Innovation, Employment and Inequality

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Innovation & employment in the labour market

Innovating firms hire more workers (Harrison et al., 2014)

But what happens in the local labour market?

- **Multiplier** (Moretti, 2010; Lee and Clarke, 2017): jobs in non tradeable sectors follow employment in **high tech sectors**
- **ICT adoption** (Autor and Dorn, 2013): employment and polarisation
- **Robots adoption** (Acemoglu and Restrepo, 2017): unemployment
- **Product innovation** (Gagliardi, 2014): patenting increase unemployment, especially with mature specialisation

Some missing links

- Investment in innovative activities (R&D)?
- Composition? good vs bad employment; entrepreneurship and S/E
- Initial conditions of the labour market?

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Post 1980s regularities

Increasing income inequality (Atkinson, 2015; Atkinson and Morelli, 2014; Piketty, 2014)

- Increased share of wealth concentrated in the top 10% and 1% (Alvaredo et al., 2013; Atkinson and Morelli, 2014)

Decreasing labour compensation and contribution

- Decline of labour shares (over GDP) since the 1970's (Karabarbounis and Neiman, 2013; Summers, 2013)
- Wage growth and productivity growth diverge (Lazonick, 2014)

Post 1980s regularities

Wage differences contribute substantially to raising inequality

- Increased compensations of top classes of workers: wages, bonuses, profit shares (Atkinson et al., 2011) and stock options (Frydman and Jenter, 2010)
- Increased firm size (Poschke, 2015; Mueller et al., 2015) and market concentration (The Economist, 2016)
  - wage dispersion (Mueller et al., 2015) and CEO pay rise (Frydman and Jenter, 2010)
- Differences between firms explains 2/3 of earnings variability across workers (Card et al., 2018; Song et al., 2015)
- Innovation is a source of rent creation, part of which may be shared with workers (Van Reenen, 1996)
- Does innovation contribute to increased wage differences? – between and within firms

Innovation and employment composition

What is the impact of **firm innovative activity** (R&D investments) on the **composition of employment** in UK local labour markets (Travel-To-Work-Areas –TTWA) – 2001-2011?

- What kind of employment is created/destroyed?

Does R&D affect **self employment**? What kind of self-employment?

Path dependency: does the effect differ by the **initial level of routinised employment**?

Innovation and wage difference

Between firms inequality: Do firms increase the wage paid to employees as they increase R&D investment?

Within firm inequality: Do all workers benefit equally from the R&D premium?

- Occupation level
- Degree of routinisation of the occupation
- Gender

Outline

The Impact of R&D on Employment and Self-Employment Composition in Local Labour Markets

- Contribution: composition, self-employment, and historical path dependence
- Data & method
- Results

Firm Innovation and Wage Inequality

- Evidence on wage differences
- Data & method
- Results

Innovation and employment composition

- Increase in R&D leads to **employment reduction**, but **‘improves’ composition**
  - Educated, in manufacturing, and in paid employment
- In **initially routinised areas**, employment **increases**, but **‘worsens’ composition**:
  - In non tradeable sectors and services (personal services?)
  - Low educated
  - self-employment increases
    - Mainly in medium and older cohorts
  - Young suffer most
- R&D does not seem to influence the type of self employment

Innovation and wage difference

Firm innovation contribute to wage differences **between** and **within** firms

- We find a positive statistically and economically significant elasticity (between 0.25 and 0.57), which varies across different groups:
  - Increase with occupation median wage: top paid occupations gain more
  - Highly routinised occupations gain less
  - Men's elasticity is 50% as much as for women (not in top occupations)

Outline

The Impact of R&D on Employment and Self-Employment Composition in Local Labour Markets

Innovation & employment in the labour market

Missing links in our understanding of the relation between innovation and employment in the **labour market**

- Investment in innovative activities (R&D)
- Composition. E.g. good vs bad employment; entrepreneurship and S/E (Relevance)?
- Initial conditions of the labour market?

R&D & employment

Commitment of resources to innovation, creating and accumulating knowledge stock: spillovers (especially when not patented)

Investment in human capital ($\sim 50\%$)

Within firm: increase employment (Bogliacino et al., 2012)

- Change in composition? Substitute or complement low skilled?

Local labour market

- Attract skilled workers
- Attract new entrepreneurs (Schump Mark I): start-ups
- Increase demand for non tradeable (personal) services
- Increase competition and exit

Composition effect on the labour market unclear from theory

R&D and self-employment

SE decision depends on current & expected employment status (*refugee* vs *entrepreneur*) (Blanchflower and Oswald, 1998; Thurik et al., 2008)

Entrepreneur: spillovers and opportunities (Feldman and Kogler, 2010)

- Depends on technological regimes (Breschi et al., 2000)

Refugee:

- Skill mismatches (Åstebro et al., 2011; Vona and Consoli, 2015)
- Skill complementarity (personal services) (Autor and Dorn, 2013; Mazzolari and Ragusa, 2013; Eeckhout et al., 2014)

Evidence from UK (Figure: w/o workers)

- With workers more likely to seek opportunities (Coad et al., 2017)
- “Hidden unemployment” (Blundell et al., 2014)
- Correlated with firm entry & innovation, in *urban areas* (Faggio and Silva, 2014)

History matters: the relevance of initial conditions

Local industrial structure (Gagliardi, 2014) and skill composition (Autor and Dorn, 2013) influence the impact of innovation on employment composition, e.g.

