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

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Abstract

This study employs matched employee-employer data from the UK to highlight the importance of social skills, in particular workers' ability to work well in a team and communicate effectively with co-workers, as a driver of wage growth for workers with lower formal education. Our findings indicate that in tasks emphasizing social skills, such workers not only enjoy greater wage progression with tenure but also accrue higher returns in environments with a higher concentration of more educated colleagues. Additionally, workers' exit occur sooner from jobs where social skills are more important. We rationalize these dynamics through a model that assesses social skills based on their complementarity with a firm's assets and where a worker's social skills, initially opaque to both the employee and employer, become increasingly apparent over time.

JEL classification: J31, J24, L25
Keywords: team work, social skills, tenure-wage profiles, individual wage growth, firm pay premium

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1 Introduction

The interplay between work experience and education markedly influences wage dynamics, notably yielding lower returns and slower wage progression for less educated workers.[1] This results in notably flatter wage experience profiles for those with lower educational qualifications. Consequently, policy strategies that solely focus on boosting employment among the less educated are unlikely to effectively elevate individuals out of low-wage positions. This raises concerns about the long-term viability of welfare-to-work programs, including in-work benefits and tax credits, and dampens the incentives for both workers and firms to pursue active earnings advancement.[2]

To guide policy aimed at boosting wage growth for less educated workers, a deeper understanding of the factors driving stronger wage progression is essential. Specifically, identifying the skills that can lead to steeper tenure-wage profiles and the types of firms that value these skills is critical. Recent literature has underscored the increasing significance of social skills in the labor market, mainly in occupations requiring high levels of education and cognitive skills, such as roles in management, teaching, medicine, and law (Caines et al., 2017; Deming, 2017; Edin et al., 2022; Weinberger, 2014). We expand on this body of work by exploring the impact of employment in social skill-intensive occupations, including those involving teamwork and effective communication with co-workers, on workers who exit school with minimal formal qualifications.

We make three contributions in this paper.

First, we document that the wage growth of less educated workers has been stronger in occupations where social skills are important. We show that employment of less educated workers in more social skill intensive occupations has expanded relative to other occupations. We use new administrative panel data for the UK, which has the key advantages that it is longitudinal, so we follow individual workers as they progress in a firm, and that we observe the detailed formal education qualifications of each worker. To our knowledge we are the first to document these facts; the previous literature has largely focused on the higher wages and stronger employment growth

[1] Blundell et al. (2016) explores the causal impact of work experience on wage profiles across education levels in the UK, while the phenomenon of steeper experience profiles among more educated workers has been documented since Mincer (1974). The presence of variations in age-wage profiles by education level across different countries is established in Lagakos et al. (2017).

[2] On-the-job training, under specific conditions, has been identified as a counterbalance to the erosion of human capital due to gaps in work experience. As highlighted by Blundell et al. (2021), the benefits of work-related training for employed individuals can be comparable to those achieved through formal education.

of high educated workers in social skill intensive occupations, and has focused largely on wage levels, rather than individual wage growth.

Second, we use matched employee-employer panel data to estimate an empirical model of the tenure-wage profiles of less educated workers, where we effectively compare similar workers in different occupations in the same firm, and show stronger individual wage growth in occupations where social skills are more important, even after including a large number of controls. We do not observe measures of individuals' social skills, we rely on the task based categorization of occupations where social skills are important. 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 occupations where they are not. The data we use allow us to condition on a number of individual, occupation, firm and local labour market controls. Measurable cognitive skills will also 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. We also investigate heterogeneity in the tenure-wage profiles across different types of workers, and show that the tenure-wage profile for less educated workers is steeper in occupations where social skills are important, and even more so in more skill intensive firms (firms that employ more workers in high skilled occupations, as a share of all workers).

Third, to provide a theoretical explanation for our empirical observations, we propose a simple model that illustrates how wage progression could be higher for certain workers in low-skilled occupations, provided these workers are employed in roles that demonstrate stronger complementarity with the firm's other assets, and where the quality of the workers is initially difficult to ascertain but becomes evident over time. This model draws upon Acemoglu and Pischke (1998)'s work on firm training and learning, expanded to include occupational heterogeneity. Each occupation is characterized by a distinct level of synergy between an employee's skills and the firm's resources, as well as by a mechanism for progressively uncovering the worker's capabilities. This approach aligns with the empirical evidence we present, and offers an explanation for the observed steeper tenure wage profiles in jobs where social skills are important. It suggests that in these roles, the interplay between an individual's abilities and the firm's assets is more pronounced, especially in organizations with a greater accumulation of these complementary assets. Our theoretical analysis generates two additional empirical predictions that we take to the data - that wage growth in social skill intensive occupations should be increasing in the quality of the firms other assets, and that early in a worker's tenure exit rates should be higher in social skill intensive occupations as the firm and worker learn about the workers quality of social skills.

Active labour market policies such as in-work benefits and tax-credits have been favoured in the US and UK as a means of reforming welfare systems on the basis that they encourage work and reduce poverty (see for example Brewer and Hoynes, 2019). If the wages of less educated workers show little growth with tenure or experience this means these policies will be less effective at helping low wage workers to work their way out of poverty and remain self-sufficient.

Changes in technology leading to a reduction in demand for workers in routine (middle income) jobs [3] and the low productivity growth in the UK are likely to be amongst the important drivers of the slow down in the returns to tenure and experience for less educated workers. What the literature on social skills has emphasised is that jobs where workers perform tasks where social skills are important are difficult to automate. In addition, these tasks often complement the tasks of other workers, in particular high productivity workers, allowing them to focus on high skilled tasks. As firms learn about, select on and invest in enhancing (training) these social skills, the wage of individuals endowed with them should grow.

Our categorisation of how occupations vary 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 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 work relates to several strands of literature. First, to the rich literature that has documented the role of technology in changing 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

[3] In particular the hollowing out of the labour market analyzed by Autor et al (XXXX)

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, our work relates 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. (2017). We emphasize the importance of firms' learning about workers' social skills, especially in jobs and firms where social skills matter. 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, our work relates 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.[4] 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 occupational characteristics, including cognitive skills and social skills, and we show some initial correlations. In Section 3 we present our empirical model and dis-

[4] 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.

cuss potential threats to our identification. In Section 4 we present our core regression results and discuss the robustness of our main findings. In Section 5 we develop our theoretical framework and we lay out its main predictions. These predictions accord with the initial empirical results and suggest further empirical predictions concerning complementary assets and worker exists. In Section 6 we take these additional predictions to the panel data model. Section 7 collects our concluding remarks.

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.[5] 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. Figure I shows that workers with high school education or less in the UK have experienced little wage growth over their career over the past few decades. We provide further description of the characteristics of these workers, their jobs and the firms they work for in Section 4.

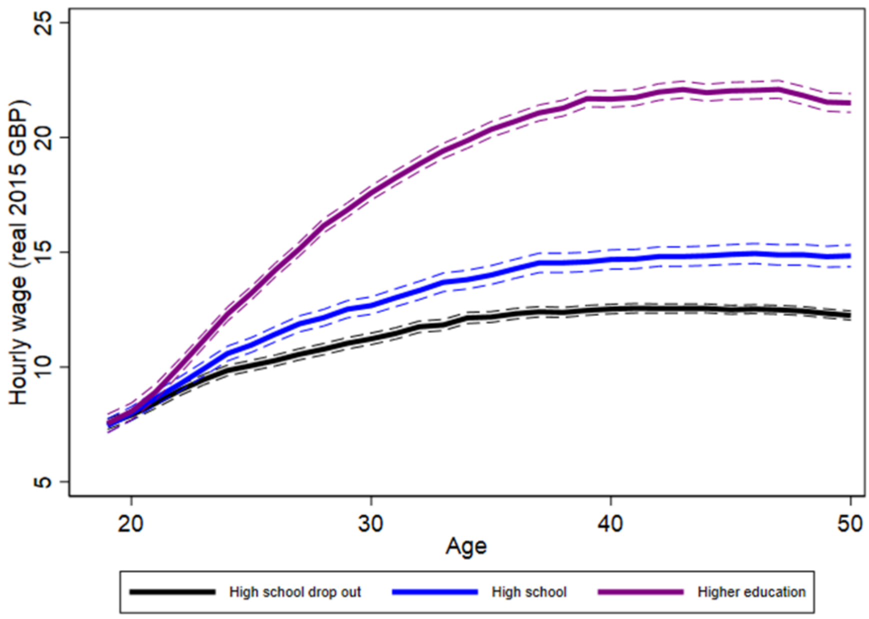
[5]Level 1 qualifications include fewer than 5 O-levels or a level 1 National Vocational Qualifications

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.

