, providing a deeper understanding of the skill set graduates are likely to possess.

Figure 6: Visualization of the graduate skill distribution



Note: Based on a simulated sample of 100,000 observations per period.

While skills such as analytical and interpersonal abilities are generally transferable, the specific mixture of these skills offers valuable insights into a graduate's adaptability across different occupations. A balanced skill set may indicate a greater capacity to navigate diverse job roles, thereby expanding employability.

Table 4 presents two main metrics for the different academic subjects for the two time periods: the Median Skill Ratio, which is the median value of the ratio of interpersonal to analytical skills, and the correlation between both skills.

Initially, most subjects exhibited a very high ratio of interpersonal to analytical skills. This suggests a specialization in interpersonal skills, with analytical skills taking a back seat. Notably, STEM and Business & Economics were exceptions, displaying a more balanced skill set and thereby categorizing these fields as more generalist in nature. From 2010 onwards, other subjects have moved towards a balanced skill set, resembling where Business & Economics was during 2001-2009. Business & Economics, in turn, has moved closer to where STEM was in the earlier period, indicating an even more evenly balanced skill set. STEM, however, has leaned more towards analytical specialization.

	Median Skill Ratio		Skill Correlation	
	2001-2009	2010-2019	2001-2009	2010-2019
Medical and Life Sciences	100.66	6.09	0.93	-0.63
STEM	1.18	0.63	-0.76	-0.79
Business & Economics	2.56	1.20	-0.71	-0.78
Arts & Humanities	7.98	2.29	0.73	-0.67
Other Degrees	1534.37	2.65	0.85	-0.66
All Degrees	7.90	2.22	-0.82	-0.86

Note: Median Skill Ratio refers to the median value of the ratio of Interpersonal to Analytical Skills.

Table 4: Skill Ratios and Correlations

Regarding skill correlations, the overall picture reflects a strong negative correlation in the later period across all subjects. Initially, there was a positive correlation between analytical and interpersonal skills within non-STEM or Business fields, suggesting that students from these backgrounds had the potential to be relatively strong in both skills. By the 2010-2019 period, however, the correlation within all subjects has turned decidedly negative, indicating that those who excel in one skill may lack in the other.

Across the whole range of subjects this is generally suggestive of a type of trade-off, whereby resource constraints mean that students have to decide on focussing on one skill, while neglecting the other. A complementary explanation would be that students self-select into different fields according to their pre-existing aptitudes. The negative within subject correlation in the later period suggests that these mechanisms might also operate within the different subjects. This is a likely explanation given that the degree categories are quite broad and there is considerable scope for differentiation within these subjects.

6.3 The Role of Skills for Employment

This paper opens with the suggestion that for many students, a main purpose of acquiring skills is to secure a prestigious graduate job after university. Using the simulation results this section sheds some light on the role of skills in determining whether a graduate manages to secure a graduate job, or any job at all.

Table 5 provides an insightful look into how mean analytical and interpersonal skills vary according to different employment statuses—typical occupation, non-typical occupation, and not in the labor force—across various fields of study. The table presents these differences for two distinct time periods, 2001-2009 and 2010-2019, highlighting how skill dynamics have evolved over time. The values in the table are percentage differences from the overall average, allowing a nuanced comparison.

	2001 - 2009					
	% Differences in Mean Analytical Skills			% Differences in Mean Interpersonal Skills		
	Typical occupation	Non-typical occupation	Not in labour force	Typical occupation	Non-typical occupation	Not in labour force
Medical and Life Sciences	-0.35	0.44	-4.41	-0.41	0.52	-2.74
STEM	1.76	-2.71	1.52	-2.72	4.19	-4.69
Business & Economics	0.30	-0.41	0.56	-1.10	1.54	-3.23
Arts & Humanities	-0.19	0.24	-0.59	-0.89	1.15	-3.44
Other Degrees	-0.02	0.03	-0.13	-0.39	0.45	-2.40
All Degrees	5.19	-6.89	0.37	-1.74	2.31	-3.20
	2010 - 2019					
	% Differences in Mean Analytical Skills			% Differences in Mean Interpersonal Skills		
	Typical occupation	Non-typical occupation	Not in labour force	Typical occupation	Non-typical occupation	Not in labour force
Medical and Life Sciences	1.50	-1.42	-1.48	-0.92	0.88	-3.52
STEM	1.26	-1.59	1.45	-2.47	3.12	-10.08
Business & Economics	1.32	-1.57	2.96	-1.78	2.12	-6.11
Arts & Humanities	1.25	-1.39	-0.04	-1.74	1.93	-3.35
Other Degrees	2.36	-2.61	2.52	-1.80	1.99	-6.19
All Degrees	3.58	-3.96	1.16	-2.56	2.83	-5.34

Note: All values are percentage differences from the overall average. Typical occupation refers to the set of occupations that had a >5 % share in 2001-2009.

Table 5: Mean Skills by employment status.

Generally, individuals in typical or "graduate" employment tend to have higher levels of analytical skills compared to the overall average. This is consistent with the nature of these roles, which often require strong analytical capabilities. However, these same individuals usually have lower interpersonal skills on average, which is a result of the negative correlation between both skills. Over time, this trend has slightly lessened for analytical skills but has deepened for interpersonal skills. The analysis suggests that while analytical prowess continues to be important, the gap in interpersonal skills for those in typical roles is widening.

Conversely, those employed in non-typical occupations generally have lower levels of analytical skills but higher interpersonal skills compared to the average. This likely reflects the skill sets that are most valued in these types of jobs, which might prioritize social skills and emotional intelligence over analytical reasoning. Across the time periods the analytical skills gap in non-typical occupations has been closing by just under half, while the interpersonal gap has increased slightly. Together with the trend observed for typical occupations this suggests that the level of analytical skill a graduate possesses becomes less important when it comes to determine whether to choose a typical occupation or not. Likely other factors such as preferences, individual circumstances and the return to interpersonal skills have become more important.

Individuals who choose not to be part of the labor force tend to have analytical skills that are marginally above the average. However, their interpersonal skills are considerably lower than average. This divergence has been growing over time, indicating an increasing skills mismatch for this group. While there are a large number of possible reasons why a graduate might not enter the labour force this analysis suggests that a lack of interpersonal skills might be playing an increasingly important role.

6.4 The Role of Skills for Wages

Changes in the distribution of skills and the wider structure of the economy necessarily lead to changes in how productivity accrues to different parts of a worker's human capital.

To assess changes over time, I decompose graduate's wages into their constituent parts, using the log wage equation (5):

$$E(w) = E(\eta_o) + E(\lambda_{analytical} s_{analytical}) + E(\lambda_{interpersonal} s_{interpersonal}) + E(\beta x_i). \quad (24)$$

This decomposition allows us to analyse how relevant different factors are for determining the wages of graduates. This decomposition complements the analysis of the average skill endowments in the previous section, by including the effects of skill price changes.[23]

Figure 7 presents the share of a workers log wage that is on average due to analytical skills, interpersonal skills, occupation specific factors and any residual factors, such as work experience. The simulation results shed light on the complex interplay of various factors that contribute to graduate wages. Interpersonal skills are the main contributing factor to hourly wages, particularly in the Medical and Life Sciences, Arts and Humanities, and Other Degrees categories. Interpersonal skills continue to be the most significant contributor to wages for graduates in these fields, while analytical skills appear to only play a marginal role.