- The larger the initial share of routine intensive jobs in the local labour market, the more pronounced is the polarisation that follows technical change (Autor and Dorn, 2013)
- Local skill complementarity (Eeckhout et al., 2014)
- Extent of skill mismatch
- Ability of individuals to capture opportunities
- R&D in different sectors command different skills, and offer differ opportunities (technological regimes)

Data

- Innovation
  - R&D private expenditure from the Business Enterprise Research and Development Survey (BERD). 400-500 firms responsible for 80% UK's R&D expenditure.
  - For the remaining 20% BERD targets 80-90% of medium to large businesses. Small firms under-sampled (Map)
- Employment
  - UK census data for employment variables.
  - Business Structure Database (BSD) for employment shares used in instrumentation.
- Trade Instrument
  - UN Comtrade
- Period of analysis: 2001-2011

Empirical Strategy

- The impact of firm R&D in a TTWA on employment outcomes (y_i):

$$\Delta y_i = \alpha + \beta \Delta RD_i + \gamma_c + \varepsilon_i \tag{1}$$

- By initial level of routinisation ϕ (Distribution, Map)

$$\Delta y_{it} = \alpha + \beta_1 \Delta RD_{it} + \beta_2 [\phi_{it_0} \times \Delta RD_{it}] + \gamma_c + \varepsilon_{it} \tag{2}$$

Empirical Strategy: identification

- Instrumentation for ΔRD IV
  - Shift share (Bartik): $Z_i^B = \sum_j \omega_j^i \Delta RD_{-ij}$. Based on national R&D change and initial TTWA industry composition.
  - Trade induced $Z_i^T = \sum_j \omega_j^i \kappa_j \Delta M_j^{USA}$. Based on exposure of (US→UK) sectors to China access to WTO (2001)
    - ★ i: TTWA; j: sector; ω: employment share; κ share of imports from China in 2001; M_j^{USA}: log US imports from China

Identification: Intuition

We exploit the variation in the sectoral composition of local labour markets

1. Different industries have different propensity to invest in R&D (Pavitt, 1984)
   - National change in R&D is exogenous to the firm
   - Each industry contributes x% to such change
   - ⇒ A local labour market contribution depends on the industrial composition (employment)
2. Different industries where exposed to a different extent to the China accession to the WTO (2001) (Bloom et al., 2016)
   - Competition and lower input costs increases R&D (Bloom et al., 2016) (innovate or dye (Bloom et al., 2013))
   - Exposed sectors are expected to increase R&D post 2001
     - ⋆ Estimate the import in US (similar to UK, but exogenous)
   - Each industry contributes to R&D depending on exposure
   - ⇒ A local labour market contribution depends on the industrial composition (employment)

Baseline: R&D on employment level (First Stage)

	Pop.	Employment		Unemployment		Ratio
	Ln(P)	Ln(E)	Ln(E/P)	Ln(U)	Ln(U/P)	Ln(E/U)
	(1)	(2)	(4)	(4)	(5)	(6)
a. Bartik						
ΔRD	-0.09***	-0.08***	0.00	-0.10***	-0.02	0.02
	(0.01)	(0.02)	(0.01)	(0.03)	(0.04)	(0.05)
Obs.	212	212	212	212	212	212
b. Trade Induced						
ΔRD	-0.07***	-0.06***	0.02***	-0.11***	-0.04***	0.04***
	(0.01)	(0.01)	(0.00)	(0.02)	(0.01)	(0.01)
Obs.	212	212	212	212	212	212

R&D on employment level by routinisation

	Pop.	Employment		Unemployment		Ratio
	Ln(P)	Ln(E)	Ln(E/P)	Ln(U)	Ln(U/P)	Ln(E/U)
	(1)	(2)	(4)	(4)	(5)	(6)
a. Bartik						
ΔRD	-0.09***	-0.11***	-0.01	-0.01	0.08	-0.09
	(0.01)	(0.03)	(0.01)	(0.04)	(0.06)	(0.07)
$\Delta RD \times \phi$	0.04**	0.20***	0.15***	-0.71***	-0.76***	0.91***
	(0.02)	(0.08)	(0.06)	(0.21)	(0.23)	(0.28)
b. Trade Induced						
ΔRD	-0.05*	-0.08***	-0.04*	0.23**	0.28***	-0.31***
	(0.02)	(0.01)	(0.02)	(0.12)	(0.10)	(0.12)
$\Delta RD \times \phi$	-0.07	0.08***	0.15***	-1.26***	-1.19***	1.34***
	(0.05)	(0.02)	(0.05)	(0.29)	(0.26)	(0.30)

