

Wage Progression of Low Skill Workers: The Role of Soft Skills and Firms

ESCoE Conference on Economic Measurement 2021

Richard Blundell

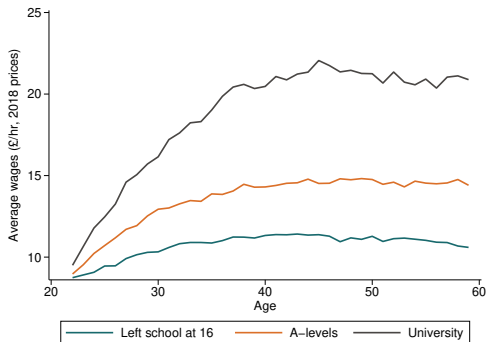
(University College London and Institute for Fiscal Studies)

joint work with Philippe Aghion (College de France and LSE),
Antonin Bergeaud (Banque de France),
and Rachel Griffith (University of Manchester and IFS)

May 11, 2021

Wage progression - it's depressing at the bottom!

- Low-wage and low-educated workers experience **little wage progression**

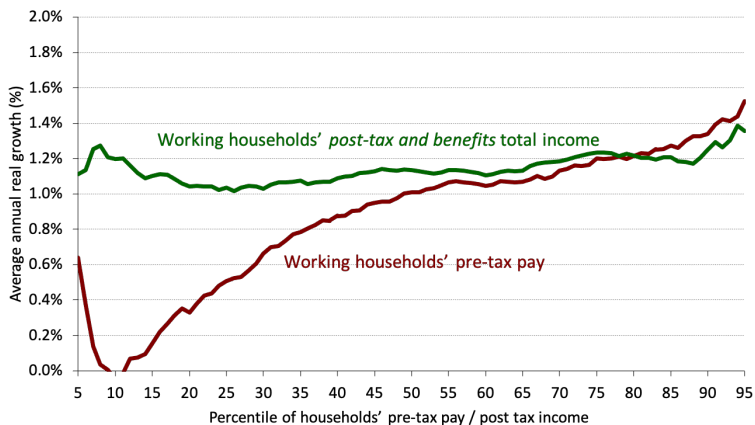


Source: BHPS and USoc, 1992-2016, authors' calculations.

- Employment is increasingly **not enough to move families out of poverty or for longer run self-sufficiency.**

Tax credits and benefits have boosted incomes at the bottom, until recently

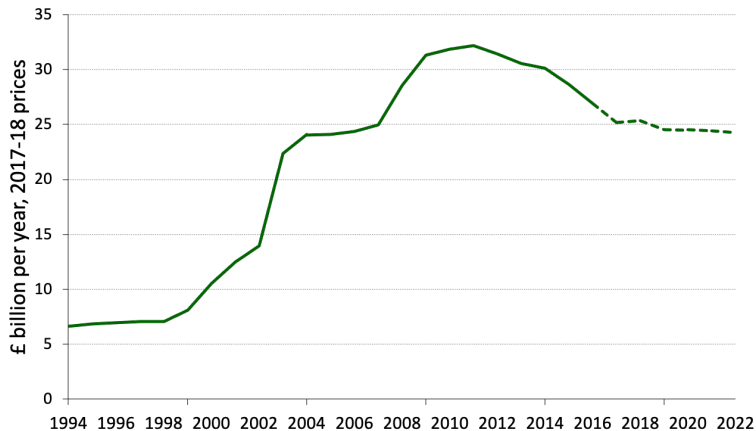
Household income growth for working households in UK 1994/5 to 2016/7



Source: Blundell, Joyce, Norris Keiller and Ziliak (2018)

* Minimum wages can help but also do little for wage progression

Real spending on working-age benefits



Source: IFS calculations from DWP (UK) benefit expenditure tables

Wage progression is a key issue for labour market inequality

- Differential progression over the working life is a central part of the story about labour market inequality and concerns about it (EWCS).
- Understanding the determinants of progression also has important policy implications.
 - ① The role of education, labour market attachment/part-time work, and gender.
 - ② The role of human capital investments during working life - learning-by-doing and (access to) on-the-job training.
 - ③ The role of firms - what attributes among the lower educated are valued by firms and which types of firms value them most - soft skills?
- Here we focus on (3), building on earlier work on wage progression and exploiting the employer-employee matched data to investigate the role of soft skills.
- Develop a "good jobs" agenda to examine an appropriate policy mix.
- The issue of wage progression and good jobs for the lower educated has become even more urgent for the post-covid labour market.

Wage progression is a key issue for labour market inequality

- Differential progression over the working life is a central part of the story about labour market inequality and concerns about it (EWCS).
- Understanding the determinants of progression also has important policy implications.
 - ① The role of education, labour market attachment/part-time work, and gender.
 - ② The role of human capital investments during working life - learning-by-doing and (access to) on-the-job training.
 - ③ The role of firms - what attributes among the lower educated are valued by firms and which types of firms value them most - soft skills?
- Here we focus on (3), building on earlier work on wage progression and exploiting the employer-employee matched data to investigate the role of soft skills.
- Develop a "good jobs" agenda to examine an appropriate policy mix.
- The issue of wage progression and good jobs for the lower educated has become even more urgent for the post-covid labour market.

Wage progression is a key issue for labour market inequality

- Differential progression over the working life is a central part of the story about labour market inequality and concerns about it (EWCS).
- Understanding the determinants of progression also has important policy implications.
 - ① The role of education, labour market attachment/part-time work, and gender.
 - ② The role of human capital investments during working life - learning-by-doing and (access to) on-the-job training.
 - ③ The role of firms - what attributes among the lower educated are valued by firms and which types of firms value them most - soft skills?
- Here we focus on (3), building on earlier work on wage progression and exploiting the employer-employee matched data to investigate the role of soft skills.
- Develop a "good jobs" agenda to examine an appropriate policy mix.
- The issue of wage progression and good jobs for the lower educated has become even more urgent for the post-covid labour market.

