The innovation premium to low skill jobs

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Motivation

- This paper results from an unexpected fact we found in the data.
- At first we started with the view of combining findings of Aghion et al. (2015) that more innovation generates inequality and the findings of Song et al. (2017) that wage inequality is mostly driven by between firms variance.
- We thus looked at whether innovative firms pay higher wages.

Background

- Rising inequalities have been driven by differences in wage between firms in many countries:
  - **US**: Barth et al. (2014); Song et al. (2017)
  - **Germany**: Baumgarten (2013); Card et al. (2013)
  - **Italy**: Card et al. (2014)
  - **UK**: Faggio et al. (2010)
  - **Sweden**: Hakanson et al. (2015)
  - etc...
- Rents from innovation translate to higher wage in the firm: Kline et al. (2017); Aghion et al. (2018)

Our contribution

- We document that innovation is one (important) driver of between-firm differences in wages
  - using matched employer-employee data for the UK we show that workers in R&D firms get a higher wage (conditional on observables).

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- Somewhat surprisingly, this premium is particularly high for workers in low-skilled occupations.

Our contribution

- We document that innovation is one (important) driver of between-firm differences in wages
  - using matched employer-employee data for the UK we show that workers in R&D firms get a higher wage (conditional on observables).
- Somewhat surprisingly, this premium is particularly high for workers in low-skilled occupations.
- We develop a model where innovative firms exhibit higher complementarity between high and low skill workers.
  - the model captures the idea that low-skilled workers can have a potentially more damaging effect on the firm's value if the firm is more technologically advanced.
  - show additional empirical support for the model.

Literature

- **Role of the firm:** Abowd et al. (1999); Barth et al. (2014); Song et al. (2017); Card et al. (2016);
- **Skill bias technical change:** Acemoglu (2002); Goldin and Katz (2010); Acemoglu and Autor (2011)
- **Innovation and inequality:** Bell et al. (2016); Aghion et al. (2015); Akcigit et al. (2017);
- **Wages and rents from innovation:** Kline et al. (2017); Aghion et al. (2018)

Plan

Plan

Data

- Data for the UK 2004 - 2015
- Wages
  - Annual Survey of Hours and Earning (ASHE)
  - 1% sample of UK based workers (based on National Insurance number)
  - panel data - we observe the same individual over a long time
  - information on labour income *including bonuses*
- Research and Development (R&D) expenditure
  - Business Enterprise Research and Development (BERD)
  - census of firms with 400+ employees, below that random stratified sample
- Results today for private firms with 400+ employees
  - sample includes around 186,000 employees, working in a little more than 7,300 firms
  - accounts for around 70% of R&D
  - we show robustness to other samples

ASHE and wages

- ASHE includes detailed information on labour income and hours worked, we use hourly wages including bonuses and incentive pay
- ASHE also records gender, age, tenure in firm, firm and occupation
- we do not have individual level data on education, skills, etc.; we use a classification of occupations based on the National Qualification Framework (NQF); used to determine UK immigration rules

Low skill, no formal qualifications necessary	
Skill cat 1	process plant operative, basic clerical, cleaning, security
Skill cat 2	drivers, specialist plant operative or technician, sales
Intermediate skill, typically requires A-level or some qualification	
Skill cat 3	trades, specialist clerical, associate professionals
Skill cat 4	medical or IT technicians, some managerial occupations
High skills, typically required first or higher degree	
Skill cat 5	most managerial and executive occupations, engineers
Skill cat 6	scientists, R&D manager, other professions

Pay by skill categories

Occupation	Hourly pay	% incentive pay	% overtime	Annual earnings
Low-skill				
Skill cat 1	8.64	2.54	5.64	13,612
Skill cat 2	11.59	2.25	5.32	21,970
Intermediate-skill				
Skill cat 3	13.59	5.21	3.56	25,936
Skill cat 4	16.83	5.21	2.13	32,820
High-skill				
Skill cat 5	25.62	7.64	1.42	54,075
Skill cat 6	22.39	6.33	1.11	43,868

How much of inequality do these measures capture?

- OECD data on the ratio of the average income (including taxes, benefits, etc.) of the 10% highest paid workers to the 10% lowest paid is
  - the top are paid 11 times the bottom in the UK
  - 19 in the US, 7 in France and Germany and 6 in Scandinavia
- If we take all of ASHE the 90/10 ratio of wages is 6.17
- If we take our sample of large firms the 90/10 ratio of wages is 6.00

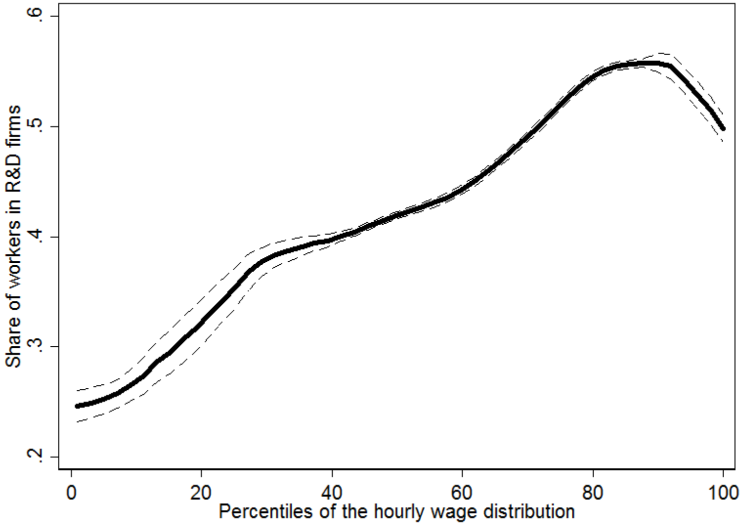
Measure of innovation intensity

- Expenditures on research
  - at the **firm** – not enterprise – level
  - includes both intramural and extramural R&D expenditures
  - we use R&D intensity, so we divided by employment