R&D on employment composition by industry

	Man.	Cons.	Trans.	Wholesale, retail accom., food	Business & financial services	Public sector, education, arts and entert.
	(1)	(2)	(3)	(4)	(5)	(6)
a. Baseline						
ΔRD	0.29***	-0.12***	0.23***	-0.08***	0.04***	-0.01**
	(0.03)	(0.05)	(0.02)	(0.02)	(0.01)	(0.01)
Obs.	212	212	212	212	212	212
b. By TTWA routinisaiton						
ΔRD	0.35***	-0.18***	0.18***	-0.13***	-0.04	0.00
	(0.01)	(0.05)	(0.01)	(0.02)	(0.02)	(0.01)
$\Delta RD \times \phi$	-0.46***	0.48***	0.40***	0.40***	0.59***	-0.13***
	(0.17)	(0.08)	(0.12)	(0.06)	(0.15)	(0.03)
Obs.	212	212	212	212	212	212

R&D on employment composition by education

	Ln(H)	Ln(L)	Ln(H/L)
	(1)	(2)	(3)
a. Baseline			
ΔRD	0.13***	-0.04	0.16***
	(0.01)	(0.02)	(0.04)
Obs.	212	212	212
b. By TTWA routinisation			
ΔRD	0.12***	-0.07**	0.20***
	(0.01)	(0.03)	(0.04)
$\Delta RD \times \phi$	0.03	0.31***	-0.28***
	(0.05)	(0.08)	(0.08)
Obs.	212	212	212

R&D on employment composition by type of employment

	By Emp. Type			Ratio in (3) by age group		
	Employee	Self-Emp.	Ratio			
	$Ln(E_E)$	$Ln(E_{SE})$	$Ln(\frac{E_E}{E_{SE}})$	16-24	25-34	35-65
	(1)	(2)	(3)	(4)	(5)	(6)
a. Baseline						
ΔRD	-0.06***	-0.17***	0.11***	0.32***	0.19***	0.07***
	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)	(0.00)
b. By TTWA routinisation						
ΔRD	-0.08***	-0.22***	0.14***	0.41***	0.23***	0.08***
	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)
$\Delta RD \times \phi$	0.15*	0.45***	-0.30***	-0.77***	-0.36***	-0.10**
	(0.08)	(0.08)	(0.09)	(0.25)	(0.13)	(0.04)

R&D on employment composition by cohorts

	16-24		25-34		35-64	
	$Ln(E_k)$	$\frac{E_k}{E}$	$Ln(E_k)$	$\frac{E_k}{E}$	$Ln(E_k)$	$\frac{E_k}{E}$
	(1)	(2)	(3)	(4)	(5)	(6)
a. Employee						
			Baseline			
ΔRD	0.03*	0.01***	-0.21***	-0.03***	-0.03	0.02***
	(0.02)	(0.00)	(0.03)	(0.00)	(0.02)	(0.00)
			By TTWA routinisation			
ΔRD	0.12***	0.03***	-0.25***	-0.04***	-0.06***	0.01***
	(0.01)	(0.00)	(0.05)	(0.01)	(0.02)	(0.00)
$\Delta RD \times \phi$	-0.69***	-0.12***	0.32*	0.04	0.28***	0.08**
	(0.17)	(0.02)	(0.20)	(0.03)	(0.03)	(0.03)
Obs.	212	212	212	212	212	212
b. Self-Employed						
			Baseline			
ΔRD	-0.29***	-0.01***	-0.39***	-0.04***	-0.10***	0.05***
	(0.01)	(0.00)	(0.06)	(0.01)	(0.02)	(0.01)
			By TTWA routinisation			
ΔRD	-0.30***	-0.01***	-0.48***	-0.05***	-0.14***	0.06***
	(0.01)	(0.00)	(0.07)	(0.01)	(0.02)	(0.01)
$\Delta RD \times \phi$	0.08	-0.01***	0.68***	0.05**	0.38***	-0.05*
	(0.11)	(0.00)	(0.22)	(0.03)	(0.04)	(0.03)

R&D on self-employment composition by type

	Total	SE with employees			SE without employees		
		Total	Part-time	Full-time	Total	Part-time	Full-time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a. Baseline							
ΔRD	-0.14***	-0.18***	-0.22***	-0.17***	-0.09***	-0.06**	-0.09***
	(0.03)	(0.04)	(0.05)	(0.03)	(0.02)	(0.02)	(0.02)
Obs.	212	212	211	212	212	212	212
b. Interaction: slope							
ΔRD	-0.19***	-0.23***	-0.31***	-0.21***	-0.15***	-0.12***	-0.16***
	(0.03)	(0.04)	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)
$\Delta RD \times \phi$	0.40***	0.41***	0.72***	0.35***	0.52***	0.46***	0.55***
	(0.06)	(0.10)	(0.13)	(0.10)	(0.06)	(0.11)	(0.07)
Obs.	212	212	211	212	212	212	212