FIGURE I. Age-wage profiles by highest educational qualification in the UK



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

(NVQs); Level 2 qualifications include 5+ O-levels or level 2 NVQ; Level 3 qualifications include

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.[6] We describe these data in Section 6.2.

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, we refer the reader 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

A-levels and level 3 NVQs.

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

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.[7]

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 to define our indicators of occupations with high, intermediate and low levels of social skill intensity (see A.3 for details).[8]

2.3 Employment growth and age-wage profiles

Employment in occupations where social skills are important increased relative to those occupations where they are less important. Figure II 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.

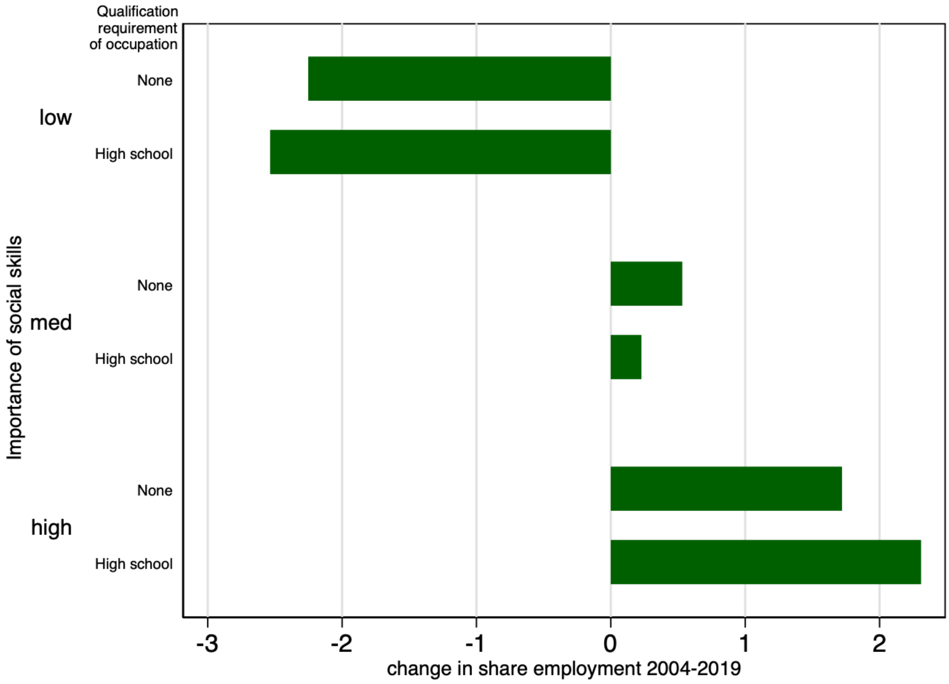
Figure III shows that, in the raw data, average wages of workers with less education increase more over the career in occupations where social skills are more important. Workers in these occupations get on average higher wages with age (experience) relative to workers in occupations where the requirements 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 3 we will discuss how our econometric analysis controls for these and other potentially confounding factors. We demonstrate in Section 4 that our basic results remain robust even after these controls are applied.

[7]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.

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

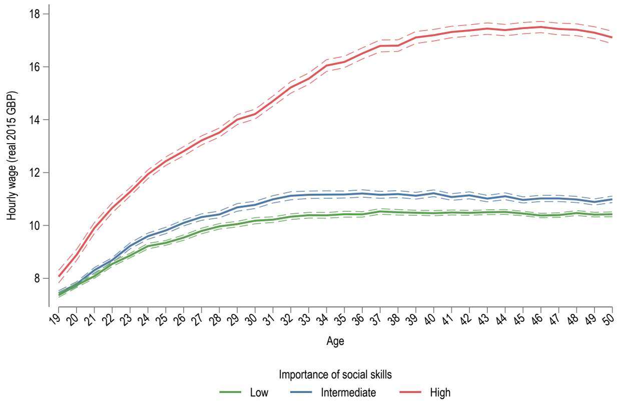
FIGURE II. Change in employment shares



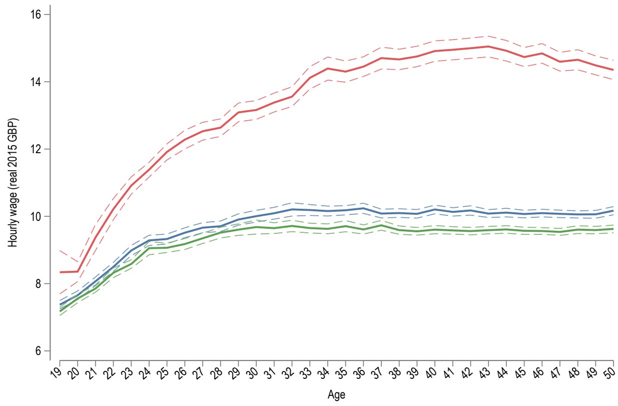
Notes: Figure shows changes in share of employment from 2004 to 2019 of workers in occupations classified by the typical qualification requirements (see Appendix A.2) and the importance of social skills for that occupation. Low/med/high are defined by terciles of workers based on our aggregate measure 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).

FIGURE III. Wage-age profiles by importance of social skills in occupation

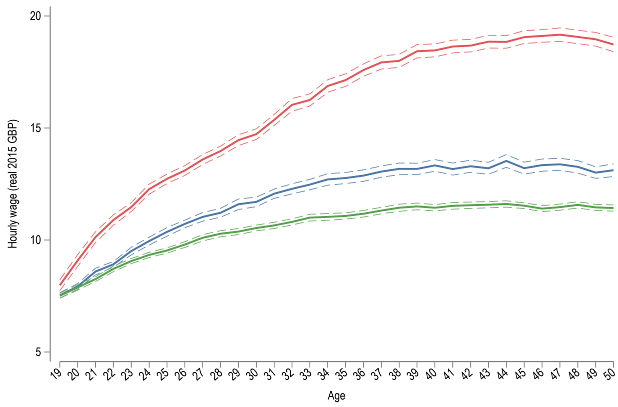
(a) All



(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 An empirical model of tenure wage growth

We develop a panel data specification of log wages for less-educated workers to apply to our firm-worker data. Figure III showed the simple regression of individual wages on worker age for less educated workers, and pointed to higher wages and *steeper* age-wage profiles for workers in occupations where social skills are important. For less educated workers wage profiles appear flat except in occupations where social skill are important. Building on this observation, our objective in this section is to specify a panel data framework to estimate the impact of working in a social skill intensive occupation on the tenure-wage profile for a less educated worker, controlling for other differences across workers, occupations, labour markets and firms.

Our underlying view, which we spell out in the theoretical model developed in Section 5, is that social skills are not certifiable and not observable, except through direct interaction between the worker and employer. Workers who possess social skills can enhance the productivity of a firm when matched with an occupation that utilises these social skills. This increased productivity in turn creates a joint surplus that can be shared between the worker and the firm. When a worker first joins a firm the wage premium in social skill intensive occupations is small, but thereafter the wage premium grows with the worker's tenure in the high social skill intensive occupation as the firm and the worker learn about the worker's social skill ability progressively over time during the match. The speed of this wage growth should depend upon the worker's underlying level of social skills. Moreover, whenever the worker's underlying social skills are revealed to lie below the required level the worker should exit the firm

3.1 A firm-worker panel data framework

We use the notation $j(it)$ to indicate that worker i is matched to occupation j at time t, and denote $\lambda_{j(it)}$ as a binary indicator of whether social skills are important in occupation j: namely, $\lambda_{j(it)} = 1$ for worker i in a high-λ job in period t and zero otherwise. 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, we expect the premium for worker i will rise with tenure T_{ift} in a high-λ job.