Our contribution

- Our earlier research on UKHLS found that **some lower educated workers do see wage progression**.
- Dig deeper into why and ask: **Do firms matter and what skills bring largest returns?**
- High quality **linked firm-worker panel data** allows us to understand patterns of wage progression, and learn about what drives them.
- We draw on two broad literatures:
 - task content of jobs is key to understanding labour market dynamics (e.g. Autor, Levy, Murane (2003), Acemoglu and Autor (2011))
 - what are the **tasks** and **skills** that firms value in workers in low-educated occupations? how important are **soft skills** for low-educated workers?
 - the firm match is important in explaining differences in pay and pay growth, even when we compare observationally similar workers (e.g. Abowd, Kramatz and Margolis (1999), Card (various))
 - we drill down to see what are the characteristics of the **occupations** and **firms** in which workers in low-educated jobs do well
- Ultimately we want to ask: what are the **potential policy levers** to improve pay progression for low-wage/low-educated workers?

Our contribution

- Our earlier research on UKHLS found that **some lower educated workers do see wage progression**.
- Dig deeper into why and ask: **Do firms matter and what skills bring largest returns?**
- High quality **linked firm-worker panel data** allows us to understand patterns of wage progression, and learn about what drives them.
- We draw on two broad literatures:
 - task content of jobs is key to understanding labour market dynamics (e.g. Autor, Levy, Murane (2003), Acemoglu and Autor (2011))
 - what are the **tasks** and **skills** that firms value in workers in low-educated occupations? how important are **soft skills** for low-educated workers?
 - the firm match is important in explaining differences in pay and pay growth, even when we compare observationally similar workers (e.g. Abowd, Kramatz and Margolis (1999), Card (various))
 - we drill down to see what are the characteristics of the **occupations** and **firms** in which workers in low-educated jobs do well
- Ultimately we want to ask: what are the **potential policy levers** to improve pay progression for low-wage/low-educated workers?

Our contribution

- Our earlier research on UKHLS found that **some lower educated workers do see wage progression**.
- Dig deeper into why and ask: **Do firms matter and what skills bring largest returns?**
- High quality **linked firm-worker panel data** allows us to understand patterns of wage progression, and learn about what drives them.
- We draw on two broad literatures:
 - task content of jobs is key to understanding labour market dynamics (e.g. Autor, Levy, Murane (2003), Acemoglu and Autor (2011))
 - what are the **tasks** and **skills** that firms value in workers in low-educated occupations? how important are **soft skills** for low-educated workers?
 - the firm match is important in explaining differences in pay and pay growth, even when we compare observationally similar workers (e.g. Abowd, Kramatz and Margolis (1999), Card (various))
 - we drill down to see what are the characteristics of the **occupations** and **firms** in which workers in low-educated jobs do well
- Ultimately we want to ask: what are the **potential policy levers** to improve pay progression for low-wage/low-educated workers?

Summary

- We show evidence that workers in low-educated occupations
 - get higher returns to experience in occupations where **soft skills** are important than workers in other low-educated occupations
 - these jobs are more common, and workers experience higher wage progression, in **more innovative firms** and **firms with a large share of higher educated workers**.
- In order to help us understand the possible channels (and thus inform policy) we develop (in the paper) a model that is consistent with the data
 - our interpretation is that these workers are **complementarity** to the firms other assets, in particular high-educated (high wage) workers
 - for workers in some low-educated occupations, soft skills form a large part of their abilities
 - **soft skills are difficult to observe** (for the employer and us)
 - this means that firm wants to **keep and train** workers with these skills
 - workers capture some of the surplus of the firm, and **drives returns to experience**

Summary

- We show evidence that workers in low-educated occupations
 - get higher returns to experience in occupations where **soft skills** are important than workers in other low-educated occupations
 - these jobs are more common, and workers experience higher wage progression, in **more innovative firms** and **firms with a large share of higher educated workers**.
- In order to help us understand the possible channels (and thus inform policy) we develop (in the paper) a model that is consistent with the data
 - our interpretation is that these workers are **complementarity** to the firms other assets, in particular high-educated (high wage) workers
 - for workers in some low-educated occupations, soft skills form a large part of their abilities
 - **soft skills are difficult to observe** (for the employer and us)
 - this means that firm wants to **keep and train** workers with these skills
 - workers capture some of the surplus of the firm, and **drives returns to experience**

Matched worker-firm data for the UK 2004 - 2019

- **Workers**
 - Annual Survey of Hours and Earning (ASHE)
- **Firms**
 - Annual Respondents Database (ARD)
 - Business Enterprise Research and Development (BERD)
- **Nature of occupations**
 - O*NET
 - Regulatory Qualifications Framework (RQF)

For robustness

- Labour Force Survey (LFS) on workers
- European Working Conditions Survey (EWCS) on occupations

Annual Survey of Hours and Earning (ASHE)

- 1% random sample of UK based workers
- panel data, collected from firms based on tax records
- wages, hours and earnings, including bonuses and incentive pay
- firm identifier allowing match with firm data
- no data on individual's education or skills
- our baseline sample - males aged 18-49, for the period 2004-2019.