Summary of results

R&D has a significant impact especially on employment compositions

Depends on the initial conditions of the labour market

Low share of routinised jobs: $\downarrow$ employment

- $\uparrow$ manufacturing, educated, & paid employment

High share of routinised jobs: $\uparrow$ employment

- $\uparrow$ non tradeable services, low educated, self-employed
- young cohort badly affected, middle cohort move to S/E

Although refuge S/E increases in the UK, does not seem to be because of R&D: need for a closer look

- Earlier evidence suggests refuge S/E mainly in rural areas

Outline

Firm Innovation and Wage Inequality

Innovation and inequality in the UK

Do firms increase the premium paid to employees as they increase R&D investment? Figure

Do all workers benefit equally from the R&D premium?

- By type of occupation
  - Ranked by median earnings: Wage quintiles
  - Ranked by the routine content (Autor et al., 2003): RTI quintiles
- By gender Figure

Data (Table)

Innovation

- Business Enterprise Research and Development Survey (BERD): R&D private expenditure
  - 400-500 firms responsible for 80% UK's R&D expenditure.
  - For the remaining 20% BERD targets 80-90% of medium to large businesses.
  - Small businesses are under-represented: focus on large firms R&D

Earnings

- Annual Survey of Hours and Earnings (ASHE): 1% of working population

Trade

- Comtrade

Period of analysis: 2009-2015. Sector: manufacturing

Empirical Strategy

$$\ln w_{ift} = \alpha + \beta \ln RD_{ft} + X_{it} + \tau_t + \mu_{if} + \varepsilon_{ift} \tag{3}$$

- RD_{ft}: firm's total R&D expenditure in year t
- X_{it}: vector of individual controls: age, tenure in years, full-time
- τ_t: year dummies
- μ_{if}: match individual-firm fixed effect – individual & firm unobservable and their interaction

OLS estimation of β may be downward biased: unobserved heterogeneity influencing R&D and W, and measurement error (Table)

Empirical Strategy: Identification

Predict RD_{jt} using the growth of US imports from China following China's accession to the WTO

$$Z = \eta_j \times \Delta M_{jt}^{USA} \tag{4}$$

- η_j: Chinese import shares of UK+US+EU by industry j (3-digits) before China's accession to WTO (1995-2000)
- ΔM_{jt}^{USA}: 5Y log change of USA import for industry j
- changes for 5 periods from 2004 (2004-1999) to 2009 (2009-2004)

Empirical Strategy: Identification

We exploit the variation across industries in the manufacturing sector

Different industries where exposed to a different extent to the China accession to the WTO (2001) (Bloom et al., 2016)

- Initial set back of innovative activities (Autor et al., 2017)
- Competition and lower input costs increase R&D (Bloom et al., 2016) (innovate or dye (Bloom et al., 2013))
- Exposed industries are expected to increase R&D post 2001, after an initial setback: different lags
- Import competition also affects local employment (Autor et al., 2013, 2015):
    - R&D special relationship between USA and UK (Griffith et al., 2006)
- ⇒ A firm R&D depends on the industry exposure in US to Chinese trade shock

Empirical Strategy

Direct import competition may affect directly local labour markets (Autor et al., 2013, 2015)

Industrial dynamics may affect profits and wages

$$\ln w_{ift} = \alpha + \beta \ln \hat{RD}_{ft} + X_{it} + M_{jt} + conc_{jt} + \tau_t + \gamma_c(t) + \mu_{if} + \varepsilon_{ift} \quad (5)$$

- M_{jt}: Chinese import in the UK by industry j (3-digits)
- $conc_{jt}$: Herfindahl-Hirschman index (turnover) for industry j
- $\gamma_c(t)$ Travel to Work Area trends

Results: Baseline

	t=0	t=-1	t=-2	t=-3	t=-4	t=-5
Panel a. Second-stage						
$Ln(R\&D)$	0.152**	0.006	0.255***	0.571*	0.394**	0.342***
	(0.077)	(0.045)	(0.093)	(0.334)	(0.159)	(0.132)
M_{jt}	0.001	0.006***	-0.002	-0.012	-0.006	-0.005
	(0.003)	(0.002)	(0.004)	(0.011)	(0.006)	(0.005)
Conc.	-0.064	0.006	-0.112**	-0.261	-0.178**	-0.153**
	(0.040)	(0.026)	(0.054)	(0.170)	(0.084)	(0.070)
Obs.	51836	51836	51836	51836	51836	51836
Panel b. First-stage						
Z_t	-1.011***					
	(0.369)					
Z_1		-1.081***				
		(0.308)				
Z_2			0.971***			
			(0.276)			
Z_3				0.495*		
				(0.278)		
Z_4					0.742***	
					(0.283)	
Z_5						0.781***
						(0.278)
M_{jt}	0.036***	0.037***	0.023***	0.026***	0.023***	0.021***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Conc.	0.480***	0.484***	0.452***	0.462***	0.469***	0.481***
	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)
Obs.	51836	51836	51836	51836	51836	51836
F-Stat	29.1	29.8	29.3	29.1	29.5	29.4