To operationalise the learning process we assume that a proportion θ_0 of a worker's social skills κ_i are observed upon hiring by 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:

$$\theta(T_{ift}) = \theta_0 + \theta_1(T_{ift}), \tag{1}$$

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 $T_{ift} = 0$, so 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 the learning process, the size of the wage premium for a worker i matched with a high-λ job will also increase with tenure T_{ift}. This premium for worker i in a high social skill intensive job is the product of the level of underlying social skills κ_i, the learning process (1) and the bargaining share:

$$\alpha(\kappa_i, T_{ift}) = \alpha_0\kappa_i + \alpha_1(T_{if})\kappa_i, \tag{2}$$

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 initial premium term to be small.

The wage premium (2) contains the main parameters of interest in the wage equation specification. This term provides the central building blocks for our panel data specification of individual log wages. In our baseline specification we assume $\alpha_1(T_{if})$ is a quadratic function of the worker's tenure T_{if}.[9]

Recalling that $\lambda_{j(it)}$ is a binary indicator equal to one when worker i is in a high-λ job and assuming the quadratic specification for the tenure profile, the contribution of the social skill occupation wage premium terms for worker i at tenure T_{ift} in firm f at time t is given by:

$$\alpha_0\kappa_i\lambda_{j(it)} + \alpha_{1T}\kappa_i\lambda_{j(it)}T_{ift} + \alpha_{1T2}\kappa_i\lambda_{j(it)}T_{ift}^2 \tag{3}$$

To form our panel data specification for log wages we add this premium term to the more standard elements of a panel data log wage specification. For worker i at tenure

[9]We relax this assumption in the robustness analysis.

T_{ift} in firm f at time t we write the log wage as:

$$
\begin{aligned}
\ln w_{ijft} =& \beta_{Li}\lambda_{j(it)} + \beta_{LTi}\lambda_{j(it)}T_{ift} + \beta_{LT2i}\lambda_{j(it)}T_{ift}^2 \\
&+ \beta_{CT}C_{j(it)}(T_{ift}) + \beta_{CT2}C_{j(it)}T_{ift}^2 \\
&+ \beta_T T_{ift} + \beta_{T2}T_{ift}^2 + \beta_E E_{it} + \beta_{E2}E_{it}^2 \\
&+ \beta_{FT}FT_{it} + \beta_{QL}QL_i + \beta_M M_i \\
&+ \beta_S S_f + \beta_P P_f + \beta_C C_{j(it)} \\
&+ \gamma_{if} + \eta_{tr} + e_{ijft},
\end{aligned}
\tag{4}
$$

where the β_* are unknown parameters to be estimted.

The first line of the right hand side of the log wage equation (4) is the high-λ wage premium term for social skill intensive occupations as defined in (2). Note that the β parameters in this expression is heterogeneous across individuals, reflecting unobservable social skill ability κ_i multiplying each λ in (3). Below we show how our panel data estimator recovers interpretable averages of these key parameters of interest.

The remaining terms in (4) describe the baseline wage of worker i who is not working in a social skill intensive occupation. This depends on occupation-level cognitive skills measure $C_{j(it)}$ interacted with tenure, firm tenure itself, potential experience E_{it}, full-time work FT_{it}, recorded qualifications QL_i, gender M_i, firm size S_i,[10] public sector P_f, and the occupation-level cognitive skills measure $C_{j(it)}$ itself. Notice that although our focus is on social skills to guard against misspecification we treat occupational-level cognitive skills symmetrically with social skills.[11]

The final three terms in (4) 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}. The assumptions on these terms are crucial for the identification of the parameters of interest. We discuss threats to identification below. First we examine the key parameters of interest.

As noted above, the parameters in the wage premium term on the *right hand side* of (4) are heterogeneous across individuals i, reflecting unobservable social skill ability κ_i in (3). The coefficients that we estimate in our panel data regressions therefore recover specific averages of these heterogeneous effects. For example, the first term will identify the average premium for social skills of newly hired to an occupation in

[10] In the empirical application, firm size is measured at the outset of a job.

[11] 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.

which social skill are important:

$$\mathbb{E}\left[\beta_{Li}|T=0,\lambda=1\right]=\mathbb{E}\left[\alpha_0\kappa_i|T=0,\lambda=1\right]. \tag{5}$$

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 firm f at tenure $T = T_{ift}$:

$$\mathbb{E}\left[\alpha_1(T_{ift})\kappa_i|T=T_{ift},\lambda=1\right]. \tag{6}$$

We interpret the worker-firm effect, γ_{if}, in (4) 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 that the initial wage, and other observable individual time invariant covariates, capture the level of skills of the worker at *entry*.[12] A further advantage of the initial wage specification is that it allows us to identify the leading wage premium term in (4) , $\beta_{Li}\lambda_{j(it)}$, even when a worker is only observed in a high-λ job in firm f. We present both specifications in our empirical analysis.

3.2 Identification discussion

Identification of the wage premium term requires that we control for individual heterogeneity in the wage specification (4). 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

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

the theoretical model developed in Section 5 we shall assume a 'utility' shock which is 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 check we also examine younger workers in their first jobs. We find that our results pass all these robustness tests.

4 Estimated wage growth in social skill occupations

Before presenting the estimates of the panel data model developed in the previous section, we first 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 III. 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 on 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.

4.1 Individual wage growth results

Table III presents estimates of the main parameters of interest in the individual wage growth equation (4), 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 (4). These are the binary indicator for an occupation that requires 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 in columns (3)-(5), and estimated as a more flexible function of tenure in columns (6) and (7).

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 (4), 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.

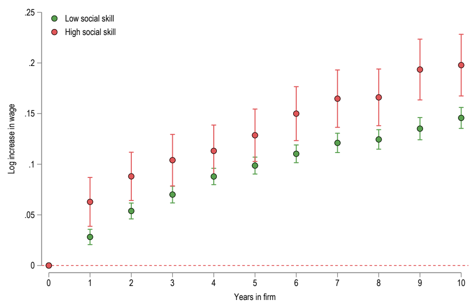
In column (3) we add the interaction between the high social skills indicator, λ, and a quadratic term in tenure. We see that the linear term is positive and statistically significant, indicating an increase of 0.5 log points with each year of tenure. In column (4) we include the worker initial wage as a control for unobserved worker heterogeneity (see the discussion on Section 3.1). 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.

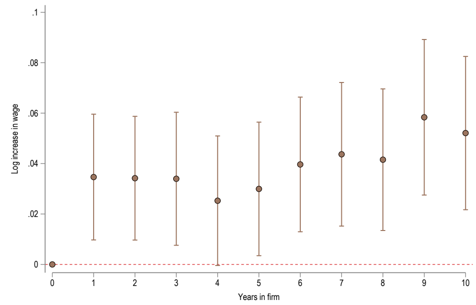
The quadratic term in tenure could be overly restrictive, so we also estimate a more flexible specification by interacting the high λ indicator with a full set of tenure dummies (one for each year of tenure up to 15 and a single dummy for 16 and over). These estimates are shown in columns (6) and (7) of Table III; the estimated coefficients on the individual dummies are shown in the Appendix Table B 2. In Figure IV 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 IV. Wage growth from working in high λ occupation

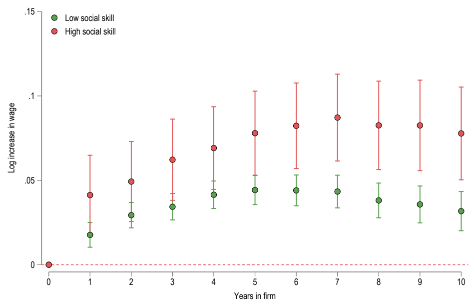
(a) mean individual wage growth, initial wage



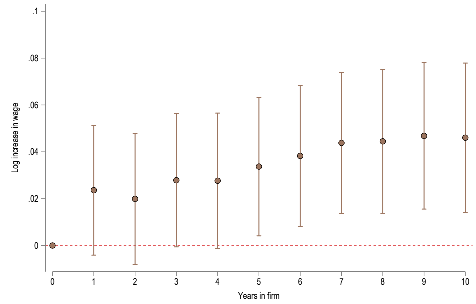
(b) difference in mean individual wage growth between high and low social skill occupations, initial wage



(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 analysis 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 across 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. The complete set of coefficient estimates are displayed in Table B 3, and we present the results from using the equivalent tenure dummy specification in Table B 4.[13]

Our findings in column (6) are particularly interesting. In particular, 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 such an occupation is considerably higher than in a low λ occupation, with a 1 log point difference for each year of tenure. This suggests that there is little information on a worker's social skills available to firms early on a worker's career. The steep wage 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.

