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ABSTRACT

Social Skills and the Individual Wage Growth of Less Educated Workers*

We use matched employee-employer data from the UK to highlight the importance of social skills, including the ability to work well in a team and communicate effectively with co-workers, as a driver for individual wage growth for workers with few formal educational qualifications. We show that lower educated workers in occupations where social skills are more important experience steeper wage growth with tenure, and also higher early exit rates, than equivalent workers in occupations where social skills are less important. Moreover, the return to tenure in occupations where social skills are important is stronger in firms with a larger share of higher educated workers. We rationalize our findings using a model of wage bargaining with complementarity between the skills and abilities of less educated workers and the firm's other assets.

JEL Classification: J31, J24, L25

Keywords: team work, social skills, individual wage growth, firm pay premium

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1 Introduction

There is increasing concern in developed economies over growing income inequality and in particular the lack of opportunities for those on low incomes for wage growth and progression (see, for example, Chetty et al., 2014, Blundell et al., 2018). While highly educated workers have consistently enjoyed robust pay growth over their working lives, wages for those with less education have stagnated, showing little growth with age or with firm tenure. An important body of recent literature has highlighted the growing importance of social skills in the labor market. However, this research has predominantly focused on occupations that also demand high cognitive skills, including roles such as managers, teachers, doctors, and lawyers (Caines et al., 2017; Deming, 2017; Edin et al., 2022; Weinberger, 2014).[1] In this context, our investigation centers on the importance of social skills, such as teamwork and effective communication with co-workers, for workers who exit school with a low level of formal qualifications.

We make three contributions in this paper. First, we document the importance of social skills for the individual wage growth of less educated workers using new administrative panel data for the UK. An advantage of our data is that we follow individual workers as they progress in a firm and we also observe the formal education qualifications of each of the workers. The previous literature has largely focused on the importance of social skills for high educated workers, and has also focused largely on wage levels, rather than individual wage growth.

Second, we propose a simple theory to predict how individual wage dynamics vary both across occupations and across firms. This hinges on both: (i) the extent to which an occupation requires social skills, because they are complementarity with the firm's other assets, and; (ii) the importance of the other assets in each individual firm, for example on the extent to which the firm is skill intensive. Our theory builds on Acemoglu and Pischke (1998)'s model of firm training and learning, which it extends by introducing occupational heterogeneity - where each occupation involves an O-Ring (Kremer, 1993) production technology with a task-specific degree of complementarity

[1]Notable exceptions include studies by Lindqvist and Vestman (2011), who explore the significance of soft skills for the labor market earnings of young men enlisted in the Swedish military; Barrera-Osorio et al. (2020), who demonstrate that vocational training in soft skills boosts employment and wages in a randomized experiment in Colombia; and Adhvaryu et al. (2023), who find that soft skills training for garment workers in India enhances productivity without affecting wages. Heckman and Kautz (2012) establish the key importance of noncognitive and soft skills for labor market and other adult outcomes in the US. The Weinberger (2014) study examines the growth of social and cognitive skills across male workers in the US and finds that growth in demand for cognitive skills affected only those individuals with strong endowments of both social and cognitive skills.

between the worker's skill and the firm's other assets. Our model predicts not only a higher wage premium but also a steeper individual wage growth for occupations where social skill are important, i.e. in occupations with higher complementarity between the worker's skills and the firm's other assets, and the more so in firms that are more endowed with the other assets. It also predicts that the labor turnover rate - more specifically, the rate at which workers exit early from their current firm - should be higher for workers in occupations that require more social skills.

Third, we confront the predictions of the model to the data. For that purpose, we lay out an empirical model of the wage premium and the tenure-wage profile that mirrors our theoretical model by interacting the returns to worker's ability with a dummy variable that reflects whether the worker is employed on a job for which social skills matter, and by allowing for interactions with other complementary assets used by the firm in production. Then we estimate the empirical model using matched employee-employer panel data. Our empirical results are in line with the theory: in particular, workers in occupations where social skills are more important experience stronger wage growth compared to equivalent workers in occupations where such skills are less important, and all the more so in more skill intensive firms. Moreover, the probability that a worker exits a firm in their first few years of tenure is higher for workers in occupations that involve more social skills. Our results suggest that the returns to social skills for workers with few formal educational qualifications can be high; on average they result in significantly higher individual wage growth per year, and can be up to twice that amount earlier in a person's career and for a worker that matches to a high skills share firm.

To gain intuition for what type of skills we consider, and the role they play in production, think of a worker in a low skilled occupation, for example a personal assistant, an operative who has to coordinate with other workers, or a maintenance worker. People are better at these jobs if they can effectively communicate with other workers, listen to the problems they face, coordinate their activities with other workers, and reliably engage in team work. These attributes may be difficult to measure and verify *ex-ante*. Yet, they allow the worker to perform tasks which complement the tasks performed by other workers, and perhaps most importantly of workers in high skilled occupations within the firm. If these workers perform their tasks well they can increase the productivity of the high skilled employees, which increases their value to the firm. As the firm learns about these skills - thereby selecting out low-skill workers while also enhancing high skills through training - the wages of the individual worker will grow.

Our categorisation of how occupations differ in terms of the requirements for social skills are detailed below (in Section 2.2 and Appendix A.3), but broadly they incorporate how important it is that a worker is able to communicate and interact effectively with other actors in the firm. We measure this at the occupation level by using the widely known O*NET survey data to construct an index of occupations for which these skills are important. The O*NET data describes the mix of knowledge, skills and abilities required in an occupation and the activities and tasks performed. The data is collected through surveys of US workers and occupational workers. Our measures overlap to some extent with those used in the literature (most closely by Deming, 2017 and Caines et al., 2017, but also by Acemoglu and Autor, 2011a and Cortes et al., 2021).

Our identification strategy, designed to address the usual concern that selection is a potential confounding factor, relies on a comparison of individual wage growth of workers in occupations where social skills are important, relative to observably similar workers in occupation where they are not. It is clearly important that we are able to condition on a number of important individual, occupation, firm and local labour market controls. Measurable cognitive skills will obviously play a key role. We use detailed information on individual workers education qualifications. In addition, we include occupation level measures of the importance of cognitive skills in a symmetric way to social skills.

Our work relates to several strands of literature. First, to the rich literature that has documented the role of technology in changing in the level and distribution of skill requirements across occupations and the consequences for wages (Autor et al., 2003, 2006; Goos et al., 2014; Michaels et al., 2014), and has estimated the returns to cognitive skills (Krusell et al., 2000; Acemoglu, 2002; Goldin and Katz, 2010) and non-cognitive skills (Beaudry et al., 2016; Castex and Dechter, 2014; Lindqvist and Vestman, 2011; Deming, 2017; Heckman and Kautz, 2012; Hurst et al., 2021; Edin et al., 2022). We contribute to this literature by estimating the premium to social skills among less educated workers, and by providing evidence linking innovation to the rate at which the returns to these increase with tenure.

Second, to a labor and wage literature that studies the drivers of individual wage growth, emphasizing the importance of workers mobility and of moving up the occupation ladder, see for example Abowd et al. (1999), Postel–Vinay and Robin (2002), Adda and Dustmann (2023) and Deming (2023); and the importance of different individual age-experience wage profiles with education, see for example, Blundell et al. (2016) and Lagakos et al. (2018). We emphasize the importance of learning on the job for workers who have found a good match with a firm that invests in their skills. Recent work by Leth-Petersen et al. (2022) for example reports that around half of a representative sample of Danish firms report that at least 3 years of tenure in the firm is needed for a worker to reach maximal productivity.[2] Our work also relates to the wage and labor literature that emphasizes firm heterogeneity as an important source of wage differences across workers (Gibbons and Katz, 1992; Groshen, 1991; Abowd et al., 1999; Bonhomme et al., 2019 among others). This literature has also pointed at the fact that in many countries there is considerable wage inequality among seemingly similar workers (see e.g. Card et al., 2016). Our analysis brings social skills - the ability to work in a team and communicate effectively with co-workers - and firms' ability to enhance them by creating good jobs as another important source of wage heterogeneity across firms and among less educated workers.

Third, to a literature on soft and social skills (Brunello and Rocco, 2017; Barrera-Osorio et al., 2020; Carruthers and Jepsen, 2020; Silliman and Virtanen, 2019; Hanushek et al., 2017; Rodrik and Stantcheva, 2021; Battiston et al., 2017; Deming, 2017) that looks at how the development of these skills in firms affects workers' satisfaction on the job and also their long-term career outcomes.[3] We contribute to this literature by looking at how social skills affect the wage level and individual wage growth of less educated workers, and how this depends upon characteristics of tasks/occupations – e.g. the extent to which these complement hard skills or other firm's assets – and upon characteristics of the firm, in particular its degree of innovativeness.

The paper is organized as follows. In Section 2 we describe the data and how we measure occupation characteristics, including cognitive skills and social skills, and we show some initial correlations. In Section 3 we develop our theoretical framework and we lay out its main predictions. In Section 4 we present our empirical model and discuss potential threats to our identification. In Section 5 we present our core regression results and discuss the robustness of our main findings. Section 6 collects our concluding remarks.

[2]Table B 1 shows with our data that tenure, moving firm and moving occupation have similar orders of magnitude effects on wages.

[3]Lindqvist and Vestman (2011) study the importance of non-cognitive skills for labour market earnings of young men enlisted in Swedish military. They find that both cognitive and non-cognitive skills are strong predictors of labor market earnings. However, non-cognitive skills have a much stronger effect at the low end of the earnings distribution. At the tenth percentile, the effect of non-cognitive skills is between two and-a-half and four times the effect of cognitive skills depending on the exact specification.

2 Data

2.1 Data on workers, firms and jobs

In this section we describe the data, how we measure the extent to which an occupation requires social skills, and we provide some first descriptive evidence pointing at a positive relationship between the importance of social skills in an occupation and the steepness of the dynamic wage profile in that occupation. We use data from the Annual Survey of Hours and Earnings (ASHE) matched to the Census of 2011 (ONS-ASHE-Census, 2022). ASHE is a longitudinal dataset that tracks a random 1% sample of the UK working population and is administered by the Office of National Statistics (ONS). This survey provides comprehensive information on various aspects such as earnings, working hours, employer details, gender, age, tenure, occupation, and travel-to-work area. However, ASHE lacks information on qualifications; this data is obtained through the match with the Census. Contrary to ASHE, Census 2011 is a cross-sectional study, meaning that qualifications are not time-varying in our data.

We select workers whose highest qualification is UK Level 1, 2 or 3.[4] Level 1 and 2 qualifications are approximately the equivalent of high school dropouts in the US context and Level 3 qualifications of high school graduates (Table A 1 provides further detail). Table I shows the number of observations over the period 2003-2018 and the number of workers. The full sample includes male and female workers and workers in the public and private sector. Our main results focus on workers aged 18-39. 70% of the workers in our sample are "high school drop outs", and 30% are high school graduates. We provide further description of the characteristics of these workers, their jobs and the firms they work for in Section 5.

In auxiliary results we use ONS-ASHE (2022) which we match to the Workplace Employment Relations Survey (WERS, ONS-WERS 2013). WERS is a national survey of the state of employment relations and working life inside British workplaces.[5] We describe these data in Section 5.2.

[4]Level 1 qualifications include fewer than 5 O-levels or a level 1 National Vocational Qualifications (NVQs); Level 2 qualifications include 5+ O-levels or level 2 NVQ; Level 3 qualifications include A-levels and level 3 NVQs.

[5]WERS and Census cannot be matched due to ONS confidentiality rules.

TABLE I. Workers' qualifications, all ASHE-Census

	ASHE all workers		ASHE-Census aged 19-39	
	Observations	Workers	Observations	Workers
High school or less	**629,406**	**58,331**	**260,012**	**39,442**
of which:				
High school drop outs	*465,808*	*42,852*	*173,631*	*27,496*
No qualifications	79,772	7,283	18,462	3,135
Level 1	166,633	14,971	61,494	9,972
Level 2	219,404	20,598	93,675	14,389
High school graduate				
Level 3	163,597	15,479	86,381	11,946
Higher education	**426,065**	**39,621**		
of which:				
Level 4	389,156	35,850		
Other	36,909	3,771		
Total	**1,055,471**	**97,952**	**260,012**	**69,442**

Notes: See Table A 2 for a detailed definition and breakdown of UK qualifications.
Source: Authors' calculations using ONS-ASHE-Census (2022) 2003-2018.

2.2 Occupation characteristics

Cognitive skills and social skills are both likely to be important for worker productivity. The difference between these is that cognitive skills are well measured through the system of standard educational qualifications, and so observed by the worker and the firm. An additional advantage of the link between our employer-employee panel, ASHE, and the population Census is that we have detailed measurement of the various qualifications that each worker has achieved, which largely measure a workers' cognitive skills. We use these in our regression analysis. Social skills, on the other hand, are not as easily measured or observed at the individual level. Consequently, we turn to occupation-level measures for our analysis.

We categorize occupations based on the importance of social skills using the O*NET data to gauge these skill requirements. The O*NET data is a comprehensive description of the knowledge, skills, and abilities necessary for a comprehensive list of around 1000 occupations, as well as the activities and tasks typically performed by workers in each occupation. The data are collected from surveys of large numbers of workers, human resource and occupation specialists. The data are summarised in ratings on a large number of job-related characteristics on a scale from 1 to 5. A rating of

1 signifies that a characteristic is irrelevant to the job, while a rating of 5 denotes high relevance. The O*NET data originates from surveys conducted in the US, but they are designed to capture the characteristics of occupations that are likely to be relevant in various labour markets. For example, Goos et al. (2014) have applied these data to the UK labour market. For a more comprehensive understanding of the O*NET data and our utilization of it, please refer to Appendix A.3.

Our approach to measuring occupational characteristics builds on a substantial body of literature that utilizes O*NET data to analyze the task-based nature of occupations and to categorize them based on the similarity of required skills and abilities. The specific measures we use are similar to those used by researchers such as Acemoglu and Autor (2011b), Deming (2017), Autor et al. (2003), and Caines et al. (2017), among others. Drawing on this work to capture variation in the importance of social skills across occupations, we use the following dimensions in the O*NET data:

- **Work With Work Group or Team**: How important is it to work with others in a group or team in this job?
- **Coordinate or Lead Others**: How important is it to coordinate or lead others in accomplishing work activities in this job?
- **Social Perceptiveness**: To which extent is the worker aware of other parties' reactions and to which extent does she understand why the other parties react as they do?
- **Coordination**: To which extent does the worker adjust her actions to the actions taken by the other parties?
- **Problem Sensitivity**: How big is the worker's ability to tell when something is wrong or is likely to go wrong?
- **Active Listening**: To which extent does the worker devote full attention to what other parties are saying, and how much time does she devote to understand the points that are made by other parties, asking questions whenever appropriate and not interrupting at inappropriate times?
- **Responsibility for Outcomes and Results**: How responsible is the worker for work outcomes and results of other workers?
- **Impact on Others:** Complementarity with firm's other assets.
- **Consequence of Error**: How serious would the result usually be if the worker made a mistake that was not readily correctable?

- **Impact of Decisions on Co-workers or Company Results**: What results do your decisions usually have on other people or the image or reputation or financial resources of your employer?

We conduct our analysis at the 4-digit SOC 2010 occupation level, which identifies 361 distinct occupations. We use factor analysis to aggregate the dimensions listed above into a single score, normalizing the result to fall within a range of 0 to 1. This process allows us to create a measure that reflects the multifaceted nature of occupational skills and abilities. A detailed list of these measures at the 4-digit industry level, along with the underlying data, code and an explanation of how they are calculated, can be found in an Online Appendix.[6]

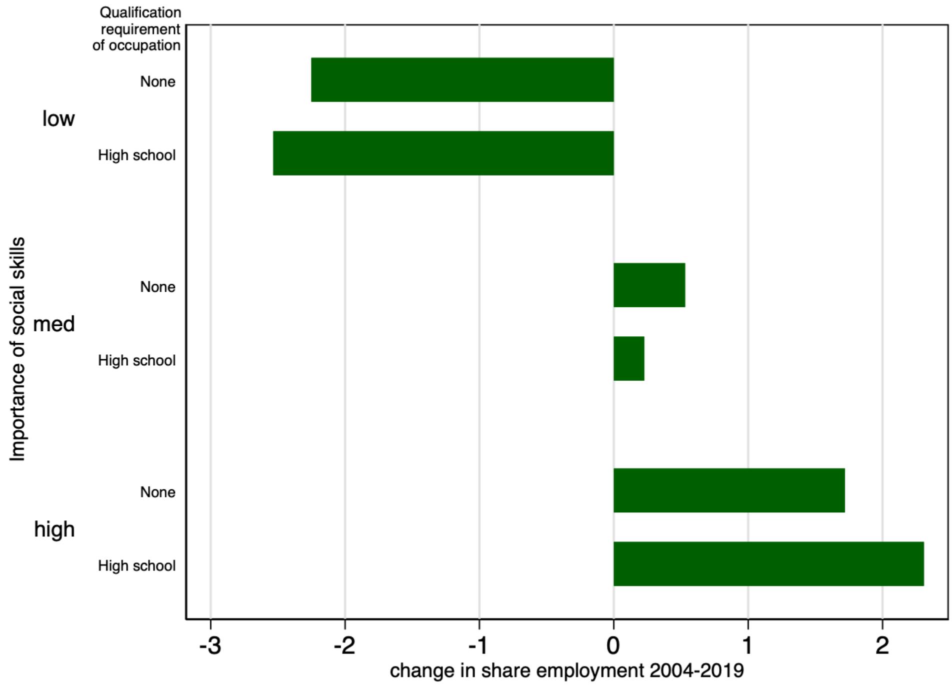
Throughout this paper we primarily use a discrete version of this measure of the importance of social skills where we divide the sample up into terciles (see A.3 for details).[7]

Employment in occupations where social skills are important increased relative to those occupations where they are less important. Figure I shows the change in share of employment between 2004 to 2019 in occupations where the typical formal qualifications requirement of the occupation is high school graduate or less, by the importance of social skills (measured as described above). The share of workers in occupations where there are low formal qualification requirements has fallen by over 2% in occupations where social skills are less important, and increased by a similar amount in occupations where social skills are more important.

[6]See "How we construct measures of social skills using O*NET data (data and code)" at https://www.rachelgriffith.org/soft-skills-and-wage-progression-of.

[7]The results also hold with the continuous measure.

FIGURE I. Change in employment shares



Notes: Figure shows changes in share of employment from 2004 to 2019 of workers in occupations classified by the typical qualification requirements (see Appendix A.2) and the importance of social skills for that occupation. Low/med/high are defined by terciles of workers based on our aggregate measure of social skills described in the text.
Source: Authors' calculations using ONET (2016) matched with employment from the UK ONS Annual Population Survey (https://www.nomisweb.co.uk/datasets/aps168).

2.3 The importance of social skills and individual wage progression

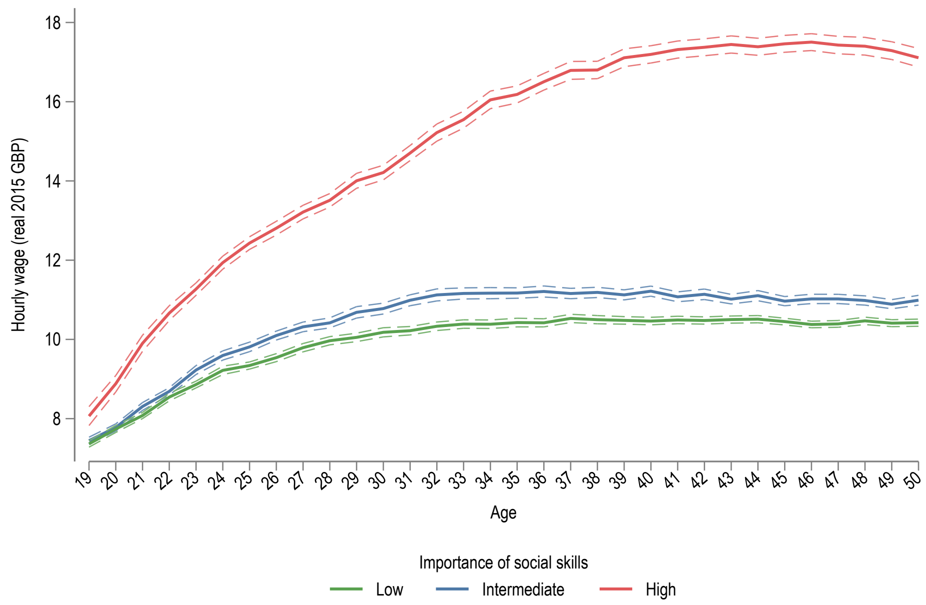
Our motivation is to investigate the importance of the ability to engage effectively with their coworkers for the individual wage growth of less educated workers. Figure II shows that, in the raw data, average wages of workers with less education increase more over the career in occupations where social skills are more important. Workers in these occupations get on average higher wages with age (experience) relative to workers in occupations where the requirements for social skills ability are lower. This is true for both females and males.

Workers in occupations where social skill skills are important may differ on many characteristics. In Section 4 we will discuss how our econometric analysis controls for these and other potentially confounding factors. We demonstrate in Section 5 that our basic results remain robust even after these controls are applied.

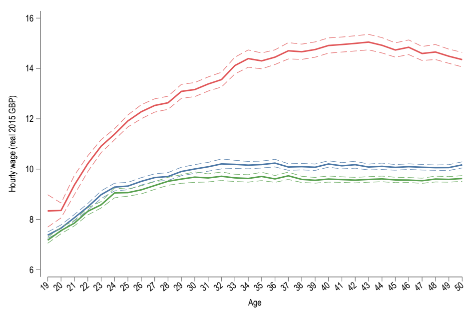
Prior to delving into the detailed empirical analysis, in the next section we develop a simple theoretical model to rationalize our intuition. In this model individual wage dynamics vary across both occupations and firms, as they depend both on the importance of social skills across different occupations, and on the importance of other assets across different firms.

FIGURE II. Average hourly wage by importance of social skills in occupation

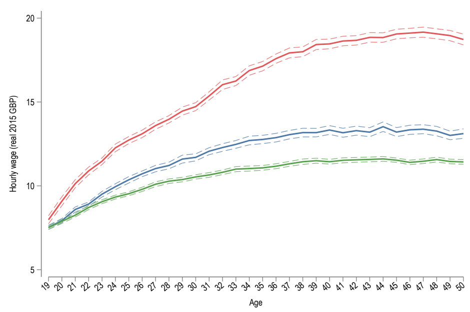
(a) All



(b) Females



(c) Males



Notes: Wage is deflated by Consumer Price Index (CPI), 2015=100.
Source: Authors' calculations using ONS-ASHE-Census (2022) matched with ONET (2016) and ONS-CPI (2023).

3 Theory

3.1 Baseline model

The baseline model has two periods $t = 0$ (ex-ante) and $t = 1$ (ex-post). We consider a representative firm which employs an asset of quality Q which it combines with tasks,[8] each of which is performed by a different worker in on a specific occupation (or job).

Each task (and its corresponding job) is characterized by a parameter $\lambda \in [0, 1]$ that quantifies the degree of complementarity between the worker's quality and the firm's asset quality Q. A larger value of λ corresponds to a task requiring a higher degree of complementarity. Workers vary in their competence to leverage the complementarity with the firm's other assets, a capability we denote as κ. This capability essentially represents their potential level of social skills and is initially unobserved by both the firm and the worker.

In our model, workers are young and in their first job. The worker's social skill ability κ is initially unknown and discovered over time. In the baseline model, we assume that κ can take only two values, $\kappa \in \{\underline{\kappa}, \bar{\kappa}\}$, with $\underline{\kappa} < \bar{\kappa}$ while λ can take any value between 0 and 1. In Appendix D.2, we extend the model to a more general distributions of κ.