Labour Force Survey (LFS)

- household survey, @ 35,000 households per quarter
- information on individual's education, skills
- some information on training
- mainly cross-section, no firm identifier

Annual Respondents Database (ARD)

- census of data on firm structure, location and employment
- census of production activities for firms with 250+ employees
- random stratified sample for smaller firms
- we use information on jobs in incorporated firms (excluding the public sector and private firms)

Business Enterprise Research and Development (BERD)

- Research and Development (R&D) expenditure
- census of firms with 400+ employees (70% of R&D)
- random stratified sample for smaller firms

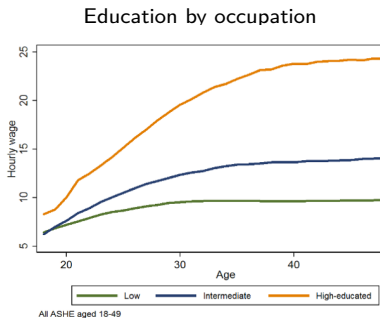
Education level by occupation

ASHE does not include data on individual's education; we use the **Regulatory Qualification Framework (RQF)**, by Ofqual.

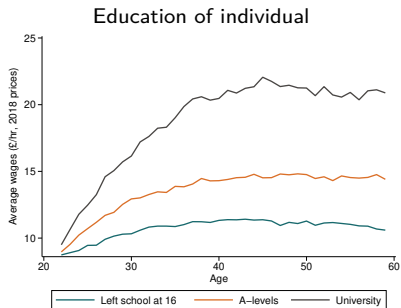
Use Appendix J which defines the education level required for each 4-digit occupation for immigration purposes.

- **Low-educated**, no formal qualifications necessary
 - operatives, assemblers, clerical, secretaries, cleaners, security drivers, technicians, sales
- **Medium-educated**, typically requires A-level or some basic professional qualification
 - trades, specialist clerical, associate professionals, medical or IT technicians, some managerial occupations
- **High-educated**, typically required higher education or an advanced professional qualification
 - most managerial and executive occupations, engineers, scientists, R&D manager, bankers, other professions

Wage progression by education level of occupation is similar to progression by education of individuals



Source: ASHE



Source: BHPS and USoc

Data on task and skill content of occupations

We use O*NET to identify the task and skill content of occupations.

- O*NET data describes the mix of knowledge, skills and abilities required in an occupation and the activities and tasks performed,
- We work at the 4-digit SOC 2010 occupation level, this includes 361 occupations, 124 of which are low-educated occupations.

The aims of O*NET are to provide

- individuals with information about the nature of different occupations to help them make job, education and training decisions
- firms and policymakers with standardised information about the skill requirements of occupations, and to help in decisions about training
- researchers to undertake research on the nature of work

We combine 10 items in O*NET to create a single index of importance of soft skills.

Data on task and skill content of occupations

We use O*NET to identify the task and skill content of occupations.

- O*NET data describes the mix of knowledge, skills and abilities required in an occupation and the activities and tasks performed,
- We work at the 4-digit SOC 2010 occupation level, this includes 361 occupations, 124 of which are low-educated occupations.

The aims of O*NET are to provide

- individuals with information about the nature of different occupations to help them make job, education and training decisions
- firms and policymakers with standardised information about the skill requirements of occupations, and to help in decisions about training
- researchers to undertake research on the nature of work

We combine 10 items in O*NET to create a single index of importance of soft skills.

Data on task and skill content of occupations

We use O*NET to identify the task and skill content of occupations.

- O*NET data describes the mix of knowledge, skills and abilities required in an occupation and the activities and tasks performed,
- We work at the 4-digit SOC 2010 occupation level, this includes 361 occupations, 124 of which are low-educated occupations.

The aims of O*NET are to provide

- individuals with information about the nature of different occupations to help them make job, education and training decisions
- firms and policymakers with standardised information about the skill requirements of occupations, and to help in decisions about training
- researchers to undertake research on the nature of work

We combine 10 items in O*NET to create a single index of importance of soft skills.

- ➊ **Problem Sensitivity:** how big is the worker's ability to tell when something is wrong or is likely to go wrong?
- ➋ **Active listening:** to which extent does the worker devote full attention to what other parties are saying?
- ➌ **Social Perceptiveness:** to which extent is the worker aware of other parties' reactions ?
- ➍ **Coordination:** to which extent does the worker adjust her actions to the actions taken by the other parties?
- ➎ **Work With Work Group or Team:** How important is it to work with others in a group or team in this job?
- ➏ **Coordinate or Lead Others:** How important is it to coordinate or lead others in accomplishing work activities in this job?
- ➐ **Responsibility for Outcomes and Results:** How responsible is the worker for work outcomes and results of other workers?
- ➑ **Consequence of Error:** how serious would the result usually be if the worker made a mistake that was not readily correctable?
- ➒ **Importance of Being Exact or Accurate:** How important is being very exact or highly accurate in performing this job?
- ➓ **Impact of Decisions on Co-workers or Company Results:** What results do your decisions usually have on other people or the reputation of employer?

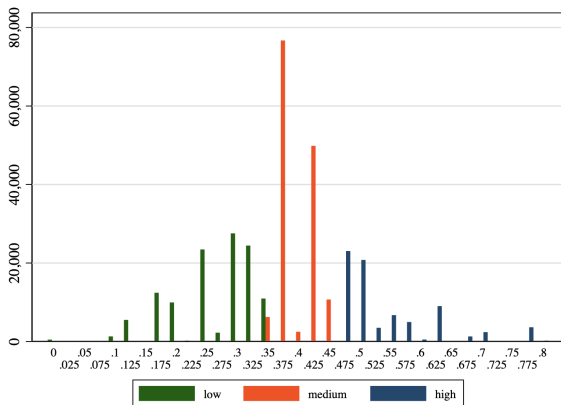
We create a single index of the importance of soft skills

- The O*NET data is available at the US occupation level
- We match to UK 4-digit occupations, at one point in time (so no within occupation variation)
- We use principle components analysis to combine into a single index
 - normalise to $[0,1]$
 - we refer to this as "lambda" (λ), a measure of "soft skills"
- We descretise this into terciles, dividing the UK workforce in low-educated occupations into three equal bins
 - this defines occupations as low, medium or high λ