Robustness checks

IV used:	Z_3	Z_4	Z_5
Panel a. R&D net of salaries			
Ln (R&D excl. salaries)	0.279***	0.200***	0.272***
	(0.101)	(0.050)	(0.093)
Obs.	51793	51793	51793
Panel b. R&D net of capital			
Ln (R&D excl. capital)	0.443**	0.290***	0.239***
	(0.206)	(0.091)	(0.070)
Obs.	51836	51836	51836
Panel c. Excluding top 1% R&D per employee performers			
$Ln(R\&D)$	0.631	0.461**	0.433**
	(0.443)	(0.230)	(0.217)
Obs.	50196	50196	50196
Panel d. Excluding top 5% R&D per employee performers			
$Ln(R\&D)$	0.733	0.677	0.578
	(0.608)	(0.529)	(0.397)
Obs.	46805	46805	46805

Heterogeneity across occupations

	Wage Quantile (1)	RTI (2)	Routinisation NS-SEC 7 (3)	NS-SEC 6+7 (4)
$Ln(R\&D)$	0.280**	0.384***	0.416**	0.447**
	(0.129)	(0.128)	(0.168)	(0.184)
$Ln(R\&D) \times quintile\ 2$	0.036	-0.009		
	(0.022)	(0.010)		
$Ln(R\&D) \times quintile\ 3$	0.066***	0.006		
	(0.024)	(0.015)		
$Ln(R\&D) \times quintile\ 4$	0.059**	-0.020		
	(0.023)	(0.014)		
$Ln(R\&D) \times quintile\ 5$	0.079***	-0.054***		
	(0.026)	(0.018)		
$Ln.(R\&D) \times \phi(7)$			-0.143***	
			(0.050)	
$Ln.(R\&D) \times \phi(6,7)$				-0.111***
				(0.037)
M_{jt}	-0.005	-0.005	-0.007	-0.006
	(0.005)	(0.005)	(0.006)	(0.006)
Conc.	-0.148**	-0.145**	-0.175**	-0.192**
	(0.071)	(0.066)	(0.085)	(0.093)
Obs.	51831	50281	51836	51836

Heterogeneity across gender & occupations

D =	Gender Gap	Wage Distribution			Routinisation	
		Top Half	Top 20%	Top 10%	Top Half RTI	$\phi(7)$
	(1)	(2)	(3)	(4)	(5)	(6)
$Ln(R\&D)$	0.261**	0.199*	0.243*	0.254*	0.276**	0.288**
	(0.133)	(0.110)	(0.125)	(0.132)	(0.129)	(0.133)
$Ln(R\&D) \times D$		0.042**	0.041*	0.018	-0.030*	-0.136**
		(0.017)	(0.025)	(0.045)	(0.017)	(0.067)
$Ln(R\&D) \times Male$	0.116**	0.093**	0.113**	0.118**	0.092*	0.085
	(0.054)	(0.047)	(0.053)	(0.053)	(0.055)	(0.061)
$Ln(R\&D) \times D \times Male$		-0.009	-0.020	-0.012	0.026	0.059
		(0.022)	(0.028)	(0.047)	(0.020)	(0.071)
M_{jt}	-0.006	-0.005	-0.005	-0.006	-0.005	-0.006
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Conc.	-0.165**	-0.140**	-0.155**	-0.163**	-0.158**	-0.155**
	(0.075)	(0.063)	(0.071)	(0.075)	(0.073)	(0.070)
Obs.	51836	51831	51831	51831	50281	51836

Summary of results

Does (formal) investment in innovation contribute to wage inequality?

- An increase in R&D expenditure leads to an increase in wages: estimated elasticity ranges between 0.25 and 0.57
  - Explains part of the between firms wage inequality
  - Mainly driven by large companies
- But the innovation rent is unevenly distributed
  - Top 20% occupations gain 0.08 percentage points more (30% higher) than bottom 20%
  - Highly routinised occupations gain 0.054 percentage points less (14% lower)
  - Male gap: 0.12 percentage points more than women (44% higher)
  - No evidence significant differences in top occupation or routinised
- Controlling for everything else, R&D rents seem to create inequality between and (although less) within firms

Conclusions

Does innovation activity – even before innovation output or the adoption of new technologies – have an impact on employment and wages?

Controlling for everything else, we find

- A significant impact of R&D expenditures on the composition of local labour markets – even if there are low differences in the level
  - There is compensation at the level of the local labour market but with significant differences between areas
    - Low routinised areas benefit
    - High routinised areas reduce skilled ratio, move to services, and self-employment
- A significant impact on firm wages, heterogeneous across workers
  - Contribute to increased inequality between firms
  - Contribute to increased inequality within firms

Policy implications

Innovation policies are not neutral

Trade off between reducing regional inequalities (R&D in left-behind places) and local inequalities (employment polarisation)

- "Counterbalancing" policies: re-training, job protection, access to resources, inclusion of local talents, real opportunities for migration
- Focus on quality of jobs

May take some time to transform an area from mining to AI, with local workers

Employment polarisation may be accompanied by higher increase in wages for top occupations

Trade-off between increasing firm innovation activity and increasing inequality

- Re-distribution?
  - How to attract talents?
- Gender differences?