3.1.1 Production

Our model posits that in each period $t \in \{0, 1\}$, the extra output produced by the worker within the firm is defined by a partially "O-Ring" production function (Kremer, 1993; Kremer and Maskin, 1996):

$$f(\lambda, \tau_t, \kappa, Q) = \lambda Q \kappa (1 + \tau_t) + \mu Q,$$

where μ is a positive constant and τ_t is the worker's training level at date t. We normalize τ_0 at zero, and assume for simplicity that $\tau_1 = \tau$ is given - it automatically results from the worker's experience inside the firm after one period.

[8] This complementary asset may just boil down to the high-educated employees in the firm, in which case we can think of Q as the average skill of these high-educated employees.

3.1.2 Timing

In this two period model, we assume that initially in period 0 both the firm and the worker ignore the worker's true social skill capability κ, and we denote by p the proportion of high ability workers in the economy, i.e. the *ex-ante* probability of facing a high ability worker. Then, in the next period, the firm and the worker both learn κ perfectly.

The timing of moves is as follows: (1) in period 0, the firm hires its (young) workers at the *ex-ante* competitive wage, then training and period 0 production take place; (2) the firm learn about each of its workers' ability κ at the beginning of period 1 and the training investment becomes effective; (3) the firm bargains with its workers, decides whether or not it wants to retain each of them, and each worker decides whether or not to leave the firm; (4) period 1 production takes place.

3.1.3 Outside option

We assume symmetric Nash bargaining between the firm and each of its workers. Let $\overline{w}(\tau, \lambda)$ denote the worker's outside option if she leaves the firm and goes on the market, and let $w_1(\lambda, Q, \tau, \kappa)$ denote the worker's wage in period 1 if she stays with the firm. As in Acemoglu and Pischke (1998), the worker will decide to leave the initial firm in period 1 whenever:

$$\overline{w}(\tau, \lambda) + \widetilde{\Phi} > w_1(\lambda, Q, \tau, \kappa),$$

where $\widetilde{\Phi}$ is a preference shock. We assume that $\widetilde{\Phi} = 0$ with probability φ and is equal to a very large number $\overline{\Phi}$ with probability $(1 - \varphi)$ so that workers always leave their current firm whenever $\widetilde{\Phi} = \overline{\Phi}$.

The worker's outside option is $\overline{w}(\tau, \lambda)$, whereas the firm's outside option is to hire another young worker on the (junior) labor market. We assume that the firm must incur search cost C to find a new worker; the firm will not know the worker's quality upon hiring her, nor will it have time to train that worker, thus the corresponding τ_1' is equal to zero for that worker. The firm's outside option is then equal to the expected surplus generated with a new untrained worker minus the search cost C.

3.1.4 Equilibrium

We focus attention on an equilibrium where, for some cut-off $\bar{\lambda} > 0$: (i) at the beginning of period 1, a firm chooses to lay off those among its workers that are revealed to be of low ability $\kappa = \underline{\kappa}$ in jobs characterized by $\lambda > \bar{\lambda}$ whereas if $\lambda \leq \bar{\lambda}$ then the firm will chose to retain both types of workers. In the latter case, workers of ability $\underline{\kappa}$ will leave the firm only if they receive a desutility shock (with probability φ). We will then derive the parameter restrictions that ensure the existence of such an equilibrium.

3.2 Solving the basic model

3.2.1 Bargaining

The *ex-post* wage is determined as follows. Consider first a high-λ job with $\lambda > \bar{\lambda}$. Then on such a job in period 1 the firm only bargains with $\bar{\kappa}$ workers. The firm's net surplus from keeping a $\bar{\kappa}$ worker on that job, is equal to:

$$S^F = \lambda Q\bar{\kappa}(1+\tau) + \mu Q - w_1(\lambda, Q, \tau, \bar{\kappa}) - (1-\omega)[\lambda Q\widehat{\kappa} + \mu Q] + C,$$

where $\widehat{\kappa}$ is the unconditional average value of κ: $\widehat{\kappa} \equiv p\bar{\kappa} + (1-p)\underline{\kappa}$, and $(1-\omega)$ is the firm's share of the surplus generated with the outside worker. The worker's net surplus from its relationship with the firm, is equal to:

$$S^W = w_1 - \overline{w}(\tau, \lambda).$$

Assuming that the worker receives a fraction $0 < \beta < 1$ of the total surplus, in equilibrium we must have $S^W = \beta(S^F + S^W)$, so that:

$$w_1(\lambda, Q, \tau, \bar{\kappa}) = \beta\{\lambda Q\bar{\kappa}(1+\tau) + \mu Q - (1-\omega)[\lambda Q\widehat{\kappa} + \mu Q] + C\} + (1-\beta)\overline{w}(\tau, \lambda).$$

To determine the outside option $\overline{w}(\tau, \lambda)$, we assume that it is simply equal to the expected marginal productivity of a worker who leaves its initial firm, as perceived by the market. Formally, the market knows both, which firm the worker originates from and also which type of job the worker was employed on by that firm, i.e. the market knows both, λ and Q. However, the market ignores the worker's true social skill ability κ, but can infer information on it.[9] More precisely, given that the initial firm lays off low ability workers for sure in high-λ jobs with $\lambda > \bar{\lambda}$, and that high ability workers leave the initial firm with probability $(1-\varphi)$, Bayes' rule implies that

[9] In this simple version of the model with only two types of workers, the market infers its information from observing whether the worker originates from job with a λ lower than $\bar{\lambda}$, in which case the only reason she would be on the market is because of the exogenous disutility shock, or whether it originates from a job λ larger than $\bar{\lambda}$. In Appendix D.2, we generalize the model to a continuum of κ which clarifies the role of λ in the formation of the labor market priors.

the *ex-post* probability, as assessed by the market, of the worker being of high ability, is equal to:

$$q = \frac{p(1-\varphi)}{p(1-\varphi)+1-p}.$$

We further denote by $u \in [0,1]$ the extent to which the training acquired in the initial firm is transferable to other firms in the market, then the expected outside option wage of a high-ability worker, is equal to:

$$\overline{w}(\tau,\lambda) = \mathbb{E}\left[\lambda Q\right](1+\tau u)\Lambda(\lambda) + \mu\mathbb{E}\left[Q\right], \tag{1}$$

where $\Lambda(\lambda) = q\bar{\kappa} + (1-q)\underline{\kappa}$ is the average value of κ conditional on being on the market and coming from a high-λ job with $\lambda > \bar{\lambda}$. Hence:

$$\begin{aligned} w_1(\lambda, Q, \tau, \bar{\kappa}) = \beta &\left\{\lambda Q\left[\bar{\kappa}(1+\tau) - (1-\omega)\hat{\kappa}\right] + \mu Q\omega + C\right\} \\ &+ (1-\beta)\left\{\mathbb{E}\left[\lambda Q\right](1+\tau u)\Lambda(\lambda) + \mu\mathbb{E}\left[Q\right]\right\}. \end{aligned}$$

3.2.2 Equilibrium conditions

We now derive sufficient conditions for the existence of a cut-off $\bar{\lambda}$ such that the firm will lay off a low quality $\underline{\kappa}$ worker in high-λ jobs with $\lambda > \bar{\lambda}$, whereas it will choose to keep high and low ability workers on low-λ jobs with $\lambda < \bar{\lambda}$.

For given λ, whether she is of high or low ability a worker will always choose to leave the firm if:

$$\overline{w}(\tau,\lambda) + \widetilde{\Phi} > w_1(\lambda, Q, \tau, \kappa).$$

How about the firm's choice whether or not to keep a low-ability worker on a λ-job? The firm will choose to keep a low ability worker whenever:

$$\lambda Q\underline{\kappa}(1+\tau) + \mu Q - \overline{w}(\tau,\lambda) < (1-\omega)(\lambda Q\widehat{\kappa} + \mu Q) - C,$$

or equivalently

$$\lambda < \bar{\lambda}$$

where:

$$\bar{\lambda} = \frac{C + \mu\omega Q - \mathbb{E}\left[\lambda Q\right](1+\tau u)\Lambda(\lambda) - \mu\mathbb{E}\left[Q\right]}{Q\left[(1-\omega)\hat{\kappa} - \underline{\kappa}(1+\tau)\right]}.$$

To guarantee that $\bar{\lambda} > 0$, we assumed that:

$$(1-\omega)\hat{\kappa} - \underline{\kappa}(1+\tau) > 0 \text{ and } C + \mu\omega Q > \mathbb{E}\left[\lambda Q\right](1+\tau u)\Lambda(\lambda) + \mu\mathbb{E}\left[Q\right].$$

The second assumption is automatically satisfied if C is sufficiently large. The first assumption requires that:[10]

$$\frac{\bar{\kappa}}{\underline{\kappa}} > 1 + \frac{\tau + \omega}{p(1-\omega)}.$$

3.2.3 Comparative statics

From the equilibrium value of w_1, it is straightforward to prove the following proposition:

Proposition 1. *For given τ and as long as $\bar{\kappa} > \underline{\kappa}\left(1 + \frac{\tau+\omega}{p(1-\omega)}\right)$, the equilibrium wage $w_1(\lambda, Q, \tau, \bar{\kappa})$ of retained high-ability workers, satisfies:*

$$\frac{\partial w_1(\lambda, Q, \tau)}{\partial \lambda} > 0.$$

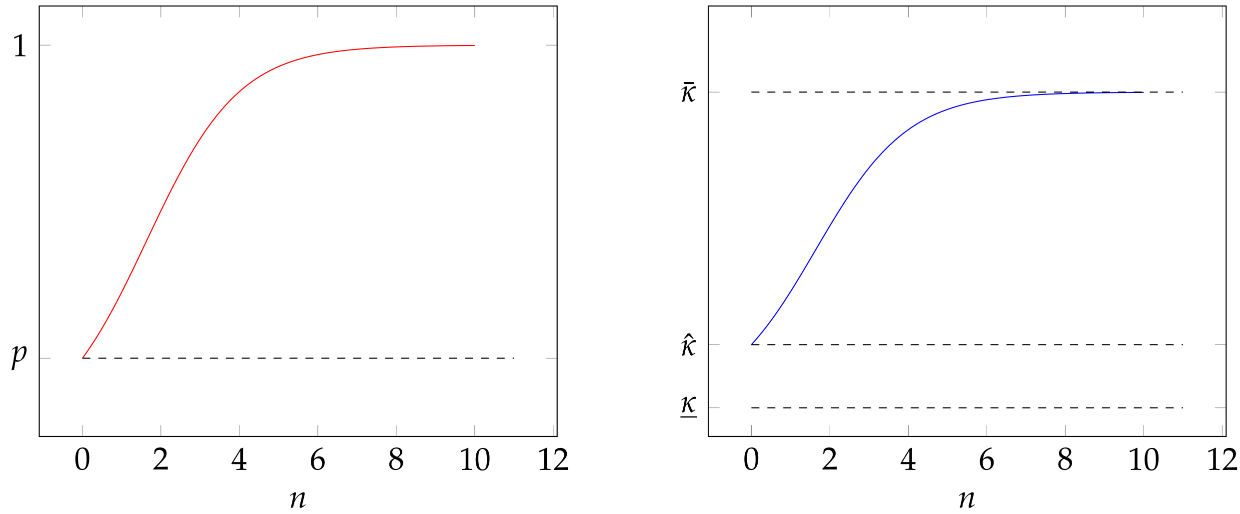
3.3 Progressive learning and individual wage growth

We now explore the relationship between a worker's dynamic wage profile and the nature - high versus low λ - of the job the worker is employed on. For that purpose, we extend the baseline model by introducing more periods. In each period, the initial firm acquires some information about its incumbent worker's true social skill ability κ. More precisely, at each period $t > 0$ the firm and the worker both discover the worker's true ability κ with probability $1 - \varepsilon > 1/2$ and they observe the wrong ability with probability ε. And in each period, the worker undergoes a disutility shock and then leaves the firm, as in the baseline model. We also assume that the level of training $\tau(t)$ is progressive, increasing with t and exogenous.

Our focus remains on cases where only on high-λ (i.e. $\lambda > \bar{\lambda}$) jobs do firms find it optimal to lay off low ability workers. When a worker enters the job market, as before the market can observe the λ of the worker's job in the original firm, and in addition we assume that the market knows about the worker's tenure in the original firm. Other firms in the market make job offers at a wage that matches the worker's expected productivity given that information. Finally, in each period, incumbent workers bargain for a new wage with their current employer by taking into account their outside option from entering the labor market at that period. For simplicity and without any loss of insight, we assume that $\beta = 1/2$.

[10] Note that the model relies on the fact that a worker with capabilities $\underline{\kappa}$ in a $\lambda > \bar{\lambda}$ job would prefer to leave the firm rather than being reallocated to a low λ job within the firm, even though the firm might find it profitable. This point is discussed in Appendix D.1.

FIGURE III. Value of p_n and the corresponding average value of κ



3.3.1 Law of motion

To solve the model, we need to derive the posterior probability $q(n,\varepsilon)$ that a worker entering the job market after a tenure of n years in her initial firm be of high ability $\bar{\kappa}$. To that end, we need to consider three possible reasons that would lead a worker to leave her initial firm: (i) she is of high ability $\bar{\kappa}$ but subject to a high preference shock (which occurs with probability $p_{n-1}(1-\varphi)$); (ii) she is of high ability but found out to be of low ability (which occurs with probability $p_{n-1}\varphi\varepsilon$) ; (iii) she is of low ability $\underline{\kappa}$ and found out to be of low ability (this happens with probability $(1-p_{n-1})(1-\varepsilon)$). Bayes' rule implies that the probability, as assessed by the market, that a worker leaving her initial firm after an n- year tenure, is of high ability $\bar{\kappa}$, is equal to:

$$q(n,\varepsilon) = \frac{p_{n-1}(1-\varphi+\varphi\varepsilon)}{p_{n-1}(1-\varphi+\varphi\varepsilon)+(1-p_{n-1})(1-\varepsilon)},$$

where p_n is the share of $\bar{\kappa}$ workers in the firm after n periods. This share evolves with n according to:

$$p_n = \frac{p_{n-1}(1-\varepsilon)}{p_{n-1}(1-2\varepsilon)+\varepsilon} = \frac{p(1-\varepsilon)^n}{p(1-\varepsilon)^n+(1-p)\varepsilon^n}.$$

It clearly appears that p_n is increasing with n if $\varepsilon < 0.5$: namely, as tenure increases, the share of $\bar{\kappa}$ workers in the firm increases and ultimately approaches 1 (see Figure III). We can also easily show that $q(n,\varepsilon)$ increases with n.[11]

[11]Indeed $q(n,\varepsilon) - q(n-1,\varepsilon)$ has the same sign as $p_n - p_{n-1}$. In fact, $q(n,\varepsilon)$ has the following close-form

3.3.2 Wage determination

The outside option $\overline{w}(n)$ of a worker with tenure n originating from a high λ task is thus equal to:

$$\overline{w}(n) = \mathbb{E}\left[\lambda Q\right](1+\tau(n)u)\Lambda(n,\varepsilon) + \mu\mathbb{E}\left[Q\right],$$

where as before $\Lambda(n,\varepsilon) = q(n,\varepsilon)\bar{\kappa} + (1-q(n,\varepsilon))\underline{\kappa}$ is the expected value of κ conditional on entering the job market after a tenure period of n in the initial firm. We clearly see that $\overline{w}(n)$ is increasing with tenure n.

Proposition 2. *The equilibrium wage of an incumbent worker that remains in the initial firm on a high-λ job, is increasing with tenure, and it is higher and the more increasing with tenure the higher Q.*

The proof immediately follows from the fact that this wage verifies:[12]

$$w(n,\lambda,Q) \propto \left\{\lambda Q\left[(p_n\bar{\kappa} + (1-p_n)\underline{\kappa})(1+\tau(n)) - (1-\omega)\hat{\kappa}\right] + \overline{w}(n) + C + \omega\mu Q\right\}, \quad (2)$$

which is increasing with n and Q, and satisfies $\frac{\partial^2 w(n,\lambda,Q)}{\partial n \partial Q} > 0$ (see Figure IV for an illustration).

3.4 Predictions

In the next section, we will confront the main predictions of the model with the data. In particular:

- **Prediction 1:** There is a higher wage premium for workers on higher λ jobs (this directly follows from Proposition 1).

- **Prediction 2:** The equilibrium wage of workers increase with tenure the more so in higher λ jobs (this follows from Proposition 2).[13]

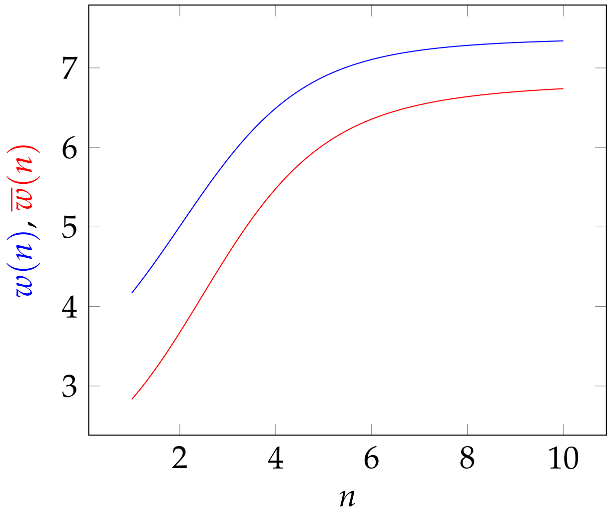
expression:

$$q(n,\varepsilon) = \frac{p(1-\varphi+\varphi\varepsilon)(1-\varepsilon)^{n-1}}{p(1-\varphi+\varphi\varepsilon)(1-\varepsilon)^{n-1} + (1-p)\varepsilon^{n-1}(1-\varphi+\varphi(1-\varepsilon))}$$

[12]To derive this formula, we have assumed that the wage bargaining rests on the worker's and firm's current surpluses. This assumption was made without any loss of generality in the baseline (static) model. In the current model with progressive learning and wage progression, this remains valid as long as the wage progression is the same no matter whether the worker stays in its current firm or if she moves to a new firm. This in turn amounts to assuming that the worker's training over time is the same in both cases.

[13]On a low-λ job the only reason for why a worker's wage should increase with tenure, is training

FIGURE IV. Value of w as a function of tenure n



- **Prediction 3:** Both the wage premium and wage growth with tenure n, are larger in firms with higher Q. The first statement follows immediately from the definition of w in equation (2) while the second statement follows from Proposition 2.

- **Prediction 4:** The labor turnover rate is higher from high-λ jobs (indeed, on low λ-jobs the only source of turnover is the exogenous disutility shock, whereas on high-λ jobs all $\underline{\kappa}$ workers are dismissed upon being discovered and only those $\bar{\kappa}$ workers that undergo a high disutility shock decide to leave the firm on their own initiative).

4 An empirical model of individual wage growth

In this section we develop an empirical specification which will allow us to confront the above predictions with the data.

We do not directly observe the degree of complementarity of a task/occupation (λ). Instead, we make use our measurement of the importance of social skills (high-λ) and of firms with a high share of complementary assets (high-Q). Under the production technology assumed in the previous section the value of social skills arises

$\tau(n)$ which we took to be increasing with n; indeed, we know that a low-λ firm wants to keep all its workers, so that the high disutility shock is the only reason for which any worker would leave the firm; since all workers face the same disutility shock, we have, in a low-λ firm: (1) $p_n = p$ and (2) $\Lambda(n) = p(1-\varphi+\varphi\varepsilon)/(p(1-\varphi+\varphi\varepsilon)+(1-p)(1-\varepsilon))$ which are both independent of n.

through the worker's ability to leverage the complementarity with the firms other assets. Under this assumption, we are able to map the categorisation of occupations by the importance of soft skills to the complementarity parameter λ.

Our data, described in Section 2, follows workers in a matched firm-worker panel. Figure II suggested a higher wage and a steeper wage profile for workers in high-λ occupations, and our objective in the empirical analysis is to see whether these differences in premium and in profile hold up once we control for other differences across workers, occupations, labour markets and firms.

The theoretical discussion in the last section made four key predictions. First, a wage premium for a worker in a high-λ job. Second, higher wage growth with tenure for a worker in a high-λ job. Third, a higher wage premium and higher tenure profile for a worker in a high-λ job in a firm with more complementary assets Q. Fourth, a higher exit rate at short tenures for a worker in a high-λ.

We specify a panel data model for the wage premium and tenure-wage profile of an individual worker as they progress in a firm, and allow this profile to differ depending on the other complementary assets used by the firm in production. We also specify an empirical model for worker exit rates.

4.1 A firm-worker panel data framework

When a worker first joins a firm we expect the surplus in a high-λ job, and therefore the wage premium, to be small. Thereafter we expect the wage premium to grow with the worker's tenure in the high-λ job, depending on their social skills and as their contribution to the surplus increases.

We define the *wage premium* as the fraction of the joint surplus recovered by worker i in the match with a high-λ job in firm f. Because it takes time and effort for the firm (and worker) to learn about the *potential* level of social skills κ_i, the premium for worker i will rise with tenure T_{ift} in a high-λ job. Our analysis in Section 3 predicts that this wage premium should increase with the *quality* of the complementary assets Q in the firm. In particular, the share of the firm's workforce that works in high educated occupations. To motivate our panel data model we first specify the learning process and then consider the distinction between high and low Q firms.

To operationalise the learning process we assume a proportion θ_0 of a worker's social skills κ_i are observed at hiring in firm f and an additional proportion $\theta_1(T_{ift})$ is revealed after tenure $T_{ift} > 0$ in a high-λ job. That is learning about social skills in a high-λ job in firm f evolves according to:

$$\theta(T_{ift}) = \theta_0 + \theta_1(T_{ift}), \tag{3}$$

where $0 \leq \theta(T_{ift}) \leq 1$, $\theta_1(T_{ift})$ is weakly increasing in tenure T_{ift}, and where we normalise $\theta_1(T_{ift}) = 0$, for $T_{ift} = 0$. Note that θ_0 recovers the initial proportion of social skills revealed at the outset of the high-λ job. In the empirical application we allow $\theta_1(T_{ift})$ to be a quadratic function of firm tenure T_{ift}. We also estimate a flexible specification for $\theta_1(.)$ with individual tenure dummies.

As a consequence of this learning process, the size of the joint surplus from a worker i matched with a high-λ job will also increase with tenure T_{ift}. The wage premium going to worker i from this match is the product of the level of underlying social skills κ_i, the learning process (3) and the bargaining share. We specify this wage premium for worker i as:

$$\alpha(\kappa_i, T_{ift}) = \alpha_0\kappa_i + \alpha_1(T_{if})\kappa_i, \tag{4}$$

where again we normalise $\alpha_1(T_{if}) = 0$, for $T_{if} = 0$, so that $\alpha_0\kappa_i$ measures the wage premium at the outset of the match. Since social skills cannot be easily verified prior to a worker joining a firm we expect this term to be small.

Our theory predicts that this wage premium will be higher in a firm where there is a larger share of higher educated workers, high-Q firms. We define Q_f as the binary indicator that selects firms in which the share of workers in high educated occupations is above the median. For a less-educated worker in a high-λ job in a high-Q firm there is an additional premium:

$$\alpha_2\kappa_i Q_f + \alpha_3(T_{ift})\kappa_i Q_f. \tag{5}$$

The wage premium terms (4) and (5) are the main parameters of interest in the wage equation specification to which we now turn.