▶ Comparison of individual components

Distribution of workers in low-educated occupations by λ

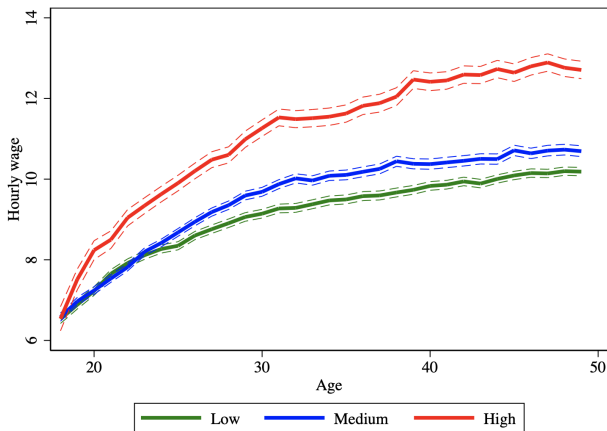
Men aged 18-49 in private sector firms with 400 or more employees



Source: Authors' calculations using O*NET and ONS employment data. 339,911 observations on 92,427 employees who work in 46,538 firms.

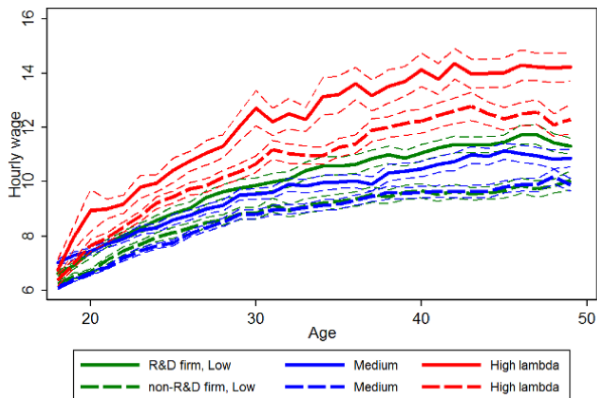
More wage progression for workers in high λ occupations

low-educated occupations only



Notes: Data from Annual Survey of Hours and Employment (ASHE) 2004-2019. Figure shows average hourly wage at each age for male workers in private sector firms in occupations with low-educational requirements categorised by the measure of the importance of soft-skills.

Wage premium higher in innovative firms



Sample is male workers aged 18-49 in low-educated occupations in private firms with 400+ employees

Source: Authors' calculations using ASHE, 2004-2018

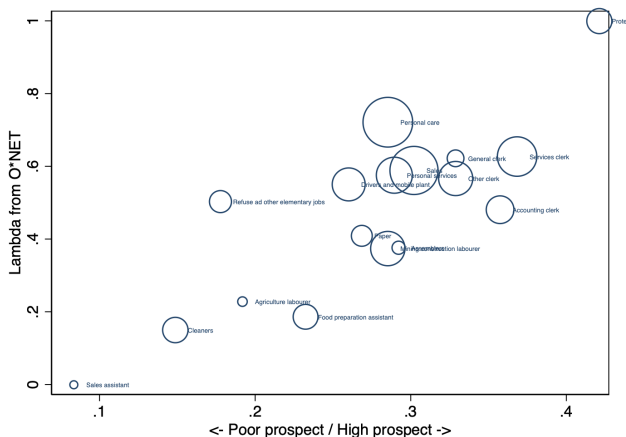
Does lambda identify “good jobs”?

European Working Conditions Survey (EWCS)

- interview @ 43,000 workers in 35 countries
 - we use data from Belgium, Denmark, Germany Spain, France, Ireland, Italy, Luxembourg, Netherlands, Austria, Portugal, Finland, Sweden, UK, Norway, and Switzerland
- we use 2015 survey
- we match EWCS to O*NET
 - EWCS is at the 2-digit ISCO80 level
 - we recalculate λ at the 2-digit ISCO80 level
- EWCS participants are asked to indicate on a Likert scale:
 - My job offers good prospects for career advancement.
 - On the whole, are you satisfied with working conditions?
 - I am enthusiastic about my job.
 - I doubt the importance of my work.

My job offers good prospects for career advancement

low-educated occupations

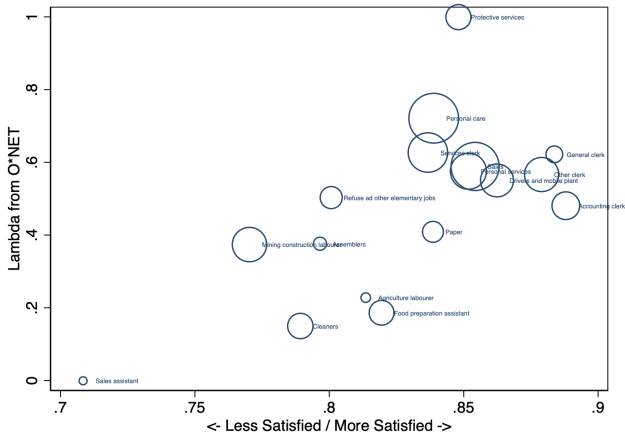


Source: Authors' calculations using EWCS, 2015.

Each dot is a 2-digit occupation, scaled by UK employment.

On the whole, are you satisfied with working conditions?

low-educated occupations

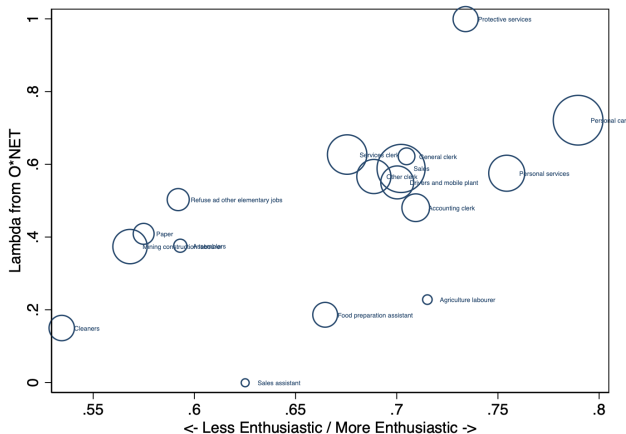


Source: Authors' calculations using EWCS, 2015.

