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

ESCoE Conference on Economic Measurement 2021

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joint work with Philippe Aghion (College de France and LSE),
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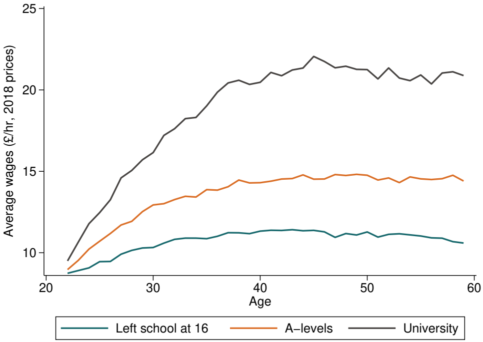
Wage progression - it's depressing at the bottom!

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

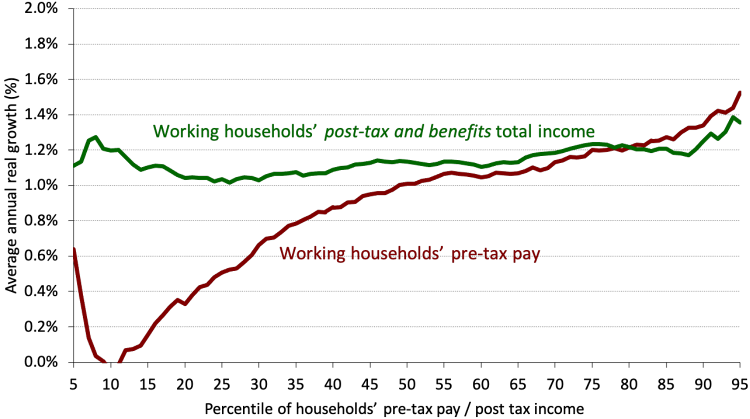


Source: BHPS and USoc, 1992-2016, authors' calculations.

- 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

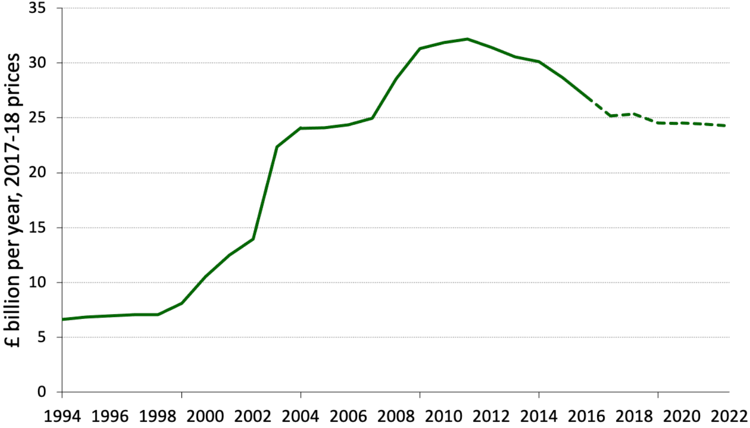
Household income growth for working households in UK 1994/5 to 2016/7



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.

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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?

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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
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Data

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

Data on workers

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

Data on firms

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

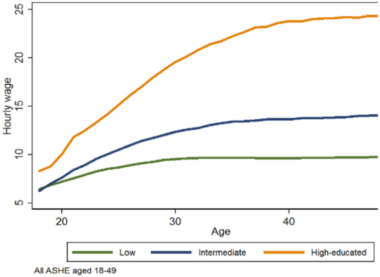
ASHE does not include data on individual's education; we use the Regulatory Qualification Framework (RQF), by Ofqual.

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

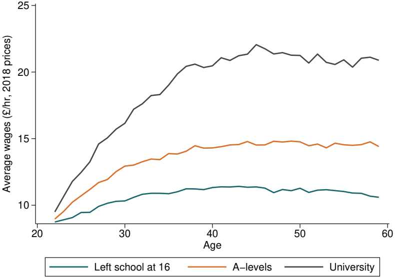
Wage progression by education level of occupation is similar to progression by education of individuals

Education by occupation



Source: ASHE

Education of individual



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

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

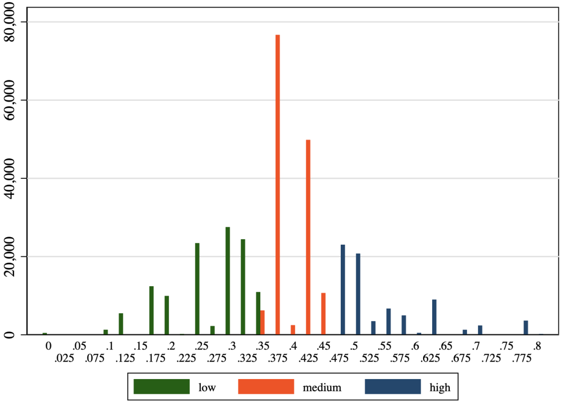
We create a single index of the importance of soft skills