Defining the binary indicator $\lambda_{j(it)} = 1$ for worker i in a high-λ job in period t and zero otherwise, we specify the log wage for worker i at tenure T_{ift} in firm f at time t as:

$$\begin{aligned} \ln w_{ijft} =& \alpha_0\kappa_i\lambda_{j(it)} + \alpha_1(T_{ift})\kappa_i\lambda_{j(it)} + \alpha_2\kappa_i Q_f\lambda_{j(it)} + \alpha_3(T_{ift})\kappa_i Q_f\lambda_{j(it)} \\ &+ g(A_{it}, QL_i, C_{j(it)}, FT_{it}, S_f, Q_f, T_{ift}, P_f, M_i) + \gamma_{if} + \eta_{tr} + e_{ijft} \end{aligned} \tag{6}$$

where the leading four terms on the right hand side of (6) identify the high-λ wage premium as defined in (4) and (5).

The remaining terms in (6) describe the baseline wage of worker i. The function $g(.)$ depends flexibly on potential experience A_{it}, recorded qualifications QL_i, occupation-level cognitive skills measure $C_{j(it)}$, full-time work FT_{it}, firm size S_i, high share of high educated workers Q_f, firm tenure T_{ift}, public sector P_f, and gender M_i. In the empirical application, firm size is measured at the outset of a job. Our focus is on social skills but to guard against misspecification we treat occupational-level cognitive skills symmetrically with social skills.[14] The final three terms in (6) represent unobserved components of wages, a worker-firm effect γ_{if}, a region-time effect η_{tr} that allows returns to vary over time across regions, and an idiosyncratic productivity effect e_{ijft}.

Note that the wage premium terms, the leading terms on the *right hand side* of (6), are heterogeneous across individuals, reflecting unobservable social skill ability κ_i. The coefficients that we estimate in our panel data regressions recover specific averages of these heterogeneous effects. For example, the first term will identify the average premium for social skills of newly hired workers in low-Q firms allocated to an occupation in which social skill are important:

$$\mathbb{E}\left[\alpha_0\kappa_i | T = 0, \lambda = 1\right]. \tag{7}$$

For each additional year of tenure $T_{ift} > 0$, the second term identifies the average value of the social skills wage premium for those workers in a high-λ occupation in low-Q firm f at tenure $T = T_{ift}$:

$$\mathbb{E}\left[\alpha_1(T_{ift})\kappa_i | T = T_{ift}, \lambda = 1\right], \tag{8}$$

and so on.

We interpret the worker-firm effect, γ_{if}, in (6) as capturing the initial productivity of worker i in firm f. This is assumed to be unobserved to the econometrician, but observed in the market. For workers observed in a single firm, this is equivalent to an individual worker effect. As an alternative to this specification, we include a measure of the initial wage. We assume the initial wage, and other observable individual time invariant covariates, capture the level of skills of the worker at *entry*.[15] A further advantage of the initial wage specification is that it allows us to identify the leading wage premium term in (6) even when a worker is only observed in a high-λ job in firm f. We present both specifications in our empirical analysis.

[14]Because we observe, and can control, for a workers' observed (cognitive skill) qualifications, QL_i, the interpretation of the coefficients on the cognitive skills terms will differ.

[15]This is similar to an idea developed in Blundell et al. (1999, 2002). Conveniently our data contains pre-sample observations on wages.

4.2 Worker exits

Workers will exit from a high-λ job in firm f for two reasons. Either their κ_i is revealed to be low and the firm will not be willing to pay a wage premium, or they draw an adverse productivity (or utility) shock and choose to exit the firm.

To examine this we estimate a model for the probability that a worker i exits firm f at tenure T_{ift}. We assume this probability follows a similar specification to the main wage equation:

$$\begin{aligned}\mathbb{P}[\text{Exit}_{if}] =& \beta_0 \lambda_{j(it)} + \beta_1(T_{ift})\lambda_{j(it)} \\ &+ f(A_{it}, QL_{it}, C_{j(it)}, FT_{it}, S_f, Q_f, T_{ift}, P_f, M_i) + \gamma_{if} + \eta_{tr} + e_{ijft},\end{aligned} \tag{9}$$

where $\beta_1(T_{ift})$ is a linear function in tenure allowing a different coefficient at each tenure. Workers who are not in a high-λ job will exit solely due to the adverse shock to productivity (utility). Consequently, in the first years of their tenure in firm f, we expect the exit probability to be higher for workers in high-λ occupations.

4.3 Identification discussion

Identification of the wage premium terms requires that we control for individual heterogeneity in the wage specification (6). If we did not, the estimated tenure profile could spuriously capture the impact of better workers, with higher wages, being retained for longer in the firm. This bias is due to the dependence between unobserved heterogeneity and tenure duration. We include a worker-firm effect (or the initial wage) to control for this.

We briefly explore three additional threats to identification.

A *first* threat to identification is due to endogenous selection in relation to current period shocks to e_{ijft}. The idiosyncratic shock e_{ijft} can induce a bias in our estimate of the wage premium profile if these shocks are correlated with worker exits from the firm. Note that the wage premium term measures the impact of tenure for those workers in high-λ occupations *relative* to the impact of tenure on those workers in low-λ occupations. This latter term is captured by the tenure variables in $g(.)$. In the theoretical model discussion we assumed a 'utility' shock which was drawn from the same distribution for all workers. This assumption is sufficient to eliminate the selection bias. More generally, provided the bias from selective exit on e_{ijft} is the same across high and low-λ occupations, the estimates of the wage premium will remain unbiased for the average effects for workers of tenure T_{ift} in high-λ jobs.

A *second* threat to identification could come from a combination of better firms keeping workers longer and better firms being more likely to use workers with higher social skills κ_i. The inclusion of a worker-firm effect controls for this potential bias.

A *third* threat to identification comes from persistent unobservable shocks. It is possible that the idiosyncratic shocks e_{ijft} are persistent. We allow for correlation through robust standard errors but a bias would still occur though if the wage regression included past choice variables - for example, past tenure spells in previous firms. That the ability to work in social skills is hard to verify and transfer across firms, plus the very flat tenure profiles for less educated workers in occupations where these skills are less important, suggest past tenure spells are not likely to be a key factor for less educated workers, given age, qualifications, initial wages, time etc. As a robustness we also examine younger workers in their first jobs. We find that our results pass all these robustness tests.

5 The estimated impact of social skills on individual wage growth

We first estimate a specification of the wage equation (6) in which we assume Q_f, the share of high educated workers in firm f, is the same across firms. This allows us to focus on the average tenure profile of wages for less educated workers in high-λ jobs across firms. We then make use of the additional linked survey information in WERS to measure the share of workers in high educated occupations in each firm and estimate the wage specification with differential tenure profile parameters between firms with high and low Q_f.

Before turning to the estimates of the coefficients in the empirical model discussed above, we report means of the main variable in Table II. Column (4) shows the mean across the whole sample, while columns (1)-(3) show the means by the importance of team work and social skills (λ) in the worker's occupation.

As can be seen from Table II, an important aspect of the ASHE-Census linked worker-firm data is that it provides a detailed list of educational qualifications for each worker even within this less educated sample.

Mean wages are higher in higher λ occupations, as we saw in Figure II. Workers in higher λ occupations also have other characteristics that are associated with higher wages, they are more likely to work full time, have longer tenure, are more likely to work in the public sector, work in occupations where cognitive skills are more important, have more years of experience, are more likely to be male. We control for all of these. They also work in average in smaller firms, whereas most of the literature finds that wages are higher in larger firms.

The final panel shows the sample size, which includes 39,442 workers who work in 31,770 firms.

TABLE II. Descriptive statistics ASHE-Census

	(1)	(2)	(3)	(4)
	Importance of social skills			
	Low	Intermediate ($\lambda_{j(it)} = 0$)	High ($\lambda_{j(it)} = 1$)	All
Job characteristics				
Wage (£), w_{ijft}	8.86	9.31	13.3	10.43
Full-time (%), FT_{ift}	70.5	66.2	89.7	75.2
Tenure (years in firm), T_{ift}	5.5	5.5	6.7	5.9
Public sector (%), P_f	19.5	23.8	26.6	23.2
High cognitive skills, $C_{j(it)}$	0.210	0.324	0.456	0.327
Worker characteristics				
Experience, A_{it}	12.3	11.4	13.3	12.3
Male (%), M_i	54.6	43.1	65.8	54.3
Initial wage (£), w_{i0}	6.16	6.20	7.46	6.59
No qualifications (%)	11.6	5.6	3.8	7.1
NVQ level 1, foundation GNVQ (%)	20.6	21.4	18.7	20.3
NVQ level 2, intermediate GNVQ (%)	31.0	35.2	32.1	32.8
NVQ level 3, advanced GNVQ (%)	17.5	21.8	24.7	21.2
1-4 O levels, CSE, GCSEs (%)	56.3	56.4	55.6	56.1
5+ O level (passes) (%)	31.0	40.5	47.4	39.4
2+ A levels, VCEs, 4+ AS levels (%)	9.5	14.7	17.7	13.8
Apprenticeship (%)	4.9	5.5	10.4	6.9
Other vocational or work-related qualifications (%)	17.3	19.7	26.1	20.9
Foreign Qualifications (%)	1.7	1.3	1.2	1.4
Firm characteristics				
Size (initial employment), S_{f0}	26,913	27,037	18,377	24,231
Number in our sample				
Observations	89,525	87,507	82,980	260,012
Firms	14,881	13,734	13,846	31,770
Workers	21,422	21,566	19,520	39,442

Source: Authors' calculations using ONS-ASHE-Census (2022) matched with ONET (2016).
Notes: Workers aged 19-39 with highest qualification high school or less.

5.1 Individual wage growth results

Table III presents estimates of the main parameters of interest in the individual wage growth equation (6), and summarizes the statistical significance of the controls; estimates of the full set of coefficients is shown in Appendix Table B 2.

Our focus is on the variables that characterise the social skills wage premium terms represented by the first two terms on the right hand side of (6). These are the binary indicator for high social skills $\lambda_{j(it)}$, and its interaction with the worker's tenure in the firm T_{ift}. In Table III this interaction term is specified as a quadratic function of tenure, while below we estimate more flexible functions of tenure.

In column (1) we show the raw correlation between log wage and the indicator dummy for high social skills occupation $\lambda_{j(it)}$. This is positive and statistically significant, indicating that on average wages of workers in high social skills occupations are 13 log points higher.

TABLE III. Individual wage growth and social skills

Dependent variable: $\log(w_{ijkft})$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
$\lambda_{j(it)}$	0.13101***	0.07736***	0.05327***	0.04551***	0.00596	0.02530**	-0.0095
(high social skills)	(0.00263)	(0.00343)	(0.00456)	(0.00435)	(0.00716)	(0.01142)	(0.01492)
$\lambda_{j(it)} \times T_{ift}$			0.00485***	0.00489***	0.00467***		
(high social skills times tenure in the firm)			(0.0014)	(0.00126)	(0.00155)		
$\lambda_{j(it)} \times T^2_{ift}$			-0.0001	-0.00015**	-0.00016**		
(high social skills times tenure squared)			(0.00007)	(0.00006)	(0.00007)		
w_{i0}				0.03132***		0.03133***	
(initial wage)				(0.00072)		(0.00072)	
F-test and P-values of joint significance:							
$\lambda_{j(it)} \times T_{ift}$, $\lambda_{j(it)} \times T^2_{ift}$			15.31	12.81	6.31		
F(2, 39441): p-value			0.0000	0.0000	0.0018		
$\lambda_{j(it)} \times$ tenure dummies						2.58	1.48
F(16,76707): p-value						0.0006	0.0953
T_{if}, T^2_{if}		1503.34	1242.76	1300.94	55.93		
F(2, 39441): p-value		0.0000	0.0000	0.0000	0.0000		
Tenure dummies						177.88	14.59
F(16,76707): p-value						0.0000	0.0000
$C_{j(it)}$, $C_{j(it)} \times T_{ift}$, $C_{j(it)} \times T^2_{ift}$			1585.87	1289.74	51.65		
F(3, 39441): p-value			0.0000	0.0000	0.0000		
$C_{j(it)}$, $C_{j(it)} \times$ tenure dummies						255.45	11.98
F(16,767070): p-value						0.0000	0.0000
Controls		1932.16	1890.99	1289.74	224.00	1183.60	237.79
F(5, 76707): p-value		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Area-year effects		32.72	31.82	36.13		36.11	
F(1211, 258775): p-value		0.0000	0.0000	0.0000		0.0000	
Firm-Worker effects					9.84		9.86
F(76707, 183235): p-value					0.0000		0.0000
Year dummies					100.27		97.07
F(15, 76707): p-value					0.0000		0.0000
Fixed-effects							
Area-year effects		✓	✓	✓		✓	
Firm-Worker effects					✓		✓
Year effects					✓		✓
R^2	0.195	0.354	0.355	0.421	0.35	0.421	0.351
Observations	260012	260012	260012	260012	260012	260012	260012

Source: Authors' calculations using ONS-ASHE-Census (2022) matched with ONET (2016).
Notes: Samples include workers aged 19-39 with highest qualification high school or less. Numbers are estimated coefficients with robust standard errors in parentheses. $\lambda_{j(it)} = 1$ if the occupation is in the top tercile by importance of social skills, $C_{j(it)} = 1$ if the occupation is in the top tercile by importance of cognitive skills, see Section 2.2. w_{i0} is initial wage of worker. Controls include initial employer size (S_{f0}), whether worker is male (M_i), whether job is full-time (FT_{if}), workers experience in years and squared (A_{it}, A^2_{it}) , workers tenure in the current employer in years and squared (T_{ift}, T^2_{ift}), whether the employer is a public sector organisation (P_f), and which qualifications (QL_i) the worker has as indicated in the rows of Table A 1 (NVQs by levels, O-level, A-levels, apprenticeships, and other vocational qualifications). Areas are work output areas (there are 76 in our data). The full set of estimates is shown in Appendix Table B 2. Stars indicate * p<0.1, ** p<0.05, *** p<0.01.

In column (2) we add differential time effects across local areas (work census output area) and, following the specification of $g(.)$ in wage equation (6), a set of controls that includes initial employer size (S_{f0}), the cognitive skill requirement of the occupation (interacted with tenure in a symmetric way to high λ), whether worker is male (M_i), whether job is full-time (FT_{if}), workers experience in years and squared (A_{it}, A_{it}^2), whether the employer is a public sector organization (P_f), indicators of the detailed qualifications (QL_i) the worker has (NVQs by levels, O-level, A-levels, apprenticeships, and other vocational qualifications, see Table A 1), and in columns (3)-(5) workers tenure in the current employer in years and squared (T_{ift}, T_{ift}^2). These controls are all statistically significant, as indicated by the F-tests in the bottom panel of the table (the individual significance of each coefficient is reported in Appendix Table B 2). The social skills indicator remains significant.

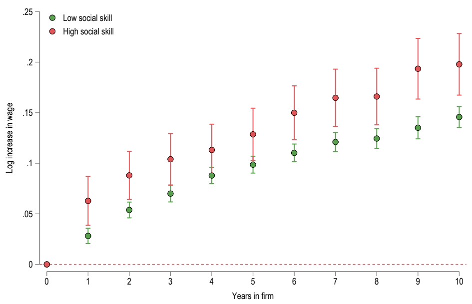
In column (3) we add the interaction between the high social skills indicator, λ, and a quadratic in tenure. We see that the linear term is positive and statistically significant, indicating an increase of 0.5 log points with each year of tenure. In column (4) we include the worker initial wage as a control for unobserved worker heterogeneity (see the discussion on Section 4.1). The social skill premium terms remain significant and of a similar size. There is some indication of curvature in the tenure interaction effect through a negative quadratic term. In column (5) we include individual worker-firm effects to control for unobserved heterogeneity. The coefficients on the linear and quadratic tenure interaction terms are robust to this specification. As workers rarely move across these broad occupation definitions within a firm, the coefficient on λ becomes small and insignificant once the worker-firm effect is included. Likewise, as firms do not move across areas, the area effects are not identified and we include common year effects.

The results across these first five columns of Table III tell a consistent story. We see a significantly positive effect of working in a higher λ occupation on wages (except in column (5) where we include worker-firm effects). As emphasized above, if our interpretation is correct then we expect that the returns to working in a higher λ occupation should increase with a worker's tenure, and more so than workers in low λ occupations. That is exactly what we see. We interpret this as reflecting the fact that the ability to engage in effective team work and social skills either take time to be valued by the firm, or require some firm-specific training to materialize.

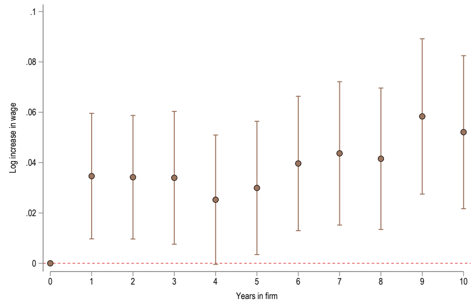
The quadratic term in tenure could be overly restrictive, so we also estimate a more flexible specification by interacting the high λ indicator with a full set of tenure dummies (one for each year of tenure up to 15 and a single dummy for 16 and over). These estimates are shown in columns (6) and (7) of Table III; the estimated coefficients on the individual dummies are shown in the Appendix Table B 2. In Figure V we plot the tenure dummies from Table B 2 with confidence intervals. Figures (a) and (b) show the dummies for the specification with the initial wage to control for worker heterogeneity and area-year effects, while figures (c) and (d) are for the specification with firm-worker and year effects. These estimates are in line with the quadratic specification, indicating an increase of between 0.4 and 0.5 log points with each year of tenure.

FIGURE V. Wage growth from working in high λ occupation

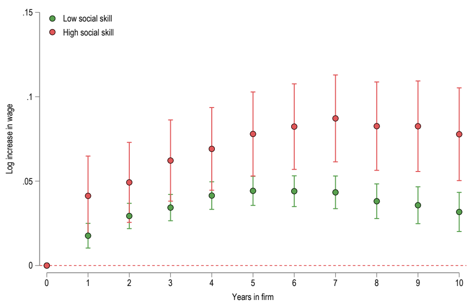
(a) mean individual wage growth, initial wage



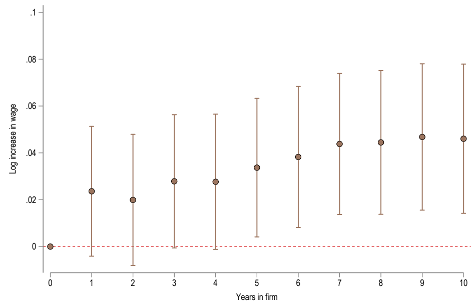
(b) difference in mean individual wage growth between high and low social skill occupations, initial wage



(c) mean individual wage growth, firm-worker effects



(d) difference in mean individual wage growth between high and low social skill occupations, firm-worker effects



Notes: Figures plot the estimated coefficients and confidence interval for the coefficient in columns (6) and (7) in Table B 2. Figures (a) and (c) show the dummy variables in tenure (green dots) and the dummy variables in tenure plus the interaction between high λ and tenure dummies (red dots); figures (b) and (d) show the difference between the two (interaction between high λ and tenure dummies).

In our results so far we have included a number of controls that allow for differences in mean log wage. However, it could be that the tenure profiles vary with other characteristics, for example, we know that women's wage profiles differ from men's. In Table IV we investigate how the returns to team work and social skills vary by different groups - males (col 1), females (col 2), workers in private sector firms (col 3), public sector organizations including charities (col 4). In column (5) we use information only on the first job we observe, and in column (6) on the first job where the worker started in that job in their 20s. We show the equivalent tenure dummy specification in Table

B 5.

These results show some differences in returns to social skills, but overall the pattern of faster wage growth in high λ occupations, relative to workers in low λ occupations, holds in all samples.

The results in column (6) are particularly interesting and are very much in line with our model. For young workers in their first observed job we see that there is little initial premium to working in a high λ occupation, but that wage growth in these occupations is considerably higher than in low λ occupations, with a 1 log point difference for each year of tenure. This suggests there is little information on a worker's social skills available to firms early on a worker's career. The stronger growth with tenure shows the importance of learning about social skill ability in the first high-λ job.

TABLE IV. Social skills and Wage growth for different samples

Dependent variable: $\log(w_{ijkft})$	**(1)** Male	**(2)** Female	**(3)** Private	**(4)** Public	**(5)** First job	**(6)** First job started in 20s
$\lambda_{j(it)}$	0.03566***	0.06049***	0.03597***	0.07376***	0.01694**	0.00043
(high social skills)	(0.00577)	(0.00688)	(0.00523)	(0.00834)	(0.00702)	(0.00831)
$\lambda_{j(it)} \times T_{ift}$	0.00531***	0.00362*	0.00410**	0.00655***	0.00892***	0.01081***
(high social skills times tenure in the firm)	(0.00164)	(0.00195)	(0.00161)	(0.00233)	(0.00176)	(0.00192)
$\lambda_{j(it)} \times T^2_{ift}$	-0.00021**	-0.00006	-0.00001	-0.00044***	-0.00032***	-0.00037***
(high social skills times tenure squared)	(0.00009)	(0.0001)	(0.00008)	(0.00013)	(0.00008)	(0.00009)
w_{i0}	0.03160***	0.02920***	0.03207***	0.02512***	0.03991***	0.03787***
(initial wage)	(0.00079)	(0.00099)	(0.00078)	(0.00091)	(0.00082)	(0.00091)
F-test and P-values of joint significance:						
$\lambda_{j(it)} \times T_{if}$, $\lambda_{j(it)} \times T^2_{if}$	7.67	5.95	21.10	8.41	17.71	23.72
F(2, 1203): p-value	0.0005	0.0027	0.0000	0.0002	0.0000	0.0000
T_{ift}, T^2_{ift}	671.31	930.58	832.68	909.96	1332.99	606.38
F(2, 1203): p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$C_{j(it)} \times T_{ift}$, $C_{j(it)} \times T^2_{ift}$	1128.55	498.87	1145.28	269.08	595.14	414.43
F(3, 1203): p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Area-year effects	18.61	18.53	25.90	13.34	12.88	11.83
F(1203, 140142): p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Controls	698.00	543.68	1215.09	342.90	658.49	518.93
F(16, 1203): p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Fixed effects						
Area-year effects	✓	✓	✓	✓	✓	✓
R^2	0.436	0.337	0.433	0.357	0.49	0.484
Observations	141370	118642	199490	60522	141673	116920

Source: Authors' calculations using ONS-ASHE-Census (2022) matched with ONET (2016).
Notes: Samples include workers aged 19-39 with highest qualification high school or less. Numbers are estimated coefficients with robust standard errors in parentheses. $\lambda_{j(it)} = 1$ if the occupation is in the top tercile by importance of social skills, $C_{j(it)} = 1$ if the occupation is in the top tercile by importance of cognitive skills, see Section 2.2. w_{i0} is initial wage of worker. Controls include initial employer size (S_{f0}), whether worker is male (M_i), whether job is full-time (FT_{if}), workers experience in years and squared (A_{it}, A^2_{it}), workers tenure in the current employer in years and squared (T_{if}, T^2_{if}), whether the employer is a public sector organisation (P_f), and which qualifications (QU_i) the worker has (NVQ levels 1, 2, 3, 4-5, 1-4)-level passes, 2+ A-levels, VCEs, 4+ AS levels, apprenticeship, and other vocational qualification; see Table A 1). The full set of estimates is shown in Appendix Table B 3. Stars indicate * p<0.1, ** p<0.05, *** p<0.01.

5.2 Variation in the social skills premium across firms

The results in the previous tables have allowed the return to workers' social skills ability to grow with firm tenure but did not allow the return to vary by type of firm. To explore variation across firms we follow the discussion in Section 4.3 and allow the tenure profile in high λ occupations to differ with the quantity of workers in high educated occupations in the firm (measured as the share of the total workforce).

