Job Polarization in Finland

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Comparative Analysis of Enterprise Data

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Contents

- Skill bias and Job polarization – some background
- Data
- Empirical results:
  - Aggregate: descriptive and some analyses using task variables
  - Firm level: effects of technology at micro level (R&D, later other technology variables)

Skill bias

- Skill-Biased technological change (SBTC), especially computer-based production technology, seen as the driving force behind increasing wage differentials, education premiums and skill uppgrading since 1980's.
- Evidence:
  - Increasing share of skilled workers within industry/plant, rather than between industry/plant, phenomenon. Within change related to technology indicators, like R&D intensity or computer investments. Berman, Bound and Griliches (1994) and many others.
  - Trends in education premiums and wage inequality in general the result of changes in supply and demand for skills, the "race between education and technology". Tinbergen (1974,1975), Bound and Johnson (1992), Goldin and Katz (2008) and many others.
  - Computer wage premium, Krueger (1993). But biased by unobserved heterogeneity and/or selection/endogeneity, DiNardo and Pischke (1997), Entorf, Gollac and Kramarz (1999) and many others.

Tasks and Computers

- Autor, Levy and Murnane (1993): adoption of computers in the workplace changes tasks performed by workers in their jobs.
  - Computers are **substitutes** for routine tasks (involving explicit rules that can be programmed into computer code)
  - Computers are **complements** for non-routine (analytic, interactive) tasks (involve complex problem-solving and communication activities, not programmable)
- Increasing computerization, caused by declining price of computing, leads to increased usage of non-routine task inputs and reduced usage of routine tasks inputs in production.
- Evidence:
  - create task measures from Dictionary of Occupational Titles (DOT) database, based on expert evaluation of job content
  - show that increasing computerization at industry level is related with increased usage of non-routine task inputs and decreased usage of routine task inputs at industry level.