$$\tilde{R}_{ft} = ln\left(1 + \frac{RDexp_{ft}}{L_{ft}}\right)$$

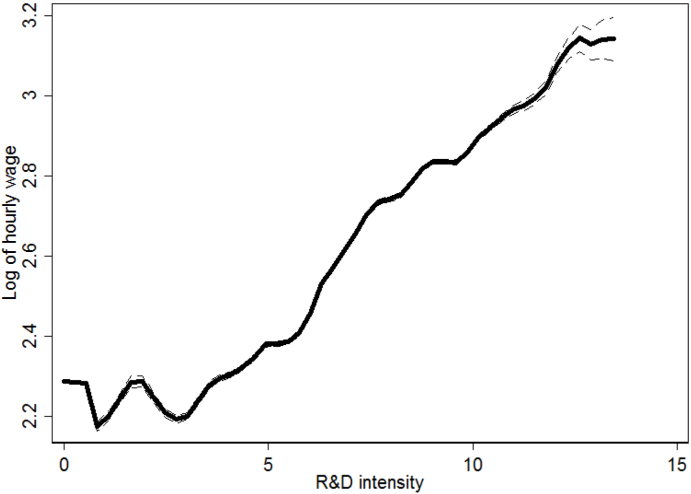
- We also use
  $RD = 1$ if a firm ever reports doing R&D
- $1/3$ of the firms have $RD = 1$

Higher paid workers more likely to work in R&D firm



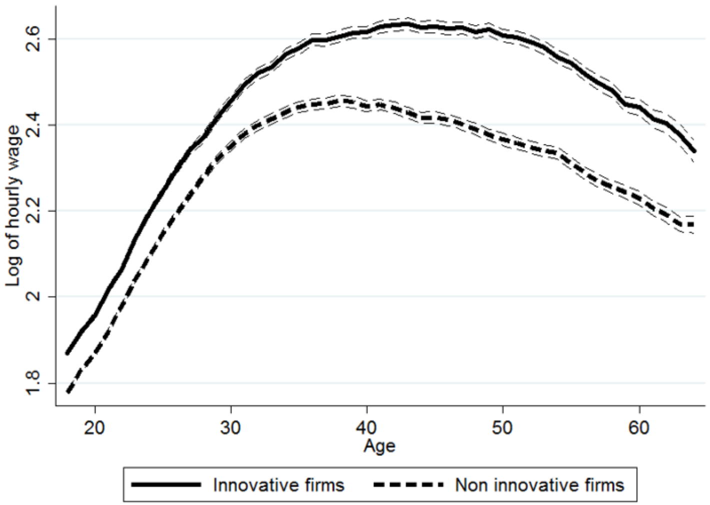
Workers in R&D firms are paid higher wages

conditional on labour market mean wage



Workers in R&D firms are paid higher wages at all ages

conditional on labour market mean wage



The effect of innovation on wages

- A correlation between innovation and wages could reflect many things
  - innovative firms hire more males workers, more experienced workers and more full-time workers.

	R&D firms	Non-R&D firms
Firm employment	2,784	2,213
Share male (%)	68	56
Share full-time (%)	90	76
Age of worker	40.4	38.1
Tenure of worker	8.9	5.7
Firms	2,332	5,032
Firms-years	12,871	25,481
Worker-firm-year	263,447	363,275

- To control for these we estimate

$$ln(w_{ijkft}) = \beta_1 \tilde{R}_{ft} + X\beta_2 + \eta_t + e_{ijkft},$$

i: individual j: occupation k: labour market f: firm t: year

	Dependent variable: $ln(w_{ijkft})$			
	(1)	(2)	(3)	(4)
$\tilde{R_{ft}}$	0.029***	0.016***	0.006***	0.001***
	(0.002)	(0.001)	(0.001)	(0.000)
Age	0.058***	0.034***		0.045***
	(0.003)	(0.002)		(0.001)
Age^2	-0.001***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.023***	0.015***	0.008***	0.015***
	(0.001)	(0.001)	(0.000)	(0.000)
Tenure^2	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Size	-0.032***	-0.010***	-0.008***	-0.031***
	(0.006)	(0.004)	(0.002)	(0.003)
Gender	0.156***	0.143***	0.000	0.155***
	(0.006)	(0.004)	(.)	(0.003)
Full-Time	0.244***	0.070***	0.004	0.142***
	(0.014)	(0.007)	(0.005)	(0.002)
FE	**(k,t)**	**(k,j,t)**	**i+t**	**f+t**
R-squared	0.385	0.624	0.887	0.561
N	626,210	626,210	626,210	626,210