Many thanks for your attention!

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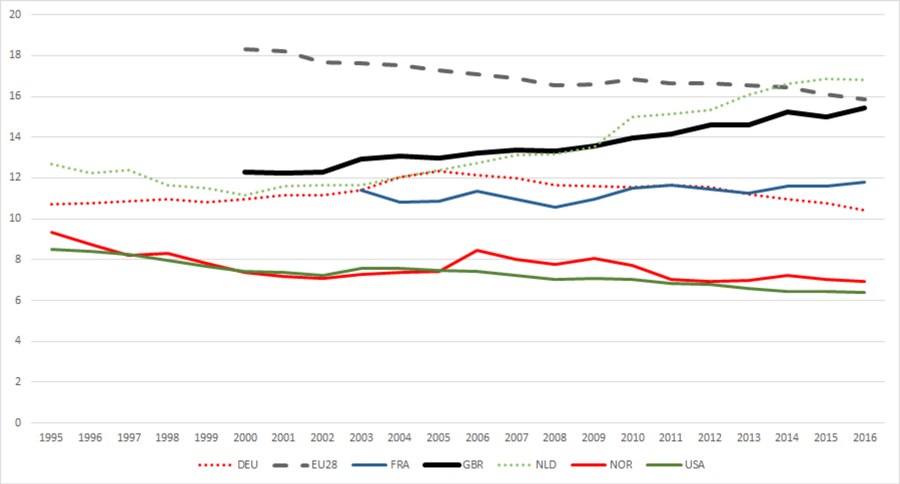
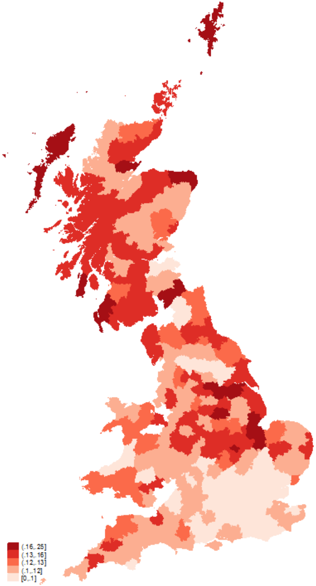
Self-Employment: % of employed labour force

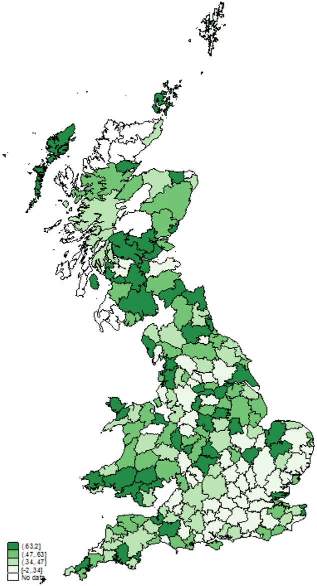


Source: ONS

back

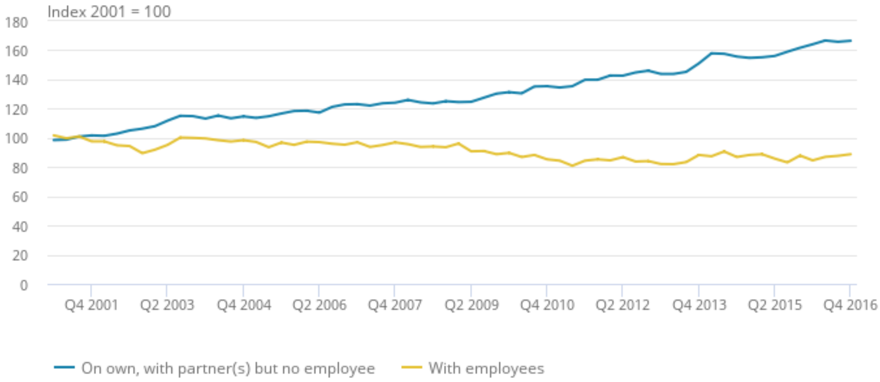
ϕ (left) and $\Delta\hat{RD}$ (right)





▸ Data ▸ Method

Self employment type: w/o workers (Back)



Source: ONS

RTA (ϕ): share of routinised labour ▸ Back

ϕ_i is defined on the basis of the share of routine occupations (National Statistics Socio-Economic Classification (NS-Sec)) in the TTWA

$$r_i = \frac{Total\, employment\, in\, routinised\, occupations}{Total\, employment}$$

$\phi_i = 1$ if r_i is larger than the median (0.13)