- 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

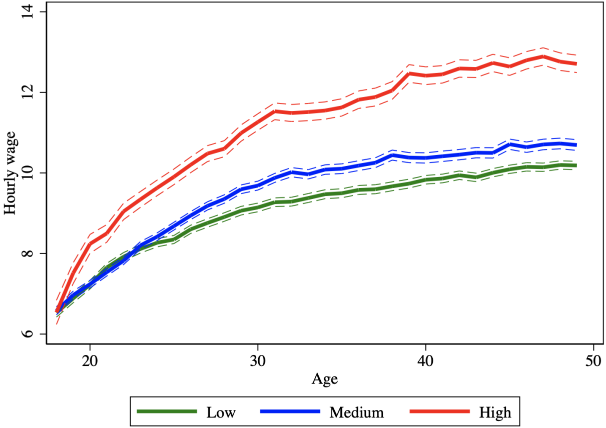
Men aged 18-49 in private sector firms with 400 or more employees



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

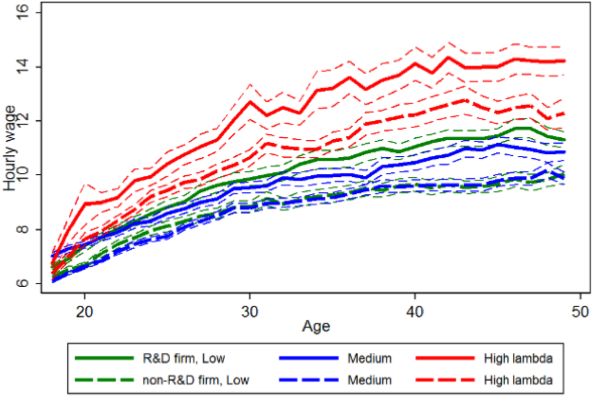
More wage progression for workers in high λ occupations

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

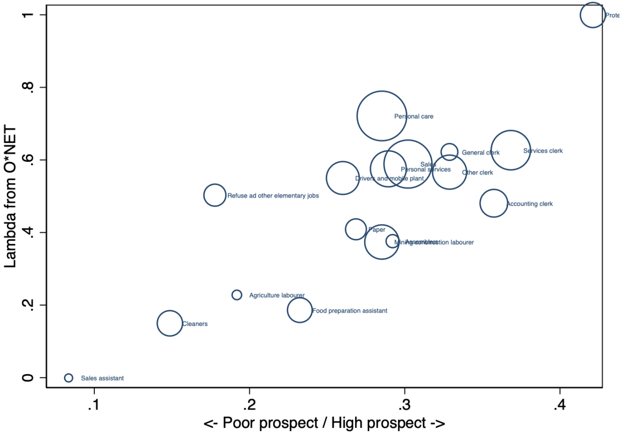
Does lambda identify "good jobs"?

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 enthusiatic 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?

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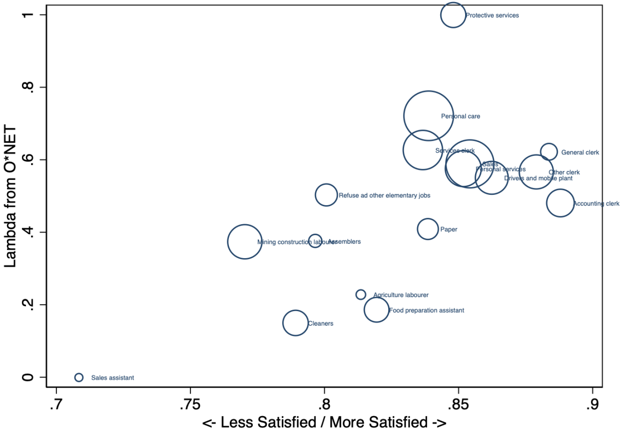

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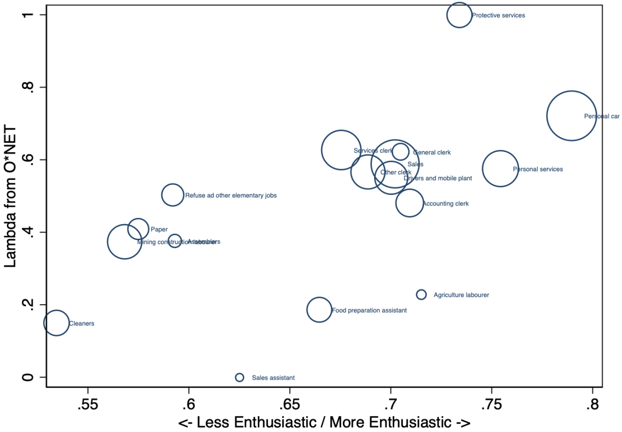
Enthusiasm for job

low-educated occupations



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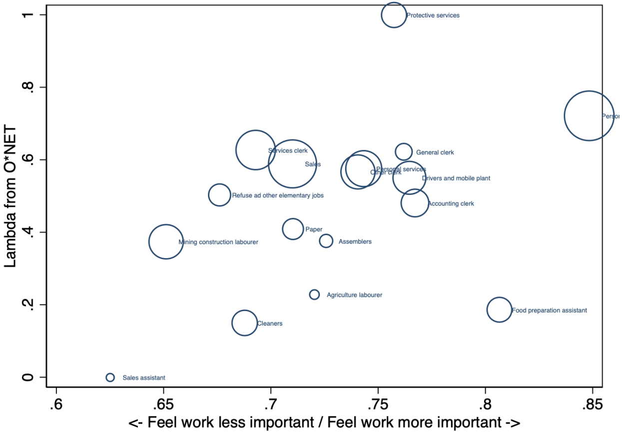
I doubt the importance of my work

low-educated occupations



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Model

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 complementarity 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.