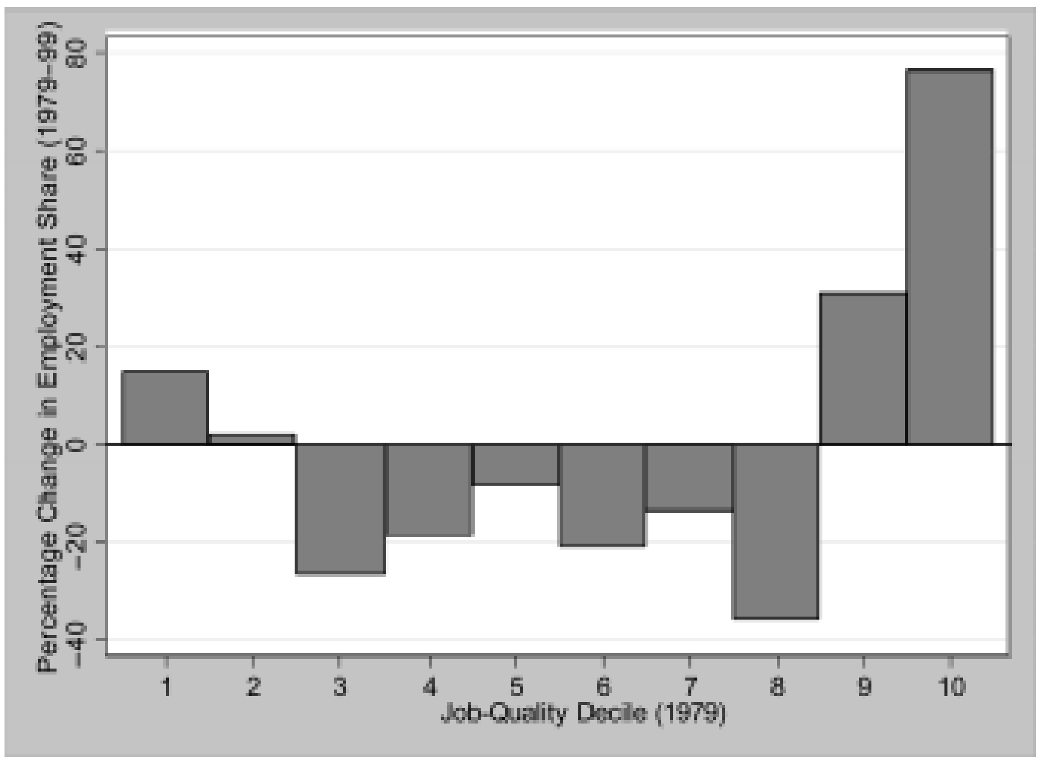
Polarization

- Goos and Manning (2007) argued that the ALM ”routinization hypothesis” may imply job polarization:
  - Many routine jobs are middle skilled/middle wage jobs
  - Non-routine jobs are either high skilled/high wage (analytic) or low skilled/low wage (service) jobs
  - Technological change (computers) leads to increasing employment in high wage and low wage jobs, but decreasing employment in the middle wage jobs.
  - Employment change is U-shaped with respect to skill/wage/education level: employment polarizations, or ”hollowing out of the middle”

Employment polarization (UK)

Source: Goos and Manning (2007)

FIGURE 1.—PERCENTAGE CHANGE IN EMPLOYMENT SHARE BY JOB-QUALITY DECILE



Notes: Employment data are taken from the LFS using three-digit SOC90 codes. Employment changes are taken between 1979 and 1999. Quality deciles are based on three-digit SOC90 median wages in 1979 taken from the NES.

Wage polarization (US)

Source: Autor, Katz and Kearney (2006)