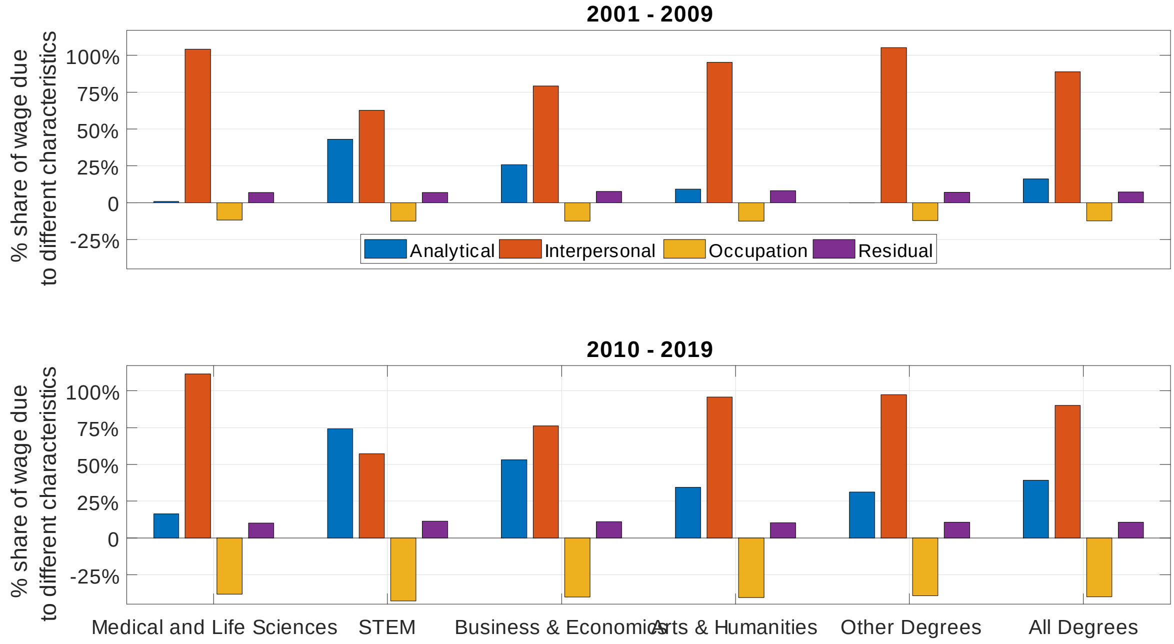
The second key observation is the unique importance of analytical skills in certain specialized fields. Specifically, for graduates in STEM and Business & Economics, analytical skills contribute significantly to their wage structure. This sets these fields apart from others where interpersonal skills play a more dominant role.

The 2010-2019 period marks an increase in the importance of analytical skills across various fields of study, in line with the increase in analytical skills overall. While interpersonal skills generally hold sway in determining wages, this period shows a shift towards a higher valuation of analytical skills. This could be indicative of changing labor market dynamics that increasingly reward analytical capabilities.

The simulation results indicate that occupation-specific factors generally have a negative contribution to wages. This is significant because it suggests that the fixed returns to being in a particular occupation are decreasing over time. Interestingly, this intensification of negative contributions from occupation-specific factors occurs in parallel with an increase in the relative importance of variable factors, particularly skills. This nuanced shift implies that while the fixed benefits of being in a specific occupation are diminishing, the returns to individual skills like analytical and interpersonal abilities are gaining in relative importance.

[23] For a graduate the quantity of a specific skill they posess is likely to be of less interest than how much compensation they can receive for supplying that quantity in the labour market.

Figure 7: Decomposition of log wages



Note: Based on a simulated sample of 100,000 observations per period.

6.5 Counterfactual Decompositions

In this section I consider a number of counterfactual experiments, in order to asses the importance of different parts of the model for the changing labour market outcomes of graduates. The model allows me to decompose the observed changes, by fixing certain parameters at their 2001-2009 values and simulating the model into 2010-2019. The differences of these counterfactual simulations with respect to the estimated full model will provide some insight into the underlying factors driving the observed patterns in the data.

The main channels I have modelled in this exercise are i) the subject specific skill distributions (μ and Σ); ii) the skill prices, proxied by the occupation specific task vectors λ; iii) other labour market factors captured by occupation, geographic region fixed effects and experience and gender based wage coefficients; iv) the demographic composition of the population of young graduates, including the share of different subjects; v) the non-pecuniary component of utility proxied by ω_o.

For this decomposition I begin by fixing all parameter at their 2001 values and then *turning on* the different model parts in sequence, allowing the relevant parameters to take on their estimated time varying parameter values. Each time I simulate the model given the new parameter configuration and record a number of relevant labour market statistics for the 2010-2019 period.[24]

Figures 8 and 9 show the results of this decomposition analysis for different measures of graduates wages, namely the change in mean log wages, and measures of upper and lower tail wage inequality between 2001-2009 and 2010-2019; as well as the change in the

[24]The different parts of the model show strong interaction effects. For simple counterfactuals where the different model parts are considered in isolation see Appendix.

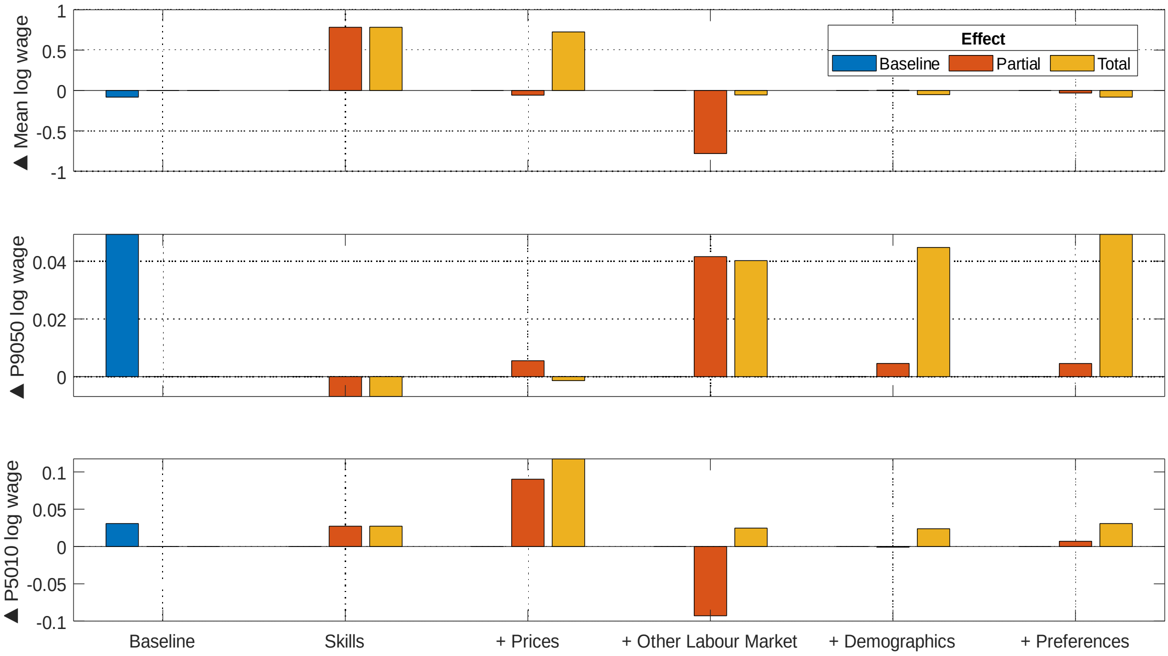
HH index of occupation concentration, the share of non-typical occupations and the share of graduates not in the labour force. The first bar in each subplot indicates the change as predicted by the full (or baseline) model which was estimated from the data.[25] The decomposition starts with the second set of bars from the left, which supposes that all parameters except those related to the subject specific skill distributions are fixed to their initial values. From then on each additional pair of bars adds another set of parameters that are now allowed to adjust over time, so that we get back to the full model once we reach the right hand side of the plot. In each case the red bars indicate the direct effect of switching on that particular model feature, while the yellow bars track the cumulative effect of all model feature until that point.