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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.

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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:

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

which generates our log wage specification:

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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

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

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Returns to soft skills

Dependent variable: $ln(w_{ijkft})$				
High lambda	0.1387***	0.0869***	0.0330***	0.0613***
	(0.0022)	(0.0032)	(0.0032)	(0.0023)
x tenure		0.0073***	0.0013***	**0.0036*** **
		(0.0004)	(0.0005)	(0.0003)
x tenure 0-5 years		0.0079***	0.0057***	**0.0085*** **
		(0.0009)	(0.0006)	(0.0008)
intial 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:

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

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***	0.0321**	0.0670***
	(0.0034)	(0.0054)	(0.0035)
x tenure	**0.0037*** **	**0.0020*** **	**0.0041*** **
	(0.0003)	(0.0004)	(0.0003)
x tenure 0-5 years	**0.0095*** **	**0.0044*** **	**0.0080*** **
	(0.0010)	(0.0009)	(0.0012)
x RD firm		0.0032	0.0076
		(0.0065)	(0.0051)
x tenure 0-5 years x RDfirm		0.0032*	**0.0045*** **
		(0.0017)	(0.0021)
RD firms		0.0408***	0.0427***
		(0.0033)	(0.0022)
tenure x RD firm		-0.0024***	-0.0002
		(0.0004)	(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	0.0321**	0.0145***	0.0281***	0.0018***	0.0323***	0.0104**
	(0.0041)	(0.0049)	(0.0043)	(0.0046)	(0.0041)	(0.0049)	(0.0043)
$\times$ T	0.0037***	0.0020***	0.0041***	0.0022***	0.0032***	0.0021***	0.0036***
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)
$\times$ T(0-5)	0.0095***	0.0044***	0.0080***	0.0051***	0.0082***	0.0039***	0.0065***
	(0.0010)	(0.0009)	(0.0012)	(0.0008)	(0.0010)	(0.0010)	(0.0012)
x R		-0.0029	-0.0215***			-0.00735	-0.0192
		(0.0059)	(0.0049)			(0.0061)	0.0049)
$\times$ T(0-5) x R		0.0032*	0.0045**			0.0034*	0.0052**
		(0.0017)	(0.0021)			(0.0017)	(0.0021)
x high-ed				0.0026***	0.0040***	0.0027***	0.0042***
				(0.0006)	(0.0005)	(0.0006)	(0.0005)
$\times$ T(0-5) $\times$ high-ed				0.0003*	0.0005***	0.0003***	0.0005***
				(0.0001)	(0.0002)	(0.0001)	(0.0002)
R		0.0408***	0.0427***			0.0386***	0.0378***
		(0.0033)	(0.0022)			(0.0034)	(0.0023)
$\times$ T		-0.0024***	0.0003			-0.0023***	0.0005**
		(0.0003)	(0.0002)			(0.0004)	(0.0003)
high-ed				0.0031***	0.0040***	0.0029	0.0038
				(0.0003)	(0.0002)	(0.0003)	(0.0002)
$\times$ T				0.0000	0.00002	0.00001	0.00003
				(0.00004)	(0.00002)	(0.00004)	(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

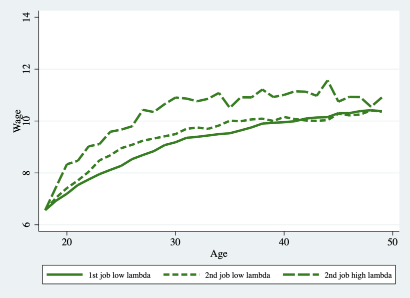
Notes: Authors' calculations using ASHE-BERD, 2004-2019. Numbers are coefficients with robust standard errors in parentheses. Travel To Work (TTW) times year, or TTW time 2-digit occupation times year are included as indicated. Stars indicate * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Robustness

- 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

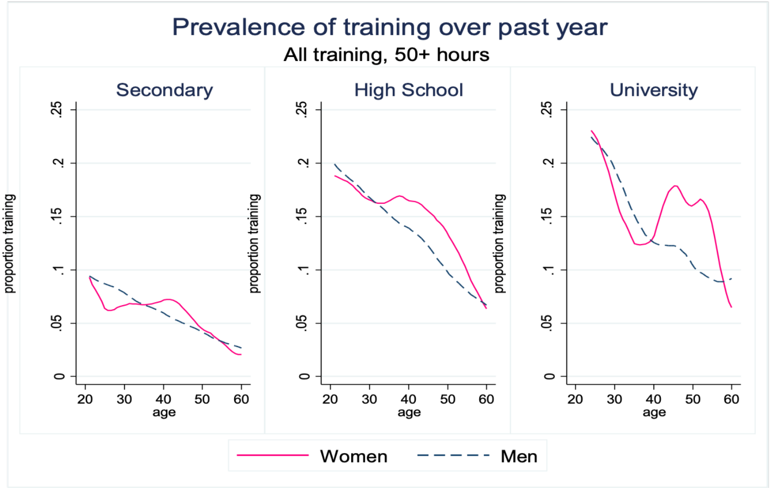
(a) 1st job low λ



(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		
	below median	above median	diff
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)