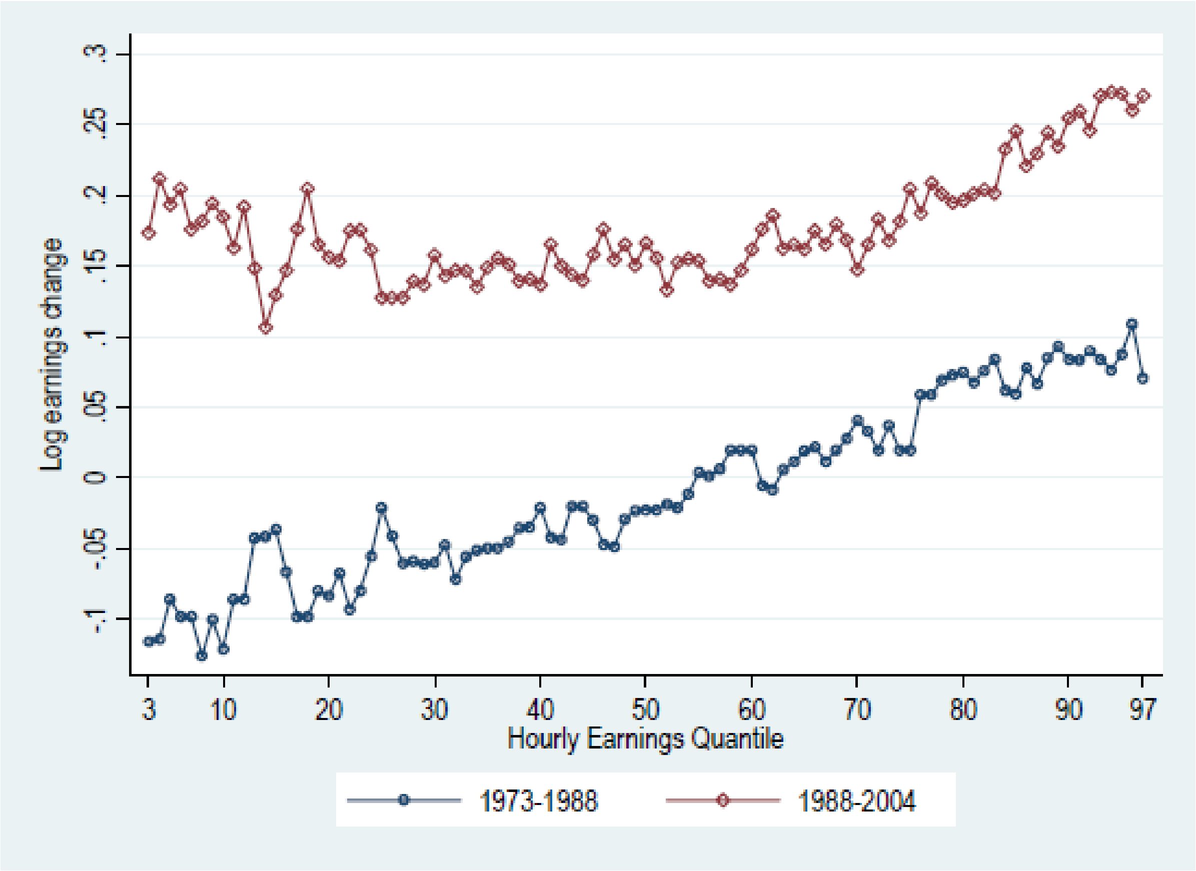


Figure 2. Changes in Male and Female Log Real Hourly Earnings by Percentile 1973 - 1988 and 1988 - 2004. Source: see Figure 1.

Data

- Finnish Employer-Employee payroll record data of the private sector collected
  - by Employers association on all of their member enterprises with some non-response and
  - by Statistics Finland for the rest using stratified random sampling.
- Sampling weights used for Statistics Finland data.
- The coverage is very good except that the smallest firms are excluded.
- Longitudinal data by employees and employers for the years 1995-2008
  - Some 600 000 – 750 000 employees per year
  - Some 30 000 firms exist at least in one year over the period 1995-2008

Data (cont.)

- "Hourly wage for regular working time" as the wage measure:
  - Includes: basic pay; supplements based on duties, professional skill, years of service etc.; supplements based on location and conditions of workplace; performance-based pay components paid regularly for salaried employees; taxation value for fringe benefits; and pay for working hours not worked. Regular wages do *not include* overtime pay or one-off items, such as holiday and performance bonuses.
  - Monthly paid and hourly paid included and made comparable

Data (cont.)

- Harmonisation over time is needed because of changes in collective wage contracts and classifications used.
- All classifications harmonised using latest codes
  - Education (formal education is available from register)
  - Industry
  - Occupation – with some problems:
    - not possible to completely harmonise some occupations for white-collar manufacturing workers over the break point 2001-2002 due to classification change in primary data
    - hence we perform all our estimations using separate data before and after this break point: periods 1995-2001 and 2002-2008
    - occupation codes in primary data converted into the international ISCO 2001 codes at the 5-digit level: analyses at 3-digit level

Change in occupation codes - Example

YEAR T
Initial codes
disappeared t+1

A
B
C
D
E
F

YEAR T+1
Initial codes
new occupation t+1

A1
A2
A3
C1
C2
D
F1
F2
F3
G1
G2
G3
G4

Harmonised
Codes ?

D is clear

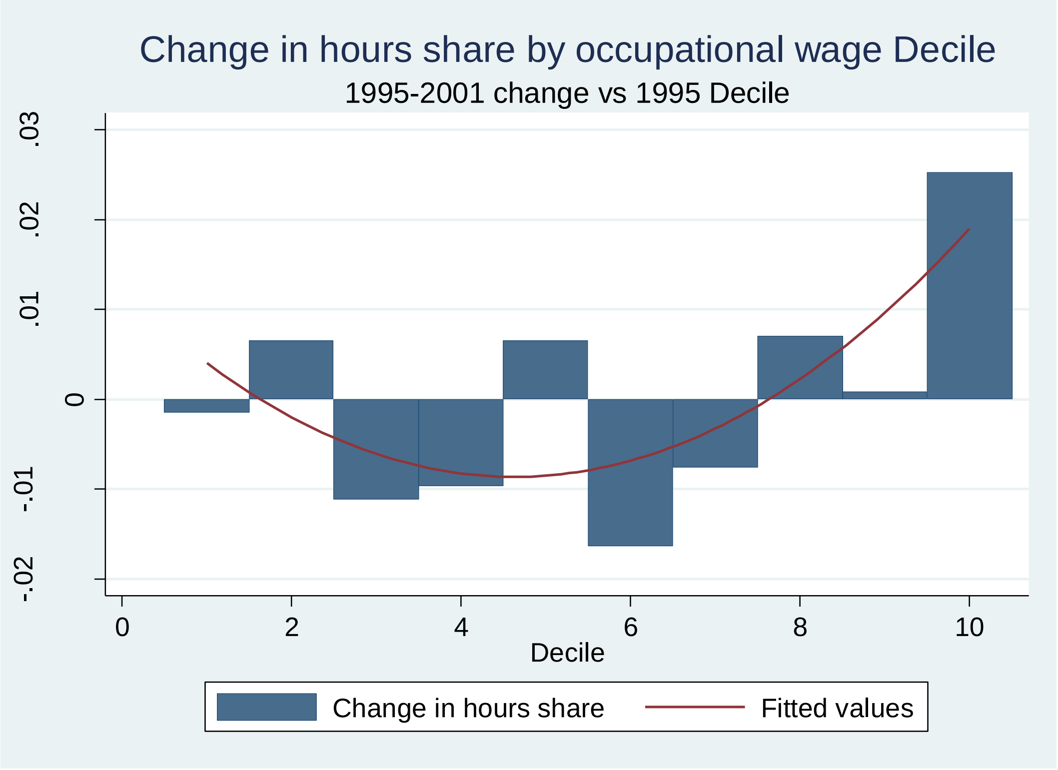
What about
Others?