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

5 Building a theoretical framework

In the previous section we documented that amongst workers with little or no observable educational qualification, those in occupations where social skills are important experience stronger wage growth than equivalent workers in occupations where social skills are not important.

In this section, we present a simple theoretical framework which rationalizes the above findings. In this model: (i) occupations where social skills are important, i.e. higher-λ occupations, involve a higher degree of complementarity between the worker and the firm's other assets; (ii) a worker's level of social skills is initially unknown to the worker and the firm, but progressively revealed to both over the worker's tenure.

In this setting we show that the wage of a worker with high social skills increases faster with tenure in occupations where social skills are important, and that workers who are discovered to have low social skills exit their current job and to a larger extent from higher -λ jobs.

5.1 The model

Time is discrete and indexed by t. We consider a representative firm which employs an asset of quality Q which it combines with tasks,[14] each of which is performed by a different worker in on a specific occupation (or job).

5.1.1 Basics

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. 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.

At any time t, the extra flow output produced by the worker within the firm is defined by the following production function:

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

[14] 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.

where μ is a positive constant. This production function integrates the importance of social skills in the occupation λ as parametrizing the complementarity between κ, the worker quality and the firm's other assets Q. On top of this, the firm also draw its production directly from its other assets Q.

We assume that initially in period 0 both the representative firm and the worker ignore the worker's true social skill capability κ, and we denote by p the ex ante proportion of high ability workers in the economy, i.e. the *ex-ante* probability of facing a high ability worker. The fact that the quality κ is unknown by both the worker and the firm is consistent with the idea that this is a model or young and inexperienced employees in their first job with little formal education and easily verifiable skills.

There is progressive (stochastic) learning and over time, the firm updates its information about the worker's capability κ. More precisely, at each period $t > 0$ the firm and the worker learn about the true ability κ. We assume the following learning process: if the received signal is that κ is low ($\kappa = \underline{\kappa}$) then there is a probability 1 that the true value of κ is indeed low. This can result from the worker making an obvious error or revealing itself to have low social skills. However, if the received signal is $\kappa = \overline{\kappa}$, then with probability ε, the signal is wrong and the true ability was indeed $\underline{\kappa}$. In addition, in each period, the worker undergoes a disutility shock and decide whether to leave the firm by herself (we come back to this point below).

The timing of moves within each period is as follows: (1) the firm updates its information about the worker's capability κ at the beginning of the period; (2) the firm bargains with its worker, decides whether or not it wants to retain her, and each worker decides whether or not to leave the firm; (3) production takes place.

5.1.2 Bargaining

At each time t, we assume symmetric Nash bargaining between the firm and each of its workers. Let $\overline{w}(\lambda, n)$ denote the outside option of a worker with tenure n, i.e. who has been employed by its current firm for n periods, if she leaves the firm and goes on the market, and let $w(n, \lambda, Q)$ denote the worker's wage if she stays with the firm.

There are two reasons a worker can be in the market. The first case is a failure in wage bargaining because the firm cannot match the outside option. The second case is the result of the disutility shock. As in Acemoglu and Pischke (1998), workers are subject to disutility shocks and we assume that the worker decides to leave the initial firm at the end of the period whenever:

$$\overline{w}(\lambda, n) + \widetilde{\Phi} > w(n, \lambda, Q),$$

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 $\overline{w}(\lambda, n)$, whereas the firm's outside option is to resort to a temporary workers provided by a temporary work agency. This is done at a cost (the markup changed by the temporary work agency) and without any information on the quality of the temporary worker. The firm's outside option is then equal to the expected surplus generated with the temporary worker minus the cost.

5.2 Solving the model

5.2.1 Law of motion

To solve the model, we first need, for any tenure level n, 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 the two possible reasons that would lead a worker to leave her initial firm: (i) she is of high ability $\bar{\kappa}$ or of low ability $\underline{\kappa}$ but subject to a high preference shock (which occurs with probability $(1 - \varphi)$); (ii) 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:

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

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

$$1 - p_n = (1 - p_{n-1})(1 - \varepsilon)$$

which implies:

$$p_n = 1 - (1 - p_{n-1})(1 - \varepsilon) = 1 - (1 - p)(1 - \varepsilon)^n$$

It clearly appears that p_n is increasing with n and converge to 1 as n goes to infinity: as tenure increases, the share of $\bar{\kappa}$ workers in the firm increases and ultimately approaches 1 because low κ workers will ultimately be discovered. As a result, $q(n, \varepsilon)$ is also increasing with n: indeed, the higher a worker's tenure n, the lower the probability that the worker will be of low ability since every period a low ability worker is found out by the firm to be of low ability and therefore laid off by the firm; in other words, the higher the worker's tenure, the lower the probability that she will be of low type because the less likely it is that she will not have been found out being of low ability before.

5.2.2 Equilibrium and comparative statics

We focus attention on an equilibrium where, for some cut-off $\bar{\lambda} > 0$: (i) at the beginning of each period, a firm chooses to lay off those among its workers which it deems 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 disutility shock (with probability φ). Appendix D shows that such an equilibrium exists under suitable parameter restrictions. We now derive the parameter restrictions that ensure the existence of such an equilibrium.[15]

The *ex-post* wage $w = w(n, \lambda, Q)$ of a worker with tenure n on a λ - job in a firm with asset quality Q, is determined as follows. Consider first a high-λ job with $\lambda > \bar{\lambda}$. Then on such a job the firm only bargains with $\bar{\kappa}$ workers. Let us assume that the firm receives the signal that a worker is of $\bar{\kappa}$ type. Then the surplus for keeping this worker is given by:

$$S^{F,\overline{\kappa}}(n, \lambda, Q) = \lambda Q(p_n\overline{\kappa} + (1 - p_n)\underline{\kappa}) + \mu Q - w(n, \lambda, Q) - (1 - \omega)[\lambda Q\widehat{\kappa} + \mu Q]$$

where $\widehat{\kappa}$ is the unconditional average value of κ: $\widehat{\kappa} \equiv p\bar{\kappa} + (1 - p)\underline{\kappa}$ which corresponds to the average quality of a fall back temporary worker sent by the temporary work agency, and $(1 - \omega)$ is the firm's share of the surplus generated with this worker which includes the cost charged by the temporary work agency. The worker's net surplus from its relationship with the firm, is equal to:

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

If we now assume that the worker receives a fraction $\beta = \frac{1}{2}$ of the total surplus, in equilibrium we must have $S^W = S^{F,\overline{\kappa}}$, so that:

$$w(n, \lambda, Q) = \frac{1}{2}\left[\lambda Q(p_n\overline{\kappa} + (1 - p_n)\underline{\kappa} - \hat{\kappa}(1 - \omega)) + \mu Q\omega + \overline{w}(\lambda, n)\right] \tag{7}$$

[15] Note that the model relies on the fact that a worker with revealed capabilities $\underline{\kappa}$ in a low λ 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 to do so. This is due to the fact that the worker is alwyas better off with an outside option where she can benefit from the uncertainty around her type.