In the analysis presented in the first row of Figure 7, several trends emerge that inform our understanding of shifts in mean log wages. Firstly, alterations in the skill distribution exert a pronounced positive influence on mean wages. This is consistent with the observed increase in analytical skills discussed in a prior section. Secondly, this positive effect is largely offset by corresponding changes in other labor market factors, which exert a compensatory negative impact. Both of these points align well with earlier observations, including the decrease in fixed occupation-specific premia. Finally, other determinants such as demographic shifts and preferences appear to have only a marginal influence on changes in mean log wages.

Regarding wage inequality, the simulation results suggest disparate forces acting on the upper and lower tails. In the upper tail, represented by the P9050 metric, inequality is notably driven by other labor market factors, which significantly push towards greater disparities in wages. This is likely attributable to diminishing occupation-specific fixed effects, implying that individuals with moderate skill levels are not benefiting as much as they might have in the past. On the other hand, lower tail inequality, indicated by the P5010 metric, reveals a more balanced interplay among skills, skill prices, and other labor market factors. While the first two factors contribute to an increase in lower-tail inequality, the latter exerts a mild counteracting effect, slightly contracting the inequality in the lower wage spectrum.

[25] For an evaluation of the models ability to fit these dimensions, see Table 2.

Figure 8: Decomposition of changes in log wages



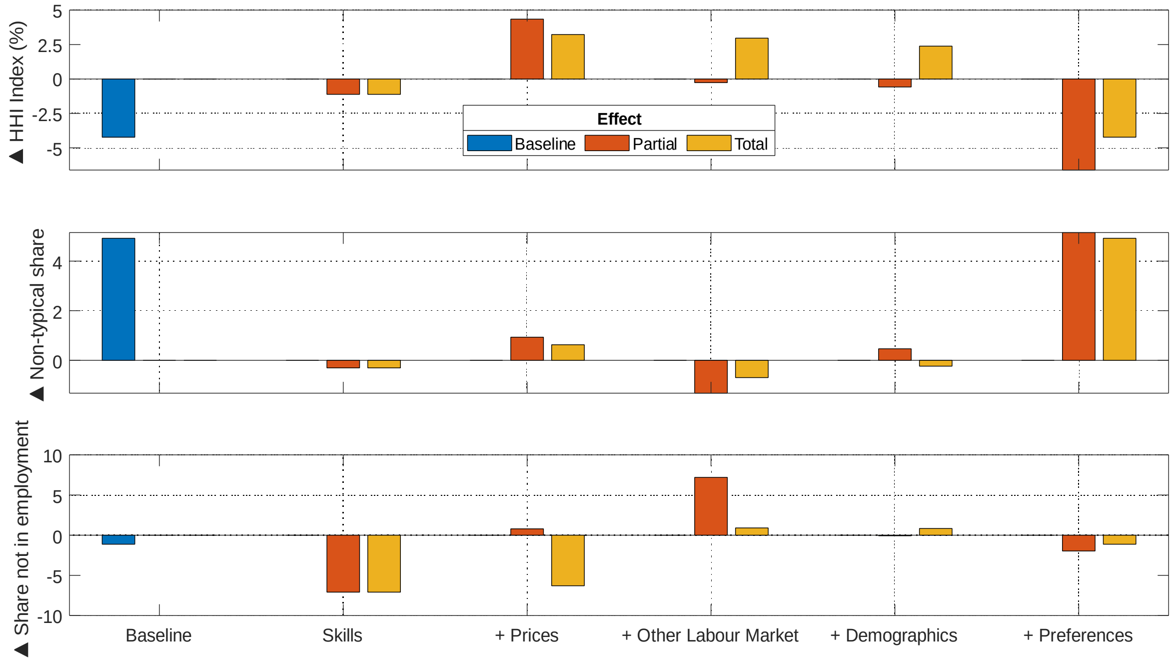
Note: Based on a simulated sample of 100,000 observations per period.

Figure 9 presents the decomposition results for the graduates' occupation choices. The decomposition results presented in Figure 8 offer nuanced insights into the dynamics of occupational choices among graduates. In the data we observed that the Herfindahl-Hirschman Index (HHI) of occupational concentration decreased, while the share of graduates selecting into non-typical occupations increased over time. The HHI of occupational concentration appears to be influenced in opposite directions by different factors. While changes in the skill distribution tend to dilute occupational concentration, the addition of skill price changes pushes the HHI upwards. This suggests that if we were to consider only changes in skill distribution and skill prices, graduates would exhibit a higher concentration in certain occupations. This trend could suggest more coordination from HEIs to provide graduate-type skills to their students.

In contrast, the negative impact on the HHI arises from changes in occupation-specific preferences, indicating that non-typical occupations are becoming relatively more attractive to graduates. This trend is further emphasized by the fact that the share of graduates entering non-typical occupations is almost exclusively driven by changes in preferences. These findings collectively suggest that the decline in occupational concentration and uptick in non-typical occupations is primarily a function of shifts in the non-pecuniary aspects related to these roles.

Regarding the share of graduates not participating in the labour force, the simulation results indicate that this is strongly influenced by changes in skills, particularly the increase in analytical skills providing more opportunities for earnings. This trend, however, is somewhat offset by other labour market factors, likely reflecting a shift toward more variable skill-based compensation at the expense of fixed occupation-specific premia. In this context, other elements such as changing demographics, preferences, or skill prices seem to play only a marginal role, reinforcing the primary drivers identified above.

Figure 9: Decomposition of changes in the distribution of occupations



Note: Based on a simulated sample of 100,000 observations per period.

7 Conclusion

The formation of human capital and the acquisition of specific skills lies at the heart of a university education. Despite their centrality to both the academic and public discourse about tertiary education, there are few quantitative studies that actually investigate what skills graduates possess at the end of their university courses. This paper has developed an economic model to rigorously estimate the changing distribution of skills among university graduates in the UK over the past two decades amidst wide ranging technological and institutional changes . Employing a structural model, my research provides quantitative evidence on how graduate skill endowments have evolved and the subsequent implications these shifts have had for labour market outcomes. The study is particularly relevant in the context of rapidly evolving labour market demands, as it illuminates the dynamic interplay between skill endowments and employability. By quantifying these changes, the paper contributes to our understanding of how higher education can adapt to better prepare graduates for the complexities of the modern workforce.

The paper identifies a noteworthy shift in the distribution of skills among graduates. Specifically, there has been an uptick in the level median analytical skills across all academic disciplines, reflecting an education system increasingly focused on quantitative and data-driven capabilities. Interpersonal skills, on the other hand, have shown a more stable trend over the study period. This change has likely allowed many graduates to benefit from a labour market that was increasingly looking for employees with "hard" cognitive skills, and might signal a response of the broader education sector to the demands of employers.

Moreover, my study reveals that skill endowments vary considerably across academic disciplines. For instance, fields such as Medical and Life Sciences and Arts & Humanities predominantly emphasize interpersonal skills. In contrast, STEM and Business & Economics exhibit a more balanced skill profile with a higher level of analytical skills. However, students in the same subjects are far from uniformly endowed and individual skill sets can exhibit considerable variation within academic disciplines.

Over time, the analysis shows a narrowing gap in analytical skill inequality, likely due to other disciplines enhancing their analytical training to catch up with traditionally strong fields like STEM. However, a concerning increase in interpersonal skill inequality has been observed. As the distinctions between disciplines begin to diminish, within-field variations are becoming increasingly relevant. This shift has significant implications for both labor market dynamics and academic research, warranting a more nuanced approach to skills analysis.

The interplay between interpersonal and analytical skills in shaping wages has evolved significantly. Initially, interpersonal skills were the primary wage determinants in most academic fields, including Medical and Life Sciences, and Arts & Humanities. However, the simulation results indicate a rising prominence of analytical skills in wage-setting, particularly in STEM and Business & Economics disciplines. This transition is in line with the broader labour market trend, moving away from fixed occupation-specific returns to more variable, skills-based compensation structures.