Data (cont.)

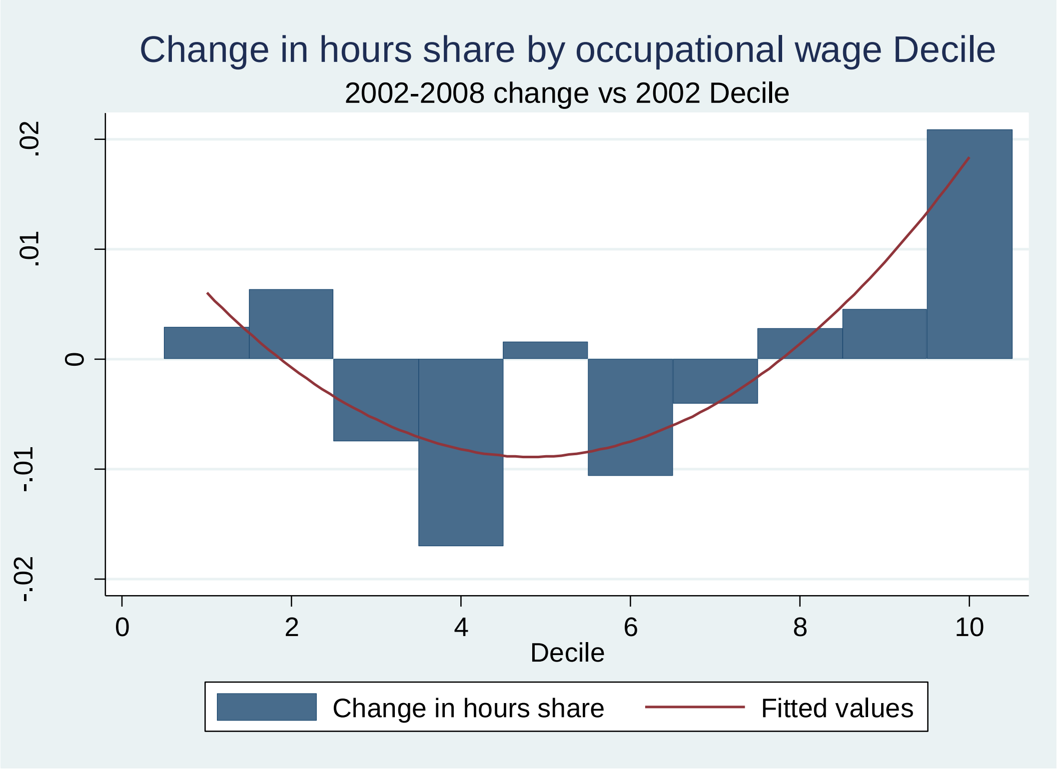
- R&D Survey matched at the firm level for years 1995, 2001, 2002, 2008.
  - Includes all large firms and sample of smaller firms, some 4000 firms per year.
  - R&D intensity defined as in-house R&D expenditures divided by firm’s sales
- Our data period covers the rapid growth after the early 90’s recession
  - Structural change in Finnish economy was profound (Nokia led ICT cluster)
  - Benefits of ICT enhanced by internet revolution