***i*: individual *j*: occupation *k*: labour market *f*: firm *t*: year**

Additive Fixed Effects

$$ln(w_{i,t}) = \alpha_i + X_{i,t}\beta + \eta_t + \gamma\tilde{R}_{J(i,t),t} + \delta ln(L_{J(i,t),t}) + \psi_{J(i,t)} + \varepsilon_{i,t},$$

	Dependent variable: $ln(w_{ijkft})$		
	(1)	(2)	(3)
$\tilde{R}_{ft}$	0.006***	0.001***	0.001***
	(0.001)	(0.000)	(0.000)
Age^2	-0.001***	-0.001***	-0.000***
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Tenure	0.008***	0.015***	0.008***
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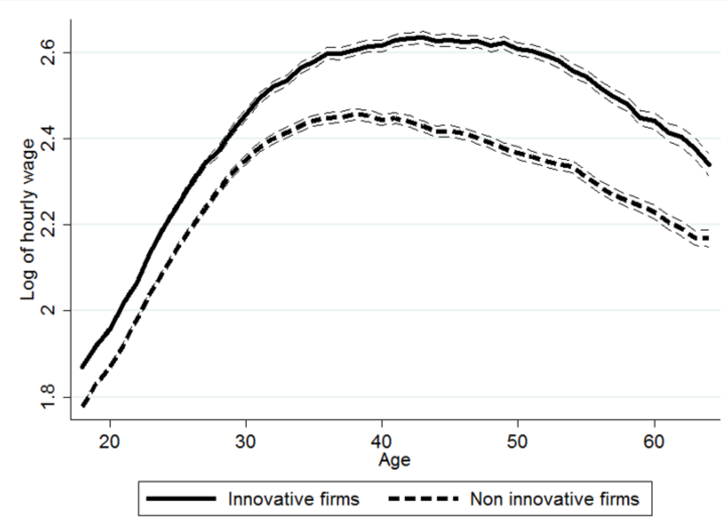
Firm Size	-0.008***	-0.031***	-0.001
	(0.002)	(0.003)	(0.002)
Full-Time	0.004	0.142***	-0.023***
	(0.005)	(0.002)	(0.002)
Age		0.045***	
		(0.001)	
Gender		0.155***	
		(0.003)	
R-squared	0.887	0.561	0.895
N	626,206	626,206	581,323

Plan

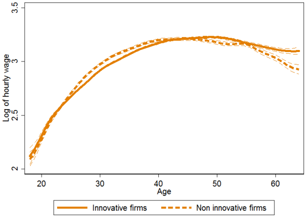
Workers in R&D firms are paid higher wages at all ages

conditional on labour market mean wage

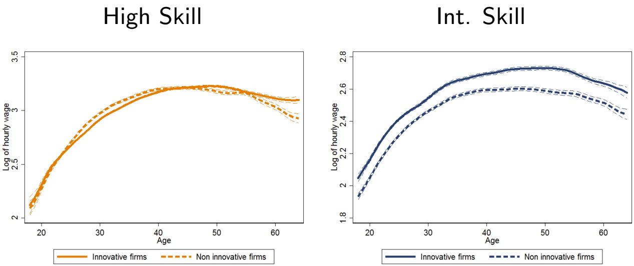


Workers in high-skill occupations are paid more at all ages

High Skill



Workers in high-skill occupations are paid more at all ages



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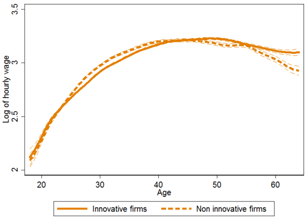
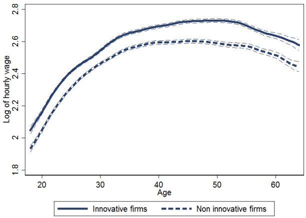
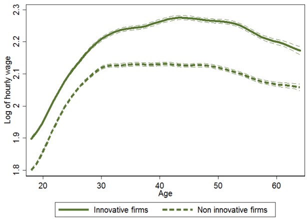
High Skill



Int. Skill

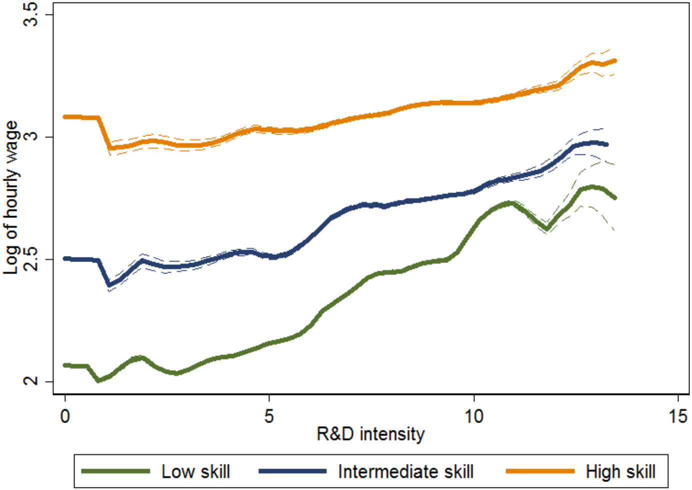


Low Skill



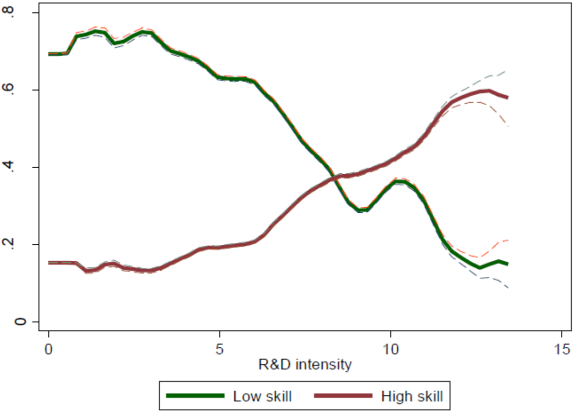
The wage premium from working in a high-R&D firm is higher for workers in low-skilled occupations