Skills also play a pivotal role in employability and occupational choice. For instance, interpersonal abilities are particularly valuable for roles that may not align directly with traditional graduate occupations. Conversely, analytical skills are increasingly becoming prerequisites for entering traditional graduate occupations. Graduates not in the labour force tend to have considerably lower levels of interpersonal skills than average.

The decomposition analysis reveals that shifts in skill distribution are primarily driving wage increases. This positive influence is, however, countered by a decline in fixed occupational returns, emphasizing a shift towards more variable, skill-based compensation. Regarding occupational choices, the decline in occupational concentration is largely attributable to changes in non-pecuniary preferences. Conversely, the increase in graduates entering non-typical roles is almost exclusively due to these preference shifts.

This study was an attempt to analyse the multidimensional skill distribution among university graduates. My analysis reveals that not only can we detect qualitative, market-relevant differences in the skill endowments of graduates, but also that there is a rich heterogeneity in these skill endowments across and within academic fields. These variations play a significant role in shaping labour market outcomes, including wages and occupational choices. Both policymakers and prospective students would do well to consider these findings when shaping educational policies or making academic and career plans for the future.

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A Additional Tables & Results

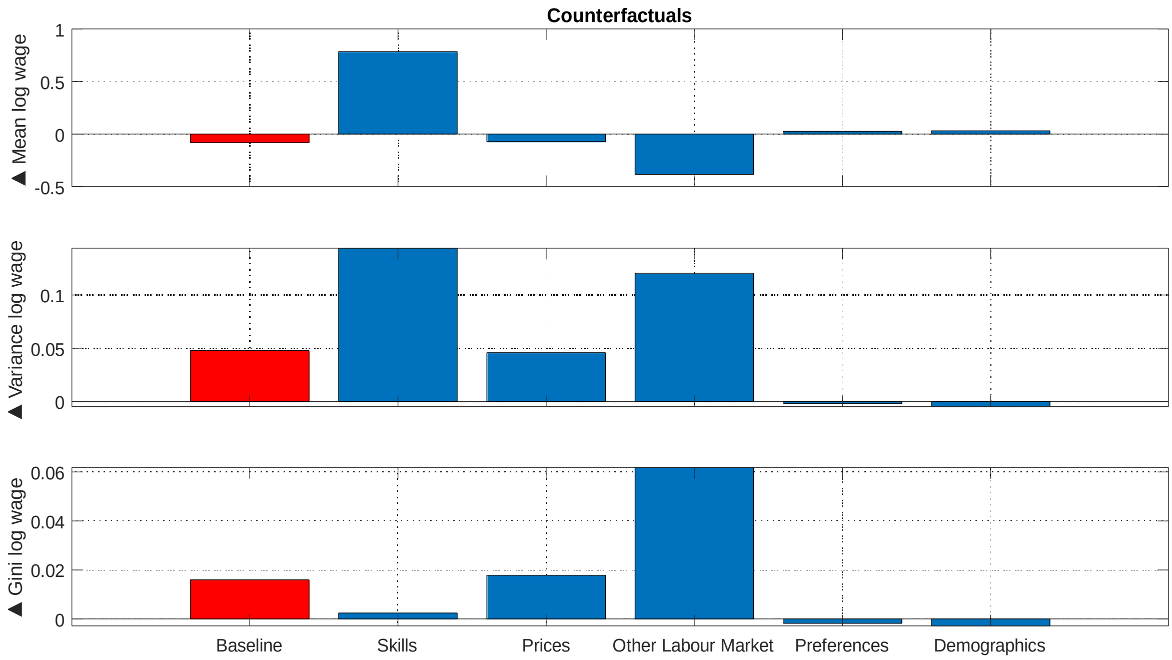
A.1 Additional Tables

	2001 - 2009				
	Medical and Life Sciences	STEM	Business & Economics	Arts & Humanities	Other Degrees
$\mu_{Analytical}$	-3.385	0.487	-0.012	-0.981	-6.132
	(2.02)	(0.28)	(0.36)	(0.56)	(7.65)
$\mu_{Interpersonal}$	1.226	0.661	0.93	1.095	1.203
	(0.13)	(0.14)	(0.12)	(0.10)	(0.12)
$\sigma_{Analytical}$	0.217	-0.289	-0.343	0.049	0.007
	(0.30)	(0.13)	(0.16)	(0.06)	(1.24)
$\sigma_{Interpersonal}$	-0.041	0.179	-0.13	-0.091	0.059
	(0.04)	(0.05)	(0.04)	(0.03)	(0.07)
$\sigma_{Correlation}$	0.109	0.261	0.151	0.098	0.097
	(0.07)	(0.08)	(0.07)	(0.03)	(0.06)
	2010 - 2019				
	Medical and Life Sciences	STEM	Business & Economics	Arts & Humanities	Other Degrees
$\mu_{Analytical}$	-0.455	1.027	0.753	0.304	0.204
	(0.23)	(0.12)	(0.14)	(0.17)	(0.17)
$\mu_{Interpersonal}$	1.348	0.562	0.922	1.132	1.181
	(0.08)	(0.11)	(0.10)	(0.09)	(0.09)
$\sigma_{Analytical}$	0.53	0.246	0.259	-0.322	0.364
	(0.11)	(0.05)	(0.06)	(0.07)	(0.07)
$\sigma_{Interpersonal}$	-0.106	0.206	0.157	-0.142	-0.145
	(0.03)	(0.05)	(0.04)	(0.03)	(0.03)
$\sigma_{Correlation}$	-0.105	-0.391	-0.238	0.144	-0.145
	(0.04)	(0.05)	(0.04)	(0.03)	(0.04)

Note: Parameter estimates from the baseline model. Numerical standard errors in parentheses.