To measure the share of workers in the firm that are high skilled we need information on the firm's entire workforce. ASHE is a 1% random sample of the workforce, so we don't observe all of the worker in a firm. Therefore we use the link with the Workplace Industrial Relations Survey (WERS) data. We use data from WERS 2011 at one point in time. We are not allowed to match both Census 2011 and WERS 2011 to ASHE.[16]

To exploit the match with WERS we take a different approach to identifying less educated workers; this turns out to be a useful robustness check. We identify 4-digit occupations by the education level that is typically required to do that job, as identified by the UK immigration authority. Details of how we do this, and a comparison with the Census data on actual qualifications by occupation are provided in A.2. Below we show that our results using this alternative definition are similar to those above using actual qualifications obtained by workers. We then show results using the WERS data to measure the share of workers in the firm that are high skilled.

Replicating baseline results using typical qualifications by occupations

Before investigating how individual wage growth in high λ occupations varies across firms where a high share of the workers are high skilled we reproduce the baseline results using observed individual qualifications presented in Section 5.1, to confirm that they hold using the measure of typical qualification requirement by occupations. This analysis uses a larger sample, because we are not restricted to individuals who can be matched to the Census data.

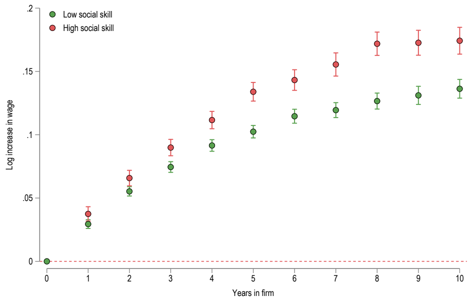
In Appendix C.1 we replicate Figure II, Table II, and Table B 3 (the detailed version of Table IV). These all tell a similar story.

Figure VI, using the typical qualification requirement by occupation, replicates Figure V, which uses individual qualifications. It shows a similar picture across the two definitions.

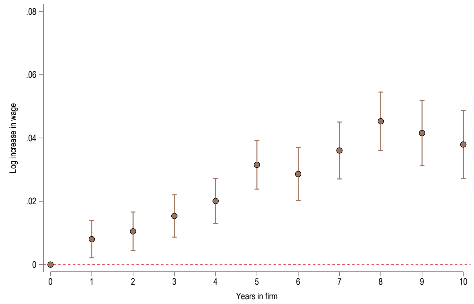
[16]The data owners of the Census data do not allow it to be matched to WERS because of concerns about maintaining confidentiality.

FIGURE VI. Wage growth from working in high λ occupations, using RQF categorization of occupations

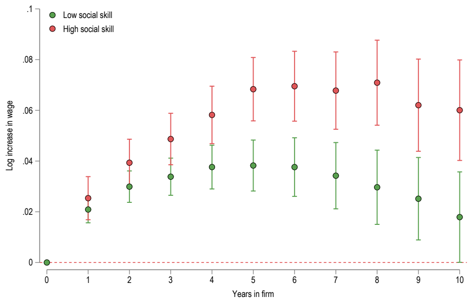
(a) mean individual wage growth, initial wage



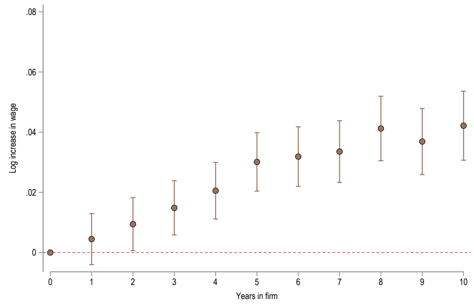
(b) difference in mean individual wage growth between high and low social skill occupations, initial wage



(c) mean individual wage growth, firm-worker effects



(d) difference in mean individual wage growth between high and low social skill occupations, firm-worker effects



Notes: Figure plots the estimated coefficients and confidence interval for the coefficient in columns (6) and (7) in Table C 2 on the dummy variables in tenure (green dots) and the dummy variables in tenure plus the interaction between high social skills and tenure (red dots).

Results using data on share of skilled workers in firm

Using the match of data from the WERS survey with the worker-firm panel from ASHE, we provide estimates where we allow the surplus to vary across firms, according to the share complementary assets - a high share of high skilled workers. Table V describes the data; in the top panel we include workers in occupations that typically require no formal qualifications, according to the immigration rules, and in the bottom panel we also include occupations that typically require the equivalent of graduating high school. The first two columns are for workers in jobs where team work and social skills are less important (low λ), the next two columns where they are important, and the final column for all occupations. Within each value of λ we split the sample into workers that work for firms where the share of all the workers in the firm that are high skilled (Q_f) is low and where it is high. We see already in the descriptive statistics that the wages of workers in occupations that typically require no qualifications (low skill occupations) are higher in those firms that employ a large share of high skilled workers, and this is more true in occupations that require team work and social skills (high λ). Workers also vary in other characteristics across these samples, so it will be important to control for these differences.

Table VI shows the estimates where we allow the surplus to vary across firms. The triple difference between high $\lambda_{j(it)}$ occupation, the share of workers in the firm that are high skilled (Q_f), and the workers tenure in the firm (T_{ift}). The full set of coefficient estimates is reported in Table C 3. We see that for workers in occupations with no formal education requirements, or when we include occupations with up to the equivalent of graduating high school, this triple difference is positive and statistically significant. These results show that wage growth is higher for workers in high λ occupations in firms that employ a higher share of skilled workers. Based on our model of production and bargaining within the firm, we interpret this to reflect the complementarity between high levels of ability for team work and social skills among workers in less educated occupations and the firms other assets. [17]

Figure VII plots the tenure dummies for the sample of workers in occupations that typically have no formal educational requirements. The equivalent figure including occupations that require up to high school is shown in Appendix Figure C 2).

[17]We confirm that our baseline results hold in this smaller sample in columns (1) and (5) of Table C 3, which replicates the results in Table III.

TABLE V. Descriptive statistics, ASHE-WERS

occupation:	Low $\lambda_{j(ijt)}$		High $\lambda_{j(ijt)}$		All
firm skill share:	low Q_f	high Q_{ft}	low Q_f	high Q_f	
Typical skill requirement of occupation: none					
Job characteristics					
Wage (£), w_{ijft}	8.39	8.81	9.13	10.54	8.88
Full-time (%), FT_{ift}	46.1	47.2	66.5	70.6	52.4
Tenure (years), T_{ift}	4.4	4.6	4.7	5.4	4.6
Public sector (%), P_f	13.8	65	30.2	70.7	34.4
High cognitive skills, $C_{j(it)}$	0.281	0.289	0.394	0.4	0.314
Worker characteristics					
Experience, A_{it}	9.7	12.2	10.4	11.6	10.6
Male (%), M_i	52.4	27.5	45.5	38.5	44.5
Initial wage (£), w_{i0}	7.15	7.23	7.35	8.09	7.32
Firm characteristics					
Size (employment), S_{f0}	115,353	22,734	39,509	18,980	73,195
Number in our sample					
observations	60,453	23,314	14,402	16,361	114,530
firms	307	399	31	51	788
workers	22,830	8,316	5,378	4,933	41,457
Typical skill requirement of occupation: up to high school					
Job characteristics					
Wage (£), w_{ijft}	8.44	9.24	10.72	12.3	10.05
Full-time (%), FT_{ift}	47.2	50.6	76.4	78.1	62.1
Tenure (years), T_{ift}	4.4	4.8	6.2	5.9	5.2
Public sector (%), P_f	13.9	63.4	40.4	72.0	42.4
High cognitive skills, $C_{j(it)}$	0.282	0.307	0.492	0.475	0.382
Worker characteristics					
Experience, A_{it}	9.8	12.1	11.8	12.4	11.2
Male (%), M_i	0.518	0.286	0.467	0.458	0.454
Initial wage (£), w_{i0}	7.17	7.43	8.05	8.97	7.86
Firm characteristics					
Size (employment), S_{f0}	112,473	22,267	59,698	21,521	63,325
Number in our sample					
observations	64,020	28,317	39,858	43,995	176,190
firms	314	430	47	61	852
workers	24,159	10,038	10,800	10,258	55,255

Source: Authors' calculations using ONS-ASHE (2022) matched with ONET (2016) and ONS-WERS (2013).

Notes: Data for years 2004-2019 for workers in occupations with no formal educational requirements (top panel), occupations with either no formal educational requirements or requiring up to high school (bottom panel).

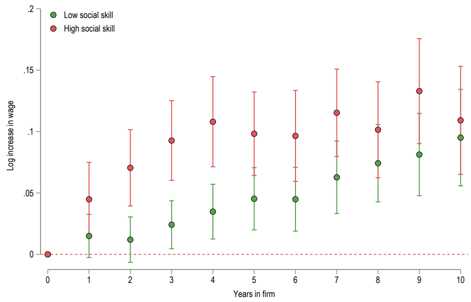
TABLE VI. Wage growth, the role of high-skill firms

Typical skill requirements of occupation:	None		High school	
Dependent variable: $\log(w_{ijkft})$	**(1)**	**(2)**	**(3)**	**(4)**
$\lambda_{j(it)}$	-0.01924***	-0.01279***	-0.01993***	-0.00555
(high social skills)	(0.0053)	(0.0047)	(0.00449)	(0.00398)
$\lambda_{j(it)} \times T_{ift}$	0.01043***	0.00953***	0.00767***	0.00695***
(high social skills times tenure in the firm)	(0.0018)	(0.00156)	(0.00144)	(0.00118)
$\lambda_{j(it)} \times T^2_{ift}$	-0.00004	-0.00013	-0.00004	-0.00012*
(high social skills times tenure squared)	(0.0001)	(0.00008)	(0.00007)	(0.00006)
$\lambda_{j(it)} \times T_{ift} \times Q_f$	0.00753***	0.00359*	0.01248***	0.00730***
(high social skills times tenure times high skills share firm)	(0.00238)	(0.002)	(0.00162)	(0.00131)
$\lambda_{j(it)} \times T^2_{ift} \times Q_f$	-0.00067***	-0.00045***	-0.00082***	-0.00059***
(high social skills times tenure squared times high skills share firm)	(0.00012)	(0.0001)	(0.00008)	(0.00006)
$\lambda_{j(it)} \times Q_f$	0.05438***	0.04596***	0.04129***	0.02981***
(high social skills times high skills share firm)	(0.0092)	(0.00844)	(0.00622)	(0.00532)
$T_{ift} \times Q_f$	0.00511***	0.00404***	0.00482***	0.00383***
(tenure times high skills share firm)	(0.00065)	(0.00054)	(0.00066)	(0.00051)
Q_f	0.00988**	0.01130***	0.02943***	0.02750***
(high skills share firm)	(0.00437)	(0.00359)	(0.00455)	(0.00347)
w_{i0}		0.03957***		0.04019***
(initial wage)		(0.00141)		(0.00114)
Area-year effects	✓	✓	✓	✓
R^2	0.254	0.386	0.365	0.498
Observations	114530	114530	176190	176190

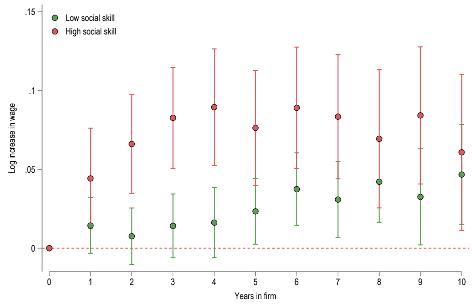
Source: Authors' calculations using ONS-ASHE (2022) matched with ONET (2016) and ONS-WERS (2013).
Notes: Sample is workers aged 19-39. In columns (1)-(2) we include workers in occupations with no formal qualification requirements; in columns (3)-(4) we include workers in occupations where workers typically require high school qualifications and where there are no formal qualification requirements. $\lambda_{j(it)} = 1$ if the occupation is in the top tercile by importance of social skills, $C_{j(it)} = 1$ if the occupation is in the top tercile by importance of cognitive skills, see Section 2.2. w_{i0} is initial wage of worker. Controls include initial employer size ((S_{f0}), whether worker is male (M_i), whether job is full-time (FT_{if}), workers experience in years and squared (A_{it}, A^2_{it}), workers tenure in the current employer in years and squared (T_{if}, T^2_{if}), whether the employer is a public sector organisation (P_f). Numbers are coefficients with robust standard errors in parentheses. Stars indicate * p<0.1, ** p<0.05, *** p<0.01.

FIGURE VII. Wage growth from working in high $\lambda_{j(it)}$ occupation in firm with high skill share

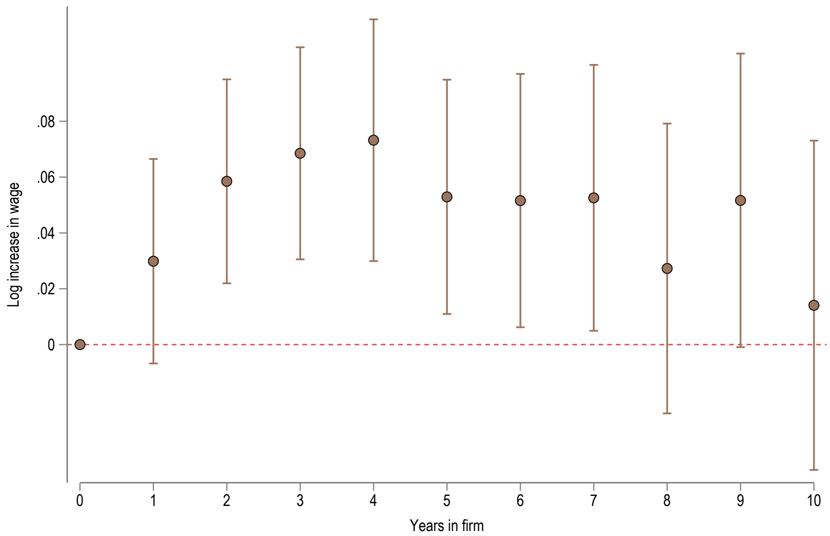
(a) Increase in wage growth from working in high skill share firm



(b) Increase in wage growth from working in a high $\lambda_{j(it)}$ occupation



(c) Increase in wage growth from working in a high $\lambda_{j(it)}$ occupation in a high skill firm



Source: Authors' calculations using ONS-ASHE (2022) matched with ONET (2016) and ONS-WERS (2013).
Notes: Figure plots the estimated coefficients and confidence interval for the coefficient in Table C 3 on : (a) differential dummies on years of tenure comparing the increased wage for working in a high skill share firm depending on whether the worker works in a low (green) or high (red) λ occupation. (b) the differential dummies on years of tenure comparing the increased wage for working in a high $\lambda_{j(it)}$ occupation depending on whether the firm is low (green) or high (red) share of skilled workers. (c) the difference between the differences in figures (a) and (b).

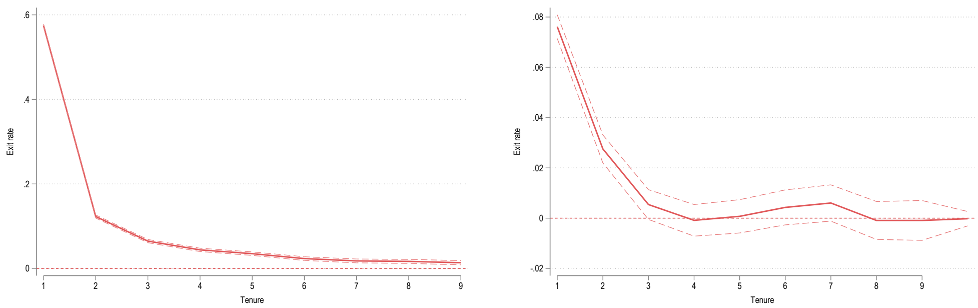
5.3 Exit rates

In line with Prediction 4 of the theory, we investigate how the labor turnover rate varies in high-λ jobs. Recall that the theory predicted turnover rates would be higher in high-λ occupations. In Table VII we estimate (9) as a linear probability model for the probability that a worker exits a firm. This is generally declining in tenure. For workers in high λ occupations it is higher in the first three years than in lower λ occupations (see Figure VIII for a graphical illustration).

FIGURE VIII. Workers' probability of exit against tenure

(a) Probability of exit by tenure

(b) Difference high and low $\lambda_{j(it)}$ occupation



Source: Authors' calculations using ONS-ASHE (2022) matched with ONET (2016) and ONS-WERS (2013).
Notes: Figure plots the estimated coefficients and confidence interval for the coefficient in Table VII (column 3) on: (a) $T_{ift} = x$ and (b) $\lambda_{j(it)} \times T_{ift} = x$ for all x between 1 and 9.

TABLE VII. Workers' probability of exit from firm

Dependent variable: change of firm	(1)	(2)	(3)
$\lambda_{j(it)} \times T_{ift} = 1$	0.08389***	0.07677***	0.07616***
(high social skills times tenure in the firm is one year)	(0.0024)	(0.00239)	(0.0024)
$\lambda_{j(it)} \times T_{ift} = 2$	0.03525***	0.02808***	0.02754***
	(0.00284)	(0.00283)	(0.00284)
$\lambda_{j(it)} \times T_{ift} = 3$	0.01292***	0.00607**	0.00542*
	(0.00302)	(0.00301)	(0.00302)
$\lambda_{j(it)} \times T_{ift} = 4$	0.00536*	-0.0002	-0.00086)=
	(0.00321)	(0.0032)	(0.00321)
$\lambda_{j(it)} \times T_{ift} = 5$	0.00459	0.00139	0.00074
	(0.00338)	(0.00337)	(0.00338)
$\lambda_{j(it)} \times T_{ift} = 6$	0.00656*	0.00495	0.00429
	(0.00355)	(0.00354)	(0.00355)
$\lambda_{j(it)} \times T_{ift} = 7$	0.00719*	0.00665*	0.00604
	(0.00369)	(0.00368)	(0.00368)
$\lambda_{j(it)} \times T_{ift} = 8$	-0.00029	-0.00034	-0.00091
	(0.00386)	(0.00385)	(0.00385)
$\lambda_{j(it)} \times T_{ift} = 9$	-0.0003	-0.00039	-0.0009
	(0.00405)	(0.00404)	(0.00404)
$T_{ift} = 1$	0.54817***	0.57486***	0.57470***
(tenure in the firm is one year)	(0.00155)	(0.00161)	(0.00162)
$T_{ift} = 2$	0.09827***	0.12299***	0.12287***
	(0.00177)	(0.00181)	(0.00182)
$T_{ift} = 3$	0.04142***	0.06469***	0.06473***
	(0.00186)	(0.0019)	(0.0019)
$T_{ift} = 4$	0.02387***	0.04384***	0.04397***
	(0.00196)	(0.00199)	(0.00199)
$T_{ift} = 5$	0.01907***	0.03488***	0.03501***
	(0.00207)	(0.00208)	(0.00209)
$T_{ift} = 6$	0.01080***	0.02318***	0.02336***
	(0.00218)	(0.00219)	(0.00219)
$T_{ift} = 7$	0.00817***	0.01767***	0.01788***
	(0.00229)	(0.00229)	(0.00229)
$T_{ift} = 8$	0.00953***	0.01650***	0.01674***
	(0.00241)	(0.00241)	(0.00241)
$T_{ift} = 9$	0.00839***	0.01333***	0.01362***
	(0.00254)	(0.00253)	0.00253)
Experience		0.01134***	0.01145***
		(0.00022)	(0.00022)
Experience squared		-0.00026***	-0.00026***
		(0.00001)	(0.00001)
Male			-0.00486***
			(0.00091)
Full-time			0.00675***
			(0.00103)
Public sector			-0.01082***
			(0.00093)
Constant	0.02740***	-0.08577***	-0.08662***
	(0.00093)	(0.00205)	(0.00221)
R-squared	0.337	0.343	0.343
N	462722	462722	462722

Source: Authors' calculations using ONS-ASHE-Census (2022) matched with ONET (2016).
Notes: Linear probability model on the probability to change firms. Sample is workers aged 19-49 with up to high school level qualifications.

Overall, our results match our theoretical predictions: workers in occupations where social-skill are more important experience stronger wage growth and higher exit rates than equivalent workers in occupations where social skills matter less.

6 Discussion and concluding comments

In this paper we use new linked administrative data in the UK, combining employee-employer records on earnings with data on qualifications, to investigate one potentially important driver of individual wage growth amongst less educated workers. We consider the task content of occupations using O*NET data and show that workers in occupations where social skills are important experience stronger wage growth than equivalent workers in occupations where these skills are not important. For those with lower formal education qualifications we find there is an important role for skills such as teamwork and effective communication with co-workers in driving individual wage growth. This is found to be particularly true in more skill intensive firms. That is firms that have a higher proportion of higher educated workers.

We develop a theoretical model to help us to interpret this finding. We posit that these wage growth results reflect a complementarity between these team and social skills with the skill intensive assets of the firm. Our model generates four predictions which we are able to confirm in our empirical analysis. First, a wage premium for a worker in a high social skills job. Second, higher wage growth with tenure for such a worker. Third, an additional premium and higher tenure profile for a worker in a high social skills job in a firm with more complementary assets. Fourth, a higher exit rate at short tenures for a worker in a these higher social skill jobs. Our empirical results align closely with these predictions.

Our analysis can be extended in several directions. First, it would be interesting to look at whether the less educated workers that yield more return to social skills are more "relational". A second idea is to explore whether our main effects are stronger in more competitive sectors or in areas where potential replacements for incumbent workers in low skilled occupations are of lower quality.

One response to the decline in social and income mobility, and more generally to the surge in income inequality over the past decades, has been to increase taxes and subsidies in order to foster redistribution. And in some countries such as the UK, taxes and benefits have been quite effective at boosting incomes at the bottom of the income distribution until quite recently (e.g. see Blundell et al., 2018). However, relying on the tax/subsidy lever is costly and insufficient to restore social and income mobility.[18] Further they do little to enhance individual wage growth.

Our work has implications for designing policies that aim to foster individual wage

[18] In the UK, spending on working age benefits, as a percentage of GDP, have nearly doubled between the end of the 1990s and the mid-2010s; while this has kept inequality from increasing it is a difficult level of expenditure to sustain.

growth for less educated workers. Policies that promote jobs where low educated workers have the opportunity to increase their marginal productivity over time, so experience wage growth, would both improve efficiency and equity. One clear policy direction from our work is to investigate the possibility of developing a system of carefully designed employer-based accredited qualifications in social skills.

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Appendix

A Data

We use data from the Annual Survey of Hours and Earnings (ASHE) matched to the Census 2011 (ONS-ASHE-Census (2022)) and separately ASHE (ONS-ASHE (2022)) matched to the Workplace Employment Relations Survey (WERS) 2011 (ONS-WERS (2013)). We were not allowed to match ASHE-Census to WERS due to concerns about maintaining anonymity of individuals in the data. We match both of these datasets to the O*NET database (ONET (2016)).

A.1 ASHE

A.1.1 ASHE-Census

ASHE is longitudinal data that follow a random sample of 1% of the UK working population and is collected by the Office of National Statistics (ONS). ASHE contains detailed information on earnings, hours of work, gender, age, tenure, occupation and travel to work area. It records the employer, and this can be matched to information about the employer. ASHE does not contain information on qualification.

ASHE has been matched to the 2011 Census, which includes detailed information on individual's qualifications. The resulting database contains panel data on all individuals that were in the ASHE data in 2011 and could be matched to the Census. Forth and Phan (2022) explain the data and methods of matching in detail.