Non routine: (1) higher managerial and professional occupations, (2) lower managerial and professional occupations, (3) intermediate occupations, (4) small employers and own account workers, (5) lower supervisory and technical occupations, (6) semi- routine occupations

Routine: (7) routine occupations

Identification strategy ▸ Back

First step: estimate R&D at the industry level for 2001 and 2011:

$$\ln RD_{fjt} = \alpha + \ln Employees_f + \theta_j + \theta_t + \varepsilon_{fjt} \tag{6}$$

where

- RD_{fjt} is the intramural R&D expenditure of firm f, in year t, in sector j
- $Employees$ is the number of employees in firm f
- θ_j is a sector dummy

Second step, IV

$$z_i = \Sigma_j \omega_{ij} * \Delta RD_{-ij} \tag{7}$$

where

- ω_{ij}: estimate of the sectoral share of output by industry in TTWA i – 2-digit UK SIC code (2000 version)
- ΔRD_{-ij}: change in the average R&D expenditure at the sector level, excluding TTWA i: $\Delta RD_{-ij} = \hat{\theta}_{-ij,2011} - \hat{\theta}_{-ij,2001}$

ϕ in 2001

TTWA	ϕ
Bottom 5: least routinised	
Reading	.0680643
Guildford and Aldershot	.0691688
London	.0721267
Crawley	.072558
Brighton	.0735549
Average	.1353318
Median	.1335365
Top 5: most routinised	
Fraserburgh	.2338129
Corby	.2335603
Hawick and Kelso	.226953
Girvan	.2176792
Mansfield	.1980037

Notes: [1] ϕ is defined as the share of routine employment over all employment. We use the National Statistics Socio-economic classification (NS-SEC) developed by ONS. ϕ is the share of NS-SEC 7, routine occupations over the rest: NS-SEC 1: Higher managerial, administrative and professional occupations, NS-SEC 2: Lower managerial, administrative and professional occupations, NS-SEC 3: Intermediate occupations, NS-SEC 4: Small employers and own account workers, NS-SEC 5: Lower supervisory and technical occupations, NS-SEC 6: Semi-routine occupations, NS-SEC 7: Routine occupations

back

Instrumenting strategy

back

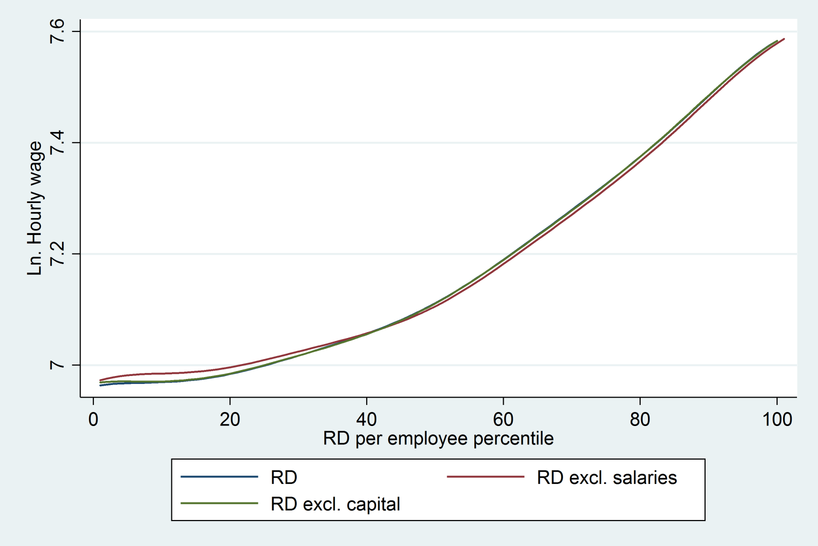
- Bartik-style:
  - 1) $lnRD_{fjt} = \alpha + lnEmployees_f + \theta_j + \theta_t + \varepsilon_{fit}$
  - 2) $\Delta RD_{-ij} = \hat{\theta}_{j2011} - \hat{\theta}_{j2001}$
  - $Z_i^B = \sum_j \omega_j^i \Delta RD_{-ij}$
- Trade induced $Z_i^T = \sum_j \omega_j^i \kappa_j \Delta M_j^{USA}$
- ω_j^i is the employment share of industry j in TTWA i. ΔRD_{-ij} is the national (net of i) change in RD per employee in industry j
- κ_j if the UK-industry exposure to China imports in 2001. ΔM_j^{USA} is the change (2011-2001) in US imports from China in industry j. China's accession to WTO in 2001.