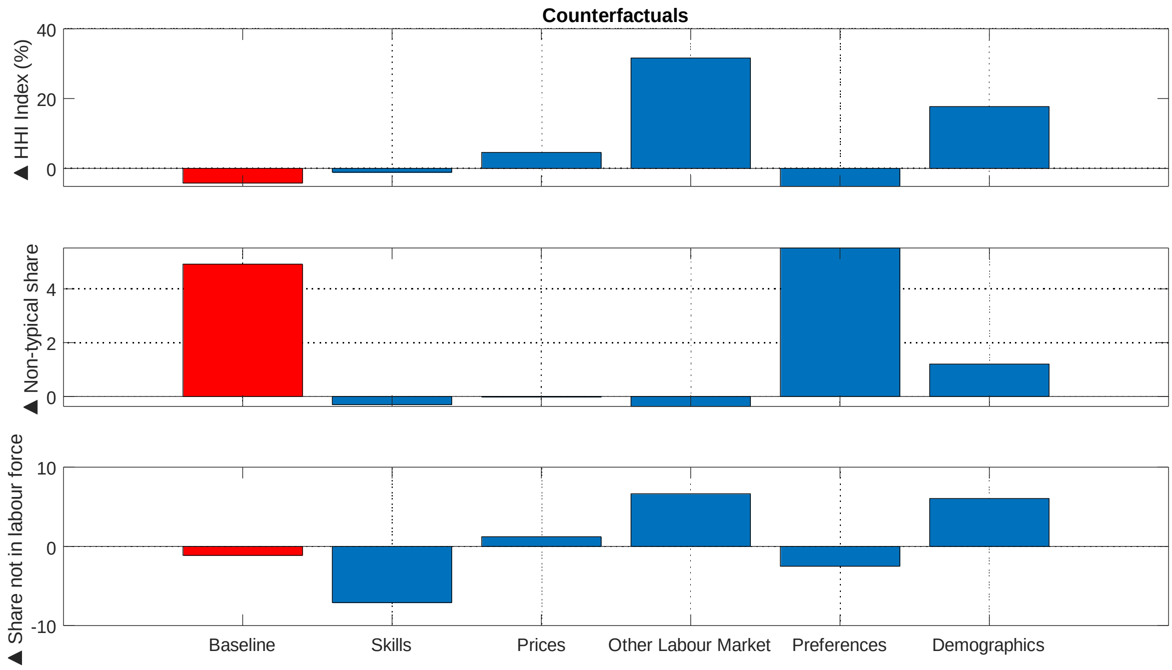
A.2 Additional Figures

Figure A1: Model counterfactuals



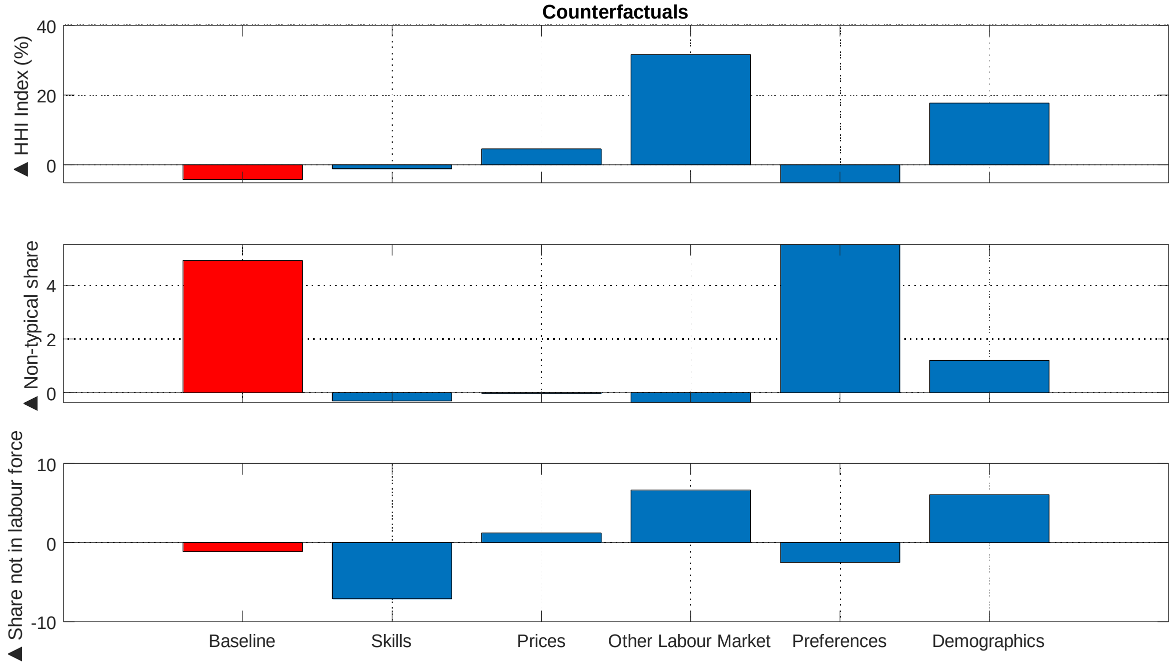
Note: Based on a simulated sample of 100,000 observations per period.

Figure A2: Model counterfactuals



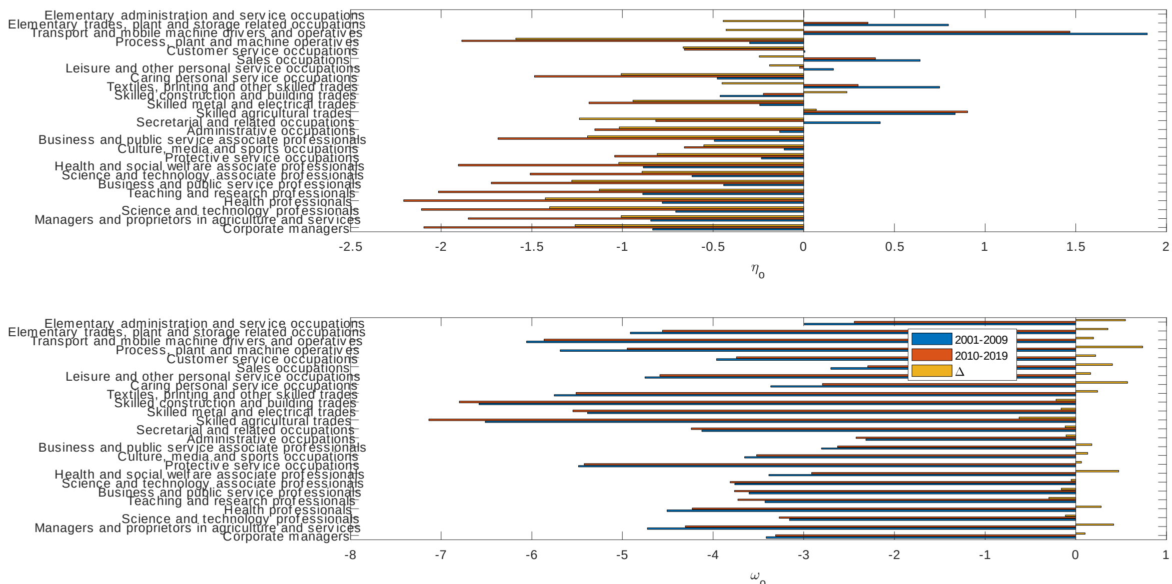
Note: Based on a simulated sample of 100,000 observations per period.

Figure A2: Model counterfactuals



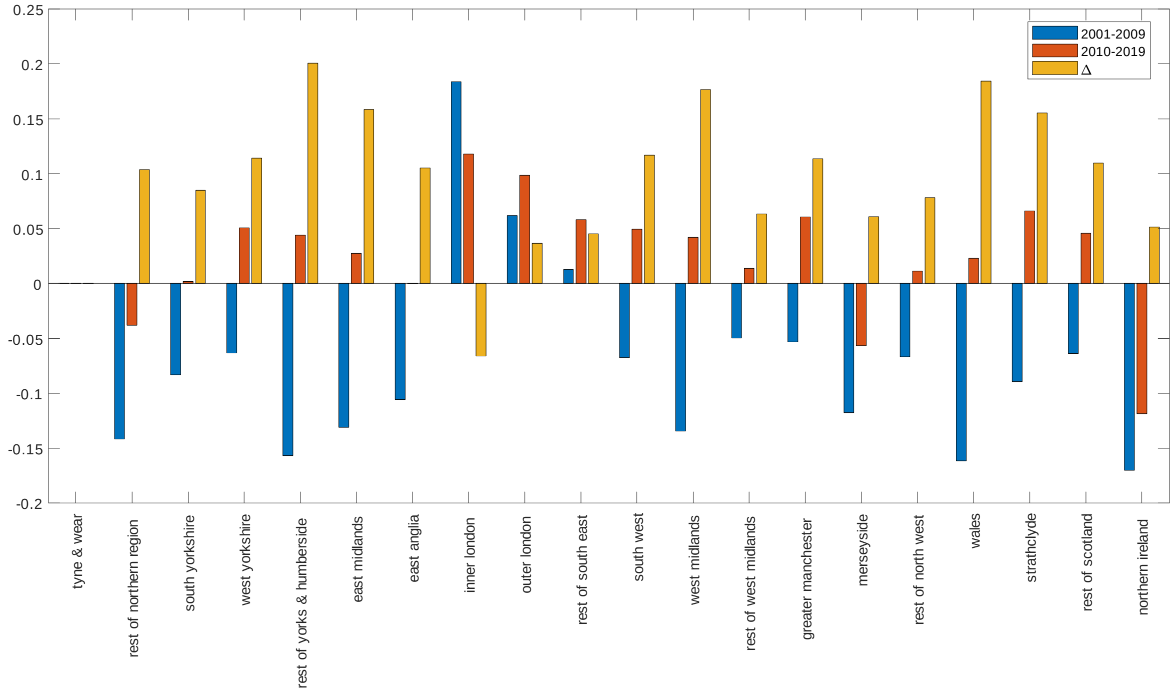
Note: Based on a simulated sample of 100,000 observations per period.