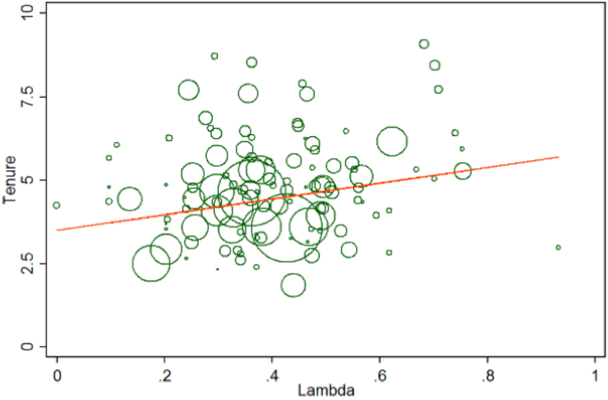
Source: Authors' calculations using LFS, 2011-2016, males 18-49 in low-skilled occupations in private firms with 400+ employees. Stars indicate * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

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.

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- 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.

EXTRA SLIDES

Wages and earnings by education level of occupation

Back

Our main measure is hourly wages including overtime, bonuses and incentive pay

Occupation	Wage (hourly) £	% incentive pay	% overtime	Annual earnings £
Low-educated	10.12	2.4%	5.5%	17,791
Medium-educated	15.21	5.2%	2.9%	29,378
High-educated	24.01	7.0%	1.3%	48,972

Source: Authors' calcuations using ASHE, 2004-2018

Are there differences in education by lambda?

One potential concern is that the workers in high lambda occupations are more educated than those in low lambda; this doesn't seem to be the case

Workers in low-educated occupations

	Lambda		
	Below median	Above median	diff
Age left education	17.8	17.7	-0.09***
	(0.02)	(0.02)	(0.03)
Has higher education degree	12.9	11.9	-1.0***
	(0.14)	(0.14)	(0.20)
N	55,546	52,818	109,364

Source: Authors' calculations using LFS, 2011-2016, males 18-49 in work

Examples of low-educated occupations by λ

Low λ (low importance of soft skills)

- cleaner, bar staff, caretaker, packer, process operator

Medium λ (medium importance of soft skills)

- finance officer, book-keeper, plasterer, clerk, sales assistant

High λ (high importance of soft skills)

- receptionist, medical or school secretary, air transport operative, assembler

Use only first job ‣ Return

Dependent variable: $ln(w_{ijkft})$		
High lambda	0.0670***	0.0683***
	(0.0035)	(0.0039)
x tenure	**0.0031*** **	**0.0020*** **
	(0.0003)	(0.0003)
x tenure 0-5 years	**0.0066*** **	**0.0050*** **
	(0.0012)	(0.0014)
x RD firm	0.0026	0.0050
	(0.0051)	(0.0051)
x tenure 0-5 years x RDfirm	**0.0053*** **	**0.0077*** **
	(0.0021)	(0.0023)
intial wage	0.0507***	0.0562***
	(0.0011)	(0.0012)
Controls for age, tenure, tenure-squared, gender, full/part-time, firm size		
Geo-Year	✓	✓
R^2	0.518	0.590
Observations	173,339	134,998

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

Use Q rather than R&D ▸ Return

Dependent variable: $ln(w_{ijkft})$		
High lambda	0.0670***	0.0590***
	(0.0035)	(0.0035)
x tenure	**0.0031*** **	**0.0027*** **
	(0.0003)	(0.0003)
x tenure 0-5 years	**0.0066*** **	**0.0070*** **
	(0.0012)	(0.0011)
x RD firm	0.0026	
	(0.0051)	
x tenure 0-5 years x RDfirm	**0.0053*** **	
	(0.0021)	
x $\bar{Q}$		0.0031***
		(0.0005)
x tenure 0-5 years x $\bar{Q}$		**0.0010*** **
		(0.0002)
intial wage	0.0507***	0.0499***
	(0.0011)	(0.0011)
Controls for age, tenure, tenure-squared, gender, full/part-time, firm size		
Geo-Year	✓	✓
R^2	0.518	0.525
Observations	173,339	173,339

Remove time effects in λ ▸ Return

Dependent variable: $ln(w_{ijkft})$			
High lambda	0.0659***	0.0504***	0.0087***
	(0.0034)	(0.0054)	(0.0044)
x tenure	**0.0029*** **	**0.0028*** **	**0.0028*** **
	(0.0003)	(0.0003)	(0.0003)
x tenure 0-5 years	**0.0082*** **	**0.0080*** **	**0.0091*** **
	(0.0011)	(0.0011)	(0.0010)
intial wage	0.0513***	0.0513***	0.0461***
	(0.0011)	(0.0011)	(0.0009)
Controls for age, tenure, tenure-squared, gender, full/part-time, firm size			
Geo-Year	✓	✓	
Lambda-Year		✓	
Geo-Year-2-digit occupation			✓
R^2	0.513	0.514	0.402
Observations	173,339	173,339	173,339