Aggregate results: descriptive

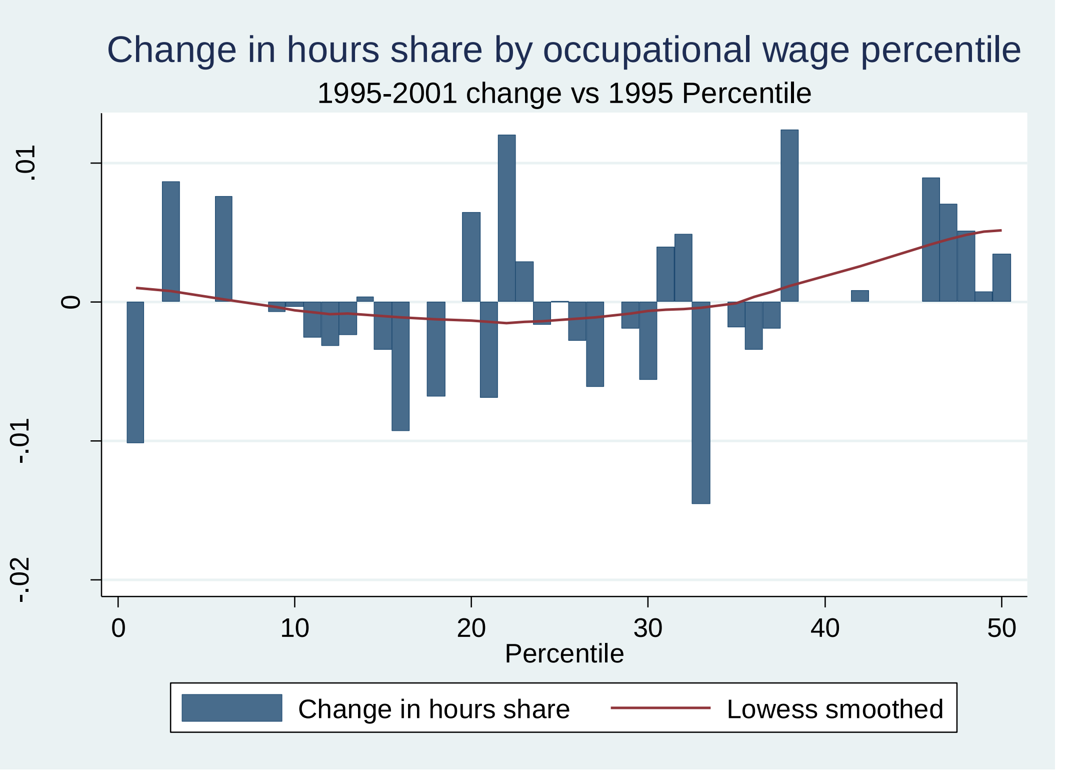
- Change in occupational employment shares by skill groups:
  - By Wage Decile and Percentile (2% bins)
  - Skill group defined by occupation's initial median wage, i.e. wage in the first year of 6-year periods 1995-2001 and 2002-2008
  - Fit a quadratic function or locally weigted regression (lowess) to highlight the general pattern