First Stage (Back)

Table: First Stage

	Bartik	Trade Induced
	ΔRD	ΔRD
	(1)	(2)
Z	0.82***	79.02***
	(0.07)	(6.16)
F-test	123.80	164.67
Obs.	212	212

R&D and wages in the UK 2009-15 Back



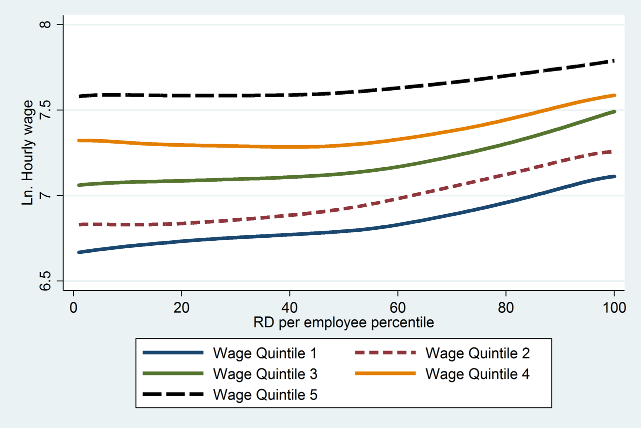
Descriptive statistics for individual variables (back)

Variable	Observations	Mean	SD
Hourly wage (in logs.)	59,277	7.217	0.480
Age	59,277	42.981	11.375
Age square	59,277	1976.744	962.688
Men proportion	59,277	0.768	0.422
Full-time(1=yes)	59,277	0.942	0.234
Tenure (in years)	59,277	11.353	10.122
Wage quintiles			
Bottom 20%	59,272	0.138	0.345
40% percentile	59,272	0.267	0.443
60% percentile	59,272	0.217	0.412
80% percentile	59,272	0.131	0.338
Top 20%	59,272	0.245	0.430
RTI quintiles			
Bottom 20%	57,663	0.146	0.353
40% percentile	57,663	0.185	0.389
60% percentile	57,663	0.148	0.355
80% percentile	57,663	0.249	0.432
Top 20% percentile	57,663	0.272	0.445
$\phi(7)$	59,277	0.167	0.329
$\phi(6,7)$	59,277	0.323	0.399

OLS Estimates (back)

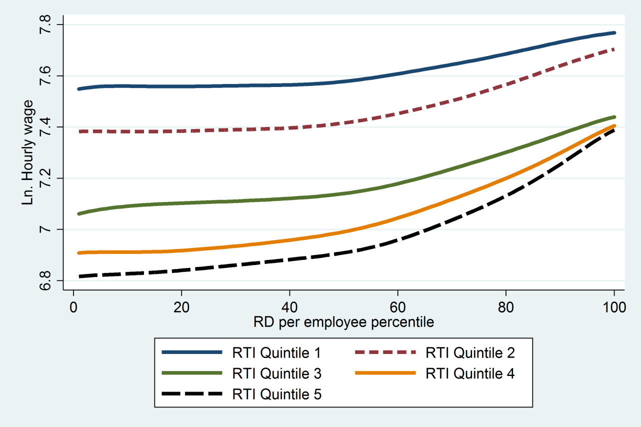
	(1)	(2)	(3)	(4)
$Ln(R\&D)$	0.049***	0.036***	0.006***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.060***	0.043***	0.038***	0.041***
	(0.002)	(0.001)	(0.006)	(0.005)
Age2	-0.001***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.190***	0.146***	-0.701	-0.900
	(0.008)	(0.006)	(27.585)	(17.679)
Full-time	0.063***	-0.002	-0.120***	-0.126***
	(0.012)	(0.010)	(0.012)	(0.011)
Tenure	0.006***	0.004***	0.002***	0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Obs.	59097	58305	54400	53201
Fixed Effects				
Year	Yes	Yes	Yes	Yes
TTWA	Yes	Yes	No	No
TTWA × Year	Yes	Yes	No	No
TTWA × Trend	No	No	No	Yes
Occupation	No	Yes	No	No
Occupation × TTWA	No	Yes	No	No
Occupation × TTWA × Year	No	Yes	No	No
Individual	No	No	Yes	Yes
Firm	No	No	No	Yes
Individual × Firm	No	No	No	Yes

Wage quintiles



Next

Routine component



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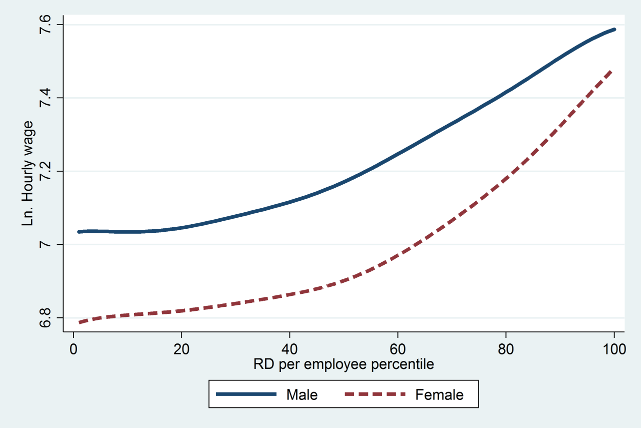
Gender


Ln. Hourly wage
6.8
7
7.2
7.4
7.6
0
20
40
60
80
100
RD per employee percentile
Male
Female

Back

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