We use data for the period 2003-2018. We use information on all (male and female) workers aged 19-39. Table A 1 shows the detailed qualifications of all observations in the data. Table A 2 shows the distribution of qualifications for the sample of less educated workers aged 19-39 that we consider.

Figure A 1 shows that workers with high school education or less have experienced little wage growth over their career over the past few decades. This motivates our paper. We study the drivers of wage growth in workers with high school qualifications or less.

TABLE A 1. Qualifications, all ASHE-Census

	Qualification level						
International definition:	High school drop out			High school	Higher education		
UK definition:	None	Level 1	Level 2	Level 3	Level 4	Other	All
Detailed UK definition:							
no qualifications	100	0	0	0	0	0	7.5
NVQ level 1, foundation GNVQ	0	15.9	17.4	17	6.6	0	11.2
NVQ level 2, intermediate GNVQ	0	0	52.1	34.7	14.5	0	21.5
NVQ level 3, advanced GNVQ	0	0	0	68.7	18.4	0	17.4
NVQ level4-5, HNC, HND	0	0	0	0	20.1	0	7.4
1-4 O levels, CSE, GCSEs	0	94.6	42.9	49.7	40	0	46.3
5+ O level (passes)	0	0	53.4	52.6	70.7	0	45.3
2+ A levels, VCEs, 4+ AS levels	0	0	0	36.3	50.3	0	24.1
degree (eg: BA, BSc)	0	0	0	0	64.9	0	23.9
apprenticeship	0	0	14	11.4	4.8	0	6.4
professional qualifications	0	0	0	0	51.5	0	19
other vocational or work-related qualifications	0	19	25.5	28.8	23.9	61.7	23.7
Foreign Qualifications (UK equivalents not stated)	0	0	0	0	0	38.2	1.3
foreign qualifications	0	1.1	1.4	1.9	5.8	41.5	4.3
Number obs	79772	166633	219404	163597	389156	36909	1055471
Number individuals	7283	14971	20598	15479	35850	3771	97952

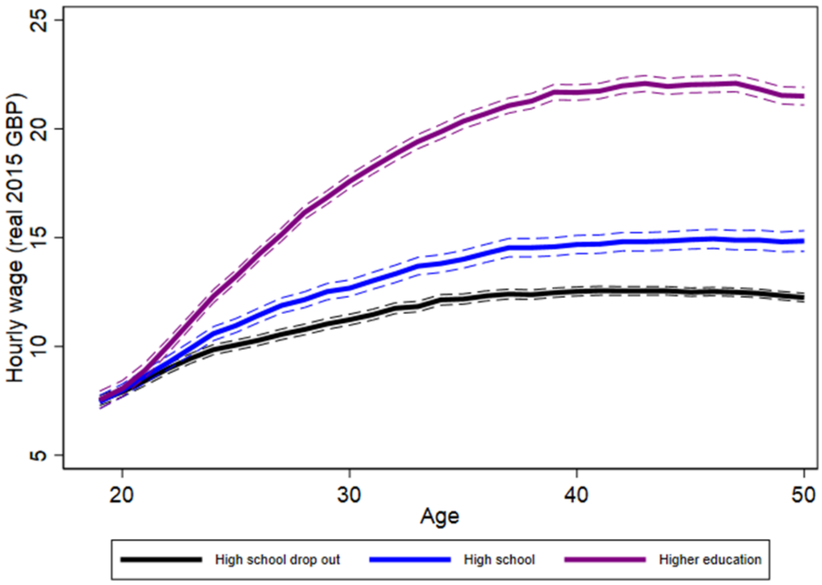
Source: Authors' calculations using ONS-ASHE-Census (2022). **Notes:** Workers of all ages. Figures are share of workers in each column with the row qualification (workers can have more than one qualification so numbers don't sum to 100 in the columns). NVQ: National Vocational Qualifications, GNVQ: General NVQ, HNC: Higher National Certificate, HNC: Higher National Diploma, O-level: ordinary level, typically taken at age 16, A-Levels: Advanced-levels, typically taken at age 18, CSE: Certificate of Secondary Education, GCSE: General CSE, VCE: Vocational Certificate of Education. For details on the classification of UK qualifications, see https://www.gov.uk/what-different-qualification-levels-mean/list-of-qualification-levels

TABLE A 2. Qualifications, our sample, high school or less, aged 19-39

	Qualification level						
International definition:	High school drop out			High school	Higher education		
UK definition:	None	Level 1	Level 2	Level 3	Level 4	Other	All
Detailed UK definition:							
no qualifications	100	0	0	0	0	0	7.1
NVQ level 1, foundation GNVQ	0	20.9	23.2	20.9	0	0	20.2
NVQ level 2, intermediate GNVQ	0	0	56.1	37.7	0	0	32.7
NVQ level 3, advanced GNVQ	0	0	0	63.9	0	0	21.2
NVQ level4-5, HNC, HND	0	0	0	0	0	0	0
1-4 O levels, CSE, GCSEs	0	94.6	46.7	50.8	0	0	56.1
5+ O level (passes)	0	0	55.5	58.4	0	0	39.4
2+ A levels, VCEs, 4+ AS levels	0	0	0	41.6	0	0	13.8
degree (eg: BA, BSc)	0	0	0	0	0	0	0
apprenticeship	0	0	9.9	9.8	0	0	6.8
professional qualifications	0	0	0	0	0	0	0
other vocational or work-related qualifications	0	17.1	22.6	26.1	0	0	20.9
Foreign Qualifications (UK equivalents not stated)	0	0	0	0	0	0	0
foreign qualifications	0	1.1	1.4	1.7	0	0	1.3
Number obs	18462	61494	93675	86381	0	0	260012
Number individuals	3135	9972	14389	11946	0	0	39442

Source: Authors' calculations using ONS-ASHE-Census (2022). **Notes:** Workers aged 19-39. See notes to Table A 1.

FIGURE A 1. Wage growth by highest educational qualification



Source: Authors' calculations using ONS-ASHE-Census (2022).
Notes: Wage is deflated by Consumer Price Index (CPI), 2015=100.

A.2 ASHE-WERS

In order to investigate how the returns to working in a high social skill occupation vary with characteristics of the firm we use ASHE (ONS-ASHE 2022) matched to WERS (ONS-WERS 2013). We are not allowed to match the Census data to WERS due to concerns about maintaining the confidentiality of workers. WERS is a national survey of the state of employment relations and working life inside British workplaces.

To measure the typical educational requirements of each occupation we use a mapping of the UK Regulatory Qualifications Framework (RQF)[19] to 4-digit occupation codes that was used by the UK government for immigration purposes until 2020 (when immigration regulation in the UK changed). Appendix J of the immigration regulation provides a definition of the typical educational requirements for each occupation (HomeOffice (2020)). We aggregate these to three educational categories - high school drop out, high school graduate, higher education - that map to the three categories of qualifications described in Section 2.1.

- **None**; equivalent of high school drop out; no or low formal educational requirements; UK level 1 or 2; occupations in this category include assemblers, clerical, secretaries, cleaners, security drivers, technicians, sales.
- **High school**; UK level 3 or vocational, typically requires A-level (the equivalent of high school in the US) or some basic professional qualification; this includes trades, specialist clericals, associate professionals, medical or IT technicians, some managerial occupations.
- **Higher education**; UK level 4 typically requires higher education or an advanced professional qualification; this includes most managerial and executive occupations, engineers, scientists, R&D manager, bankers, other professions.

Table A 3 compares workers qualifications with the skill requirements of the occupation they work in. There is a strong correlation between these two measures, though clearly they differ. Some people with a higher education degree work in low skilled jobs, and some people without any formal qualifications manage to get jobs in occupations where a degree is typically required.

[19]This framework is regulated by Ofqual (the regulator of qualifications and exams) that defines the qualifications shown in Table I.

TABLE A 3. Comparison of worker's qualifications and skill requirements of occupation

Qualifications		Skill requirements of occupation: None	High school	Higher education	All
High school drop out	Observations	133306	51169	14574	199049
	row %	67%	26%	7%	100%
	col %	59%	42%	13%	44%
High school graduate	Observations	37603	23099	8268	68970
	row %	55%	33%	12%	100%
	col %	17%	19%	8%	15%
Higher education	Observations	53368	46327	87284	186979
	row %	29%	25%	47%	100%
	col %	24%	38%	79%	41%
All	Observations	224277	120595	110126	454998
	row %	49%	27%	24%	
	col %	100%	100%	100%	100%

Source: Authors' calculations using ONS-ASHE-Census (2022) matched with ONET (2016).

A.3 O*NET

We use data from the O*NET database (ONET 2016) to classify the task and skill content of occupations by the importance of cognitive and social skill requirements. There is a large literature that uses O*NET to categories the tasks, abilities, and knowledge that are associated with different occupations. Related to our work are Caines et al. (2017), Deming (2017), Acemoglu and Autor (2011b), Autor et al. (2003), amongst others.

The O*NET data describe the mix of knowledge, skills and abilities required in an occupation and the activities and tasks performed on that occupation. Workers are surveyed across occupations and asked to grade various characteristics or "dimensions" from 1 (when this dimension is not relevant to the workers' occupation) to 5 (when this dimension is very relevant to the workers' occupation). The O*NET data is based on surveys of workers and experts in the US. Goos et al. (2014) apply these data to the UK labour market.

Our analysis is performed at the 4-digit SOC 2010 occupation level, which identifies 361 occupations. A detailed list of these measures at the 4-digit industry level, along with the underlying data, code and an explanation of how they are calculated, can be found in an Online Appendix, "How we construct measures of social skills using O*NET data (data and code)" at https://www.rachelgriffith.org/soft-skills-and-wage-progression-of.

We aggregate the relevant dimensions of social skills and of cognitive skills into a single score for each skill measure using factor analysis. We normalize the measure so as to lie between 0 and 1.

The details of the measurement of social skills are described in main paper. To measure cognitive skills across occupations, we consider the following dimensions in the O*NET.

Cognitive skill requirements

1. **Category Flexibility**: The ability to generate or use different sets of rules for combining or grouping things in different ways.
2. **Deductive Reasoning**: The ability to apply general rules to specific problems to produce answers that make sense.
3. **Fluency of Ideas**: The ability to come up with a number of ideas about a topic (the number of ideas is important, not their quality, correctness, or creativity).
4. **Inductive Reasoning**: The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).
5. **Mathematical Reasoning**: The ability to choose the right mathematical methods or formulas to solve a problem.
6. **Information Ordering**: The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).
7. **Number Facility**: The ability to add, subtract, multiply, or divide quickly and correctly.

B Empirical results using ASHE-Census

Table B 1 shows with our data that tenure, moving firm and moving occupation have similar orders of magnitude effects on wages.

Table B 2 presents the full set of parameter estimates that are summarised in Table III in the paper.

Table B 3 presents the full set of parameter estimates that are summarised in Table IV in the paper.

Table B 5 shows the dummy variable equivalent of Table IV in the paper.

TABLE B 1. Individual wage growth from tenure, moving firm, moving occupation

Highest qualification	High school dropout		High school graduate		Higher education	
	(1)	(2)	(3)	(4)	(5)	(6)
Years in this firm	0.02239***	0.00904***	0.02353***	0.00753***	0.03409***	0.00965***
	0.00054	0.00047	0.00087	0.00073	0.0007	0.00053
Years in this firm squared	-0.00060***	-0.00041***	-0.00068***	-0.00037***	-0.00137***	-0.00071***
	0.00003	0.00003	0.00005	0.00004	0.00004	0.00003
Change firm	0.03233***	0.00523*	0.03184***	0.00524	0.10865***	0.01638***
	0.00403	0.00281	0.00602	0.00423	0.00429	0.00268
Change occupation (same firm)	0.03642***	0.01290***	0.03848***	0.01769***	0.03294***	0.01379***
	0.00273	0.00188	0.00396	0.00274	0.00321	0.00197
Change firm and occupation	0.00482	-0.01396***	-0.00069	-0.01505***	-0.06440***	-0.02219***
	0.00442	0.00308	0.00655	0.00459	0.00484	0.00302
Experience	0.03329***	0.01075***	0.04601***	0.01822***	0.06597***	0.03454***
	0.00061	0.00127	0.00092	0.00173	0.00092	0.00165
Experience squared	-0.00098***	-0.00104***	-0.00132***	-0.00148***	-0.00183***	-0.00196***
	0.00002	0.00002	0.00004	0.00003	0.00004	0.00002
Full time job	0.16697***	0.00206	0.18540***	0.03471***	0.17884***	0.01969***
	0.00191	0.00187	0.0029	0.00268	0.00246	0.00198
Male	0.07531***		0.12095***		0.07116***	
	0.00169		0.00248		0.00191	
Public sector job	0.06917***	0.06402***	0.02795***	0.08404***	0.07996***	0.07163***
	0.00192	0.00282	0.00258	0.0036	0.00189	0.00262
Log wage in first year observed	0.31253***		0.27467***		0.38178***	
	0.00193		0.00277		0.00182	
Constant	1.14319***	1.82041***	1.19316***	1.76403***	1.00395***	1.95707***
	0.0047	0.00767	0.00681	0.0086	0.00623	0.01126
worker fixed effects:		✓		✓		✓
year effects	✓	✓	✓	✓	✓	✓
R-squared	0.311	0.282	0.335	0.368	0.352	0.432
N	173633	173633	86381	86381	204112	204112

Source: Authors' calculations using ONS-ASHE-Census (2022).
Notes: Samples includes workers aged 19-39. Numbers are estimated coefficients with robust standard errors in parentheses. Stars indicate * p<0.1, ** p<0.05, *** p<0.01.

TABLE B 2. Individual wage growth, aged 19-39

Dependent variable: $\log(w_{ijkft})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\lambda_{j(it)}$	0.13101***	0.07736***	0.05327***	0.04551***	0.00596	0.02530**	-0.0095
(high social skills)	0.00263	0.00343	0.00456	0.00435	0.00716	0.01142	0.01492
$\lambda_{j(it)} \times T_{if}$			0.00485***	0.00489***	0.00467***		
(high social skills times tenure in the firm)			0.0014	0.00126	0.00155		
$\lambda_{j(it)} \times T^2_{if}$			-0.0001	-0.00015**	-0.00016**		

Continued on next page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(high social skills time tenure squared)			0.00007	0.00006	0.00007		
$C_{j(it)}$	0.27218***	0.19125***	0.21842***	0.19881***	-0.02106***	0.23169***	0.01665
(high cognitive skills)	0.00261	0.00329	0.00482	0.00462	0.00737	0.01169	0.01561
$C_{j(it)} \times T_{if}$			-0.00648***	-0.00622***	0.01035***		
(high cognitive skills times tenure)			0.0014	0.00127	0.00156		
$C_{j(it)} \times T_{if}^2$			0.00021***	0.00017***	-0.00029***		
(high cognitive skills times tenure squared)			0.00007	0.00006	0.00008		
w_{i0}				0.03132***		0.03133***	
(initial wage)				0.00072		0.00072	
T_{if}		0.01637***	0.01698***	0.01844***	0.00573***		
(tenure)		0.00047	0.00051	0.00051	0.00083		
T_{if}^2		-0.00036***	-0.00040***	-0.00051***	-0.00035***		
(tenure squared)		0.00002	0.00003	0.00003	0.00003		
S_{f0}		0.00368***	0.00366***	0.00365***		0.00363***	
(initial firm size)		0.00032	0.00032	0.00029		0.00029	
M_i		0.09652***	0.09661***	0.07979***		0.07996***	
(male)		0.00177	0.00177	0.00169		0.00169	
FT_{ift}		0.11647***	0.11627***	0.11072***	-0.05256***	0.11056***	-0.05340***
(full-time)		0.00216	0.00217	0.00196	0.00317	0.00196	0.00316
P_f		0.03064***	0.03051***	0.03665***	0.05877***	0.03662***	0.05919***
(public sector)		0.00253	0.00253	0.00208	0.00726	0.00207	0.0073
A_{it}		0.03752***	0.03755***	0.03670***	0.00503*	0.03685***	0.00591**
(experience)		0.00058	0.00058	0.00058	0.00286	0.00057	0.00283
A_{it}^2		-0.00096***	-0.00096***	-0.00105***	-0.00081***	-0.00105***	-0.00083***
(experience squared)		0.00002	0.00002	0.00002	0.00003	0.00002	0.00003
1-4 O levels, CSE, GCSEs		0.00869***	0.00871***	0.01157***		0.01157***	
		0.00149	0.00149	0.00144		0.00144	
NVQ level 1, foundation GNVQ		-0.02324***	-0.02320***	-0.01688***		-0.01689***	
		0.00162	0.00162	0.00154		0.00153	
5+ O level (passes)		0.06969***	0.06969***	0.06193***		0.06192***	
		0.00168	0.00168	0.00159		0.00159	
NVQ level 2, intermediate GNVQ		-0.02348***	-0.02340***	-0.01833***		-0.01830***	
		0.0014	0.00139	0.00133		0.00133	
Apprenticeship		0.06618***	0.06608***	0.06223***		0.06222***	
		0.00296	0.00296	0.00292		0.00292	
2+ A levels, VCEs, 4+ AS levels		0.05189***	0.05181***	0.04468***		0.04473***	
		0.00216	0.00215	0.00191		0.00192	
NVQ level 3, advanced GNVQ		0.01779***	0.01780***	0.02274***		0.02277***	
		0.00149	0.00149	0.00139		0.00139	
Other vocational		0.03100***	0.03102***	0.02810***		0.02806***	
		0.00156	0.00157	0.0015		0.0015	
no qualifications		-0.08864***	-0.08856***	-0.07322***		-0.07308***	
		0.00265	0.00265	0.00257		0.00257	
Foreign Qualifications		-0.02748***	-0.02743***	-0.06619***		-0.06650***	
		0.0055	0.00551	0.00523		0.00524	

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\lambda_{j(it)} \times T_{if} = 1$						0.03465***	0.02361*
(high social skills times tenure is one year)						0.01272	0.01414
$\lambda_{j(it)} \times T_{if} = 2$						0.03420***	0.01991
						0.01252	0.01429
$\lambda_{j(it)} \times T_{if} = 3$						0.03397**	0.02787*
						0.01346	0.01451
$\lambda_{j(it)} \times T_{if} = 4$						0.02527*	0.02766*
						0.01311	0.01473
$\lambda_{j(it)} \times T_{if} = 5$						0.02995**	0.03370**
						0.01351	0.01509
$\lambda_{j(it)} \times T_{if} = 6$						0.03966***	0.03826**
						0.01362	0.01537
$\lambda_{j(it)} \times T_{if} = 7$						0.04368***	0.04381***
						0.01453	0.01537
$\lambda_{j(it)} \times T_{if} = 8$						0.04154***	0.04447***
						0.01433	0.01566
$\lambda_{j(it)} \times T_{if} = 9$						0.05836***	0.04680***
						0.01574	0.01594
$\lambda_{j(it)} \times T_{if} = 10$						0.05210***	0.04604***
						0.01551	0.01625
$\lambda_{j(it)} \times T_{if} = 11$						0.06520***	0.04377***
						0.01672	0.01676
$\lambda_{j(it)} \times T_{if} = 12$						0.06826***	0.06011***
						0.01722	0.01719
$\lambda_{j(it)} \times T_{if} = 13$						0.06044***	0.04639***
						0.01721	0.01724
$\lambda_{j(it)} \times T_{if} = 14$						0.07031***	0.04636***
						0.01959	0.01738
$\lambda_{j(it)} \times T_{if} = 15$						0.06643***	0.03829**
						0.01866	0.01806
$\lambda_{j(it)} \times T_{if} = 16$						0.05731***	0.04443***
						0.01404	0.01694

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$C_{j(it)} \times T_{if}$=1						-0.04175***	-0.03547**
(high cognitive skills times tenure is one year)						0.01273	0.01468
$C_{j(it)} \times T_{if}$=2						-0.05593***	-0.02622*
						0.01277	0.01487
$C_{j(it)} \times T_{if}$=3						-0.06160***	-0.01597
						0.01291	0.01513
$C_{j(it)} \times T_{if}$=4						-0.05415***	-0.0016
						0.0138	0.01535
$C_{j(it)} \times T_{if}$=5						-0.04733***	0.01353
						0.01415	0.01575
$C_{j(it)} \times T_{if}$=6						-0.05463***	0.02088
						0.01422	0.01598
$C_{j(it)} \times T_{if}$=7						-0.06340***	0.02279
						0.01445	0.016
$C_{j(it)} \times T_{if}$=8						-0.05107***	0.03771**
						0.01465	0.01629
$C_{j(it)} \times T_{if}$=9						-0.08183***	0.03300**
						0.01573	0.01657
$C_{j(it)} \times T_{if}$=10						-0.07954***	0.03996**
						0.01589	0.01691
$C_{j(it)} \times T_{if}$=11						-0.08557***	0.04065**
						0.01688	0.01733
$C_{j(it)} \times T_{if}$=12						-0.07952***	0.04094**
						0.01722	0.01764
$C_{j(it)} \times T_{if}$=13						-0.08554***	0.04263**
						0.01823	0.01782
$C_{j(it)} \times T_{if}$=14						-0.08775***	0.05421***
						0.01912	0.01794
$C_{j(it)} \times T_{if}$=15						-0.09242***	0.05322***
						0.01892	0.01865
$C_{j(it)} \times T_{if}$=16						-0.09762***	0.04383**
						0.01449	0.01759

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T_{if}=1						0.02817***	0.01767***
(tenure is one year)						0.00386	0.00391
T_{if}=2						0.05383***	0.02936***
						0.00399	0.00407
T_{if}=3						0.07004***	0.03433***
						0.00421	0.00428
T_{if}=4						0.08789***	0.04145***
						0.00412	0.00459
T_{if}=5						0.09865***	0.04425***
						0.00426	0.00494
T_{if}=6						0.11028***	0.04405***
						0.00447	0.00529
T_{if}=7						0.12105***	0.04337***
						0.00486	0.00566
T_{if}=8						0.12447***	0.03810***
						0.00492	0.00605
T_{if}=9						0.13512***	0.03574***
						0.00559	0.00657
T_{if}=10						0.14573***	0.03175***
						0.00528	0.00693
T_{if}=11						0.15062***	0.03301***
						0.00561	0.00734
T_{if}=12						0.15004***	0.02264***
						0.00607	0.00777
T_{if}=13						0.16554***	0.02381***
						0.00617	0.00825
T_{if}=14						0.16440***	0.01530*
						0.00649	0.00859
T_{if}=15						0.16931***	0.01603*
						0.00718	0.00924
T_{if}=16						0.18384***	0.01512
						0.00499	0.00954

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.12544***	1.60030***	1.59929***	1.43803***	1.90973***	1.42228***	1.89185***
	0.00081	0.00478	0.00476	0.00598	0.01548	0.00659	0.0156
Area-year effects		✓	✓	✓		✓	
Firm-Worker effects					✓		✓
Year effects					✓		✓
R^2	0.195	0.354	0.355	0.421	0.35	0.421	0.351
Observations	260012	260012	260012	260012	260012	260012	260012

Source: Authors' calculations using ONS-ASHE-Census (2022) matched with ONET (2016).

Notes: Samples includes workers aged 19-39 with highest qualification high school or less. Numbers are estimated coefficients with robust standard errors in parentheses. Stars indicate * p<0.1, ** p<0.05, *** p<0.01.