With Size



Employment, by (occupation) skill and (firm) R&D

R&D firms employ more skilled workers



Share of high skill workers:

No R&D firms: 13.7%; Most R&D firms: 53.8%

Occupation	**low skill**	**med skill**	**high skill**	**All**
$\tilde{R}_{ft}$	0.007***	0.003***	-0.000	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
$\tilde{R}_{ft}$ * low-skill				0.006***
				(0.001)
$\tilde{R}_{ft}$ * med skill				0.002***
				(0.001)
Age^2	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.009***	0.006***	0.001	0.007***
	(0.001)	(0.001)	(0.001)	(0.000)
Tenure^2	-0.000***	-0.000***	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Size	-0.005**	0.002	0.004	-0.006***
	(0.002)	(0.003)	(0.002)	(0.002)
Full-Time	-0.011*	-0.089***	-0.109***	-0.004
	(0.006)	(0.014)	(0.014)	(0.005)
low-skill				-0.157***
				(0.006)
med-skill				-0.073***
				(0.004)
FE	**i+t**	**i+t**	**i+t**	**i+t**
R-squared	0.774	0.851	0.885	0.889
N	407,336	104,319	114,535	626,206

Economic significance

- R&D intensity has standard deviation of around 3
- Moving up one standard deviation in the ln R&D intensity distribution leads to an increase in wages of around 2.3% for workers in low-skilled occupations. And has no significant effect for high skill workers.
- Other way of assessing the magnitude: in the model with labour market FE, moving from a non R&D firm to the most R&D intensive firm increase wage by about 16%, this is the same order of magnitude as the effect of *gender*.

Robustness

- These regression results are robust to a number of alternative specifications:
  1. Other measure of R&D Tables
  2. Keeping only innovative firms Tables
  3. Removing the financial sector
  4. Using different measures of income Tables
  5. Other measure of skill Tables
  6. Restricting to non moving workers Tables
  7. etc.

Plan

Model intuition

- What explains the stronger effect of innovation on wage for workers in low-skill occupations?
  - we built a model in which there is complementarity between (some) workers in low and high-skill occupations
  - the skills of workers in high-skilled occupations are less firm-specific
  - this provides workers in (complementary) low-skilled occupations bargaining power.

Model Setup (1)

- 2 types of occupations
  - high skill with quality Q
  - low skill with quality q
- Continuum of tasks indexed by $\lambda \in [0, 1]$
- Each task uses one worker of each type:

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

- Partial O'Ring production function (Kremer, 1993)
- λ: complementarity of the task's structure
  - $\lambda = 0$ there is pure substitutability between workers in low and high-skilled occupations and no complementarity
  - $\lambda = 1$ workers in low and high-skilled occupations are always complementary

Model Setup (2)

- Firm aggregate tasks according to:

$$F(\vec{q}, Q) = \int_0^1 f(\lambda, q(\lambda), Q)\phi(\lambda)d\lambda \text{ where } \int_0^1 \phi(\lambda)d\lambda = 1$$

- Innovative firms rely more in high complementarity tasks
  - (Garicano, 2000; Garicano and Rossi-Hansberg, 2006; Caroli and Van Reenen, 2001; and Bloom et al., 2014)
  - And evidence below.
- This is captured by an increase in

$$\mathbb{E}_{\phi}(\lambda) = \int_0^1 \lambda\phi(\lambda)d\lambda$$

with innovation.

Wage negotiation

- The firm engages in separate wage negotiation with each worker
  - yields equilibrium wages: w_q and w_Q for each task
- If negotiations fail the firm hires a substitute
  - quality q_L at wage w_L, or Q_L at w_H
  - we assume $Q > Q_L > q > q_L > 1$
- We assume $Q - Q_L < q - q_L$
  - e.g. because of less asymmetry of information
- Wage are then determined following Stole and Zwiebel (1996) with outside option for the low and high skill workers $\bar{w}^L$ and $\bar{w}^H$, respectively.

Solving the model (1)

- For simplicity, assume that surplus is split equally between the firm and the workers

$$w_q(\lambda) - \bar{w}^L = \phi(\lambda)\left[f(\lambda, q(\lambda), Q) - f(\lambda, q_L, Q)\right] - (w_q(\lambda) - w_L)$$

and similarly for the high occupation worker:

$$w_Q - \bar{w}^H = \int_0^1 \left[f(\lambda, q(\lambda), Q) - f(\lambda, q(\lambda), Q_L)\right] \phi(\lambda) d\lambda - (w_Q - w_H)$$

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- Firm needs to train the low-skill worker up to its desired quality $q(\lambda)$. Assuming quadratic cost $C\left(q(\lambda) - q_L\right)^2$, this yields:

$$q^*(\lambda) = q_L + \phi(\lambda)\frac{\lambda(Q_L - 1) + 1}{4C},$$

- Assume no training for high skill worker, so that optimal value of Q hits a corner $\overline{Q}$.