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

Acemoglu and Autor (2011) ‣ Return

Dependent variable: $ln(w_{ijkft})$		
High lambda	0.0946***	0.0652***
	(0.0025)	(0.0026)
Non-routine cognitive analytical		0.3567***
		(0.0112)
Non-routine cognitive interpersonal		-0.2519***
		(0.0121)
Routine cognitive		0.2549***
		(0.0116)
Routine manual		0.0669***
		(0.0108)
Non-routine manual physical		0.1909***
		(0.0126)
Offshorability		0.0340***
		(0.0071)
intial wage	0.0513***	0.0487***
	(0.0011)	(0.0011)
Controls for age, tenure, tenure-squared, gender, full/part-time, firm size		
Geo-Year	✓	✓
R^2	0.513	0.535
Observations	173,339	173,339

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

Fortin and Lemieux (2016) ▸ Return

Dependent variable: $ln(w_{ijkft})$		
High lambda	0.0946***	0.0652***
	(0.0025)	(0.0026)
Information content		0.2571***
		(0.0103)
Automation routinization		0.1042***
		(0.0108)
Face-to-face		0.2489***
		(0.0107)
On-site job		0.1487***
		(0.0081)
Decision making		0.0267***
		(0.0165)
intial wage	0.0513***	0.0491***
	(0.0011)	(0.0011)
Controls for age, tenure, tenure-squared, gender, full/part-time, firm size		
Geo-Year	✓	✓
R^2	0.513	0.532
Observations	173,339	173,339

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

Cortes, Jaimovich and Siu (2020) ‣ Return

Dependent variable: $ln(w_{ijkft})$		
High lambda	0.0946***	0.0652***
	(0.0025)	(0.0026)
Cognitive tasks		0.3942***
		(0.0116)
Social tasks		0.0895***
		(0.0075)
Routine tasks		0.1602***
		(0.0065)
Manual tasks		0.0410***
		(0.0066)
intial wage	0.0513***	0.0489***
	(0.0011)	(0.0011)
Controls for age, tenure, tenure-squared, gender, full/part-time, firm size		
Geo-Year	✓	✓
R^2	0.513	0.530
Observations	173,339	173,339

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

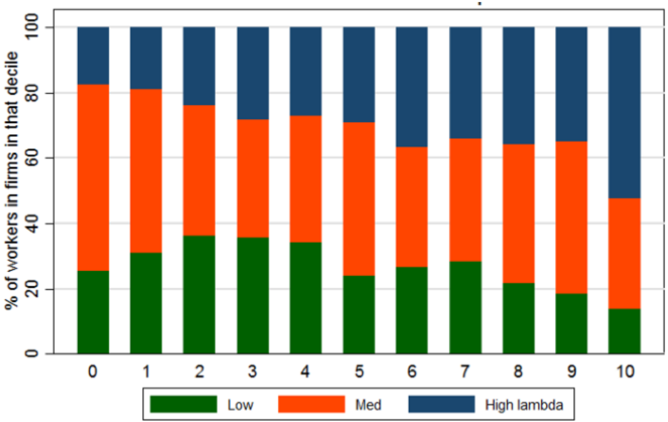
Difference in skills and abilities by lambda ‣ Back

Skill/ability	low lambda	high lambda	difference	% differen
Social perceptiveness	2.55	3.08	0.527***	21%
skLV_2_B_1_a	(0.04)	(0.08)	(0.08)	
Coordination	2.68	3.21	0.538***	20%
skLV_2_B_1_b	(0.03)	(0.03)	(0.03)	
Active listening	2.89	3.34	0.451***	16%
skLV_2_A_1_b	(0.05)	(0.06)	(0.09)	
Problem sensitivity	2.92	3.33	0.409***	14%
abLV_1_A_1_b_3	(0.03)	(0.04)	(0.05)	
Responsibility for outcomes	2.91	3.58	0.671***	23%
wc_4_C_1_c_2	(0.06)	(0.09)	(0.10)	
Consequence of error	2.64	3.17	0.528***	20%
wc_4_C_3_a_1	(0.07)	(0.07)	(0.10)	
Coordinate others	3.18	3.73	0.548***	17%
wc_4_C_1_b_1_g	(0.04)	(0.05)	(0.07)	
Impact of decisions on co-workers	3.49	4.06	0.571**	16%
wc_4_C_3_a_2_a	(0.04)	(0.04)	(0.06)	
Work with group	3.95	4.33	0.380***	10%
wc_4_C_1_b_1_e	(0.05)	(0.03)	(0.07)	
Importance of being accurate	3.96	4.22	0.252	7%
wc_4_C_3_b_4	(0.06)	(0.05)	(0.08)	