As in Acemoglu and Pischke (1998), we assume that the outside option wage $\overline{w}(\lambda, n)$ is simply equal to the expected marginal productivity of a worker who leaves its initial firm, as perceived by the market, namely for a worker with tenure n originating from a high λ task:

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

where

$$\Lambda(n, \varepsilon) = q(n, \varepsilon)\overline{\kappa} + (1 - q(n, \varepsilon))\underline{\kappa}$$

is the expected value of κ conditional on entering the job market after a tenure period of n in the initial firm. We clearly have that $\overline{w}(\lambda, n)$ is increasing with tenure n. Note that the value of the outside option depends upon λ. Indeed, the market knows in which job the worker was previously employed and from this can infer the value of q. If the worker was employed on a low λ job, then the market will only infer that the type of the worker is on average equal to $\hat{\kappa}$ as the only reason she will be on the market in that case, is the preference shock which is independent of the worker's ability type. If instead the worker was employed on a $\lambda > \bar{\lambda}$ job, then the market can more precisely infer the worker's type as explained above. This establishes:

Proposition 1. *In an equilibrium where, for sufficiently high λ, at the beginning of each period, firms lay off workers on λ - jobs which they deems to be of low ability $\kappa = \underline{\kappa}$, then the equilibrium wage of an incumbent worker that remains in the initial firm on a high-λ job, is increasing with tenure, all the more the higher Q and λ.*

Proof. The proof follows direclty from the equilibrium value of $w(n, \lambda, Q)$ in (7) given that p_n and $\overline{w}(\lambda, n)$ are both increasing with tenure. □

6 Extending the empirical model of tenure wage growth

The theoretical analysis in the previous section not only rationalized our earlier empirical results, but it also generated additional predictions. More precisely, Proposition 1 stated that workers in social skill occupations should attract a high wage premium and that incumbent workers that remain in the firm on a higher social skill occupation should experience faster wage growth with tenure, which is exactly what our empirical analysis in section 4 revealed. But Proposition 1 also entails two additional predictions. First, that wage growth in high-*lambda* occupations should be faster the higher the quality Q of the firm's other assets. Second, that over a worker's tenure, the worker's exit should occur faster from a higher-λ occupations. In this section we take these two additional predictions to the data.

We use the share of the firm's workforce that works in high educated occupations as our proxy for Q; what we have in mind is the idea that less educated workers in high social skill occupations have the potential to enhance the productivity of workers in high educated occupations, for example by facilitating team work and communicating more effectively. We define a binary indicator Q_f that equals unity for 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:

$$\alpha_2 \kappa_i Q_f + \alpha_3(T_{ift}) \kappa_i Q_f. \tag{8}$$

The wage premium terms (2) and (8) are the main parameters of interest in the wage equation specification. They provide the central building blocks for our panel data specification of individual log wages. In our baseline specification we assume $\alpha_1(T_{if})$ and $\alpha_3(T_{ift})$ are quadratic functions in tenure T_{if}.[16]

Recall that $\lambda_{j(it)}$ is a binary indicator equal unity when worker i is in a high-λ job. The contribution of the social skill occupation wage premium terms for worker i at tenure T_{ift} in firm f at time t is now given by:

$$\begin{aligned} &\alpha_0 \kappa_i \lambda_{j(it)} + \alpha_{1T} \kappa_i \lambda_{j(it)} T_{ift} + \alpha_{1T2} \kappa_i \lambda_{j(it)} T_{ift}^2 \\ &+ \alpha_2 \kappa_i \lambda_{j(it)} Q_f + \alpha_{3T} \kappa_i \lambda_{j(it)} Q_f T_{ift} + \alpha_{3T2} \kappa_i \lambda_{j(it)} Q_f T_{ift}^2. \end{aligned} \tag{9}$$

We bring this premium term together with a more standard panel data log wage specification. For worker i at tenure T_{ift} in firm f at time t we write the log wage as:

$$\begin{aligned} \ln w_{ijft} =& \beta_{Li} \lambda_{j(it)} + \beta_{LTi} \lambda_{j(it)} T_{ift} + \beta_{LT2i} \lambda_{j(it)} T_{ift}^2 \\ &+ \beta_{LQi} \lambda_{j(it)} Q_f + \beta_{LQTi} \lambda_{j(it)} Q_f T_{ift} + \beta_{LQT2i} \lambda_{j(it)} Q_f T_{ift}^2 \\ &+ \beta_{CT} C_{j(it)} (T_{ift}) + \beta_{CT2} C_{j(it)} T_{ift}^2 \\ &+ \beta_T T_{ift} + \beta_{T2} T_{ift}^2 + \beta_E E_{it} + \beta_{E2} E_{it}^2 \\ &+ \beta_{FT} FT_{it} + \beta_{QL} QL_i + \beta_M M_i \\ &+ \beta_S S_f + \beta_Q Q_f + \beta_P P_f + \beta_C C_{j(it)} \\ &+ \gamma_{if} + \eta_{tr} + e_{ijft}, \end{aligned} \tag{10}$$

where the β_* are unknown parameters. The first two lines of the right hand side of the log wage equation (10) are the two high-λ wage premium terms for social skill intensive occupations as defined in (2) and (8) respectively. Note that the β parameters

[16]We relax this assumption in the robustness analysis.

in these expressions are heterogeneous across individuals, reflecting unobservable social skill ability κ_i multiplying each λ in (9). As before our panel data estimator recovers interpretable averages of these key parameters of interest.

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.[17]

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 regulations. Details of how we do this, and a comparison with the Census data on actual qualifications by occupation are provided in A.2. First, in section 2.1, we show that our results using this alternative definition are similar to those above using actual qualifications obtained by workers in section 4. We then show results using the ASHE data matched to the WERS data to measure the share of workers in the firm that are high skilled in section 6.2.

6.1 Replicating baseline results using typical qualifications by occupations

We reproduce the baseline results using observed individual qualifications presented in Section 4.1, 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.[18] Figure V plots the estimated tenure dummies which are the equivalent of Figure IV, but use the typical qualification requirement by occupation rather than the individual qualifications. It shows a similar picture.

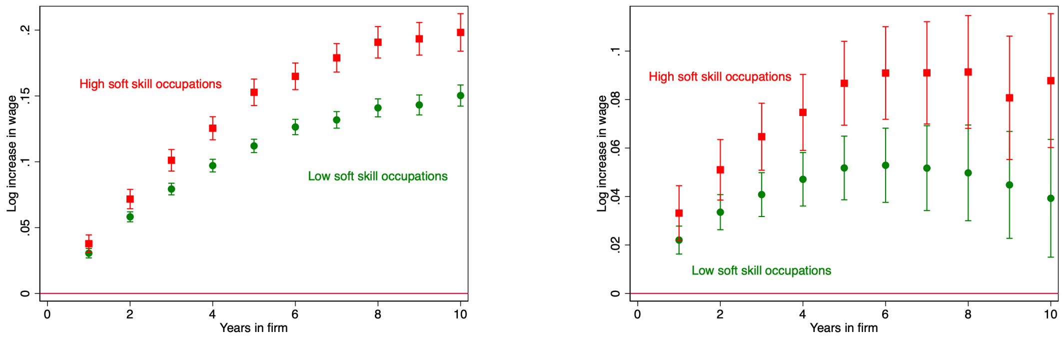
[17]The data owners of the Census data do not allow it to be matched to WERS because of concerns about maintaining confidentiality.

[18]In results available from the authors on request we show that the results in Section 4 also hold in the larger ASHE sample.

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

(a) mean individual wage growth, initial wage

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



Source: Authors' calculations using ONS-ASHE (2022) matched with ONET (2016). **Notes:** Figure plots the estimated coefficients and confidence interval for the coefficient 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).

6.2 Variation in the social skills premium across firms

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 for workers in occupations that typically require low formal qualifications, according to the immigration rules.[19] The first two columns are for workers in jobs where team work and social skills are less important (low λ), the next two columns are for workers in jobs where team work and social skills are more 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, where 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}) is our main interest.

[19]We confirm that our baseline results hold in this smaller sample in columns (1) and (5) of Table C 1, 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	
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

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 low formal educational requirements.