Figure A3: Occupation fixed effects



Note: Based on a simulated sample of 100,000 observations per period.

Figure A4: Region fixed effects



Note: Based on a simulated sample of 100,000 observations per period.

B Task requirements

The following table summarizes the survey items from the SES that were used to obtain the task requirements:

Variable name	Description
csolutn	importance of: thinking of solutions to problems
canalyse	importance of: analysing complex problems in depth
ccalca	importance of: arithmetic (adding, subtracting, multiplying, dividing)
cstats	importance of: advanced mathematics/ statistics
cpercent	importance of: arithmetic involving fractions (decimals, percentages, fractions)
ccause	importance of: working out cause of problems/ faults
skcimp	importance of computer use
skcomp	complexity level of computer use
cteach	importance of: teaching people (individuals or groups)
cspeech	importance of: making speeches/ presentations
cteamwk	importance of: working with a team
cpersuad	importance of: persuading or influencing others
ccoop	importance of: cooperating with colleagues
clisten	importance of: listening carefully to colleagues

Table A1: Variables used in the construction of task intensity measures

The rotated factor loadings are presented in the next figure:

Figure B1: Rotated principal components loadings

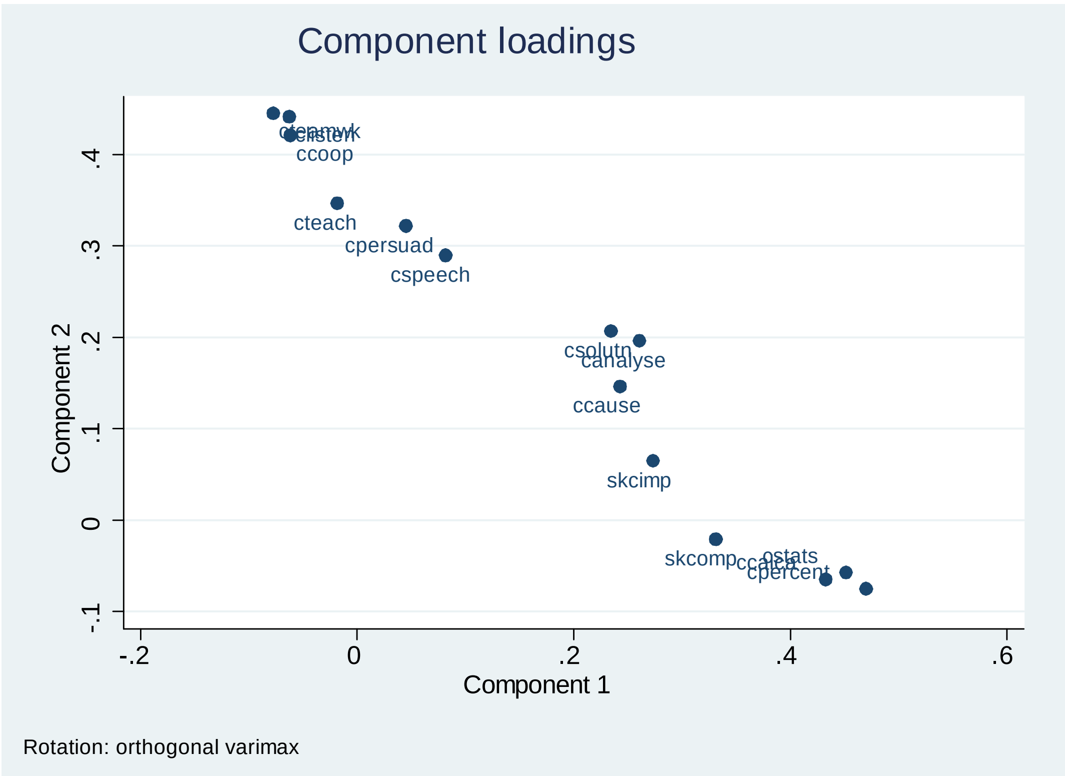
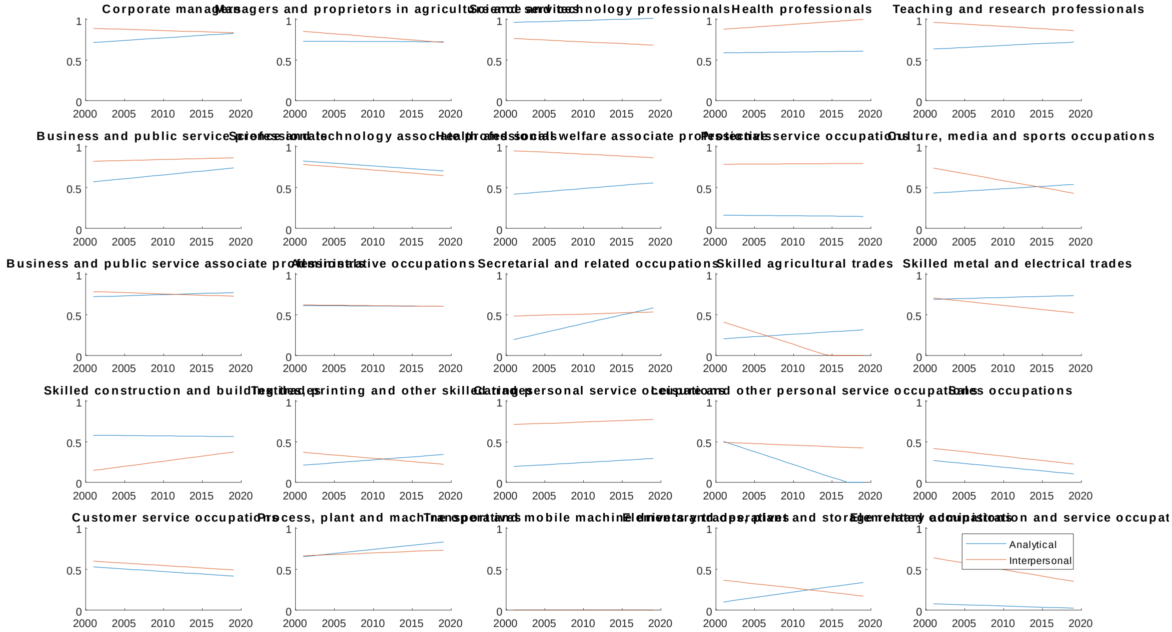


Figure B2: Task Weights by 2-Digit SOC 2000 Occupation



Note: 2-digit SOC 2000 occupations.

C Technical Details

C.1 Calibration of ϕ^2

Wave 3 of the Understanding Society Survey contains a module assessing the cognitive and psychological traits of adult (16+) respondents. Questionnaire items include test measuring 1. Numeric Ability, 2. A Subtraction Exercise, 3. Completion of a Number Sequence, 4. A word recall exercise & 5. Verbal Fluency. As well as measures of the "Big 5" personality traits. I use these items to generate 2 measures of skill, mapping into the dimensions of analytical and interpersonal skill used in the model, using principal component analysis on the standardized survey responses. Then I use these measures to run a cross sectional (log) wage regression, controlling for 2 Digit SOC (2000) occupation as well as the full set of interactions with the two skill measures. The resulting regression equation is exactly the proxy analogue to the log wage equation:

$$w_i = \sum_O \mathbf{1}_{(o_i^*=o)} \tilde{\eta}_o + \sum_O \mathbf{1}_{(o_i^*=o)} \tilde{\eta}_o \tilde{s}_{i,analytic} + \sum_O \mathbf{1}_{(o_i^*=o)} \tilde{\eta}_o \tilde{s}_{i,interpersonal} + \tilde{\nu}_i$$

The residual variance of $\tilde{\nu}_i$ provides an estimate for ϕ^2.