Each dot is a 2-digit occupation, scaled by UK employment.

Enthusiasm for job

low-educated occupations

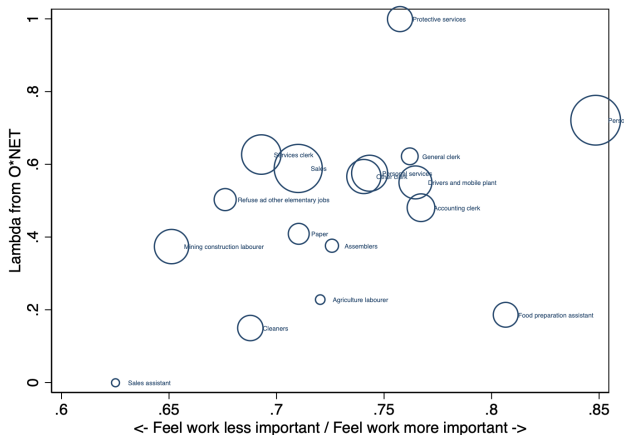


Source: Authors' calculations using EWCS, 2015.

Each dot is a 2-digit occupation, scaled by UK employment.

I doubt the importance of my work

low-educated occupations



Source: Authors' calculations using EWCS, 2015.

Each dot is a 2-digit occupation, scaled by UK employment.

Firms employ

- an asset of quality Q , e.g. high-educated workers
- combines with tasks, each of which is performed by a different worker in a low-educated occupation of quality q
 - q_L : quality of an outside worker hired on that task

A task is a pair $(\mu, q_L) = \Gamma$

- $\mu \in [0, 1]$ measures degree of complementarity between the task and qualities of the firm's asset Q
 - $\mu = 0$ fully substitutable
 - $\mu = 1$ fully complementary
 - higher μ corresponds to a task that requires higher soft skills

Output produced on that task is assumed to be determined by the following O-Ring production function (Kremer 1993, Kremer and Maskin 1996):

$$f(\mu, q, Q) = \mu q Q + (1 - \mu)(q + Q)$$

Model implications for wage progression

In some low-educated occupations workers are complementary to the firms other assets.

Returns to experience are driven by the soft skills that are valuable to the firm because they are complementary with other assets, - but soft skills are difficult to observe, both for employer and for us.

Hard skills still matter but are more easily observable and verifiable, e.g. formal qualifications. For workers in these occupations, soft skills form a large proportion of their abilities and are important in determining wages.

Main predictions:

- 1 a higher wage premium for low-educated workers in higher- λ jobs,
- 2 low-educated workers in higher- λ jobs receive more training by the firm,
- 3 the wage premium for low-educated workers increases faster in higher- λ jobs in more skill-intensive or more innovative firms.

Model implications for wage progression

In some low-educated occupations workers are complementary to the firm's other assets.

Returns to experience are driven by the soft skills that are valuable to the firm because they are complementary with other assets, - but soft skills are difficult to observe, both for employer and for us.

Hard skills still matter but are more easily observable and verifiable, e.g. formal qualifications. For workers in these occupations, soft skills form a large proportion of their abilities and are important in determining wages.

Main predictions:

- 1 a higher wage premium for low-educated workers in higher- λ jobs,
- 2 low-educated workers in higher- λ jobs receive more training by the firm,
- 3 the wage premium for low-educated workers increases faster in higher- λ jobs in more skill-intensive or more innovative firms.

A panel data framework

Each worker will have a different ability to perform the soft skill tasks that comprise high- λ occupations, depending on their own level of soft-skills.

Let κ_i be the *potential* level of soft-skills of worker i , and λ_j be a binary indicator selecting "high- λ occupations".

The **log wage** of a worker i in occupation j in firm f at time t is

$$\ln w_{ijft} = \phi_f(\kappa_i, \lambda_j, T_{if}) + g(A_{it}, FT_{if}, S_{ft}, T_{if}) + \gamma_i + \eta_t + e_{ijft}$$

where $\phi_f(\kappa_i, \lambda_j, T_{if})$ is the return to tenure T_{if} in high- λ occupations.

$g(A_{it}, FT_{if}, S_{ft}, T_{if})$ is a flexible function of worker age A , a binary indicator FT equal to one if the worker is in full time employment, the size of the firm (number of employees) S , and the tenure T in the firm.

γ_i , η_t and e_{ijft} represent unobserved individual heterogeneity, time effects and transitory shocks, respectively.

A panel data framework

Each worker will have a different ability to perform the soft skill tasks that comprise high- λ occupations, depending on their own level of soft-skills.

Let κ_i be the *potential* level of soft-skills of worker i , and λ_j be a binary indicator selecting "high- λ occupations".

The **log wage** of a worker i in occupation j in firm f at time t is

$$\ln w_{ijft} = \phi_f(\kappa_i, \lambda_j, T_{if}) + g(A_{it}, FT_{if}, S_{ft}, T_{if}) + \gamma_i + \eta_t + e_{ijft}$$

where $\phi_f(\kappa_i, \lambda_j, T_{if})$ is the return to tenure T_{if} in high- λ occupations.

$g(A_{it}, FT_{if}, S_{ft}, T_{if})$ is a flexible function of worker age A , a binary indicator FT equal to one if the worker is in full time employment, the size of the firm (number of employees) S , and the tenure T in the firm.