Solving the model (2)

- Backward induction solving:

$$w_q(\lambda) = \frac{\phi(\lambda)^2}{8C}\left(\lambda(Q_L - 1) + 1\right)\left(\lambda(\overline{Q} - 1) + 1\right)$$

and

$$\begin{aligned} w_Q(\lambda) \quad = \quad & \left(\overline{Q} - Q_L\right)\int_0^1 \lambda \frac{\phi(\lambda)^2}{8C}\left[\lambda(Q_L - 1) + 1\right] d\lambda \\ & + \left(\overline{Q} - Q_L\right)\int_0^1 \frac{\phi(\lambda)}{2}\left[\lambda(q_L - 1) + 1\right] d\lambda \end{aligned}$$

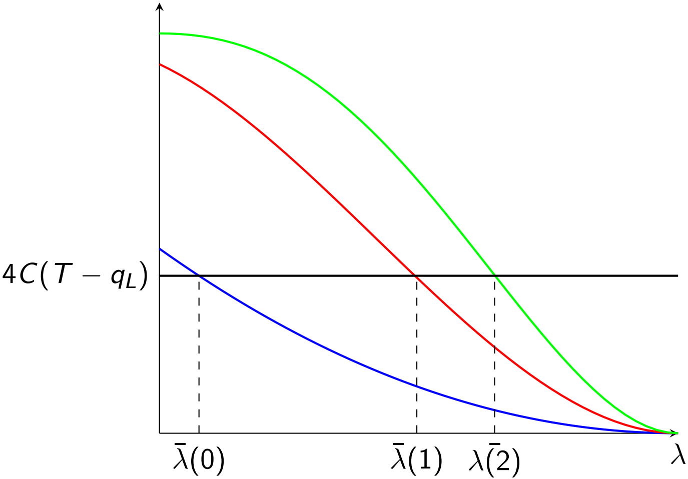
- Effect on innovation only through $\phi(\lambda)$.
- On average, $w_q(\lambda)$ increases more with innovation than w_Q as long as $\overline{Q} > Q_L > q^* > q_L$ and $Q - Q_L < q - q_L$.

Outsourcing

- Recall that $q^*(\lambda) = q_L + \phi(\lambda)\frac{\lambda(Q_L-1)+1}{4C}$
  $\longrightarrow$ Optimal value of q^* is always larger than q_L
- What if there is limited training resources?
  $T \geq \int_0^1 C\left(q(\lambda) - q_L\right)^2 d\lambda$
- Then for some λ it is optimal to have $q(\lambda) = q_L$. We interpret it as outsourcing the task.
- The cutoff value of λ below which the firm outsource increases with innovation.

Outsourcing (2)

Assuming $\phi(\lambda) = (z+1)\lambda^z$, and $z \in \mathbb{N}$, cutoff value $\bar{\lambda}$ as a function of z



Extensions

- Extend to more than two workers by task
- Endogenous innovation
- Allowing Q to depend with λ as well

Empirical assumptions and predictions

- More innovative firms exhibit more complementarity
- Low-skilled workers that remain in a firm benefit more from an increase in $R\&D$ of the firm than high-skilled workers in that firm
- Low-skilled workers stay longer in more innovative firms (as more time and money is invested in them to getting them from q_L to q^*) and have more training
- Innovative firms tend to outsource the less complementary low skill occupations

Plan

Complementarity of workers

- We use data collected by the US Department of Labor called the Occupational Information Network (O*Net)
- These data are collected from workers in the US and aggregated to the occupation level
- They provide detailed measures on the characteristics of occupations and the training of workers in those occupations (among other things)

Complementarity of workers

- Four questions capture the extent to which low skill workers are more complementary to other workers.
  1. What are the consequences of you making an error (1=no consequences, 2, 3, 4, 5= very large consequences)
  2. What is the impact of decisions that you make (1=no impact, 2, 3, 4, 5= very large impact)
  3. On-site or in-plant training (none, up to 6 months, 6 months - 1 year, a year or more)
  4. On-the-job training (none, up to 6 months, 6 months - 1 year, a year or more)
- Aggregate this by skill for different level of R&D intensity
- These are occupation level measures, so any change reflects a change in occupation composition

Consequences of an error

- The consequences of a worker in a low-skilled occupation making an error are larger in a high-R&D firm than in a low-R&D firm
  - Mean "consequences of an error"

Consequence of an error

	Tercile of R&D intensity			
Skill level	None (1)	Low (2)	Middle (3)	High (4)
Low	1.00	1.02	1.12	1.14
Intermediate	1.00	1.00	1.02	1.03
High	1.00	1.02	1.00	0.99

Impact of decisions

- The impact of decisions of a worker in a low-skilled occupation are larger in a high-R&D firm than in a low-R&D firm
  - Mean "impact of decisions"

Impact of decision

	Tercile of R&D intensity			
Skill level	None (1)	Low (2)	Middle (3)	High (4)
Low	1	1.00	1.00	1.01
Intermediate	1	0.99	0.98	0.98
High	1	1.00	0.98	0.97