TABLE B 3. Wage growth in high λ occupations, different samples, quadratic specification, aged 19-39

Dependent variable: $\log(w_{ijkft})$

	(1) Male	(2) Female	(3) Private	(4) Public	(5) First job	(6) First job started in 20s
$\lambda_{j(it)}$	0.03566***	0.06049***	0.03597***	0.07376***	0.01694**	0.00043
(high social skills)	0.00577	0.00688	0.00523	0.00834	0.00702	0.00831
$\lambda_{j(it)} \times T_{if}$	0.00531***	0.00362*	0.00410**	0.00655***	0.00892***	0.01081***
(high social skills times tenure in the firm)	0.00164	0.00195	0.00161	0.00233	0.00176	0.00192
$\lambda_{j(it)} \times T^2_{if}$	-0.00021**	-0.00006	-0.00001	-0.00044***	-0.00032***	-0.00037***
(high social skills time tenure squared)	0.00009	0.0001	0.00008	0.00013	0.00008	0.00009
$C_{j(it)}$s	0.21421***	0.17875***	0.20758***	0.15407***	0.16088***	0.13511***
(high cognitive skills)	0.00601	0.00689	0.00524	0.00886	0.00724	0.00846
$C_{j(it)} \times T_{if}$	-0.00610***	-0.00673***	-0.00427***	-0.00872***	-0.00125	0.00272
(high cognitive skills times tenure)	0.0016	0.00193	0.00155	0.00235	0.00177	0.00195
$C_{j(it)} \times T^2_{if}$	0.00022***	0.00011	0.00005	0.00038***	-0.00001	-0.00013
(high cognitive skills times tenure squared)	0.00009	0.0001	0.00008	0.00013	0.00008	0.00009
w_{i0}	0.03160***	0.02920***	0.03207***	0.02512***	0.03991***	0.03787***
(initial wage)	0.00079	0.00099	0.00078	0.00091	0.00082	0.00091
T_{if}	0.01934***	0.01811***	0.01748***	0.02154***	0.02681***	0.02254***
(tenure)	0.00072	0.00067	0.00057	0.00094	0.00075	0.00086
T^2_{if}	-0.00063***	-0.00041***	-0.00051***	-0.00051***	-0.00078***	-0.00065***
(tenure squared)	0.00004	0.00004	0.00003	0.00005	0.00003	0.00004
S_{f0}	0.00660***	0.00027	0.00408***	0.00479***	0.00426***	0.00472***
(initial firm size)	0.00036	0.00036	0.0003	0.00068	0.00033	0.00036
M_i			0.08392***	0.06771***	0.07924***	0.07446***
(male)			0.00191	0.00256	0.00212	0.0023
FT_{ift}	0.09742***	0.10892***	0.11327***	0.09416***	0.10293***	0.09867***
(full-time)	0.00385	0.00209	0.00228	0.00303	0.00251	0.00287
P_f	0.01469***	0.06116***			0.03227***	0.03718***
(public sector)	0.00262	0.00249			0.00252	0.00278
A_{it}	0.04066***	0.03263***	0.03671***	0.02761***	0.03172***	0.03327***
(experience)	0.00073	0.0008	0.00063	0.00105	0.00071	0.0008
A^2_{it}	-0.00108***	-0.00102***	-0.00100***	-0.00089***	-0.00091***	-0.00092***
(experience squared)	0.00003	0.00003	0.00003	0.00004	0.00003	0.00003
1-4 O levels, CSE, GCSEs	0.01421***	0.01004***	0.01167***	0.01183***	0.01270***	0.01176***
	0.00207	0.00201	0.00171	0.00266	0.00199	0.0021
NVQ level 1, foundation GNVQ	-0.01574***	-0.01806***	-0.01897***	-0.00939***	-0.01257***	-0.00881***
	0.00212	0.00223	0.00177	0.00291	0.00209	0.00234
5+ O level (passes)	0.06684***	0.05749***	0.06658***	0.04844***	0.06258***	0.06469***
	0.00238	0.00218	0.00188	0.00285	0.00226	0.00241
NVQ level 2, intermediate GNVQ	-0.01316***	-0.02482***	-0.01533***	-0.03012***	-0.01350***	-0.01251***
	0.00194	0.00187	0.00161	0.00241	0.00175	0.00189
Apprenticeship	0.06221***	0.02896***	0.06209***	0.04539***	0.05119***	0.05601***
	0.00337	0.00623	0.00319	0.00628	0.00361	0.00383
2+ A levels, VCEs, 4+ AS levels	0.03653***	0.04931***	0.04812***	0.03513***	0.03481***	0.03187***
	0.00268	0.00266	0.00238	0.00318	0.00261	0.00277
NVQ level 3, advanced GNVQ	0.03476***	0.00637***	0.02368***	0.01601***	0.02965***	0.03058***
	0.00211	0.00215	0.00173	0.00239	0.00188	0.00209
Other vocational	0.03257***	0.02017***	0.02990***	0.02466***	0.02937***	0.03101***
	0.00205	0.00211	0.00191	0.00244	0.00195	0.00217
no qualifications	-0.06922***	-0.07703***	-0.07384***	-0.06151***	-0.06356***	-0.06577***
	0.00339	0.00378	0.00285	0.00617	0.00331	0.00384
Foreign Qualifications	-0.08586***	-0.03903***	-0.06954***	-0.03448***	-0.06058***	-0.05360***
	0.00648	0.00784	0.00577	0.0109	0.00653	0.0079
Constant	1.46162***	1.52399***	1.41684***	1.61290***	1.32554***	1.35786***
	0.00739	0.00858	0.00642	0.01077	0.00672	0.0076
Area-year effects	✓	✓	✓	✓	✓	✓
R^2	0.436	0.337	0.433	0.357	0.49	0.484
Observations	141370	118642	199490	60522	141673	116920

Source: Authors' calculations using ONS-ASHE-Census (2022) matched with ONET (2016).
Notes: Samples includes workers aged 19-39 with highest qualification high school or less. Numbers are estimated coefficients with robust standard errors in parentheses. Stars indicate * p<0.1, ** p<0.05, *** p<0.01.

TABLE B 4. Tests of joint significance of variables in Table B 3

	(1)	(2)	(3)	(4)	(5)	(6)
F-test and P-values of joint significance:						
Cognitive skills ($C_{j(it)}$), $timesT_{if}$, $\times T_{if}^2$	1128.55	498.87	1145.28	269.08	595.14	414.43
F(3, 1203)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
High cognitive skills ($C_{j(it)}$) $timesT_{if}$, $\times T_{if}^2$	11.25	21.77	15.81	9.36	3.12	1.22
F(2, 1203)	0.0000	0.0000	0.0000	0.0001	0.0445	0.2966
High social skills ($\lambda_{j(it)}$) $\times T_{if}$, $\times T_{if}^2$	7.67	5.95	21.10	8.41	17.71	23.72
F(2, 1203)	0.0005	0.0027	0.0000	0.0002	0.0000	0.0000
Area-year effects	18.61	18.53	25.90	13.34	12.88	11.83
F(1203, 140142)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
T_{if}, T_{if}^2	671.31	930.58	832.68	909.96	1332.99	606.38
F(2, 1203)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Controls	698.00	543.68	1215.09	342.90	658.49	518.93
F(16, 1203)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: See notes to Table B 3.

TABLE B 5. Dummies of tenure specification, aged 19-39

Dependent variable: $\log(w_{ijkft})$	(1)	(2)	(3)	(4)	(5)	(6)
	Male	Female	Private	Public	First job	First job started in 20s
$\lambda_{j(it)}$	0.02351	0.03517**	0.01879	0.05135**	-0.00987	-0.005
(high social skills)	0.01498	0.01714	0.01318	0.02432	0.0258	0.02939
$\lambda_{j(it)} \times T_{if} = 1$	0.02496	0.04406**	0.03219**	0.03496	0.04095	0.02384
(high social skills times tenure is one year)	0.01668	0.01899	0.01465	0.02615	0.02804	0.03097
$\lambda_{j(it)} \times T_{if} = 2$	0.02379	0.03966**	0.03181**	0.0329	0.05703**	0.03786
	0.01682	0.01888	0.01445	0.02651	0.02754	0.03141
$\lambda_{j(it)} \times T_{if} = 3$	0.02943	0.03168	0.02666*	0.04932*	0.05475*	0.03621
	0.01795	0.01934	0.01545	0.02669	0.02805	0.03144
$\lambda_{j(it)} \times T_{if} = 4$	0.01926	0.02246	0.0202	0.0313	0.04877*	0.03742
	0.01709	0.01947	0.01522	0.02657	0.02725	0.03189
$\lambda_{j(it)} \times T_{if} = 5$	0.03104*	0.01786	0.02451	0.04027	0.04785*	0.03654
	0.01816	0.01999	0.01606	0.02719	0.02766	0.03203
$\lambda_{j(it)} \times T_{if} = 6$	0.02656	0.04699**	0.03599**	0.04182	0.06161**	0.04361
	0.01822	0.0208	0.01566	0.02715	0.02794	0.03228
$\lambda_{j(it)} \times T_{if} = 7$	0.03735**	0.03703*	0.04381**	0.04044	0.07369***	0.06094*
	0.0186	0.02189	0.01735	0.02702	0.0284	0.03191
$\lambda_{j(it)} \times T_{if} = 8$	0.02313	0.05828***	0.03497**	0.04819*	0.07154**	0.06058*
	0.01924	0.02175	0.01727	0.02829	0.02777	0.03152
$\lambda_{j(it)} \times T_{if} = 9$	0.05607***	0.05214**	0.05995***	0.04499	0.08678***	0.07509**
	0.02014	0.0241	0.01895	0.02901	0.02889	0.0322
$\lambda_{j(it)} \times T_{if} = 10$	0.03801*	0.06210**	0.05748***	0.03639	0.07283**	0.07016**
	0.02021	0.02486	0.01915	0.02971	0.02861	0.03198
$\lambda_{j(it)} \times T_{if} = 11$	0.04970**	0.07593***	0.07176***	0.04296	0.10024***	0.09619***
	0.02186	0.02588	0.02077	0.0303	0.0295	0.03273
$\lambda_{j(it)} \times T_{if} = 12$	0.05636**	0.07496***	0.07338***	0.05993*	0.09196***	0.08736***
	0.02201	0.02736	0.02152	0.03189	0.02925	0.03266
$\lambda_{j(it)} \times T_{if} = 13$	0.04637**	0.07402***	0.06864***	0.04983	0.09147***	0.08678***
	0.02257	0.02738	0.02219	0.03116	0.02911	0.03223
$\lambda_{j(it)} \times T_{if} = 14$	0.07477***	0.06290**	0.09606***	0.02796	0.10019***	0.09554***
	0.02412	0.03177	0.02431	0.03336	0.03099	0.03396
$\lambda_{j(it)} \times T_{if} = 15$	0.04899**	0.08083***	0.09686***	0.00335	0.09211***	0.08814**
	0.02429	0.02883	0.02367	0.03498	0.03055	0.03422
$\lambda_{j(it)} \times T_{if} = 16$	0.04238**	0.06814***	0.09118***	-0.00539	0.08075***	0.07799***

Continued on next page

	(1)	(2)	(3)	(4)	(5)	(6)
$C_{j(it)}$	0.25071***	0.20545***	0.24555***	0.15981***	0.19098***	0.12992***
(high cognitive skills)	0.01509	0.01771	0.01346	0.0243	0.02911	0.03267
$C_{j(it)} \times T_{if}$ =1	-0.04507***	-0.03582*	-0.04648***	-0.0123	-0.04235	0.00173
(high cognitive skills times tenure is one year)	0.01698	0.01881	0.01465	0.02583	0.03035	0.03441
$C_{j(it)} \times T_{if}$ =2	-0.05978***	-0.04927**	-0.06081***	-0.01928	-0.05564*	-0.02579
	0.01705	0.0197	0.01465	0.02698	0.03102	0.03489
$C_{j(it)} \times T_{if}$ =3	-0.06663***	-0.05597***	-0.06168***	-0.04163	-0.04362	-0.00219
	0.01726	0.01996	0.01475	0.02669	0.03098	0.03455
$C_{j(it)} \times T_{if}$ =4	-0.06298***	-0.04355**	-0.05039***	-0.04236	-0.0305	0.02156
	0.01779	0.02073	0.01584	0.02747	0.03037	0.03476
$C_{j(it)} \times T_{if}$ =5	-0.05687***	-0.03540*	-0.04138**	-0.04095	-0.0129	0.03887
	0.01877	0.01993	0.01667	0.02822	0.03123	0.03491
$C_{j(it)} \times T_{if}$ =6	-0.05095***	-0.06001***	-0.04823***	-0.05021*	-0.01794	0.04232
	0.01862	0.02218	0.01646	0.02804	0.03093	0.0348
$C_{j(it)} \times T_{if}$ =7	-0.05912***	-0.06974***	-0.06436***	-0.03643	-0.0335	0.02424
	0.01838	0.0225	0.01714	0.02717	0.03168	0.03514
$C_{j(it)} \times T_{if}$ =8	-0.03991**	-0.06795***	-0.04591***	-0.03266	-0.02347	0.03989
	0.01983	0.02212	0.01731	0.02855	0.03159	0.03539
$C_{j(it)} \times T_{if}$ =9	-0.07806***	-0.08788***	-0.07893***	-0.05352*	-0.04927	0.01701
	0.02031	0.02424	0.01869	0.0292	0.03181	0.0351
$C_{j(it)} \times T_{if}$ =10	-0.06257***	-0.10211***	-0.08318***	-0.04056	-0.03952	0.02348
	0.02061	0.02492	0.01902	0.03001	0.03187	0.03515
$C_{j(it)} \times T_{if}$ =11	-0.07074***	-0.10426***	-0.08259***	-0.05960**	-0.06209*	0.00186
	0.02139	0.0254	0.02101	0.02983	0.03272	0.03591
$C_{j(it)} \times T_{if}$ =12	-0.07382***	-0.08926***	-0.07492***	-0.06488**	-0.04122	0.02348
	0.02238	0.0266	0.02132	0.03151	0.03255	0.03587
$C_{j(it)} \times T_{if}$ =13	-0.08370***	-0.08439***	-0.08807***	-0.05220*	-0.0509	0.01376
	0.02362	0.02715	0.02278	0.03139	0.03321	0.03694
$C_{j(it)} \times T_{if}$ =14	-0.10676***	-0.06476**	-0.09161***	-0.05497*	-0.05704*	0.00729
	0.02391	0.03063	0.02386	0.032	0.03405	0.03698
$C_{j(it)} \times T_{if}$ =15	-0.08465***	-0.09742***	-0.10288***	-0.03838	-0.05897*	0.00571
	0.02438	0.02914	0.02358	0.03429	0.03359	0.03726
$C_{j(it)} \times T_{if}$ =16	-0.08466***	-0.11560***	-0.10869***	-0.04800*	-0.05937*	0.0045
	0.0182	0.02173	0.01694	0.02821	0.03116	0.03451

Continued on next page

	(1)	(2)	(3)	(4)	(5)	(6)
T_{if} =1	0.03676***	0.01864***	0.02731***	0.02860***	0.01947***	0.02654***
(tenure is one year)	0.00543	0.00498	0.00427	0.0088	0.00625	0.00732
T_{if} =2	0.06707***	0.04107***	0.05192***	0.05594***	0.05316***	0.06085***
	0.00579	0.00512	0.00438	0.00903	0.00644	0.00776
T_{if} =3	0.08415***	0.05706***	0.06824***	0.07462***	0.07610***	0.07899***
	0.00575	0.00544	0.00457	0.00934	0.0064	0.00763
T_{if} =4	0.10580***	0.07211***	0.08471***	0.09818***	0.10141***	0.10162***
	0.00581	0.00531	0.0046	0.00928	0.00659	0.00783
T_{if} =5	0.11207***	0.08776***	0.09484***	0.10872***	0.11587***	0.11397***
	0.00619	0.00569	0.00468	0.00979	0.00691	0.00808
T_{if} =6	0.12422***	0.10018***	0.10392***	0.13123***	0.13617***	0.12795***
	0.00639	0.00587	0.00496	0.00974	0.00696	0.00831
T_{if} =7	0.13197***	0.11412***	0.11525***	0.13824***	0.15031***	0.13930***
	0.00683	0.00648	0.00534	0.00989	0.00727	0.00845
T_{if} =8	0.13277***	0.12060***	0.11575***	0.15124***	0.16265***	0.14762***
	0.00691	0.00653	0.00551	0.01038	0.0075	0.00882
T_{if} =9	0.13784***	0.13602***	0.12214***	0.17065***	0.17605***	0.15964***
	0.00751	0.00743	0.00615	0.01125	0.00767	0.00873
T_{if} =10	0.14628***	0.14738***	0.13692***	0.16905***	0.19475***	0.17520***
	0.00729	0.00709	0.00595	0.01109	0.00788	0.00903
T_{if} =11	0.14903***	0.15455***	0.13748***	0.18608***	0.20449***	0.18434***
	0.00776	0.00797	0.00637	0.01111	0.00803	0.00917
T_{if} ==12	0.15477***	0.14684***	0.13692***	0.18341***	0.20555***	0.18430***
	0.00812	0.00837	0.007	0.01151	0.00817	0.00928
T_{if} =13	0.16437***	0.16835***	0.15412***	0.19561***	0.21849***	0.19705***
	0.00845	0.00884	0.00727	0.01175	0.00856	0.00962
T_{if} =14	0.16589***	0.16517***	0.15043***	0.20279***	0.21772***	0.19605***
	0.00886	0.0091	0.0078	0.01199	0.00856	0.00977
T_{if} =15	0.16681***	0.17563***	0.15195***	0.22190***	0.22275***	0.20121***
	0.00951	0.0102	0.00843	0.01234	0.00918	0.00986
T_{if} =16	0.17027***	0.20292***	0.16682***	0.23494***	0.22715***	0.20409***
	0.00667	0.00683	0.00574	0.0098	0.00713	0.00845

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	(1)	(2)	(3)	(4)	(5)	(6)
w_{i0}	0.03162***	0.02920***	0.03208***	0.02517***	0.03992***	0.03787***
(initial wage)	0.00079	0.00099	0.00078	0.00091	0.00082	0.00091
S_{f0}	0.00656***	0.00026	0.00404***	0.00486***	0.00423***	0.00466***
(initial firm size)	0.00036	0.00036	0.0003	0.00068	0.00033	0.00036
M_i			0.08408***	0.06792***	0.07949***	0.07473***
(male)			0.0019	0.00256	0.00211	0.00229
FT_{ift}	0.09682***	0.10892***	0.11312***	0.09392***	0.10271***	0.09843***
(full-time)	0.00385	0.00209	0.00228	0.00303	0.00251	0.00287
P_f	0.01477***	0.06117***			0.03257***	0.03767***
(public sector)	0.00261	0.00249			0.00252	0.00278
A_{it}	0.04104***	0.03261***	0.03697***	0.02746***	0.03190***	0.03325***
(experience)	0.00072	0.0008	0.00062	0.00105	0.00069	0.00077
A_{it}^2	-0.00110***	-0.00102***	-0.00101***	-0.00089***	-0.00091***	-0.00091***
(experience squared)	0.00003	0.00003	0.00003	0.00004	0.00003	0.00003
1-4 O levels, CSE, GCSEs	0.01419***	0.01007***	0.01167***	0.01181***	0.01268***	0.01172***
	0.00207	0.00202	0.00171	0.00266	0.00198	0.0021
NVQ level 1, foundation GNVQ	-0.01576***	-0.01800***	-0.01896***	-0.00927***	-0.01249***	-0.00865***
	0.00212	0.00223	0.00176	0.0029	0.00209	0.00233
5+ O level (passes)	0.06684***	0.05751***	0.06655***	0.04856***	0.06266***	0.06476***
	0.00237	0.00218	0.00188	0.00285	0.00225	0.00241
NVQ level 2, intermediate GNVQ	-0.01312***	-0.02482***	-0.01526***	-0.03037***	-0.01342***	-0.01239***
	0.00193	0.00186	0.00161	0.00241	0.00175	0.00188
Apprenticeship	0.06204***	0.02909***	0.06212***	0.04511***	0.05069***	0.05542***
	0.00336	0.00623	0.00319	0.00627	0.0036	0.00383
2+ A levels, VCEs, 4+ AS levels	0.03657***	0.04925***	0.04818***	0.03503***	0.03506***	0.03209***
	0.00269	0.00266	0.00238	0.00319	0.00261	0.00278
NVQ level 3, advanced GNVQ	0.03488***	0.00631***	0.02376***	0.01588***	0.02965***	0.03059***
	0.00211	0.00215	0.00173	0.00239	0.00188	0.0021
Other vocational	0.03256***	0.02010***	0.02988***	0.02456***	0.02935***	0.03098***
	0.00205	0.0021	0.00191	0.00244	0.00195	0.00218
no qualifications	-0.06903***	-0.07696***	-0.07363***	-0.06163***	-0.06348***	-0.06564***
	0.00339	0.00378	0.00285	0.00619	0.00331	0.00384
Foreign Qualifications	-0.08624***	-0.03922***	-0.06979***	-0.03492***	-0.06064***	-0.05344***
	0.00649	0.00785	0.00578	0.01093	0.00654	0.00792
Constant	1.43512***	1.51967***	1.40055***	1.59992***	1.32400***	1.34378***
	0.00831	0.00968	0.00706	0.01329	0.00846	0.0097
Area-year effects	✓	✓	✓	✓	✓	✓
R^2	0.436	0.337	0.433	0.357	0.491	0.485
Observations	141370	118642	199490	60522	141673	116920

Source: Authors' calculations using ONS-ASHE-Census (2022) matched with ONET (2016).

Notes: Samples includes workers aged 19-39 with highest qualification high school or less. Numbers are estimated coefficients with robust standard errors in parentheses. Stars indicate * p<0.1, ** p<0.05, *** p<0.01.

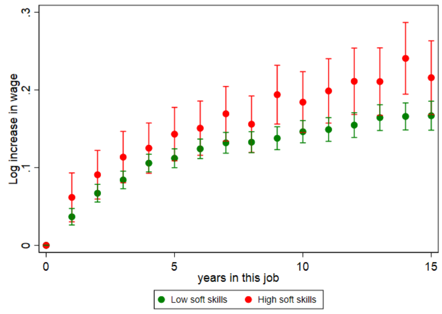
TABLE B 6. Tests of joint significance of variables in Table B 5

	(1)	(2)	(3)	(4)	(5)	(6)
F-test and P-values of joint significance:						
High cognitive skills ($C_{j(it)}$), $\times$ tenure dummies,	2.89	3.46	4.33	1.31	2.20	2.48
F(15, 1203)	0.0002	0.0000	0.0000	0.1887	0.0052	0.0014
High social skills ($\lambda_{j(it)}$) $\times$ tenure dummies	1.55	1.68	3.61	1.40	2.72	3.36
F(16, 1203)	0.0760	0.0440	0.0000	0.1340	0.0003	0.0000
Tenure dummies	95.01	122.76	114.92	116.48	175.86	82.07
F(16, 1203)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Controls	632.45	466.90	1032.73	297.43	632.62	504.49
F(16, 1203)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

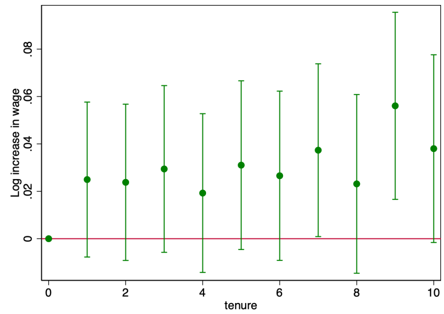
Notes: See notes to Table B 5.