γ_i , η_t and e_{ijft} represent unobserved individual heterogeneity, time effects and transitory shocks, respectively.

The leading term $\phi_f(\kappa_i, \lambda_j, T_{if})$ in the log wage equation measures the part of the joint surplus recovered by i in firm f working in a high- λ occupation "j".

We write this surplus term as:

$$\phi(\kappa_i, \lambda_j, T_{if}) = \alpha_1 \kappa_i \lambda_j + \alpha_2 \kappa_i k(T_{if}) \lambda_j. \quad (1)$$

which generates our log wage specification:

$$\ln w_{ifft} = \alpha_1 \kappa_i \lambda_j + \alpha_2 \kappa_i k(T_{if}) \lambda_j + g(A_{it}, FT_{if}, S_f, T_{if}) + \gamma_i + \eta_t + e_{ifft} \quad (2)$$

which contains two dimensions of unobserved heterogeneity κ_i and γ_i .

After controlling for individual worker effects γ_i , the estimated coefficients will identify the average over workers selected on their soft skills, that is

$$\alpha_1 \mathbb{E}(\kappa_i | T_{if} = 0, i \in j) \quad \text{and} \quad \alpha_2 \mathbb{E}(\kappa_i | T_{if}, i \in j) k(T_{if})$$

The later term shows the degree to which workers with higher soft skills experience higher wage progression with tenure.

The leading term $\phi_f(\kappa_i, \lambda_j, T_{if})$ in the log wage equation measures the part of the joint surplus recovered by i in firm f working in a high- λ occupation "j".

We write this surplus term as:

$$\phi(\kappa_i, \lambda_j, T_{if}) = \alpha_1 \kappa_i \lambda_j + \alpha_2 \kappa_i k(T_{if}) \lambda_j. \quad (1)$$

which generates our log wage specification:

$$\ln w_{ijft} = \alpha_1 \kappa_i \lambda_j + \alpha_2 \kappa_i k(T_{if}) \lambda_j + g(A_{it}, FT_{if}, S_f, T_{if}) + \gamma_i + \eta_t + e_{ijft} \quad (2)$$

which contains two dimensions of unobserved heterogeneity κ_i and γ_i .

After controlling for individual worker effects γ_i , the estimated coefficients will identify the average over workers selected on their soft skills, that is

$$\alpha_1 \mathbb{E}(\kappa_i | T_{if} = 0, i \in j) \quad \text{and} \quad \alpha_2 \mathbb{E}(\kappa_i | T_{if}, i \in j) k(T_{if})$$

The later term shows the degree to which workers with higher soft skills experience higher wage progression with tenure.

The leading term $\phi_f(\kappa_i, \lambda_j, T_{if})$ in the log wage equation measures the part of the joint surplus recovered by i in firm f working in a high- λ occupation "j".

We write this surplus term as:

$$\phi(\kappa_i, \lambda_j, T_{if}) = \alpha_1 \kappa_i \lambda_j + \alpha_2 \kappa_i k(T_{if}) \lambda_j. \quad (1)$$

which generates our log wage specification:

$$\ln w_{ijft} = \alpha_1 \kappa_i \lambda_j + \alpha_2 \kappa_i k(T_{if}) \lambda_j + g(A_{it}, FT_{if}, S_f, T_{if}) + \gamma_i + \eta_t + e_{ijft} \quad (2)$$

which contains two dimensions of unobserved heterogeneity κ_i and γ_i .

After controlling for individual worker effects γ_i , the estimated coefficients will identify the average over workers selected on their soft skills, that is

$$\alpha_1 \mathbb{E}(\kappa_i | T_{if} = 0, i \in j) \quad \text{and} \quad \alpha_2 \mathbb{E}(\kappa_i | T_{if}, i \in j) k(T_{if})$$

The later term shows the degree to which workers with higher soft skills experience higher wage progression with tenure.

Returns to soft skills

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

| | | | | |
|---------------------------|-----------------------|-----------------------|-----------------------|------------------------------|
| High lambda | 0.1387*** (0.0022) | 0.0869*** (0.0032) | 0.0330*** (0.0032) | 0.0613*** (0.0023) |
| x tenure | | 0.0073*** (0.0004) | 0.0013*** (0.0005) | 0.0036*** (0.0003) |
| x tenure 0-5 years | | 0.0079*** (0.0009) | 0.0057*** (0.0006) | 0.0085*** (0.0008) |
| initial wage | | | | 0.0459*** (0.0009) |

Controls for age, tenure, tenure-squared, gender, full/part-time, firm size

| | | | | |
|----------------|---------|---------|---------|---------|
| TTW-Occ-Year | ✓ | ✓ | ✓ | ✓ |
| TTW-Year | | | | ✓ |
| Year effects | | | ✓ | |
| Worker effects | | | ✓ | |
| R^2 | 0.241 | 0.248 | 0.347 | 0.439 |
| Observations | 339,911 | 339,911 | 339,911 | 339,911 |

Notes: Authors' calculations using ASHE-BERD, 2004-2019. Sample is male workers aged 18-49 in low-educated occupations in private sector firms. Numbers are coefficients with robust standard errors in parentheses. Travel To Work (TTW) times year, or TTW time 2-digit occupation times year are included as indicated. Stars indicate * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Adding innovativeness and other firm-level factors

The model predicts that the positive effect on wages and wage progression for workers in low-educated occupations should **increase with the quality of the other assets in the firm**. This may refer to the high-educated workers in the firm, or to the innovativeness of the firm.

- To explore this we allow the wage progression associated with soft skills to vary with measures of the quality of **workers in high-educated occupations, and the R&D intensity of the firm**.

We add the term:

$$\alpha_3 R_{ft} \lambda_j + \alpha_4 k(T_{ift}) R_{ft} \lambda_j \quad (3)$$

where R_{ft} denotes either the quality of the workers in high-educated occupations in firm f or whether firm f does R&D.