The full set of coefficient estimates is reported in Table C 1. We see that for workers in occupations with low formal education requirements this triple difference is positive and statistically significant. Figure VI plots the tenure dummies.

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.

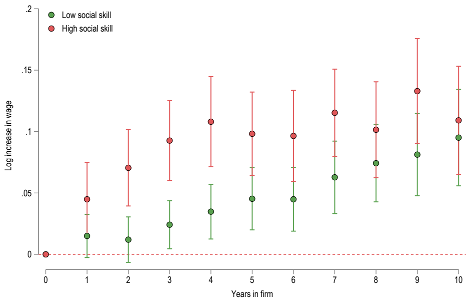
TABLE VI. Wage growth, the role of high-skill firms

Dependent variable: $\log(w_{ijkft})$	(1)	(2)
$\lambda_{j(it)}$	-0.01924***	-0.01279***
(high social skills)	(0.0053)	(0.0047)
$\lambda_{j(it)} \times T_{ift}$	0.01043***	0.00953***
(high social skills times tenure in the firm)	(0.0018)	(0.00156)
$\lambda_{j(it)} \times T^2_{ift}$	-0.00004	-0.00013
(high social skills times tenure squared)	(0.0001)	(0.00008)
$\lambda_{j(it)} \times T_{ift} \times Q_f$	0.00753***	0.00359*
(high social skills times tenure times high skills share firm)	(0.00238)	(0.002)
$\lambda_{j(it)} \times T^2_{ift} \times Q_f$	-0.00067***	-0.00045***
(high social skills times tenure squared times high skills share firm)	(0.00012)	(0.0001)
$\lambda_{j(it)} \times Q_f$	0.05438***	0.04596***
(high social skills times high skills share firm)	(0.0092)	(0.00844)
$T_{ift} \times Q_f$	0.00511***	0.00404***
(tenure times high skills share firm)	(0.00065)	(0.00054)
Q_f	0.00988**	0.01130***
(high skills share firm)	(0.00437)	(0.00359)
w_{i0}		0.03957***
(initial wage)		(0.00141)
Area-year effects	✓	✓
R^2	0.254	0.386
Observations	114530	114530

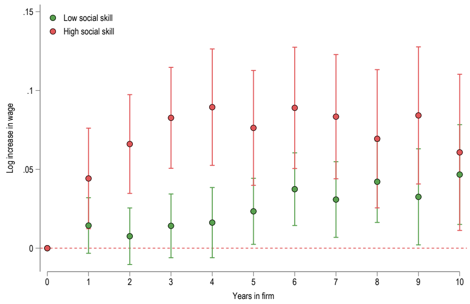
Source: Authors' calculations using ONS-ASHE (2022) matched with ONET (2016) and ONS-WERS (2013).

Notes: Sample is workers aged 19-39 in occupations with low 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.

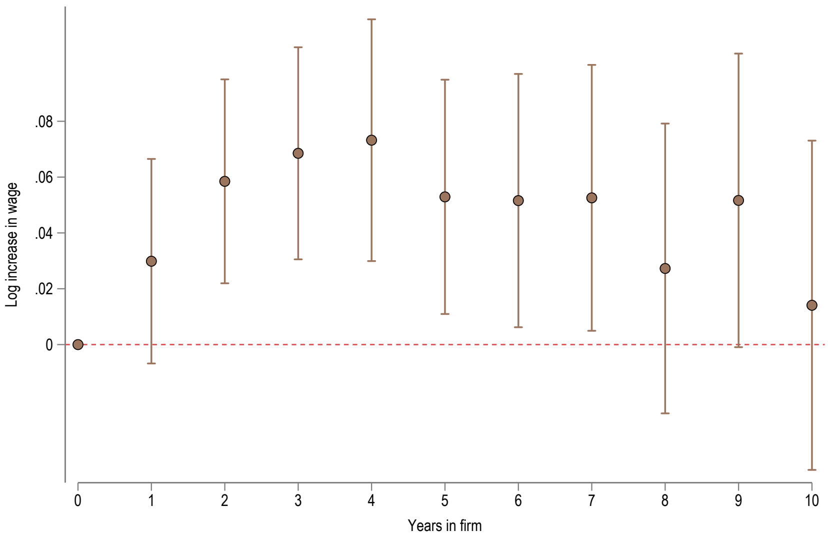
FIGURE VI. Wage growth from working in high $\lambda_{j(it)}$ occupation in firm with high skill share



(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 1 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).

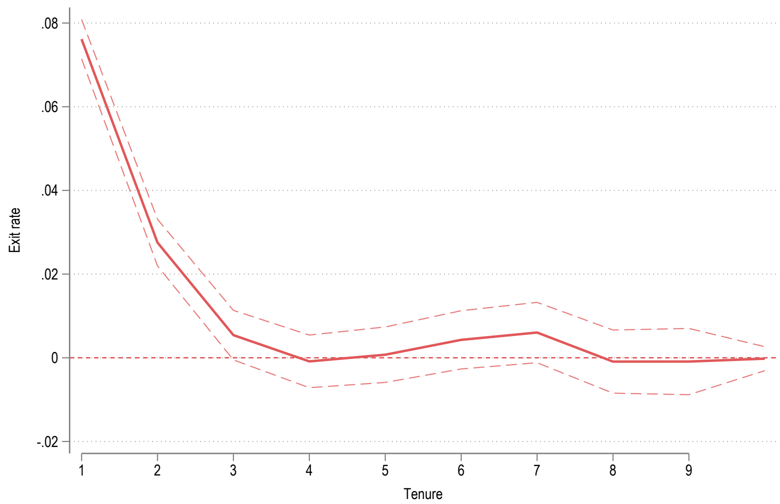
6.3 Evidence on exit rates

In our theoretical model analysed in section 5, workers would exit from a high-λ job in firm f for two reasons. Either their social skills, 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. Workers who are not in a high-λ job should exit solely due to an 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.

To examine this empirically we estimate a model for the probability that a worker i exits firm f at tenure T_{ift}. We assume that this probability follows a similar specification to the main wage equation where we replace the log wage with the exit probability conditional on being employed in firm f, at tenure T_{ift} and time t.

In Table VII we show the estimated coefficients of a linear probability model for the probability that a worker exits a firm. This is declining in tenure. For workers in high λ occupations it is higher in the first three years than in lower λ occupations (see Figure VII for a graphical illustration).

FIGURE VII. Difference in workers' probability of exit against tenure in 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 $\lambda_{j(it)} \times T_{ift} = x$ 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 empirical results match our theoretical predictions. Workers in occupations where social skills are more important experience stronger wage growth. This growth is all the more higher in firms where there is a high share of higher educated workers. They also experience a higher exit rate at short tenures from firms when compared to equivalent workers in occupations where social skills matter less.

7 Discussion and concluding comments

In this paper we used 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 considered the task content of occupations using O*NET data and showed that workers in occupations where social skills are important experience stronger wage growth than equivalent workers in occupations where these skills are not important. We interpreted these results as suggesting that for workers with lower formal education qualifications there is an important role for skills such as teamwork and effective communication with co-workers in driving individual wage growth.

We then developed a simple theoretical model to rationalize these findings. We posited that these wage growth results reflect a complementarity of these team and social skills with the skill intensive assets of the firm. The model generated two additional predictions, which we took to matched firm-worker data. First, we found a steeper tenure-wage profile for workers in high social skills jobs in firms with a higher share of complementary assets, namely with a higher share of highly educated workers. Second, we found higher exit rates at short tenures for workers in higher social skill jobs.

Our analysis can be extended in several directions. First, 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 earnings 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 exclusively on the tax/subsidy lever is costly, it is insufficient to restore social and income mobility, and does little to enhance individual wage growth.[20]

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

[20]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.

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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.

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.

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)[21] 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.

[21]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 4 shows the dummy variable equivalent of Table IV in the paper.

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		
$\lambda_{j(it)} \times T_{if}^2$			-0.0001	-0.00015**	-0.00016**		
(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	

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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 4. 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***

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	(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

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	(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 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.