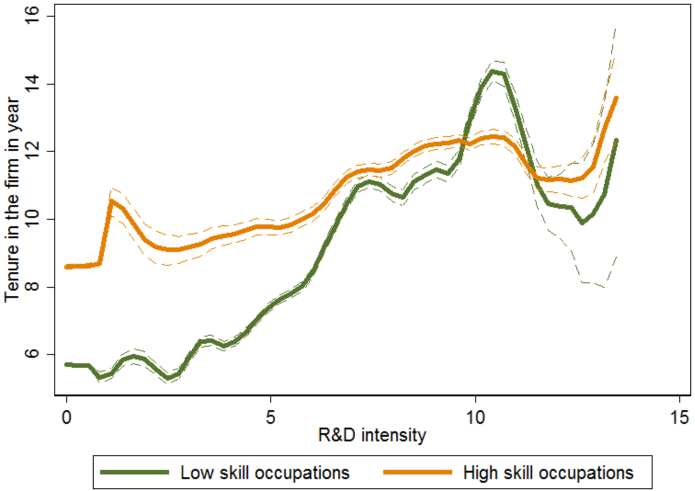
Training in low-skilled occupations

Back

- The table show the mean share of workers in low-skilled occupations that receive training (on average in the US, O*NET data)

	R&D intensity			
	None	lowest tercile	middle tercile	highest tercile
On-site or in-plant				
none	20.3	19.7	18.6	18.5
up to 6 months	65.6	64.3	59.6	54.4
6 months - 1 year	7.7	8.4	10.9	12.9
a year or more	6.4	7.6	10.9	14.3
On-the-job				
none	10.1	10.0	9.3	9.1
up to 6 months	74.8	72.5	66.1	59.9
6 months - 1 year	7.9	9.0	12.5	14.9
a year or more	7.2	8.5	12.1	16.2

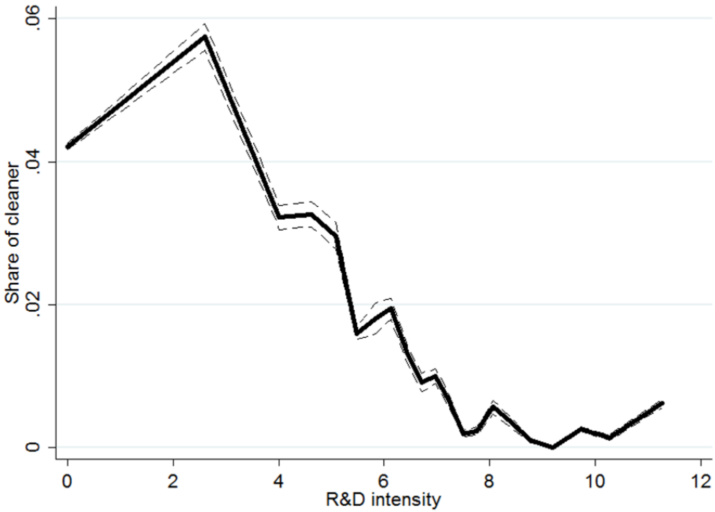
Tenure by skill and R&D



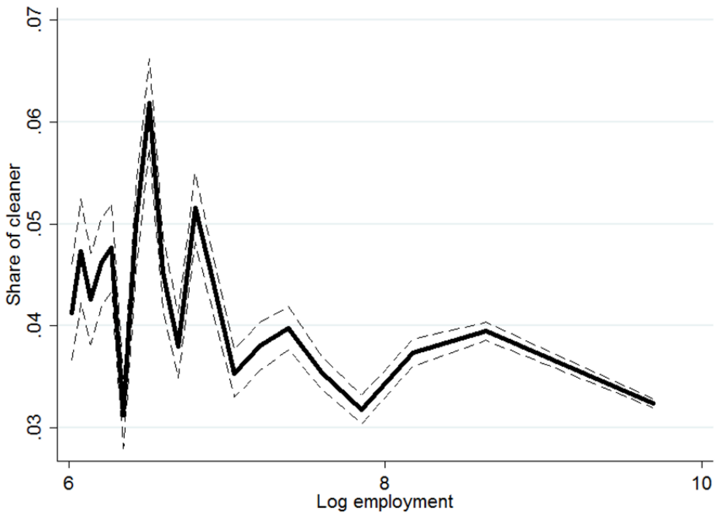
How to measure outsourcing?

- Our model predicts that innovative firms with outsource the task that have little complementarity between high and low skill occupation workers.
- Problem: not enough time dimension to observe this directly as in Goldschmidt and Schmieder (2017).
- Instead, we focus on one specific occupation
- Latter: use BHPS to look at outsourcing by industry in a very long period of time

Share of cleaners decrease with R&D



Not with employment



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Conclusion

- We use new employee-employer matched data that includes information on R&D to show:
  - workers in innovative firms earn higher wages on average than workers in non-innovative firms
  - the premium for working in an innovative firm is higher for workers in low-skilled occupations
- We propose a model that is consistent with this finding
  - some low-skilled occupations are essential for high-R&D firms, these workers are complementary to the high skilled workers, and this allows them to capture a high share of the surplus than equivalent workers in low-R&D firms
- We show empirical support for this model
  - Low skill workers are more essential for high innovative firms.
  - tenure of workers in low-skilled occupations is longer in high-R&D firms than in low-R&D firms