Source: Authors' calculations using O*NET

Share of workers in low-educated occupations by lambda and R&D intensity

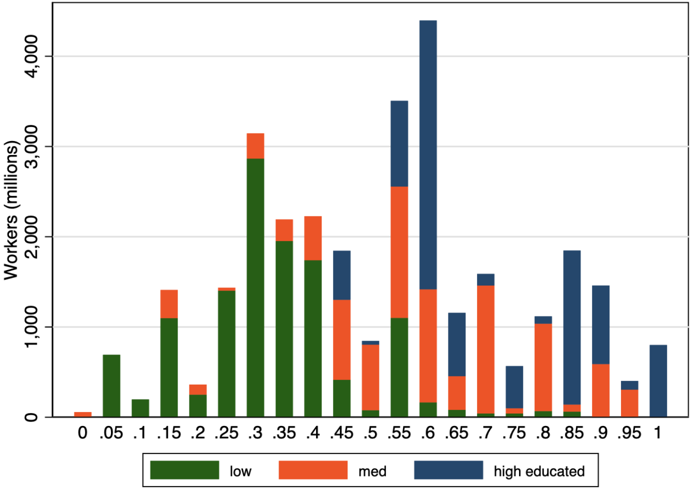
Back



Horizontal axis is deciles of R&D intensity of firm in which the worker works

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

Distribution of soft skills by education group ‣ Back



Source: Authors' calculations using O*NET and ONS employment data

The return to soft skills ‣ Back

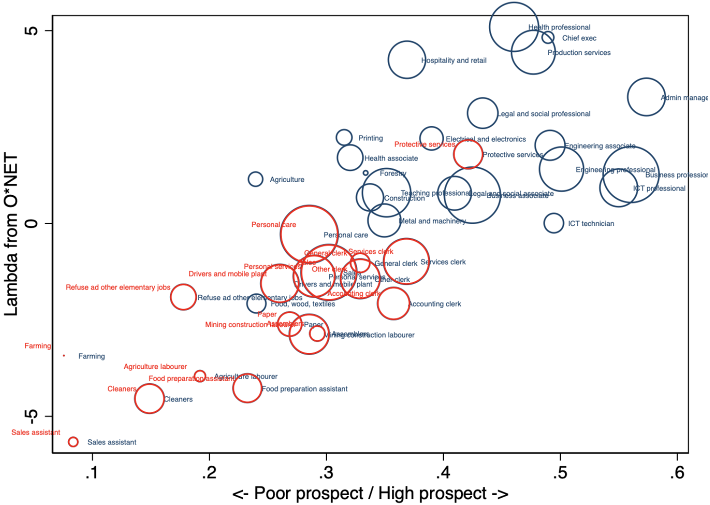
- hard skills are observable and verifiable, e.g. formal qualifications
- soft skills are difficult to observe, both for employer and us
- in model what drives the returns to experience in some low-educated occupations is the soft skills that are valuable to the firm because they are complementary with other assets

We are not claiming that the *absolute* importance of soft skills is greater for workers in low than high-educated occupations ‣ Evidence

- soft skills are relatively more important for workers in low-educated occupations
- eg a researcher and an administrative assistant
    - researcher might have higher soft skills than the admin assistant
    - but her income will be mostly determined by her track record of publications and inventions, which are verifiable
    - the admin assistant might have lower soft skills than the researcher, but these will represent a higher share of her value to the researcher, and so play a more important role in determining the assistant's wage