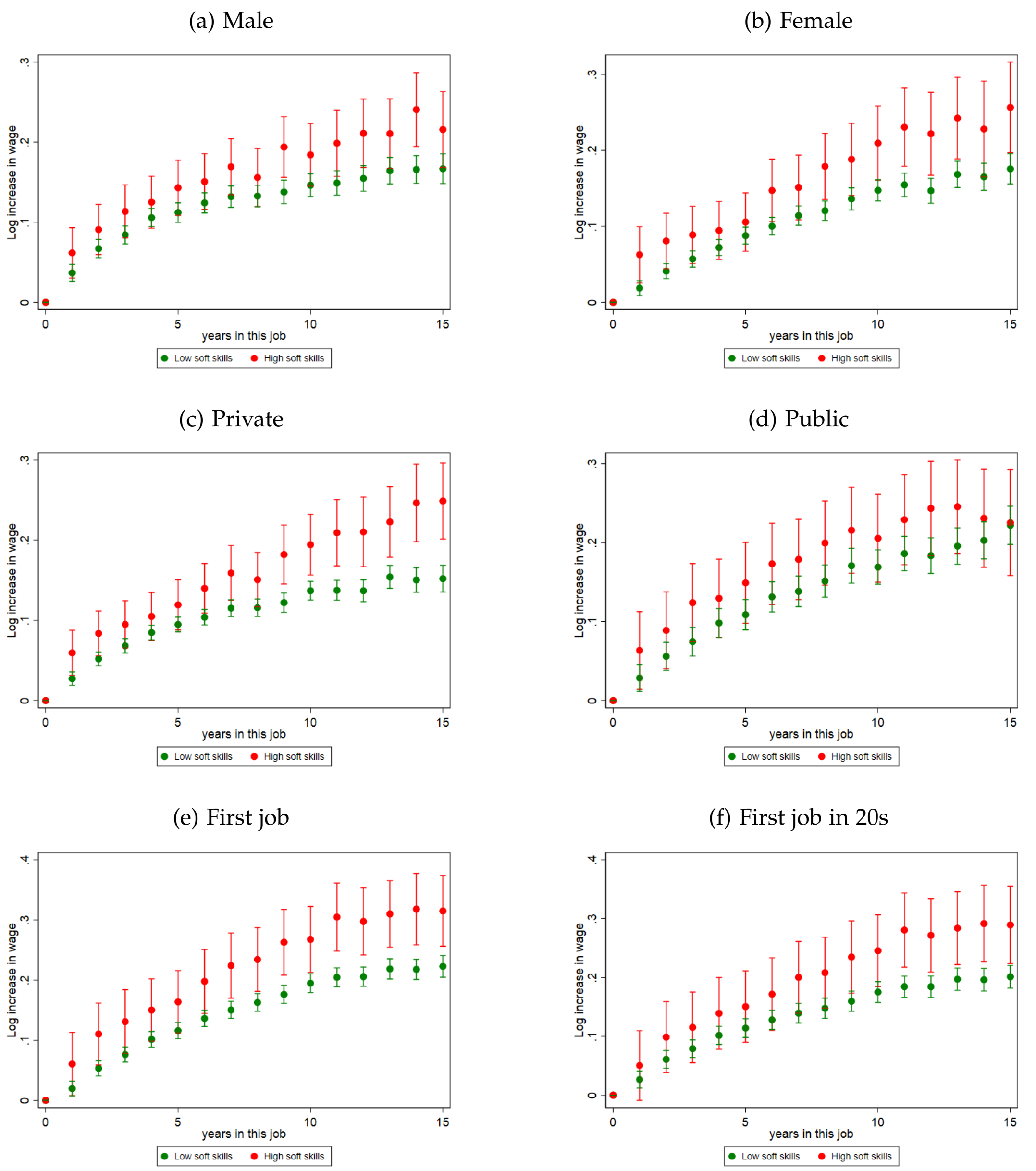
TABLE B 3. Wage growth in high λ occupations, different samples, quadratic specification, aged 19-39

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
$\lambda_{j(it)} \times T_{if}^2$	-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
$C_{j(it)} \times T_{if}^2$	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_{if}^2	-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_{it}^2	-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.

FIGURE B 1. Estimated tenure profiles from estimates in Table B 4



Note: Figure plots the estimated coefficients and confidence interval for the coefficient in Table B 4 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).

TABLE B 5. Tests of joint significance of variables in Table B 4

	(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 4.

C Empirical results using ASHE and ASHE-WERS

C.1 Results using ASHE-WERS

TABLE C 1. Results using ASHE-WERS, ages 19-39

Dependent variable: $\log(w_{ijkft})$				
	(1)	**(2)**	**(3)**	**(4)**
$\lambda_{j(it)}$	0.00533	-0.01924***	-0.01279***	-0.00006
(high social skills)	0.0038	0.0053	0.0047	0.00776
$\lambda_{j(it)} \times T_{if}$	0.01349***	0.01043***	0.00953***	
(high social skills times tenure in the firm)	0.00131	0.0018	0.00156	
$\lambda_{j(it)} \times T_{if}^2$	-0.00042***	-0.00004	-0.00013	
(high social skills times tenure squared)	0.00007	0.0001	0.00008	
$\lambda_{j(it)} \times T_{ift} \times Q_{ft}$		0.00753***	0.00359*	
(high social skills times tenure times high skills share firm)		0.00238	0.002	
$\lambda_{j(it)} \times T_{ift}^2 \times Q_{ft}$		-0.00067***	-0.00045***	
(high social skills times tenure squared times high skills share firm)		0.00012	0.0001	
$\lambda_{j(it)} \times Q_{ft}$		0.05438***	0.04596***	0.00071
(high social skills times high skills share firm)		0.0092	0.00844	0.017
$Q_{ft} \times T_{ift}$		0.00511***	0.00404***	
(tenure squared times high skills share firm)		0.00065	0.00054	
Q_{ft}		0.00988**	0.01130***	0.03780***
(high skills share firm)		0.00437	0.00359	0.00833
$C_{j(it)}$	0.05720***	0.07691***	0.05450***	0.02782***
(high cognitive skills)	0.00384	0.00479	0.00377	0.00232
$C_{j(it)} \times T_{if}$	-0.00448***	-0.00726***	-0.00365***	
(high cognitive skills times tenure)	0.00106	0.00124	0.00105	
$C_{j(it)} \times T_{if}^2$	0.00005	0.0001	0	
(high cognitive skills times tenure squared)	0.00006	0.00007	0.00006	
w_{i0}	0.03993***		0.03957***	0.04028***
(initial wage)	0.0014		0.00141	0.00144
T_{if}	0.02349***	0.02094***	0.02200***	
(tenure)	0.00077	0.00099	0.00085	
T_{if}^2	-0.00071***	-0.00053***	-0.00068***	
(tenure squared)	0.00004	0.00005	0.00004	
$\lambda_{j(it)} \times T_{if}$ =1				0.01499*
(high social skills times tenure is one year)				0.00895
$\lambda_{j(it)} \times T_{if}$ =2				0.01199
				0.00944
$\lambda_{j(it)} \times T_{if}$ =3				0.02415**
				0.00997
$\lambda_{j(it)} \times T_{if}$ =4				0.03480***
				0.01137
$\lambda_{j(it)} \times T_{if}$ =5				0.04528***
				0.01292
$\lambda_{j(it)} \times T_{if}$ =6				0.04489***
				0.01325
$\lambda_{j(it)} \times T_{if}$ =7				0.06274***
				0.01504
$\lambda_{j(it)} \times T_{if}$ =8				0.07421***
				0.01605
$\lambda_{j(it)} \times T_{if}$ =9				0.08126***
				0.01708
$\lambda_{j(it)} \times T_{if}$ =10				0.09506***
				0.02003
$\lambda_{j(it)} \times T_{if}$ =11				0.12208***
				0.01811
$\lambda_{j(it)} \times T_{if}$ =12				0.11155***
				0.02115
$\lambda_{j(it)} \times T_{if}$ =13				0.07988***
				0.01814
$\lambda_{j(it)} \times T_{if}$ =14				0.07938***
				0.02143
$\lambda_{j(it)} \times T_{if}$ =15				0.10757***