I estimate the auxiliary model on a sample of working individuals aged 21-24, adding additional controls for sex, part-time work status and age as a proxy of labour market experience, region and year fixed effects.

C.2 Estimation algorithm

The estimation procedure is a simple application of simulated maximum likelihood. In maximum likelihood we find a vector of parameters so that the model maximizes the

Parameter	Description	Number of Parameters	Type
μ_{kmt}	Location parameter of the subject-period-specific skill distribution.	20	Estimated
σ_{kmt}	Scale parameter of the subject-period-specific skill distribution.	30	Estimated
η_{ot}	Occupation-period specific fixed effect.	50	Estimated
ω_{ot}	Occupation-period specific occupation preferences	50	Estimated
τ	Year fixed effects	17	Estimated
ξ_t	Region fixed effects	38	Estimated
γ_t	Period-specific gender coefficient	2	Estimated
ι_t	Period-specific parttime coefficient	2	Estimated
ε_t	Period-specific linear experience coefficient	2	Estimated
κ_t	Intercept	2	Estimated
ϕ	Standard deviation of log wage measurement errors	1	Calibrated

Table C1: Summary of Model Parameters

probability of observing the actual outcome.

The only complication, that arises here comes from the fact, that we do not have a closed form solution for the joint probability (21) and thus have to evaluate the integral via simulation. This can be done by taking draws from the distribution of s, evaluating $\Pr(o_i^*, w_i^{obs}|s_i)$ at each of these draws and then averaging over the results. Standard results suggest, that as long as one uses a large enough number of draws to approximate the integral, the Maximum Simulated Likelihood Estimation (MSLE) is asymptotically equivalent to classical Maximum Likelihood Estimation (MLE) (c.f. McFadden & Train (2000)). For a proof that the MSL estimator is unbiased and efficient see the appendix.

Denote the simulated counterpart of (21) by $\Pr^{sim}(o_i^*, w_i^{obs})$ for simplicity, and let $\theta = (\eta, \mu, \Sigma)$ be the set of our parameters, we can write down the simulated log likelihood function of the as:

$$ll^{sim}(\theta; \phi^2) = \frac{1}{N} \sum_i \sum_{o=1}^{O} \mathbf{1}_{(o=o^*)} \ln \overset{sim}{\Pr}(o_i^*, w_i^{obs}) \tag{25}$$

and we can estimate θ as:

$$\hat{\theta} = \arg\max_{\theta} ll^{sim}(\theta; \phi^2) \tag{26}$$

So to specify the complete algorithm:

1. Set $q = 1$ and make a guess for $\hat{\theta}_1$. Specify a tolerance criterion ϵ. Set R, the number of draws used to approximate the integral to a reasonably high number.

2. For each individual i, given $\hat{\theta}_q$ draw a vector of s_i, R times, denoting each as s_i^r.

3. For $r = 1$ to R :

   (a) Calculate $\nu_i^r = w_i^{obs} - [\eta_{o^*} + \sum_K \lambda_{o^*k} s_{ik}^r]$.

   (b) For a given pair s_i^r, ν_i^r calculate $\Pr^r(o_i^*, w_i^{obs})$.

4. Average over all R values of $\Pr^r(o_i^*, w_i^{obs})$ to obtain:
   $\Pr^{sim}(o_i^*, w_i^{obs}) = \frac{1}{R} \sum_{r=1}^{R} \Pr^r(o_i^*, w_i^{obs})$.

5. Repeat steps $2 - 4$ for all N individuals. Calculate the log likelihood via (25) denoting it as ll_q^{sim}.

6. If $|ll_q^{sim} - ll_{q-1}^{sim}| < \epsilon$, terminate here. Otherwise increment q and find a new value $\hat{\theta}_q$ and repeat from step 2.

Finally, for the numerical evaluation of the integral I use a grid of 10, 000 quasi random Halton draws, which have been shown to provide about an order of magnitude more accuracy than simple random draws (Train (2009)). To ensure stochastic equicontinuity I use the same set of points for each agent at each iteration.

C.2.1 The cluster refinement global optimization algorithm

The likelihood function generated by this problem is smooth, but not globally concave which makes it difficult for gradient based optimization routines that are prone to converge to local minima. This is a general problem for the class of discrete choice models, but especially here given the high dimensionality of the parameter space. To maximize the log likelihood function, I therefore develop a novel global optimization algorithm that utilizes machine learning to effectively search through the high dimensional parameter space. The algorithm proceeds as follows:

1. Define a grid of initial starting points G^θ that span the parameter space θ. For each point in G^θ evaluate the log-likelihood function.
2. Discard points where the log-likelihood is below a certain threshold criterion.
3. Use a clustering algorithm to cluster the remaining points into K clusters.
4. From each cluster select a point K^θ. The selection can either be the point with the best log-likelihood value in the cluster, or a weighted average of all points in the cluster or both.
5. Use a local solver starting at each point in K^θ to maximize the log-likelihood function.

The main idea behind the algorithm is that the clustering algorithm will group points that are *similar* together. Points that are close together in the parameter space are likely in the neighborhood of the same local maximum, so it is unnecessary to run local solvers from each of these points. The computational savings can be used to explore further regions of the parameter space.

For further refinement, steps 2-5 can be repeated using the local maxima found by the nonlinear solvers in step 5 and so on. Using this method it is practical to start with a large number of clusters in the beginning and reduce this number in each successive iteration. In doing so, it is advised to initially set the convergence criteria to relatively high values or limit the number of iterations for the local solvers in the beginning and tighten the criteria over successive iterations.

C.3 Standard errors

I calculate numerical standard errors following the well known (c.f. Train (2009)) relationship between the hessian of the likelihood function and the information identity: For the correctly specified model, the error of the MLE estimate $\hat{\theta}$ is distributed according to:

$$\sqrt{N}(\hat{\theta} - \theta^*) \rightarrow N(0, -\mathbf{H}^{-1})$$

where θ^* is the true parameter vector, and $-\mathbf{H}$ is the information matrix. To avoid complications due to the numerical procedure and the high dimensionality of the problem, I calculate a numerical hessian of the likelihood function at the SMLE estimate, and then use a pseudo inverse (c.f. Gill & King (2004)) to obtain the standard errors for the estimated parameters.

C.4 Asymptotic Equivalence of SML and ML

The asymptotic properties of the simulated maximum likelihood estimator have been well understood (c.f. Gourieroux and Monfort (1993), Lee (1995), and Hajivassiliou & Ruud (1994)). This short exposition here is based on the discussion in Train (2009, Chapter 10) for simplicity. Generally maximum likelihood estimation proceeds by maximizing the log likelihood function:

$$ll(\theta) = \sum_n \ln \Pr_n(\theta) \tag{27}$$

where θ is a vector of parameters and $\Pr_n(\theta)$ is the exact probability of the observed choice of observation n given θ.

Similarly, simulated maximum likelihood maximizes the simulated maximum likelihood function:

$$sll(\theta) = \sum_n \ln \overset{sim}{\Pr_n}(\theta) \tag{28}$$

where $\Pr_n^{sim}(\theta)$ is the simulated probability of the observed choice of observation n. It is known,that if $\Pr_n^{sim}(\theta)$ is an unbiased simulator for the exact probability - i.e. $E_r(\Pr_n^{sim}(\theta)) = \Pr_n(\theta)$, where the expectation is taken over r simulation draws, then there are three sources of bias in the SML estimator:

1. Sampling bias, which is the same as in the ML estimator and which goes to 0 as $N \to \infty$.
2. Simulation noise, which goes to 0 as the number of simulation draws $R \to \infty$.
3. Bias due to the fact, that $\ln \Pr_n^{sim}(\theta)$ is not an unbiased estimator of $\ln \Pr_n(\theta)$. This bias disappears if R grows faster than $\sqrt{N}$.