My job offers good prospects for career advancement ‣ Back

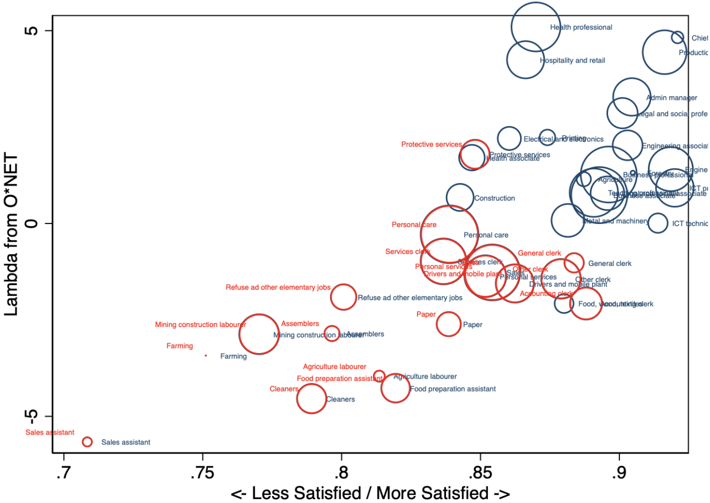
all occupations



Source: Authors' calculations using EWCS, 2015

On the whole, are you satisfied with working conditions in your job? ‣ Back

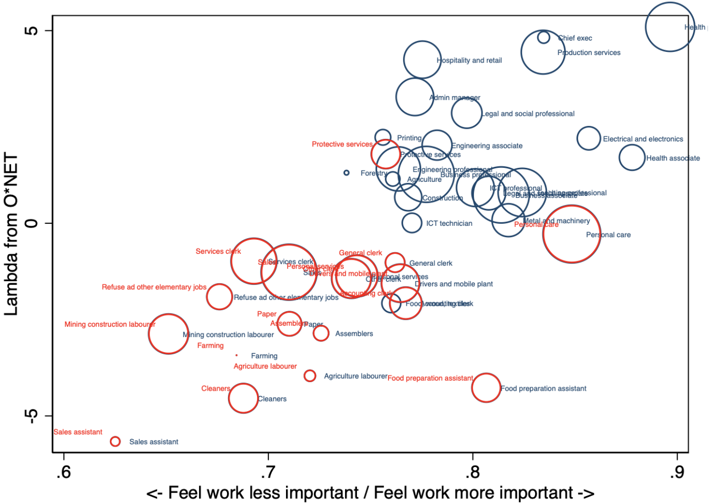
all occupations



Source: Authors' calculations using EWCS, 2015

I doubt the importance of my work ▸ Back

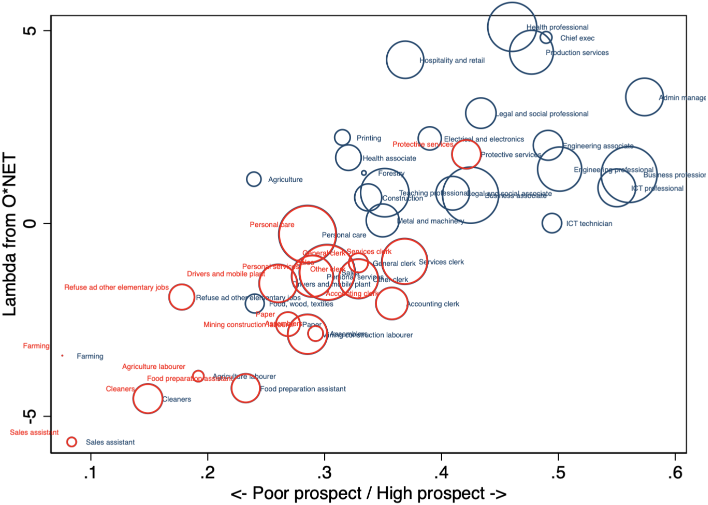
all occupations



Source: Authors' calculations using EWCS, 2015

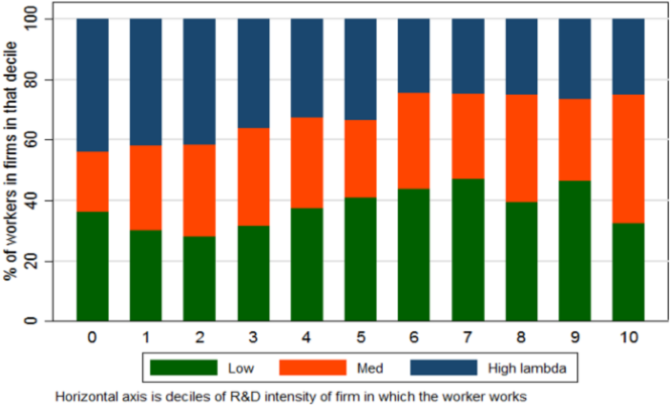
My job offers good prospects for career advancement ‣ Back

all occupations



Source: Authors' calculations using EWCS, 2015

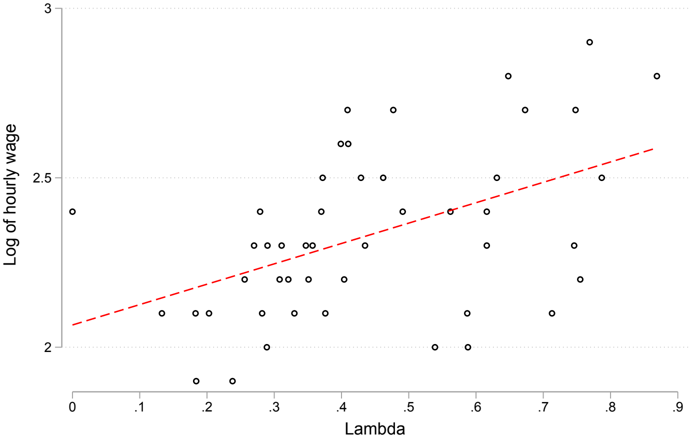
Share of workers in high-educated occupations by lambda and R&D intensity ‣ Back



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

Mean wage by λ workers in R&D firms ‣ Back

Wages are higher in higher λ occupations for workers in *low-educated* occupations in R&D firms