- We also include a term in the level of R_{ft} .

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

| | | | |
|------------------------------------|------------------------------|------------------------------|------------------------------|
| High lambda | 0.0659*** (0.0034) | 0.0321** (0.0054) | 0.0670*** (0.0035) |
| x tenure | 0.0037*** (0.0003) | 0.0020*** (0.0004) | 0.0041*** (0.0003) |
| x tenure 0-5 years | 0.0095*** (0.0010) | 0.0044*** (0.0009) | 0.0080*** (0.0012) |
| x RD firm | | 0.0032 (0.0065) | 0.0076 (0.0051) |
| x tenure 0-5 years x RDfirm | | 0.0032* (0.0017) | 0.0045*** (0.0021) |
| RD firms | | 0.0408*** (0.0033) | 0.0427*** (0.0022) |
| tenure x RD firm | | -0.0024*** (0.0004) | -0.0002 (0.0003) |

Controls for age, tenure, tenure-squared, gender, full/part-time, firm size

| | | | |
|----------------|---------|---------|---------|
| Initial wage | ✓ | | ✓ |
| TTW-Occ-Year | ✓ | | ✓ |
| Year | | ✓ | |
| Worker effects | | ✓ | |
| R^2 | 0.364 | 0.342 | 0.367 |
| Observations | 212,428 | 212,428 | 212,428 |

Notes: Authors' calculations using ASHE-BERD, 2004-2019. Numbers are coefficients with robust standard errors in parentheses. Travel To Work (TTW) times year, or TTW time 2-digit occupation times year are included as indicated. Stars indicate * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

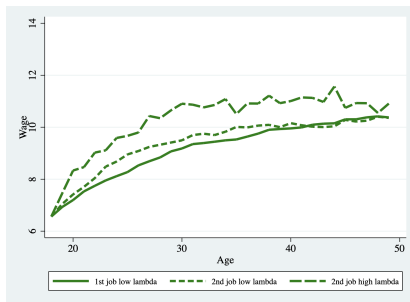
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---------------------|-----------------------|------------------------|------------------------|-----------------------|-----------------------|------------------------|-----------------------|
| High- λ | 0.0055 (0.0041) | 0.0321** (0.0049) | 0.0145*** (0.0043) | 0.0281*** (0.0046) | 0.0018*** (0.0041) | 0.0323*** (0.0049) | 0.0104** (0.0043) |
| × T | 0.0037*** (0.0003) | 0.0020*** (0.0004) | 0.0041*** (0.0003) | 0.0022*** (0.0004) | 0.0032*** (0.0003) | 0.0021*** (0.0004) | 0.0036*** (0.0003) |
| × T(0-5) | 0.0095*** (0.0010) | 0.0044*** (0.0009) | 0.0080*** (0.0012) | 0.0051*** (0.0008) | 0.0082*** (0.0010) | 0.0039*** (0.0010) | 0.0065*** (0.0012) |
| × R | | -0.0029 (0.0059) | -0.0215*** (0.0049) | | | -0.00735 (0.0061) | -0.0192 (0.0049) |
| × T(0-5) × R | | 0.0032* (0.0017) | 0.0045** (0.0021) | | | 0.0034* (0.0017) | 0.0052** (0.0021) |
| × high-ed | | | | 0.0026*** (0.0006) | 0.0040*** (0.0005) | 0.0027*** (0.0006) | 0.0042*** (0.0005) |
| × T(0-5) × high-ed | | | | 0.0003* (0.0001) | 0.0005*** (0.0002) | 0.0003*** (0.0001) | 0.0005*** (0.0002) |
| R | | 0.0408*** (0.0033) | 0.0427*** (0.0022) | | | 0.0386*** (0.0034) | 0.0378*** (0.0023) |
| × T | | -0.0024*** (0.0003) | 0.0003 (0.0002) | | | -0.0023*** (0.0004) | 0.0005** (0.0003) |
| high-ed | | | | 0.0031*** (0.0003) | 0.0040*** (0.0002) | 0.0029 (0.0003) | 0.0038 (0.0002) |
| × T | | | | 0.0000 (0.00004) | 0.00002 (0.00002) | 0.00001 (0.00004) | 0.00003 (0.00002) |
| TTW-Occupation-Year | ✓ | | ✓ | | ✓ | | ✓ |
| Worker effects | | ✓ | | ✓ | | ✓ | |
| Year effects | | ✓ | | ✓ | | ✓ | |
| R^2 | 0.364 | 0.342 | 0.367 | 0.343 | 0.373 | 0.344 | 0.376 |
| Observations | 212,428 | 212,428 | 212,428 | 198,479 | 198,479 | 198,479 | 198,479 |

Notes: Authors' calculations using ASHE-BERD, 2004-2019. Numbers are coefficients with robust standard errors in parentheses. Travel To Work (TTW) times year, or TTW time 2-digit occupation times year are included as indicated. Stars indicate * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

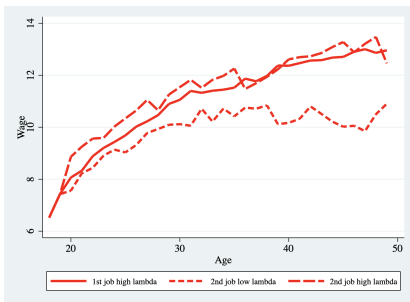
- Include time interactions with λ [▶ Evidence](#)
- Control for other task based indicators of occupations from
 - Acemoglu and Autor (2011) [▶ Evidence](#)
 - Fortin and Lemieux (2016) [▶ Evidence](#)
 - Cortes, Jaimovich and Siu (2020) [▶ Evidence](#)
- Use only first job [▶ Evidence](#)