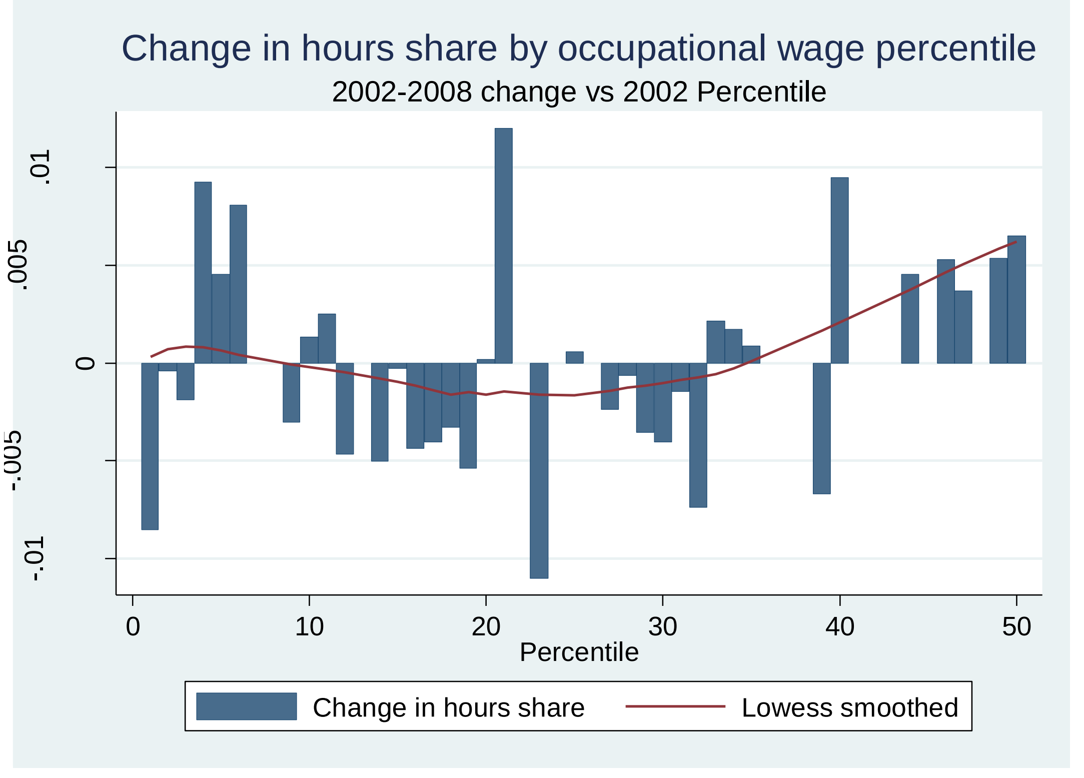


Quadratic fit



Quadratic fit


Change in hours share by occupational wage percentile
1995-2001 change vs 1995 Percentile
.01
0
-.01
-.02
0
10
20
30
40
50
Percentile
Change in hours share
Lowess smoothed


Change in hours share by occupational wage percentile
2002-2008 change vs 2002 Percentile
.01
.005
0
-.005
-.01
0
10
20
30
40
50
Percentile
Change in hours share
Lowess smoothed

Aggregate results: descriptive

- Some indications of polarization – but is it statistically significant? Following Goos and Manning (2007):
- Regress changes in occupational employment shares (three digit) on a quadratic of initial log median wage in occupation:

$$\Delta_6 occshr_t = \beta_0 + \beta_1 wage_{t-6} + \beta_2 wage_{t-6}^2 + Timedum_t + \varepsilon_t$$

- Polarization if U-shaped function:

$$\beta_1 < 0 \qquad \text{and} \qquad \beta_2 > 0$$

- Linear relationship consistent with skill bias.

- Alternatively use occupation’s median or mean education years in the first year of period instead of wage

Regressions for change in occupational employment shares on initial log median wage

(six year changes 1995-2001 and 2002-2008 pooled and separately)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Pooled Quadratic	1995-2001 Quadratic	2002-2008 Quadratic	Pooled Linear	1995-2001 Linear	2002-2008 Linear
Wage(t-6)	-0.0144	-0.0316	-0.0102	0.00647**	0.00714*	0.00603
	(0.0487)	(0.0717)	(0.0752)	(0.00275)	(0.00407)	(0.00371)
$Wage(t-6)^2$	0.00392	0.00743	0.00301			
	(0.00874)	(0.0132)	(0.0134)			
Year dummy	0.000568			0.000521		
	(0.00153)			(0.00151)		
Constant	0.0108	0.0317	0.00665	-0.0166**	-0.0183*	-0.0150
	(0.0669)	(0.0964)	(0.104)	(0.00714)	(0.0106)	(0.0100)
Observations	171	85	86	171	85	86
R-squared	0.084	0.088	0.065	0.081	0.079	0.063