FIGURE B 1. Estimated tenure profiles from estimates in Table B 5

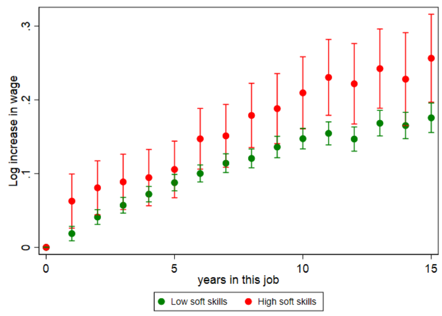
(a) Male



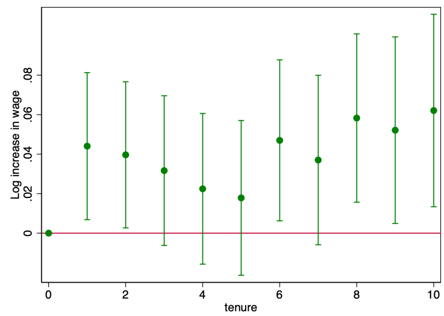
(b) Male



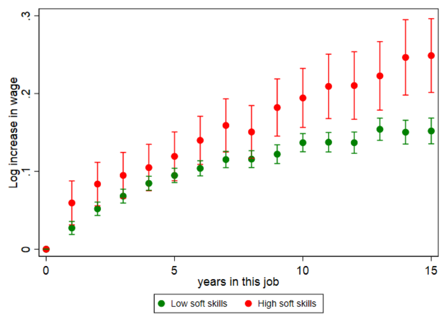
(c) Female



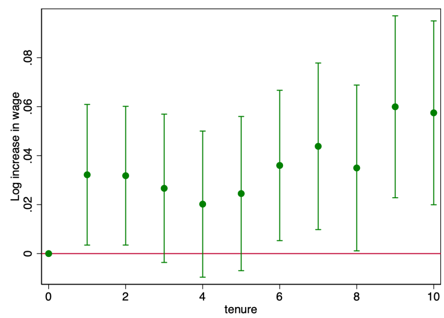
(d) Female



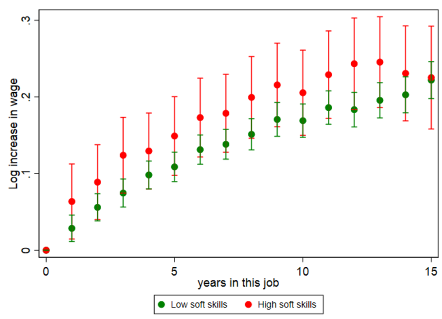
(e) Private



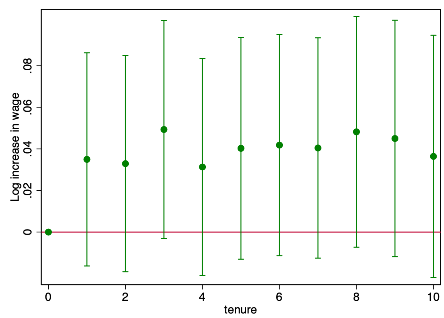
(f) Private



(g) Public

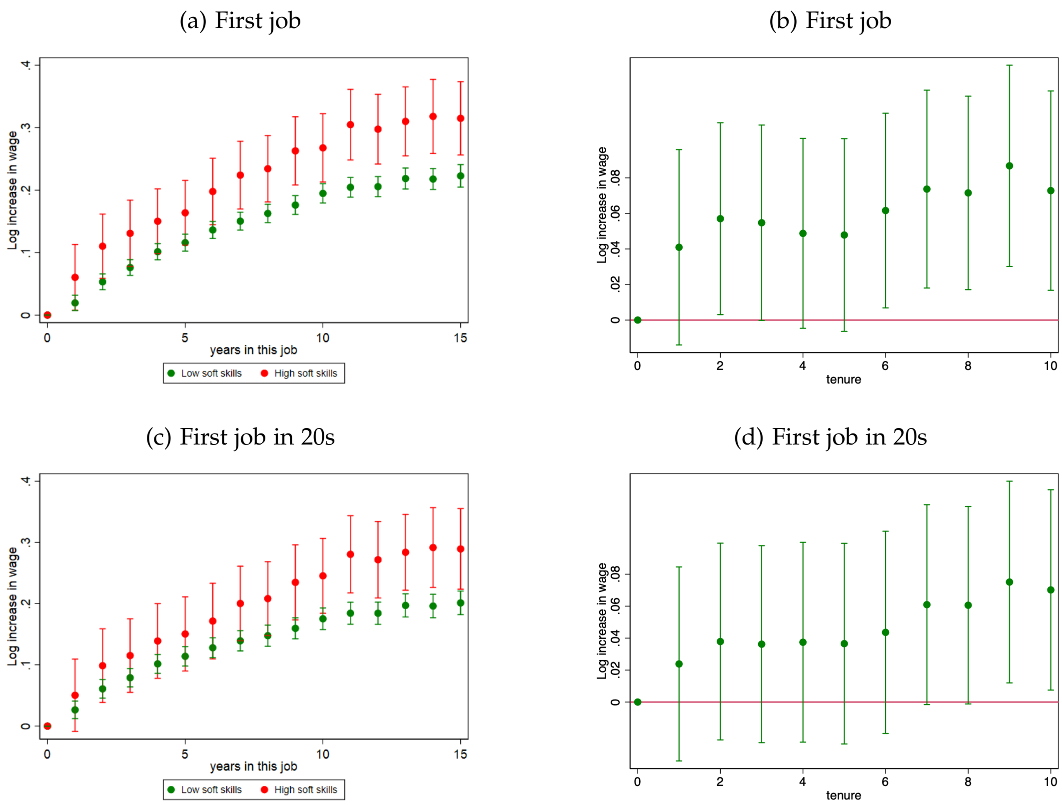


(h) Public



Note: Figure plots the estimated coefficients and confidence interval for the coefficient in Table B 5 on the dummy variables in tenure (green dots) and the dummy variables in tenure plus the interaction between high social skills and tenure (red dots).

FIGURE B 2. Estimated tenure profiles from estimates in Table B 5



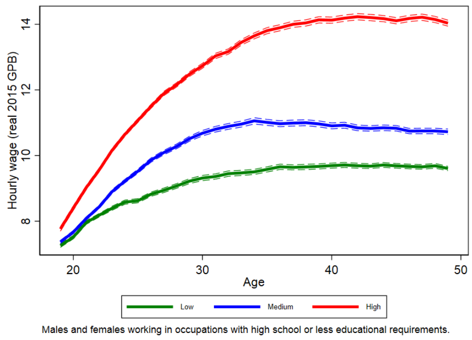
Note: Figure plots the estimated coefficients and confidence interval for the coefficient in Table B 5 on the dummy variables in tenure (green dots) and the dummy variables in tenure plus the interaction between high social skills and tenure (red dots).

C Empirical results using ASHE and ASHE-WERS

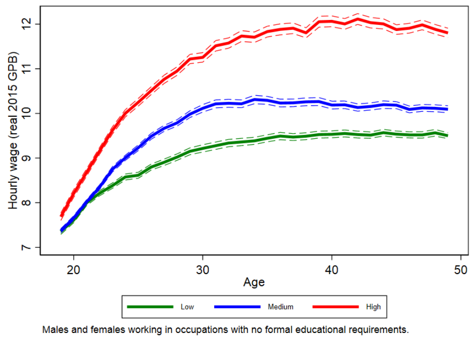
C.1 Showing that ASHE with occupation definition of qualification requirements replicates results with ASHE-Census using actual qualifications obtained

FIGURE C 1. Average wage by importance of social skills in occupation, ASHE based on skill requirements in occupation

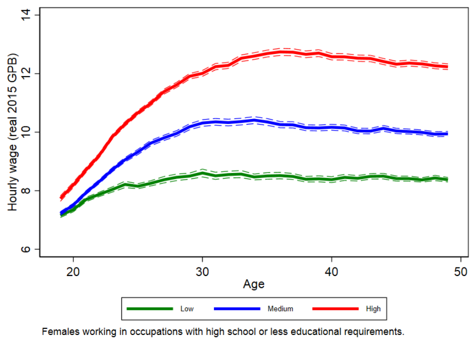
(a) Require high school



(b) No requirements

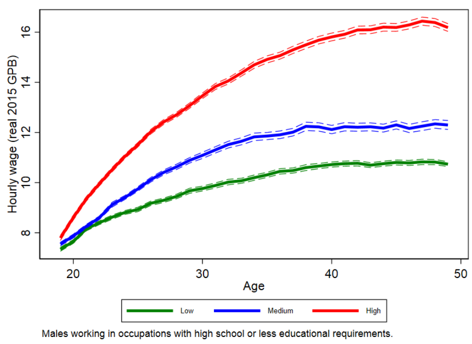


(c) Females, require high school

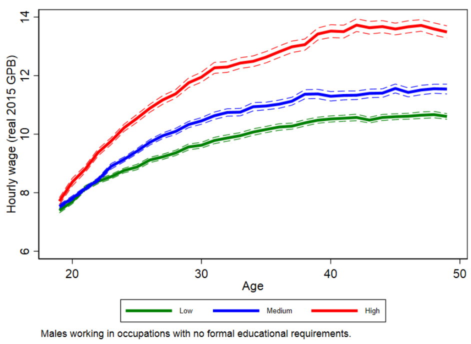


(d) Females, no requirements

(e) Males, require high school



(f) Males, no requirements



Source: Authors' calculations using ONS-ASHE (2022) matched with ONET (2016) and ONS-WERS (2013).

Notes: Sample is workers aged 19-39 in occupations with no formal qualification requirements or in occupations where workers typically require high school qualifications and where there are no formal qualification requirements. Numbers are coefficients with robust standard errors in parentheses. Stars indicate * p<0.1, ** p<0.05, *** p<0.01.

Table C 1 describes the data using workers in occupations where UK immigration rules suggest that there are typically either no formal educational requirements, or at most a high school education is required.

TABLE C 1. Descriptive statistics, ASHE, 19-39

	(1)	**(2)**	**(3)**
	importance of social skills (λ)		
	Bottom two terciles	Top tercile	All
Job characteristics			
Wage (£), w_{ijft}	8.6	9.96	9.03
Full-time (%), FT_{ift}	59.5	70.7	63.1
Tenure (years in firm), T_{ift}	3.9	4.4	4.1
Public sector (%), P_f	12.9	27.4	17.5
High cognitive skills, $C_{j(it)}$	0.294	0.408	0.33
Worker characteristics			
Experience, A_{it}	10.4	10.7	10.5
Male (%), M_i	51.6	42.2	48.6
Initial wage (£), w_{i0}	7.19	7.8	7.39
Firm characteristics			
Size (employment), S_{f0}	30,950	13,056	25,251
Number in our sample			
observations	384,764	179,784	564,548
firms	54,323	23,818	78,141
workers	125,901	39,447	165,348

Source: Authors' calculations using ONS-ASHE (2022) matched with ONET (2016) and ONS-WERS (2013).

Notes: Sample is workers aged 19-39 in occupations with no formal qualification requirements or in occupations where workers typically require high school qualifications and where there are no formal qualification requirements.

TABLE C 2. Replicating Table III / Table B 2 (ASHE-Census) using ASHE (skill 1+2), ages 19-39

Dependent variable: $\log(w_{ijkft})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\lambda_{j(it)}$	0.15185***	0.09275***	0.06786***	0.05532***	0.00591**	0.05368***	0.00486
(high social skills)	0.00089	0.00116	0.00179	0.0014	0.00283	0.00272	0.00479
$\lambda_{j(it)} \times T_{if}$			0.00781***	0.00605***	0.00584***		
(high social skills times tenure in the firm)			0.00057	0.0005	0.00065		
$\lambda_{j(it)} \times T_{if}^2$			-0.00028***	-0.00025***	-0.00021***		
(high social skills time tenure squared)			0.00003	0.00003	0.00004		
$C_{j(it)}$	0.15474***	0.13949***	0.11952***	0.09265***	-0.01882***	0.09268***	-0.01271***
(high cognitive skills)	0.00087	0.00344	0.00384	0.00265	0.0027	0.00364	0.00467
$C_{j(it)} \times T_{if}$			0.00578***	0.00464***	0.00869***		
(high cognitive skills times tenure)			0.00051	0.00048	0.00065		
$C_{j(it)} \times T_{if}^2$			-0.00015***	-0.00019***	-0.00024***		
(high cognitive skills times tenure squared)			0.00003	0.00003	0.00004		
w_{i0}				0.04111***		0.04112***	
(initial wage)				0.00089		0.00089	
T_{if}		0.02381***	0.01700***	0.01959***	0.0169		
(tenure)		0.0004	0.00047	0.00039	0.01169		
T_{if}^2		-0.00064***	-0.00045***	-0.00060***	-0.00037***		
(tenure squared)		0.00002	0.00002	0.00002	0.00003		
S_{f0}		0.00301***	0.00292***	0.00354***		0.00355***	
(initial firm size)		0.00032	0.00032	0.00021		0.00021	
M_i		0.07529***	0.07486***	0.05223***		0.05244***	
(male)		0.0024	0.0024	0.00198		0.00199	
FT_{ift}		0.13181***	0.13292***	0.11151***	-0.06313***	0.11090***	-0.06390***
(full-time)		0.00368	0.00368	0.00265	0.00176	0.00264	0.00176
P_f		0.08448***	0.08412***	0.07156***	0.04092***	0.07145***	0.04062***
(public sector)		0.00216	0.00215	0.00182	0.00467	0.00182	0.00468
A_{it}		0.03562***	0.03579***	0.03348***	0.00972***	0.03368***	0.01019***
(experience)		0.0004	0.0004	0.00032	0.00126	0.00032	0.00125
A_{it}^2		-0.00101***	-0.00101***	-0.00110***	-0.00078***	-0.00111***	-0.00079***
(experience squared)		0.00002	0.00002	0.00001	0.00002	0.00001	0.00002

Continued on next page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\lambda_{j(it)} \times T_{if} = 1$						0.00802***	0.00447
(high social skills times tenure is one year)						0.003	0.00433
$\lambda_{j(it)} \times T_{if} = 2$						0.01050***	0.00943**
						0.00312	0.00449
$\lambda_{j(it)} \times T_{if} = 3$						0.01536***	0.01485***
						0.00341	0.00459
$\lambda_{j(it)} \times T_{if} = 4$						0.02009***	0.02055***
						0.0036	0.0048
$\lambda_{j(it)} \times T_{if} = 5$						0.03153***	0.03011***
						0.00392	0.00494
$\lambda_{j(it)} \times T_{if} = 6$						0.02860***	0.03189***
						0.00427	0.00505
$\lambda_{j(it)} \times T_{if} = 7$						0.03605***	0.03356***
						0.00459	0.00523
$\lambda_{j(it)} \times T_{if} = 8$						0.04528***	0.04123***
						0.00471	0.00547
$\lambda_{j(it)} \times T_{if} = 9$						0.04155***	0.03689***
						0.00527	0.0056
$\lambda_{j(it)} \times T_{if} = 10$						0.03795***	0.04216**
						0.00545	0.00585
$\lambda_{j(it)} \times T_{if} = 11$						0.04703***	0.04076***
						0.00547	0.00607
$\lambda_{j(it)} \times T_{if} = 12$						0.04225***	0.04215***
						0.00614	0.00631
$\lambda_{j(it)} \times T_{if} = 13$						0.02556***	0.03717***
						0.00663	0.00669
$\lambda_{j(it)} \times T_{if} = 14$						0.02446***	0.03924***
						0.00705	0.00695
$\lambda_{j(it)} \times T_{if} = 15$						0.02937***	0.03488***
						0.00748	0.00732
$\lambda_{j(it)} \times T_{if} = 16$						0.02211***	0.03265***
						0.00484	0.00721

Continued on next page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$C_{j(it)} \times T_{if}$=1						0.00188	0.00085
(high cognitive skills times tenure is one year)						0.00304	0.00427
$C_{j(it)} \times T_{if}$=2						0.00883***	0.00541
						0.00334	0.00444
$C_{j(it)} \times T_{if}$=3						0.01197***	0.01767***
						0.00354	0.00455
$C_{j(it)} \times T_{if}$=4						0.01550***	0.02735***
						0.00359	0.00474
$C_{j(it)} \times T_{if}$=5						0.01855***	0.03347***
						0.00403	0.00487
$C_{j(it)} \times T_{if}$=6						0.02196***	0.03851***
						0.00409	0.00498
$C_{j(it)} \times T_{if}$=7						0.02366***	0.04498***
						0.00454	0.00518
$C_{j(it)} \times T_{if}$=8						0.02155***	0.04636***
						0.00488	0.00541
$C_{j(it)} \times T_{if}$=9						0.02594***	0.05287***
						0.00524	0.00554
$C_{j(it)} \times T_{if}$=10						0.03242***	0.05688***
						0.00579	0.00582
$C_{j(it)} \times T_{if}$=11						0.03110***	0.06342***
						0.00579	0.006
$C_{j(it)} \times T_{if}$=12						0.03645***	0.06734***
						0.00631	0.00626
$C_{j(it)} \times T_{if}$=13						0.03033***	0.05943***
						0.00692	0.00661
$C_{j(it)} \times T_{if}$=14						0.03224***	0.06630***
						0.00734	0.00684
$C_{j(it)} \times T_{if}$=15						0.02755***	0.06944***
						0.00782	0.00738
$C_{j(it)} \times T_{if}$=16						0.01514***	0.06867***
						0.00486	0.0071

Continued on next page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T_{if}=1						0.02944***	0.02090***
(tenure is one year)						0.00176	0.00268
T_{if}=2						0.05528***	0.02991***
						0.00187	0.00316
T_{if}=3						0.07450***	0.03382***
						0.00216	0.00374
T_{if}=4						0.09151***	0.03763***
						0.00234	0.00441
T_{if}=5						0.10241***	0.03823***
						0.00251	0.00513
T_{if}=6						0.11461***	0.03762***
						0.00281	0.00589
T_{if}=7						0.11945***	0.03422***
						0.00301	0.00667
T_{if}=8						0.12659***	0.02966***
						0.00322	0.00747
T_{if}=9						0.13110***	0.02514***
						0.00365	0.00829
T_{if}=10						0.13629***	0.01789**
						0.00378	0.00909
T_{if}=11						0.13918***	0.01496*
						0.00398	0.00983
T_{if}=12						0.13886***	0.00561
						0.00443	0.01076
T_{if}=13						0.15655***	0.00799
						0.00487	0.01154
T_{if}=14						0.15918***	-0.00025
						0.00501	0.01233
T_{if}=15						0.16080***	-0.00186
						0.00536	0.01326
T_{if}=16						0.17933***	-0.00534
						0.00348	0.01455

Continued on next page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.0688						
	0.00054	0.00489	0.0051	0.00569	0.03663	0.00574	0.00621
Area-year effects		✓	✓	✓		✓	
Firm-Worker effects					✓		✓
Year effects					✓		✓
R^2	0.109	0.289	0.291	0.446	0.281	0.446	0.283
Observations	890694	889866	889866	889866	889865	889866	889865

Source: Authors' calculations using ONS-ASHE-Census (2022) matched with ONET (2016).
Notes: Samples includes workers aged 19-39 with highest qualification high school or less. Numbers are estimated coefficients with robust standard errors in parentheses. Stars indicate * p<0.1, ** p<0.05, *** p<0.01.

C.2 Results using ASHE-WERS

TABLE C 3. Results using ASHE-WERS, ages 19-39

Dependent variable: $\log(w_{ijkft})$								
Typical skill requirement of occupation:	None				High school			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$\lambda_{j(it)}$	0.00533	-0.01924***	-0.01279***	-0.00006	0.00570*	-0.01993***	-0.00555	0.00565
(high social skills)	0.0038	0.0053	0.0047	0.00776	0.00346	0.00449	0.00398	0.00713
$\lambda_{j(it)} \times T_{if}$	0.01349***	0.01043***	0.00953***		0.01215***	0.00767***	0.00695***	
(high social skills times tenure in the firm)	0.00131	0.0018	0.00156		0.0011	0.00144	0.00118	
$\lambda_{j(it)} \times T_{if}^2$	-0.00042***	-0.00004	-0.00013		-0.00048***	-0.00004	-0.00012*	
(high social skills times tenure squared)	0.00007	0.0001	0.00008		0.00006	0.00007	0.00006	
$\lambda_{j(it)} \times T_{ift} \times Q_{ft}$		0.00753***	0.00359*			0.01248***	0.00730***	
(high social skills times tenure times high skills share firm)		0.00238	0.002			0.00162	0.00131	
$\lambda_{j(it)} \times T_{ift}^2 \times Q_{ft}$		-0.00067***	-0.00045***			-0.00082***	-0.00059***	
(high social skills times tenure squared times high skills share firm)		0.00012	0.0001			0.00008	0.00006	
$\lambda_{j(it)} \times Q_{ft}$		0.05438***	0.04596***	0.00071		0.04129***	0.02981***	0.02530**
(high social skills times high skills share firm)		0.0092	0.00844	0.017		0.00622	0.00532	0.01281
$Q_{ft} \times T_{ift}$		0.00511***	0.00404***			0.00482***	0.00383***	
(tenure squared times high skills share firm)		0.00065	0.00054			0.00066	0.00051	
Q_{ft}		0.00988**	0.01130***	0.03780***		0.02943***	0.02750***	0.02398***
(high skills share firm)		0.00437	0.00359	0.00833		0.00455	0.00347	0.00735

Continued on next page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$C_{j(it)}$	0.05720***	0.07691***	0.05450***	0.02782***	0.08329***	0.10853***	0.08077***	0.06826***
(high cognitive skills)	0.00384	0.00479	0.00377	0.00232	0.00371	0.00457	0.00374	0.00247
$C_{j(it)} \times T_{if}$	-0.00448***	-0.00726***	-0.00365***		-0.00264***	-0.00391***	-0.0014	
(high cognitive skills times tenure)	0.00106	0.00124	0.00105		0.00087	0.00107	0.00088	
$C_{j(it)} \times T_{if}^2$	0.00005	0.0001	0		0.00008	0.00017***	0.00001	
(high cognitive skills times tenure squared)	0.00006	0.00007	0.00006		0.00005	0.00006	0.00005	
w_{i0}	0.03993***		0.03957***	0.04028***	0.04101***		0.04019***	0.04033***
(initial wage)	0.0014		0.00141	0.00144	0.00113		0.00114	0.00115
T_{if}	0.02349***	0.02094***	0.02200***		0.02253***	0.02010***	0.02083***	
(tenure)	0.00077	0.00099	0.00085		0.00069	0.00096	0.00077	
T_{if}^2	-0.00071***	-0.00053***	-0.00068***		-0.00068***	-0.00056***	-0.00065***	
(tenure squared)	0.00004	0.00005	0.00004		0.00004	0.00004	0.00004	
$\lambda_{j(it)} \times T_{if} = 1$				0.01499*				0.01221
(high social skills times tenure is one year)				0.00895				0.00855
$\lambda_{j(it)} \times T_{if} = 2$				0.01199				0.00951
				0.00944				0.00856
$\lambda_{j(it)} \times T_{if} = 3$				0.02415**				0.01227
				0.00997				0.00889
$\lambda_{j(it)} \times T_{if} = 4$				0.03480***				0.02901***
				0.01137				0.00912
$\lambda_{j(it)} \times T_{if} = 5$				0.04528***				0.02917***
				0.01292				0.00924
$\lambda_{j(it)} \times T_{if} = 6$				0.04489***				0.03295***
				0.01325				0.01019
$\lambda_{j(it)} \times T_{if} = 7$				0.06274***				0.04792***
				0.01504				0.01082
$\lambda_{j(it)} \times T_{if} = 8$				0.07421***				0.06134***
				0.01605				0.01189
$\lambda_{j(it)} \times T_{if} = 9$				0.08126***				0.06955***
				0.01708				0.01117
$\lambda_{j(it)} \times T_{if} = 10$				0.09506***				0.06868***
				0.02003				0.01263
$\lambda_{j(it)} \times T_{if} = 11$				0.12208***				0.08276***
				0.01811				0.01317
$\lambda_{j(it)} \times T_{if} = 12$				0.11155***				0.08443***
				0.02115				0.01479
$\lambda_{j(it)} \times T_{if} = 13$				0.07988***				0.06122***
				0.01814				0.01414
$\lambda_{j(it)} \times T_{if} = 14$				0.07938***				0.05437***
				0.02143				0.01569
$\lambda_{j(it)} \times T_{if} = 15$				0.10757***				0.06195***
				0.02066				0.01384
$\lambda_{j(it)} \times T_{if} = 16$				0.10511***				0.06521***
				0.01366				0.00991