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

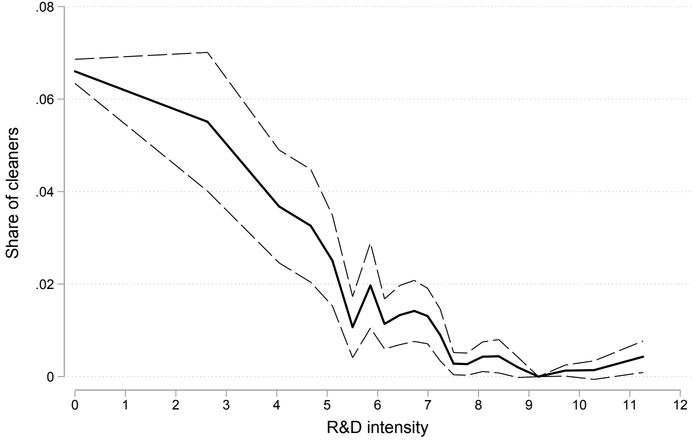
Payoff to λ by education ‣ Back

Dependent variable: $ln(w_{ijkft})$	low educated	high educated
High lambda	0.1511***	0.0750***
	(0.0022)	(0.0036)
Medium lambda	0.0968***	0.0578***
	(0.0023)	(0.0037)
Firm size	0.0026***	0.0287
	(0003)	(0004)
Male	0.0971***	0.1690***
	(0.0020)	(0.0024)
Full-time	0.1351***	0.0266***
	(0.0029)	(0.0038)
Age	0.0295***	0.0688***
	(0.0002)	(0.0007)
Age-squared	-0.0004***	0.0007***
	(0.0001)	(0.0001)
Tenure	(0.0172***	0.0085***
	(0.0002)	(0.0003)
Tenure-squared	-0.0002***	-0.0002***
	(0.0001)	(0.0001)
Geo-Year	✓	✓
R^2	0.231	0.153
Observations	974,451	497,909

How to measure outsourcing? ‣ Back

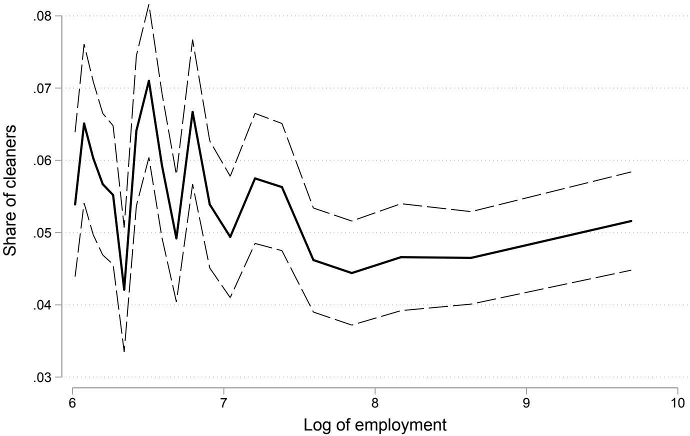
- Our model predicts that innovative firms will outsource the tasks that have little complementarity between high and low skill occupation workers
- the time dimension of our data does not allow us to look at this directly
- Indicative evidence for one specific occupation
    - the technology of cleaning does not vary much across firms
    - the share of low-skilled workers in a firm that are cleaners should be reasonably constant (recall these are all firms with 400+ employees)
    - cleaning a low λ task (not complementary with high-skilled workers)
    - the only reason this share would be lower than average in some firms is because those firms outsource cleaning

Share of cleaners decrease with R&D ▸ Back



Share of cleaners decrease with R&D, not with firm size

▸ Back



A model

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
- and experience higher wage progression in more innovative firms

We would like to

- better understand what is driving these results
- consider how effective potential policy reforms might be

We propose a model that is consistent with these empirical finding

- to understand the mechanisms at play
- we derive additional empirical predictions that we can take to data to use to verify (or not) the relevance of this model

Model: wage negotiation

- The firm engages in separate wage negotiation with each worker in occupation (task) Γ
- If negotiations fail the firm hires a substitute at reservation quality, q_L, at wage w_L
- Prior to negotiation the firm can learn about or train the low-educated worker on each task Γ
  - the optimal quality q^* is increasing in μ, the degree of complementarity
  - so the optimal level of soft skills, $q^*(\Gamma) - q_L$, is increasing in μ

Proxies for importance of soft skills and abilities in O*NET

- How important is ... to the performance of your current job?
  - Negotiation: bringing others together and trying to reconcile differences
  - Persuasion: persuading others to change their minds or behavior
  - Social Perceptiveness: Being aware of others' reactions and understanding why they react as they do
  - Active Listening: Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.
  - Coordination: Adjusting actions in relation to others' actions.
  - Problem Sensitivity: The ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing that there is a problem.
- In your current job, how important are interactions that require you to coordinate or lead others in accomplishing work activities (not as a supervisor or team leader)?

Worker heterogeneity and initial conditions

For γ_i in log wage equation:

$$\ln w_{ijft} = \alpha_1 \kappa_i \lambda_j + \alpha_2 \kappa_i k(T_{if}) \lambda_j + g(A_{it}, FT_{if}, S_f, T_{if}) + \gamma_i + \eta_t + e_{ijft} \tag{4}$$

we would like to condition on the level of skills of the worker at entry into the workforce, rather than on an average worker effect.

- we use the initial wage that the individual receives when they enter the labour market.
- pre-sample measure of wage reflects worker's initial skill level, is not influenced by evolution of soft skills in sample (Blundell, Griffith and Van Reenen (1999) and Blundell, Griffith and Windmeijer (2002)).