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	(1)	(2)	(3)	(4)
				0.02066
$\lambda_{j(it)} \times T_{if}$ =16				0.10511***
				0.01366

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	(1)	(2)	(3)	(4)
$Q_{ft} \times T_{if}$ =1				0.01437
(high skills share firm times tenure is one year)				0.00899
$Q_{ft} \times T_{if}$ =2				0.00758
				0.00915
$Q_{ft} \times T_{if}$ =3				0.01416
				0.01032
$Q_{ft} \times T_{if}$ =4				0.01622
				0.01136
$Q_{ft} \times T_{if}$ =5				0.02337**
				0.01068
$Q_{ft} \times T_{if}$ =6				0.03743***
				0.01175
$Q_{ft} \times T_{if}$ =7				0.03085**
				0.01224
$Q_{ft} \times T_{if}$ =8				0.04214***
				0.01317
$Q_{ft} \times T_{if}$ =9				0.03256**
				0.01554
$Q_{ft} \times T_{if}$ =10				0.04670***
				0.01614
$Q_{ft} \times T_{if}$ =11				0.05342***
				0.01566
$Q_{ft} \times T_{if}$ =12				0.05945***
				0.01893
$Q_{ft} \times T_{if}$ =13				0.04411**
				0.02094
$Q_{ft} \times T_{if}$ =14				0.02701
				0.0224
$Q_{ft} \times T_{if}$ =15				0.04409**
				0.02212
$Q_{ft} \times T_{if}$ =16				0.05249***
				0.01274
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =1				0.02987
(high social skills times high skills share firm times tenure is one year)				0.01869
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =2				0.05848***
				0.01864
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =3				0.06852***
				0.01938
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =4				0.07322***
				0.02209
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =5				0.05292**
				0.02141
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =6				0.05158**
				0.02315
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =7				0.05257**
				0.0243
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =8				0.02727
				0.02649
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =9				0.05166*
				0.02683
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =10				0.01408
				0.03009
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =11				-0.01903
				0.02721
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =12				-0.01675
				0.03227
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =13				0.00207
				0.03385
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =14				-0.01134
				0.03587
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =15				-0.02278
				0.03558
$\lambda_{j(it)} \times Q_{ft} \times T_{if}$ =16				-0.02003
(tenure is one year)				0.02353

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	(1)	(2)	(3)	(4)
T_{if} =1				0.03138***
(tenure is one year)				0.00402
T_{if} =2				0.06556***
				0.00452
T_{if} =3				0.08309***
				0.0047
T_{if} =4				0.09777*** *
				0.00504
T_{if} =5				0.11236***
				0.00523
T_{if} =6				0.12481***
				0.0061
T_{if} =7				0.13201***
				0.00674
T_{if} =8				0.13980***
				0.00711
T_{if} =9				0.13851***
				0.0074
T_{if} =10				0.15064***
				0.00803
T_{if} =11				0.15554***
				0.00856
T_{if} =12				0.15008***
				0.00986
T_{if} =13				0.17406***
				0.00993
T_{if} =14				0.19681***
				0.00991
T_{if} =15				0.18323***
				0.00964
T_{if} =16				0.19047***
				0.00686
S_{f0}	0.00444***	0.00685***	0.00648***	0.00765***
(initial firm size)	0.00082	0.00115	0.00088	0.00085
M_i	0.05487***	0.08231***	0.05804***	0.05299***
(male)	0.00176	0.00208	0.00177	0.00186
FT_{ift}	0.09176***	0.10829***	0.09149***	0.09219***
(full-time)	0.00205	0.00232	0.00201	0.00201
P_f	0.08543***	0.08727***	0.06872***	
(public sector)	0.00356	0.00514	0.00358	
A_{it}	0.02135***	0.02205***	0.02146***	0.02262***
(experience)	0.00052	0.00064	0.00052	0.00052
A_{it}^2	-0.00076***	-0.00073***	-0.00077***	-0.00079***
(experience squared)	0.00002	0.00003	0.00002	0.00002
Constant	1.46766***	1.68788***	1.44955***	1.42528***
	0.00858	0.00917	0.0088	0.00946
R^2	0.381	0.254	0.386	0.38
Observations	114530	114530	114530	114530
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 low formal qualification requirements. Numbers are coefficients with robust standard errors in parentheses. Stars indicate * p<0.1, ** p<0.05, *** p<0.01.

D Theoretical Appendix

D.1 Equilibrium conditions

Here we show that the type of equilibrium in which there exists a cutoff value $\bar{\lambda}$ above which a revealed low κ worker will be laid off exists for suitable parameter values. To that end, we shall derive sufficient conditions for there to be a threshold $\bar{\lambda}$ such that on $\lambda > \bar{\lambda}$ jobs a firm will choose to layoff $\underline{\kappa}$ workers whereas on $\lambda \prec \bar{\lambda}$ jobs the firm will keep both types of workers (conditional on Q).

Suppose first that such a cut-off $\bar{\lambda}$ exist, and consider a $\lambda > \bar{\lambda}$ job. If a worker on that job is revealed to be of low type, then the firm's surplus if the firm keeps the worker, is equal to:

$$S^{F,\underline{\kappa}} = \lambda Q\underline{\kappa} + \mu Q - w(\lambda, n) - (1-\omega)(\lambda Q\hat{\kappa} + \mu Q),$$

where the worker's wage $w(\lambda, n)$ must be at least equal to the worker's outside option:

$$\overline{w}(\lambda, n) = \mathbb{E}\left[\lambda Q\right] \Lambda(n, \varepsilon).$$

The firm will lay off the worker if $S^{F,\underline{\kappa}} < 0$ or equivalently if

$$\lambda Q\underline{\kappa} + \mu Q + \overline{w}(\lambda, n) - (1-\omega)(\lambda Q\hat{\kappa} + \mu Q) < 0,$$

which boils down to:

$$\lambda > \underbrace{\frac{\mu\omega + \Lambda(n,\varepsilon)\mathbb{E}[\lambda Q]/Q}{(1-\omega)\hat{\kappa} - \underline{\kappa}}}_{\equiv\bar{\lambda}}$$

In order for this threshold to be well defined, we need that $(1-\omega)\hat{\kappa}$ to be larger than $\underline{\kappa}$ which in turn holds if:

$$\frac{\overline{\kappa}}{\underline{\kappa}} > 1 + \frac{\omega}{p(1-\omega)} \tag{11}$$

Now assume that no cut-off $\bar{\lambda}$ exists: then, either all workers are retained by the firm no matter the firm's signal about their κ's or none of them are retained by the firm. In either case, the market cannot infer any information about a worker's κ from observing the worker's tenure n. This in turn implies that a worker's outside option wage is equal to:

$$\overline{w} = \mathbb{E}[\lambda Q]\hat{\kappa}$$

For an equilibrium with no cut-off $\bar{\lambda}$ to exist, it must be the case that the firm's surplus from a worker which is signaled to be $\underline{\kappa}$ on any λ job, namely

$$S^{F,\underline{\kappa}} = \frac{1}{2}\left[\lambda Q \underbrace{(\underline{\kappa} - (1-\omega)\hat{\kappa})}_{<0} + \omega\mu Q + \mathbb{E}[\lambda Q]\hat{\kappa}\right],$$

be positive for all λ, or negative for all λ. Since $S^{F,\underline{\kappa}}$is a decreasing function of λ. This in turn will *not* be the case if one simple is that $S^{F,\underline{\kappa}}$ is strictly positive for $\lambda = 0$ (which it is clearly) and strictly negative for $\lambda = 1$ which requires:

$$\omega \mu Q + \mathbb{E}[\lambda Q]\hat{\kappa} > (1 - \omega)\hat{\kappa} - \underline{\kappa} \tag{12}$$

The fact that conditions (11) and (12) together define a non-empty set of parameter values, establishes our claim.