Additional Slides

Testing different function of R&D

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	Dependent variable: $ln(w_{ijkft})$							
R&D function	$\frac{x}{l}$ (1)	$log(1+\frac{x}{l})$ (2)	$H(x)$ (3)	$H\left(\frac{x}{l}\right)$ (4)	$log(1+x)$ (5)	$x>0$ (6)	x (7)	$log(\frac{x}{l})$ (8)
$\tilde{R}_{ft}$	0.000**	0.002***	0.001**	0.013***	0.001*	0.006	0.019	0.002
	(0.000)	(0.001)	(0.001)	(0.003)	(0.000)	(0.005)	(0.014)	(0.002)
* low-skill	0.001*	0.006***	0.003***	0.024***	0.002***	0.026***	0.072**	0.005***
	(0.000)	(0.001)	(0.001)	(0.003)	(0.001)	(0.008)	(0.031)	(0.002)
* med skill	0.000*	0.002***	0.001**	0.010***	0.001**	0.011**	0.020**	0.002
	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)	(0.006)	(0.009)	(0.001)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.008***	0.007***	0.007***	0.007***	0.007***	0.007***	0.008***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Tenure^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Size	-0.006***	-0.006***	-0.007***	-0.006***	-0.007***	-0.007***	-0.006***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Full-Time	-0.003	-0.004	-0.004	-0.004	-0.004	-0.003	-0.003	-0.080***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.023)
low-skill	-0.130***	-0.136***	-0.134***	-0.132***	-0.134***	-0.134***	-0.130***	-0.067***
	(0.039)	(0.043)	(0.042)	(0.040)	(0.042)	(0.042)	(0.039)	(0.007)
med-skill	-0.051	-0.052	-0.052	-0.049	-0.052	-0.052	-0.051	-0.038***
	(0.039)	(0.043)	(0.042)	(0.040)	(0.042)	(0.042)	(0.039)	(0.005)
high-skill	0.016	0.021	0.020	0.024	0.019	0.018	0.017	0.000
	(0.040)	(0.044)	(0.043)	(0.040)	(0.043)	(0.043)	(0.040)	(.)
R^2	0.889	0.889	0.889	0.889	0.889	0.889	0.889	0.917
Observations	626,210	626,210	626,210	626,210	626,210	626,210	626,210	162,696

Testing different function of R&D

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	Dependent variable: $ln(w_{ijkft})$			
Skill Category	Low (1)	Intermediate (2)	High (3)	All (4)
Quantile 1	0.004	-0.001	0.001	0.004
Quantile 2	0.017**	0.003	-0.007	0.010
Quantile 3	0.006	0.003	-0.001	0.002
Quantile 4	0.031***	-0.018	-0.008	0.012*
Quantile 5	0.036**	0.010	-0.000	0.023***
Quantile 6	0.036***	0.012	0.011	0.027***
Quantile 7	0.037***	0.009	-0.008	0.025***
Quantile 8	0.039***	0.014	0.000	0.031***
Quantile 9	0.044***	0.021*	-0.007	0.035***
Quantile 10	0.048***	0.021	-0.001	0.038***
Quantile 11	0.065***	0.029*	-0.006	0.053***
Quantile 12	0.070***	0.046***	-0.003	0.056***
Quantile 13	0.073***	0.029**	-0.013	0.051***
Quantile 14	0.073***	0.035***	0.012	0.064***
Quantile 15	0.061***	0.035***	0.012	0.064***
Quantile 16	0.096***	0.048***	-0.011	0.081***
Quantile 17	0.085***	0.022*	-0.003	0.071***
Quantile 18	0.090***	0.043***	0.007	0.082***
Quantile 19	0.114***	0.028**	-0.013	0.077***
Quantile 20	0.147***	0.020	-0.001	0.099***
R^2	0.774	0.851	0.885	0.887
Observations	407,341	104,318	114,535	626,210

Other measures of R&D

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	Dependent variable: $ln(w_{ijkft})$				
	Baseline (1)	Only Intram (2)	Only Extram (3)	Log of R&D workers (4)	Share scientists
$\tilde{R}_{ft}$	0.002***	0.002***	-0.000	0.009***	0.012
	(0.001)	(0.001)	(0.001)	(0.002)	(0.009)
* low-skill	0.006***	0.006***	0.008***	0.005***	0.151***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.020)
* med skill	0.002***	0.002***	0.004***	0.002**	0.055***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.019)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.007***	0.007***	0.007***	0.007***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Size	-0.006***	-0.006***	-0.006***	-0.006***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Full-Time	-0.004	-0.004	-0.004	-0.004	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)
low-skill	-0.157***	-0.157***	-0.162***	-0.155***	-0.196***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)
med-skill	-0.073***	-0.073***	-0.077***	-0.071***	-0.098***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
R-squared	0.889	0.889	0.889	0.889	0.854
N	626,206	626,206	626,206	626,206	1,815,709