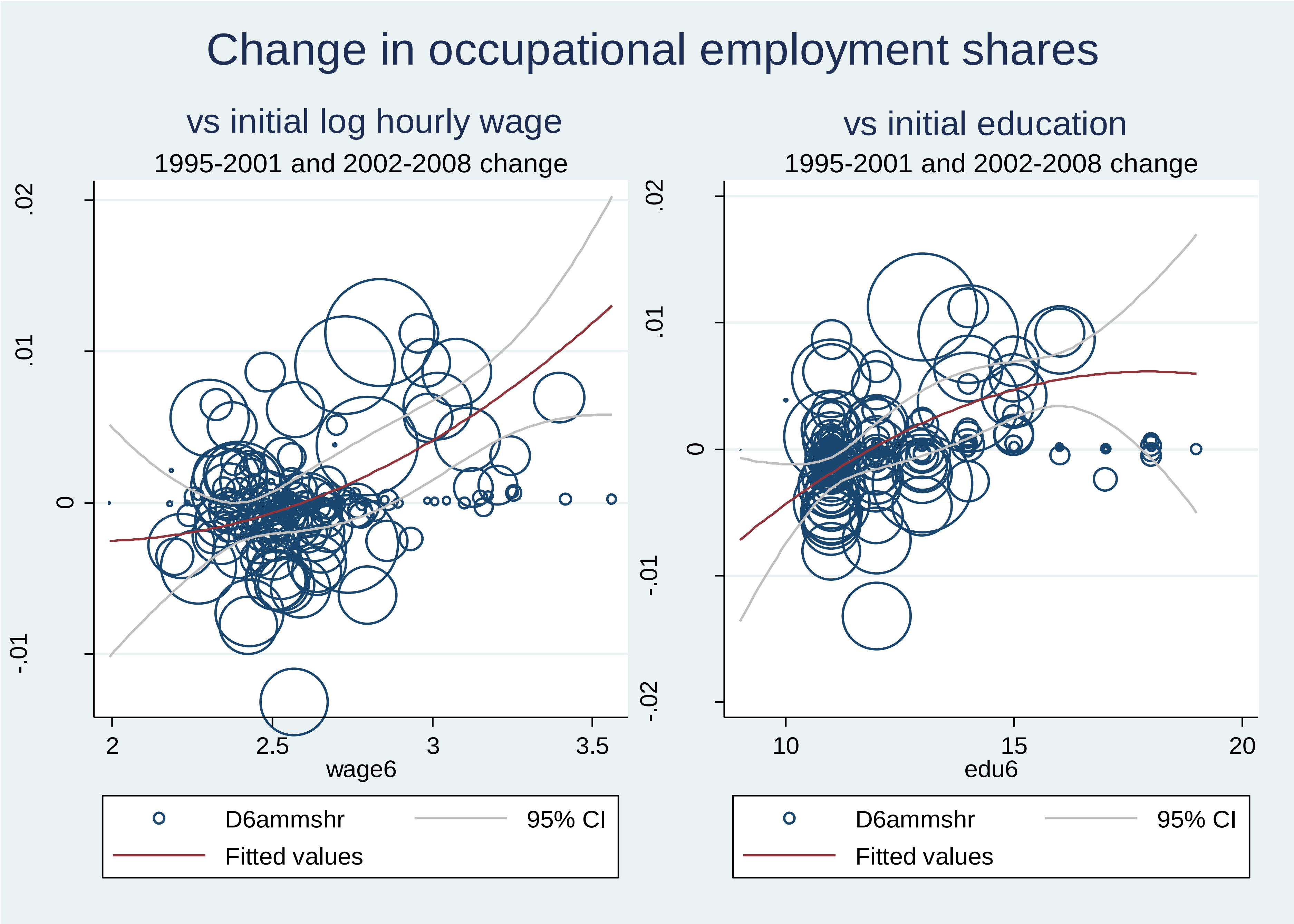
Three digit ISCO occupations, weighted by hours worked and sampling weights. Heteroscedasticity robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Regressions for change in occupational employment shares on initial education (mean or median)