Hence the results, which are derived under fairly general conditions, indicate, that if $\Pr_n^{sim}(\theta)$ is an unbiased simulator, and the number of simulation draws is sufficiently larger than $\sqrt{N}$, then the MSL estimator is consistent, asymptotically normal, efficient and equivalent to traditional ML.

Therefore, the only thing that we have to show, is that our simulated joint probability $\Pr^{sim}(o_i^*, w_i^{obs}|\theta)$ is an unbiased estimator of the exact probability $\Pr(o_i^*, w_i^{obs}|\theta)$. To show this, let's remind ourselves, of how the simulated probability is obtained:

$$\overset{sim}{\Pr}(o_i^*, w_i^{obs}|\theta) = \frac{1}{R}\sum_{r=1}^{R}\left\{\left(\frac{e^{\eta_{o^*}+\sum_K \lambda_{o^*k}s_{ik}^r}}{1+\sum_{o=1}^{O} e^{\eta_o+\sum_K \lambda_{ok}s_{ik}^r}}\right)\left(\frac{e^{(-\frac{\left(w_i^{obs}-[\eta_{o^*}+\sum_K \lambda_{o^*k}s_{ik}^r]\right)^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}}\right)\right\} \tag{29}$$

where s_i^r is the rth simulation draw of s_i. Compare this to the exact probability:

$$\Pr(o_i^*, w_i^{obs}|\theta)) = \int \left\{ \left(\frac{e^{\eta_{o*}+\sum_K \lambda_{o*k} s_{ik}}}{1+\sum_{o=1}^{O} e^{\eta_o+\sum_K \lambda_{ok} s_{ik}}} \right) \left(\frac{e^{(-\frac{\left(w_i^{obs}-[\eta_{o*}+\sum_K \lambda_{o*k} s_{ik}]\right)^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}} \right) \right\} f(s)d(s) \tag{30}$$

Now

$$\begin{aligned}
E\left(\overset{sim}{\Pr}(o_i^*, w_i^{obs}|\theta)\right) &= \\
& E\left[\frac{1}{R}\sum_{r=1}^{R} \left\{ \left(\frac{e^{\eta_{o*}+\sum_K \lambda_{o*k} s_{ik}^r}}{1+\sum_{o=1}^{O} e^{\eta_o+\sum_K \lambda_{ok} s_{ik}^r}} \right) \left(\frac{e^{(-\frac{\left(w_i^{obs}-[\eta_{o*}+\sum_K \lambda_{o*k} s_{ik}^r]\right)^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}} \right) \right\} \right] \\
&= \frac{1}{R}\sum_{r=1}^{R} E \left\{ \left(\frac{e^{\eta_{o*}+\sum_K \lambda_{o*k} s_{ik}^r}}{1+\sum_{o=1}^{O} e^{\eta_o+\sum_K \lambda_{ok} s_{ik}^r}} \right) \left(\frac{e^{(-\frac{\left(w_i^{obs}-[\eta_{o*}+\sum_K \lambda_{o*k} s_{ik}^r]\right)^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}} \right) \right\} \\
&= \frac{1}{R}\sum_{r=1}^{R} \int \left\{ \left(\frac{e^{\eta_{o*}+\sum_K \lambda_{o*k} s_{ik}}}{1+\sum_{o=1}^{O} e^{\eta_o+\sum_K \lambda_{ok} s_{ik}}} \right) \left(\frac{e^{(-\frac{\left(w_i^{obs}-[\eta_{o*}+\sum_K \lambda_{o*k} s_{ik}]\right)^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}} \right) \right\} f(s)d(s) \\
&= \int \left\{ \left(\frac{e^{\eta_{o*}+\sum_K \lambda_{o*k} s_{ik}}}{1+\sum_{o=1}^{O} e^{\eta_o+\sum_K \lambda_{ok} s_{ik}}} \right) \left(\frac{e^{(-\frac{\left(w_i^{obs}-[\eta_{o*}+\sum_K \lambda_{o*k} s_{ik}]\right)^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}} \right) \right\} f(s)d(s) \\
&= \Pr(o_i^*, w_i^{obs}|\theta))
\end{aligned} \tag{31}$$

the third line follows from the definition of the expected value operator and the fact that all s_i^r are i.i.d.

Hence, we have shown, that $\Pr^{sim}(o_i^*, w_i^{obs}|\theta)$ is an unbiased estimator for $\Pr(o_i^*, w_i^{obs}|\theta)$. Furthermore, $\Pr^{sim}(o_i^*, w_i^{obs}|\theta)$ is a continuous and twice differentiable function.

C.5 Systemic changes in skill prices

An issue that arises when comparing the models estimates across two different time periods is that of unobserved changes in the price of different skills across time. If such changes were occurring and not controlled for this might bias the models estimates leading the model to mistake changes in the value of specific skills for changes in the quantity that graduates possess.

Suppose for example that the return to skill $s_{i,k,t}$ depended on $\lambda_{o,k,t}\chi_{k,t}$ where $\chi_{k,t}$ was a general, unobserved, time varying demand shifter for skill k. Then the models estimate of $s_{i,k,t}$[26] would effectively recover $s_i, k, t^* = \frac{s_i, k, t}{\chi_k, t}$,which would make estimates of s_i, k, t incomparable across time periods.

[26]The language used in this esection is slightly imprecise since the model does only estimate the distribution of $s_{i,k,t}$, but the logic holds nontheless.

Part of the estimation strategy therefore relies on the assumption that the available controls of the model are enough to remove such systematic changes in skill prices, i.e. $\chi_{k,t} \approx 1\ \forall k, t$

Overall,I think that I can justify the assumption for the following reasons: i) We have observed that task requirements have changed over the period, which means that at least part of χ is actually observed and thus controlled for. ii) The inclusion of occupation-time specific fixed effects will soak up some of this aggregate change.

I confirm this by estimating a version of the model where I let the return to different tasks vary by a common factor across time periods, i.e. I estimate $\chi_{k,t}$ for both time periods and skill types. The estimation results in values of $\chi_{k,t}$ very close to 1 and does not change the results in any meaningful way.

C.6 Alternative interpretation of ϕ

In the main section of this paper I introduced ϕ as the standard deviation of an idiosyncratic shock to the graduates' wage that was assumed to be independent of the graduates' occupation choice. In this subsection I want to quickly outline an alternative interpretation of ϕ that doesn't rely on the structural interpretation and therefore might be easier to be accepted by some readers.

To illustrate let us return to the joint probability (21):

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

Note that this formulation shows that the estimation is essentially trying to match two conditional probabilities: i) the conditional probability of choosing occupation o_i^*; ii) the conditional probability of the observed distribution of wages w_i^{obs}. The hope is that if the model is flexible enough (i.e. has enough free parameters) there will be no conflict between these two objectives: the same parameter vector θ^* that maximizes the joint probability also maximizes the individual conditional probabilities. However in reality we might not be close to θ^* and particularly during the estimation the estimator will encounter points where trade-offs have to be made between the two counteracting objectives. In other words, the estimator needs to have an exchange rate to trade off better fit on one dimension against worse fit on another.

By looking at the way that ϕ enters the likelihood function to see that it provides an implicit weight for making this trade-off: $\frac{e^{(-\frac{\nu_i^2}{2\phi^2})}}{\sqrt{2\pi\phi^2}}$.

If ϕ is small then values of ν_i away from 0 will lead to large losses in terms of likelihood. In other words, there is a high priority on matching the wage distribution, even at the expense of the occupation distribution. If ϕ is large, then the estimator is more forgiving with respect to large deviations from the observed wage, and puts relatively more weight on matching the conditional occupation choice probabilities. In this interpretation ϕ is simply a tuning parameter that helps us find the right balance amongst our different objectives.