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Q_{ft} \times T_{if}$ =1				0.01437				0.03472***
(high skills share firm times tenure is one year)				0.00899				0.00779
$Q_{ft} \times T_{if}$ =2				0.00758				0.03017***
				0.00915				0.00843
$Q_{ft} \times T_{if}$ =3				0.01416				0.03503***
				0.01032				0.00945
$Q_{ft} \times T_{if}$ =4				0.01622				0.03679***
				0.01136				0.01018
$Q_{ft} \times T_{if}$ =5				0.02337**				0.03985***
				0.01068				0.01
$Q_{ft} \times T_{if}$ =6				0.03743***				0.05862***
				0.01175				0.01065
$Q_{ft} \times T_{if}$ =7				0.03085**				0.05440***
				0.01224				0.01141
$Q_{ft} \times T_{if}$ =8				0.04214***				0.06030***
				0.01317				0.01267
$Q_{ft} \times T_{if}$ =9				0.03256**				0.05741***
				0.01554				0.01386
$Q_{ft} \times T_{if}$ =10				0.04670***				0.06827***
				0.01614				0.01421
$Q_{ft} \times T_{if}$ =11				0.05342***				0.07427***
				0.01566				0.01387
$Q_{ft} \times T_{if}$ =12				0.05945***				0.08366***
				0.01893				0.01732
$Q_{ft} \times T_{if}$ =13				0.04411**				0.07248***
				0.02094				0.01819
$Q_{ft} \times T_{if}$ =14				0.02701				0.05832***
				0.0224				0.01983
$Q_{ft} \times T_{if}$ =15				0.04409**				0.06567***
				0.02212				0.01938
$Q_{ft} \times T_{if}$ =16				0.05249***				0.06847***
				0.01274				0.0112

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =1				0.02987				-0.00626
(high social skills times high skills share firm times tenure is one year)				0.01869				0.01457
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =2				0.05848***				0.01207
				0.01864				0.0149
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =3				0.06852***				0.02651*
				0.01938				0.01577
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =4				0.07322***				0.02455
				0.02209				0.01636
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =5				0.05292**				0.03592**
				0.02141				0.01597
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =6				0.05158**				0.02393
				0.02315				0.01633
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =7				0.05257**				0.0234
				0.0243				0.01792
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =8				0.02727				0.01281
				0.02649				0.01909
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =9				0.05166*				0.01212
				0.02683				0.01865
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =10				0.01408				-0.00211
				0.03009				0.01984
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =11				-0.01903				-0.01647
				0.02721				0.02057
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =12				-0.01675				-0.0248
				0.03227				0.0225
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =13				0.00207				-0.02091
				0.03385				0.02436
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =14				-0.01134				-0.01519
				0.03587				0.02552
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =15				-0.02278				-0.01793
				0.03558				0.02521
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =16				-0.02003				-0.03823**
(tenure is one year)				0.02353				0.01668

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T_{if} =1				0.03138***				0.02715***
(tenure is one year)				0.00402				0.00405
T_{if} =2				0.06556***				0.06220***
				0.00452				0.00458
T_{if} =3				0.08309***				0.08047***
				0.0047				0.0047
T_{if} =4				0.09777***				0.09630***
				0.00504				0.00505
T_{if} =5				0.11236***				0.10887***
				0.00523				0.00507
T_{if} =6				0.12481***				0.11702***
				0.0061				0.00585
T_{if} =7				0.13201***				0.12297***
				0.00674				0.00646
T_{if} =8				0.13980***				0.13041***
				0.00711				0.00717
T_{if} =9				0.13851***				0.13323***
				0.0074				0.00716
T_{if} =10				0.15064***				0.14204***
				0.00803				0.00784
T_{if} =11				0.15554***				0.14843***
				0.00856				0.00839
T_{if} =12				0.15008***				0.14220***
				0.00986				0.00948
T_{if} =13				0.17406***				0.16294***
				0.00993				0.00945
T_{if} =14				0.19681***				0.18205***
				0.00991				0.01027
T_{if} =15				0.18323***				0.18257***
				0.00964				0.00944
T_{if} =16				0.19047***				0.18502***
				0.00686				0.00663

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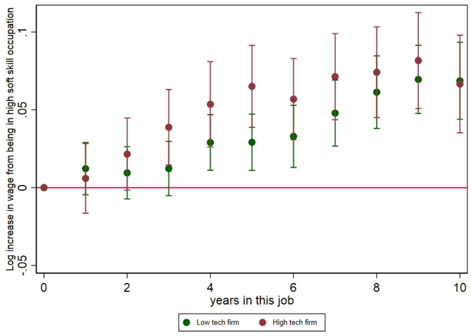
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
S_{f0}	0.00444***	0.00685***	0.00648***	0.00765***	-0.00046	0.00091	0.00380***	0.00504***
(initial firm size)	0.00082	0.00115	0.00088	0.00085	0.00065	0.00099	0.00068	0.00064
M_i	0.05487***	0.08231***	0.05804***	0.05299***	0.05953***	0.08800***	0.06072***	0.05660***
(male)	0.00176	0.00208	0.00177	0.00186	0.00168	0.00198	0.00175	0.00185
FT_{ift}	0.09176***	0.10829***	0.09149***	0.09219***	0.09595***	0.11153***	0.09651***	0.09698***
(full-time)	0.00205	0.00232	0.00201	0.00201	0.00225	0.00283	0.00224	0.00227
P_f	0.08543***	0.08727***	0.06872***		0.07016***	0.05253***	0.04665***	
(public sector)	0.00356	0.00514	0.00358		0.00328	0.00365	0.00298	
A_{it}	0.02135***	0.02205***	0.02146***	0.02262***	0.02468***	0.02500***	0.02493***	0.02595***
(experience)	0.00052	0.00064	0.00052	0.00052	0.00049	0.00061	0.00049	0.00049
A_{it}^2	-0.00076***	-0.00073***	-0.00077***	-0.00079***	-0.00083***	-0.00072***	-0.00084***	-0.00086***
(experience squared)	0.00002	0.00003	0.00002	0.00002	0.00002	0.00003	0.00002	0.00002
High school graduate					0.08708***	0.11248***	0.08618***	0.08837***
					0.0025	0.00325	0.0024	0.00242
Constant	1.46766***	1.68788***	1.44955***	1.42528***	1.47626***	1.70599***	1.43605***	1.41172***
	0.00858	0.00917	0.0088	0.00946	0.00898	0.00891	0.00839	0.00878
R^2	0.381	0.254	0.386	0.38	0.491	0.365	0.498	0.497
Observations	114530	114530	114530	114530	176190	176190	176190	176190
Area-year effects	✓	✓	✓	✓	✓	✓	✓	✓

Source: Authors' calculations using ONS-ASHE (2022) matched with ONET (2016) and ONS-WERS (2013).

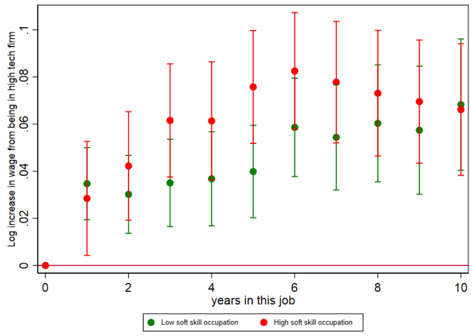
Notes: Sample is all workers aged 19-39 in occupations with no formal qualification requirements. Numbers are coefficients with robust standard errors in parentheses. Stars indicate * p<0.1, ** p<0.05, *** p<0.01.

FIGURE C 2. Wage growth from working in high λ occupation and high skill share firm

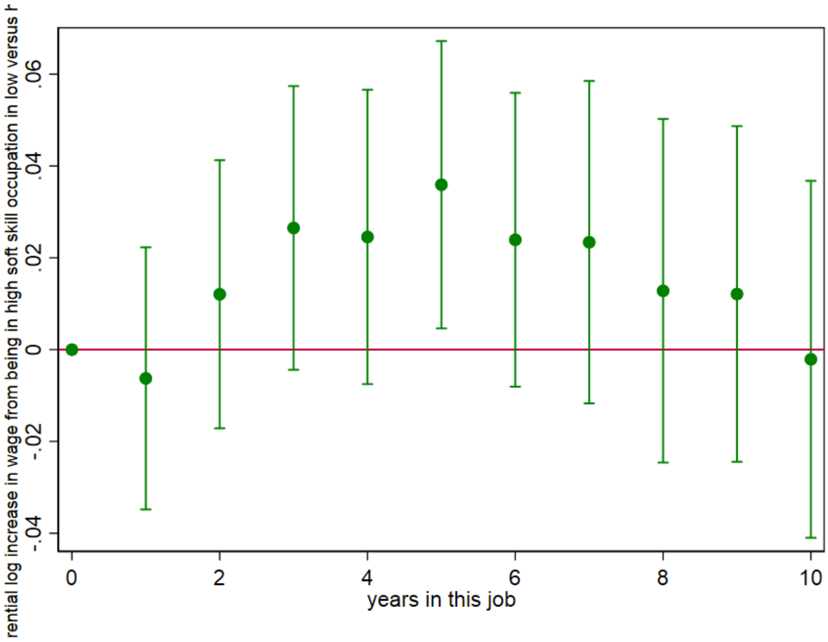
(a) Increase in wage growth from working in high skill firm



(b) Increase in wage growth from working in a high social skill occupation



(c) Increase in wage growth from working in a high social skill occupation in a high skill firm



Note: Figure plots the estimated coefficients and confidence interval for the coefficient in Table C 3 on : (a) differential dummies on years of tenure comparing the increased wage for working in a high firm depending on whether the worker works in a low (green) or high (red) social skill occupation. (b) the differential dummies on years of tenure comparing the increased wage for working in a high social skill occupation depending on whether the firm is low (green) or high (red) tech. (c) the difference between the differences in figures (a) and (b).

D Theoretical Appendix

D.1 Additional derivation

In Section 3.2.2, we have derived the condition for $\bar{\lambda}$ to be larger than 0. The definition of $\bar{\lambda}$ corresponds to a cutoff value above which, workers of high capability $\kappa = \bar{\kappa}$ will chose to remain in the firm while worker of low capabilities $\kappa = \underline{\kappa}$ will be laid off. Our model relies on the additional assumption that while a firm may find it preferable to reallocate a $\underline{\kappa}$ worker in a low λ job within the firm, the worker would be better off leaving the firm. We now derive the conditions for this to be verified.

Let us consider the surplus of a $\underline{\kappa}$ worker that moves from a $\lambda > \bar{\lambda}$ job to a $\lambda' < \bar{\lambda}$ job within the same firm. In that case, her wage will be equal to her marginal productivity:

$$w(\lambda', Q, \tau, \underline{\kappa}) = \lambda' Q(\underline{\kappa}(1+\tau) + \mu Q,$$

while the outside option of the worker would provide a wage $\bar{w}(\lambda, Q)$, with the $\lambda > \bar{\lambda}$ of the previous job. This outside option is preferable to earning $w(\lambda', Q, \tau, \underline{\kappa})$ if:

$$\lambda' Q\underline{\kappa}(1+\tau) < \mathbb{E}[\lambda Q](1+\tau u)\Lambda(\lambda) + \mu(\mathbb{E}[Q] - Q)$$

This is equivalent to:

$$\underbrace{(\lambda' - \bar{\lambda})(1+\tau)\underline{\kappa}}_{<0} + \bar{\lambda}(1-\omega)\hat{\kappa} < \frac{C}{Q}.$$

Which is true for large enough values of C, unless Q is very large. Indeed if Q is large the marginal productivity of the worker, derived namely from her training will ensure a sufficiently high wage in the firm.

D.2 Solving the model with a continuum of type

In this subsection, we extend the model to allow for a continuum of κ. Formally, we assume that κ is now following a known distribution with c.d.f $\mathcal{K}$. We assume that this distribution as a support included in $\mathbb{R}^+$ and has a density k. A job in a firm is characterized by λ and Q and the production of a worker with quality κ is given by:

$$f(\lambda, Q, \tau) = \lambda Q\kappa(1+\tau) + \mu Q$$

The bargaining is the same as in the baseline model. After one period, both the worker and the firm discover the true value of κ. The firm's surplus is given by:

$$S^F(\kappa, \lambda, Q) = \lambda Q\kappa(1+\tau) + \mu Q - w(\kappa, \lambda, Q) - (1-\omega)[\lambda Q\hat{\kappa} + \mu Q] + C,$$

and the worker's surplus is equal to:

$$S^W(\kappa, \lambda, Q) = w(\kappa, \lambda, Q) - \overline{w}(\lambda, \tau),$$

where the outside option $\overline{w}$ implicitly depends upon λ. Indeed, the market observes the λ nature of the job the worker originates from, which in turn leads to an expected κ given λ, denoted by $\Lambda(\lambda)$.

To compute $\Lambda(\lambda)$, we first need to derive the threshold value of κ, denoted by $\bar{\kappa}_\lambda$, below which a λ-firm will layoff a worker. This value is defined by the equation:

$$\lambda Q\left(\bar{\kappa}_\lambda(1+\tau)-(1-\omega)\hat{\kappa}\right)+\omega\mu Q+C-\overline{w}(\lambda,\tau)=0,$$

where, as before,

$$\overline{w}(\lambda,u)=\mathbb{E}[\lambda Q](1+\tau u)\Lambda(\lambda)+\mu\mathbb{E}[Q].$$

A worker who enters the labor market coming from a λ-firm, either has quality $\kappa<\bar{\kappa}_\lambda$ if she did not face a disutility shock, or she can be of any quality if she faced a disutility shock, which in turn occurs with probability $1-\varphi$. Hence:

$$\mathbb{P}\left[\kappa<x|\lambda\right]=\begin{cases}\frac{\mathcal{K}(x)}{1-\varphi+\varphi\mathcal{K}(\bar{\kappa}_\lambda)} & \text{if } x<\bar{\kappa}_\lambda\\ \frac{\varphi\mathcal{K}(\bar{\kappa}_\lambda)+(1-\varphi)\mathcal{K}(x)}{1-\varphi+\varphi\mathcal{K}(\bar{\kappa}_\lambda)} & \text{if } x\geq\bar{\kappa}_\lambda\end{cases}$$

It then follows that the expected κ of a worker that originates from a λ-occupation λ, is equal to:

$$\Lambda(\lambda)=\mathbb{E}\left[\kappa|\kappa<\bar{\kappa}_\lambda\right]+\underbrace{(1-\varphi)\frac{\hat{\kappa}-\mathbb{E}\left[\kappa|\kappa<\bar{\kappa}_\lambda\right]}{1-\varphi+\varphi\mathcal{K}\left(\bar{\kappa}_\lambda\right)}}_{\delta(\lambda,\varphi)} \tag{10}$$

where $\delta(\lambda,\varphi)>0$ is the distortion coming from the fact that $\varphi>0$, and this distortion is increasing with $1-\varphi$. Note that if $\varphi=1$, the uncertainty disappear and the expected value of κ conditional on having left a λ job is simply equal to the share of workers of capabilities κ lower than the threshold value $\bar{\kappa}_\lambda$.

Proposition 3. *If the distribution of κ is such that*

$$\frac{1-\mathcal{K}(\kappa)}{\kappa k(\kappa)}>\frac{\varphi}{1-\varphi},$$

then for λ above some positive value $\bar{\lambda}$, there exist a unique value κ_λ such that a firm will lay off workers in occupation λ with abilities κ below κ_λ, whereas for occupations $\lambda\leq\bar{\lambda}$, the firm will retain all its workers.

Proof. We first show that for λ larger than some value $\bar{\lambda}$ there exists at least one value for κ_λ. We then show that under some condition on the distribution of κ, this value is unique. Let us first combine the definition of $\overline{w}(\lambda,\tau)$ and equation (10) which yields:

$$\bar{\kappa}_\lambda-\underbrace{\left[\frac{(1-\omega)\hat{\kappa}}{1+\tau}-\frac{\omega\mu Q-\mu\mathbb{E}[Q]+C}{\lambda Q(1+\tau)}\right]}_{\equiv b(\lambda,Q)}=\underbrace{\frac{\mathbb{E}[\lambda Q](1+\tau u)}{\lambda Q(1+\tau)}}_{\equiv\mathcal{A}(\lambda,Q)}\left(\mathbb{E}\left[\kappa|\kappa<\bar{\kappa}_\lambda\right]+\delta(\lambda,\varphi)\right) \tag{11}$$

Existence. To show existence, we first note that the left-hand side part of equation (11) is a linear function of $\bar{\kappa}_\lambda$ which is always larger than $b(\lambda,Q)$, an increasing function of λ as long as $\omega\mu Q - \mu\mathbb{E}[Q] + C$ is larger than 0. The right-hand can be rewritten as:

$$g(\bar{\kappa}_\lambda) = \mathcal{A}(\lambda, Q)\frac{(1-\varphi)\hat{\kappa} + \varphi\int_0^{\bar{\kappa}_\lambda} \kappa d\mathcal{K}(\kappa)}{1-\varphi+\varphi\int_0^{\bar{\kappa}_\lambda} d\mathcal{K}(\kappa)},$$

where $\mathcal{A}(\lambda, Q)$ is a decreasing function of λ.

This right-hand side term is a function of $\bar{\kappa}_\lambda$ equal to $\varphi\mathcal{A}(\lambda, Q)\hat{\kappa}$ in 0 and also in $+\infty$. Taking the derivative of g with respect to $\bar{\kappa}_\lambda$ yields:

$$g'(\bar{\kappa}_\lambda) = \frac{\varphi k(\bar{\kappa}_\lambda)}{(1-\varphi+\varphi\mathcal{K}(\bar{\kappa}_\lambda))^2}\left[(1-\varphi)(\bar{\kappa}_\lambda - \hat{\kappa}) + \varphi\left(\bar{\kappa}_\lambda\mathcal{K}(\bar{\kappa}_\lambda) - \int_0^{\bar{\kappa}_\lambda} t d\mathcal{K}(t)\right)\right]$$

which is negative and then positive as $\bar{\kappa}_\lambda$ increases. This means that g is decreasing and increasing, as it has the same value in 0 and ∞, this means that:

$$g(\bar{\kappa}_\lambda) < \mathcal{A}(\lambda, Q)\hat{\kappa}.$$

Note also that $g(\bar{\kappa}_\lambda) > \mathcal{A}(\lambda, Q)\hat{\kappa}(1-\varphi)$.

Hence, if $\bar{\kappa}_\lambda$ exists, we must have that $\mathcal{A}(\lambda, Q)\hat{\kappa}\varphi < \bar{\kappa}_\lambda - b(\lambda, Q) < \mathcal{A}(\lambda, Q)\hat{\kappa}$.

This means that:

- If λ is such that $\mathcal{A}(\lambda, Q)\hat{\kappa} + b(\lambda, Q) < 0$, there is no positive value for $\bar{\kappa}_\lambda$. Because b is increasing in λ and $\mathcal{A}$ is decreasing, this defines a lower bound $\bar{\lambda}$ below which the firm will find it optimal to retain all workers (regardless of κ).
- Otherwise, there is (at least) one value of $\bar{\kappa}_\lambda$ defined by $\bar{\kappa}_\lambda = g(\bar{\kappa}_\lambda)\mathcal{A}(\lambda, Q) + b(\lambda, Q)$

Uniqueness: To show uniqueness, we can get back to equation (11) and multiply both side by $1-\varphi+\varphi\mathcal{K}(\bar{\kappa}_\lambda)$. We then take the derivative of the left-hand side terms minus the right hand-side terms with respect to $\bar{\kappa}_\lambda$. This yields:

$$\varphi k(\bar{\kappa}_\lambda)(\bar{\kappa}_\lambda - b(\lambda, Q)) + 1 - \varphi + \varphi\mathcal{K}(\bar{\kappa}_\lambda) - \varphi\bar{\kappa}_\lambda k(\bar{\kappa}_\lambda)\mathcal{A}(\lambda, Q)$$

or equivalently:

$$\bar{\kappa}_\lambda(1 - \mathcal{A}(\lambda, Q)) - b(\lambda, Q) + \frac{1-\varphi+\varphi\mathcal{K}(\bar{\kappa}_\lambda)}{\varphi k(\bar{\kappa}_\lambda)} > 0$$

Dividing by $\bar{\kappa}_\lambda$ we can derive the following simple sufficient condition on the distribution of κ:

$$\frac{1-\mathcal{K}(\kappa)}{\kappa k(\kappa)} > \frac{\varphi}{1-\varphi}\mathcal{A}(\lambda, Q),$$

which comes from the fact that $\bar{\kappa}_\lambda$ must be larger than $b(\lambda, Q)$. In addition, assuming that $\mathcal{A}(\lambda, Q) < 1$ for λ larger than $\bar{\lambda}$ (which is true if u is not too close to 1) this means that the elasticity of κ must be lower than $1-\varphi/\varphi$, at least for κ between $b(\lambda, Q) + \mathcal{A}(\lambda, Q)(1-\varphi)\hat{\kappa}$ and $b(\lambda, Q) + \mathcal{A}(\lambda, Q)\hat{\kappa}$.

∎

Note that the condition on the distribution of κ stated in Proposition 3 is a sufficient condition and there are many cases where the property would still be true with other distributions (for example if $b(\lambda, Q) < 0$). The next proposition considers the link between λ and the wage.

Proposition 4. *The equilibrium wage $w(\kappa, \lambda, Q)$, is increasing in λ for a given Q.*

Proof. To show this, we first consider a case where λ is lower than $\bar{\lambda}$. In this case, the market can infer that a worker would leave the original firm only did it because of the desutility shock and $\Lambda(\lambda) = \hat{\kappa}$. From the bargaining we therefore have:

$$w(\lambda, Q, \tau) = \frac{1}{2}\left[\lambda Q\left(\kappa(1+\tau) - \hat{\kappa}(1-\omega)\right] + \overline{w}(\lambda, \tau) + \mu\omega Q + C\right],$$

with $\overline{w}(\lambda, \tau) = \mathbb{E}\left[\lambda Q\right]\hat{\kappa}(1+\tau u) + \mu\mathbb{E}[Q]$ which is independent of λ. Hence the wage is clearly increasing in λ as long as τ is sufficiently large.

If λ is larger than $\bar{\lambda}$, we still have:

$$w(\lambda, Q, \tau) = \frac{1}{2}\left[\lambda Q\left(\kappa(1+\tau) - \hat{\kappa}(1-\omega)\right] + \overline{w}(\lambda, \tau) + \mu\omega Q + C\right],$$

but this time $\overline{w}(\lambda, \tau) = \mu\omega Q + C + \lambda Q\left(\bar{\kappa}_\lambda(1+\tau) - \hat{\kappa}(1-\omega)\right)$ increases with λ as long as $\hat{\kappa}_\lambda$ increases with λ (see Proposition 3).

Here again, as long as τ is sufficiently large, the wage will increase with λ. ∎