Importance of first job

(a) 1st job low λ

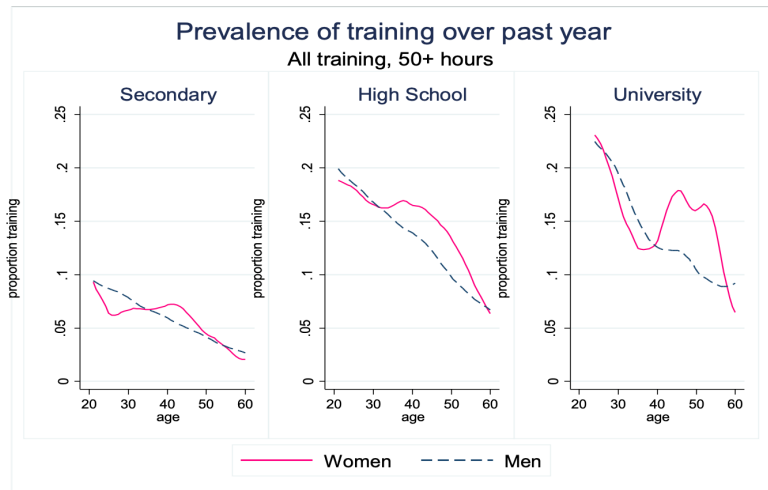


(b) 1st job high λ



Notes: Data is from ASHE 2004-2019. The figure uses wages for males working in private sector firms in their first and second job (observed in that period).

Training by Education and Gender in the UK



Source: Blundell, Costa-Dias, Goll and Meghir (2021), Notes: UK HLS

Workers in high λ occupations get more training

Data from LFS on training of individual workers

| | Lambda of occupation | | diff |
|--|----------------------|----------------|------------------|
| | below median | above median | |
| Whether employer has offered training | 13.9 (0.17) | 15.7 (0.18) | 1.7*** (0.24) |
| In education or training (of any kind) | 9.5 (0.12) | 10.9 (0.13) | 1.5*** (0.18) |
| Training during work | 4.9 (0.29) | 5.8 (0.31) | 0.9*** (0.42) |

Source: Authors' calculations using LFS, 2011-2016, males 18-49 in low-skilled occupations in private firms with 400+ employees. Stars indicate * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

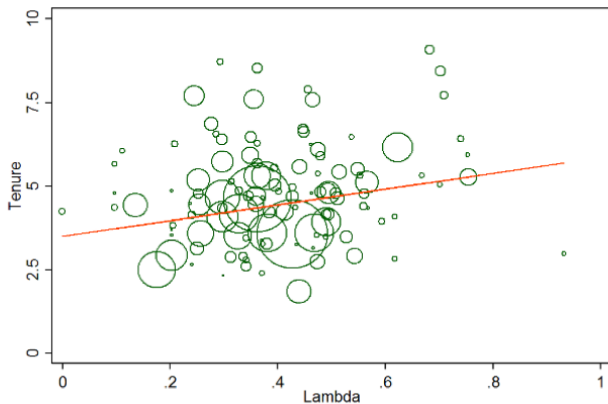
Over the past 12 months, have you undergone any training paid for or provided by your employer?

Data from EWCS on individual European workers



Source: Authors' calculations using EWCS, 2015

Workers in high λ occupations have longer tenure



Sample is male workers aged 18-49 in low-educated occupations in private firms.

Source: Authors' calculations using ASHE-BERD, 2004-2018

Further Robustness

- non-discrete λ ▶ Evidence
- comparison with high-educated occupations ▶ Evidence
- outsourcing ▶ (weak) Evidence
- non-discrete R&D ▶ Evidence (not yet available)
- other measures of wages ▶ Evidence (not yet available)
- including females ▶ Evidence (not yet available)

Summary and Conclusions

Our earlier research found **little overall earnings progression for lower educated workers** - employment alone is (increasingly) not enough to escape poverty and low earnings

- diverging wage profiles by education and by part-time work,
- low rates of on-the-job training for lower educated workers.

But **some lower educated workers experience higher wage progression** - we find this (partly) reflects the value of soft skills.

- these workers see more training and longer tenures,
- more likely to occur in innovative firms and firms with a larger share of higher educated.
- Also find workers in soft skill occupations are less likely to be out-sourced, look at cleaners as a case study.
- Robust to including a variety of other skill measurements and to including time interactions with high (top tercile of) lambda.
- Soft skills impact on progression appear even larger for women.

Summary and Conclusions

Our earlier research found **little overall earnings progression for lower educated workers** - employment alone is (increasingly) not enough to escape poverty and low earnings

- diverging wage profiles by education and by part-time work,
- low rates of on-the-job training for lower educated workers.

But **some lower educated workers experience higher wage progression** - we find this (partly) reflects the value of soft skills.

- these workers see more training and longer tenures,
- more likely to occur in innovative firms and firms with a larger share of higher educated.
- Also find workers in soft skill occupations are less likely to be out-sourced, look at cleaners as a case study.
- Robust to including a variety of other skill measurements and to including time interactions with high (top tercile of) lambda.
- Soft skills impact on progression appear even larger for women.

The Policy Mix

Earned income tax credits and minimum wages?

- offset adverse means-testing, encourage employment, well-targeted to low earning families but little wage progression.
- min wages are less well-targeted, little incentive for wage progression, should be a complement to other policies.

Human capital/training?

- focus on firm-based accredited training for lower educated, emphasis on firm match and "soft skills", more likely to attract training and less likely to be out-sourced; a "good jobs" policy agenda.
- increasing (solo) self-employment among lower educated workers, line up benefit eligibility, training, min wage and effective tax rates.

Place-based policies?

- policies to attract R&D firms and firms that employ a mix of educational groups, hand-in-hand with human capital policies.
- policies to reverse educational flight.