Robustness to using different measures of income

Back

	(1)	(2)	(3)	(4)
$\tilde{R}_{ft}$	0.002***	0.002***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
* low-skill	0.006***	0.005***	0.011***	0.011***
	(0.001)	(0.001)	(0.002)	(0.002)
* med skill	0.002***	0.002**	0.001	0.000
	(0.001)	(0.001)	(0.002)	(0.002)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.007***	0.006***	0.068***	0.066***
	(0.000)	(0.000)	(0.003)	(0.003)
Tenure^2	-0.000***	-0.000***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Size	-0.006***	-0.009***	-0.024***	-0.022***
	(0.002)	(0.001)	(0.005)	(0.005)
Full-Time	-0.004	0.009	0.493***	0.489***
	(0.005)	(0.006)	(0.014)	(0.014)
low-skill	-0.157***	-0.151***	-0.194***	-0.189***
	(0.006)	(0.006)	(0.010)	(0.010)
med-skill	-0.073***	-0.070***	-0.060***	-0.059***
	(0.004)	(0.004)	(0.008)	(0.008)
Fixed Effects	i+t	i+t	i+t	i+t
R-squared	0.889	0.908	0.796	0.785
N	626,206	625,982	624,208	623,859

Alternative definition of skill levels

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	Dependent variable: $ln(w_{ijkft})$				
Skill Category	1 (low)	2	3	4 (high)	All
	(1)	(2)	(3)	(4)	(5)
$\tilde{R}_{ft}$	0.005***	0.007***	0.002**	-0.000	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
* low-skill					0.004***
					(0.001)
* med-low skill					0.005***
					(0.001)
* med-high skill					0.002**
					(0.001)
Age^2	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.007***	0.009***	0.004***	0.002***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
$Tenure^2$	-0.000***	-0.000***	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Size	0.003	-0.007***	0.000	0.004	-0.006***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Full-Time	-0.038***	-0.014**	-0.115***	-0.110***	-0.006
	(0.006)	(0.007)	(0.014)	(0.014)	(0.005)
low-skill					-0.170***
					(0.006)
med-low-skill					-0.143***
					(0.006)
med-high-skill					-0.049***
					(0.004)
R-squared	0.706	0.781	0.872	0.901	0.889
N	103,129	293,545	113,803	115,729	626,206

Appendix: model

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- In case where $n \geq 1$ low-occupation workers and $m \geq 1$ high-occupation workers. We determine equilibrium wages using ex post negotiation Stole and Zwiebel (1996).
- If the n^{th} low-occupation worker refuses the wage offer w_n^L, then the remaining $n-1$ low-occupation workers renegotiate a wage w_{n-1}^L.
- By induction, this provides a generic expression for the two equilibrium wages $w_{n,m}^L(Q,q,\lambda)$ and $w_{n,m}^L(Q,q,\lambda)$ (up to a constant in q, Q and λ):

$$w_{n,m}^L(Q,q,\lambda) = \frac{(q-q_L)\lambda\theta}{n(n+1)} \sum_{i=0}^{n} iQ^m q^{i-1} - \frac{\theta(1-\lambda)}{2}(q-q_L)$$

$$w_{n,m}^H(Q,q,\lambda) = \frac{(Q-Q_L)\lambda\theta}{m(m+1)} \sum_{i=0}^{m} iq^n Q^{i-1} - \frac{\theta(1-\lambda)}{2}(Q-Q_L),$$

Appendix: model

- Assume $n = 1$ and $m = 2$

$$\frac{\partial w^L_{1,2}(Q, q, \lambda)}{\partial \lambda} = \frac{\theta(q - q_L)(Q^2 - 1)}{2}$$

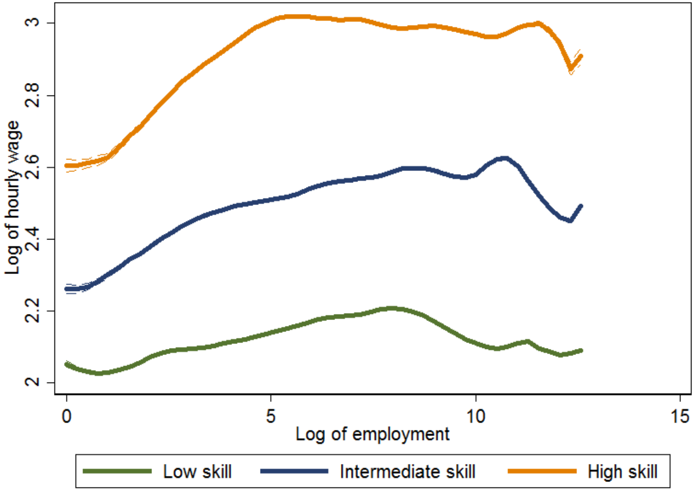
and

$$\frac{\partial w^H_{1,2}(Q, q, \lambda)}{\partial \lambda} = \frac{\theta(Q - Q_L)\left(\frac{q(1+2Q)}{3} - 1\right)}{2},$$

- And since $Q > q$ implies that: $q(1 + 2Q) < Q(1 + 2Q) < Q(Q + 2Q)$ (recall $Q > 1$), we have $\frac{q(1+2Q)}{3} - 1 < Q^2 - 1$, which, combined with the assumption that $(Q - Q_L) < (q - q_L)$, immediately implies that:

$$\frac{\partial w^L_{1,2}(Q, q, \lambda)}{\partial \lambda} > \frac{\partial w^H_{1,2}(Q, q, \lambda)}{\partial \lambda}.$$

The story is different with employment



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The story is different with employment

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Non movers

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