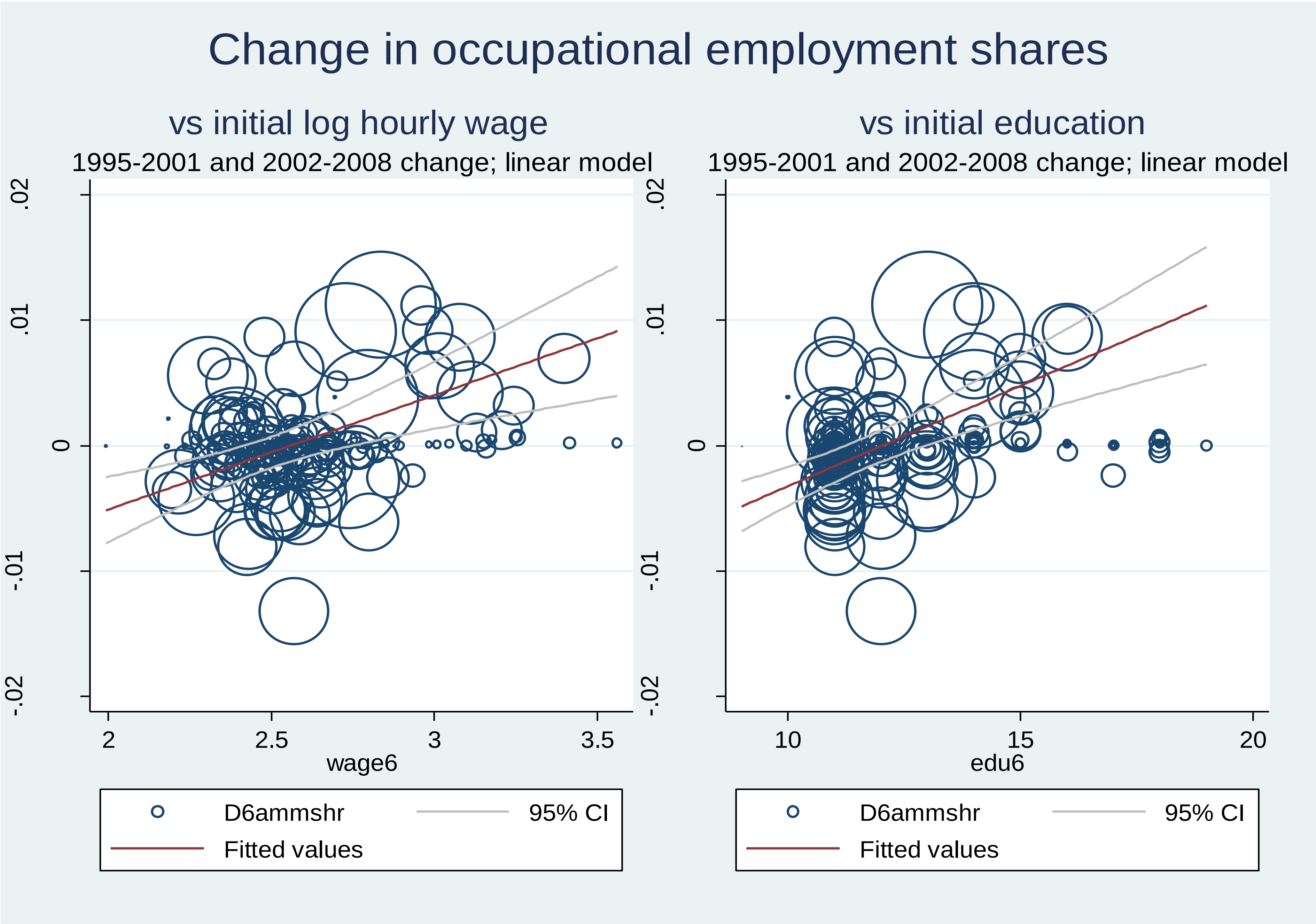
(six year changes 1995-2001 and 2002-2008 pooled)

	(1)	(2)	(3)	(4)
VARIABLES	Mean education	Mean education	Median education	Median education
Education	0.00725	0.00138***	0.00415	0.00150***
	(0.00504)	(0.000335)	(0.00298)	(0.000363)
Education^2	-0.000225		-0.000101	
	(0.000187)		(0.000108)	
Year dummy	0.000525	0.000647	0.000109	0.000217
	(0.00141)	(0.00143)	(0.00143)	(0.00143)
Constant	-0.0545	-0.0171***	-0.0361*	-0.0189***
	(0.0332)	(0.00430)	(0.0202)	(0.00467)
Observations	171	171	171	171
R-squared	0.158	0.147	0.156	0.151

Three digit ISCO occupations, weighted by hours worked and sampling weights. Heteroscedasticity robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.



Quadratic model



Linear model

Aggregate results: some analyses

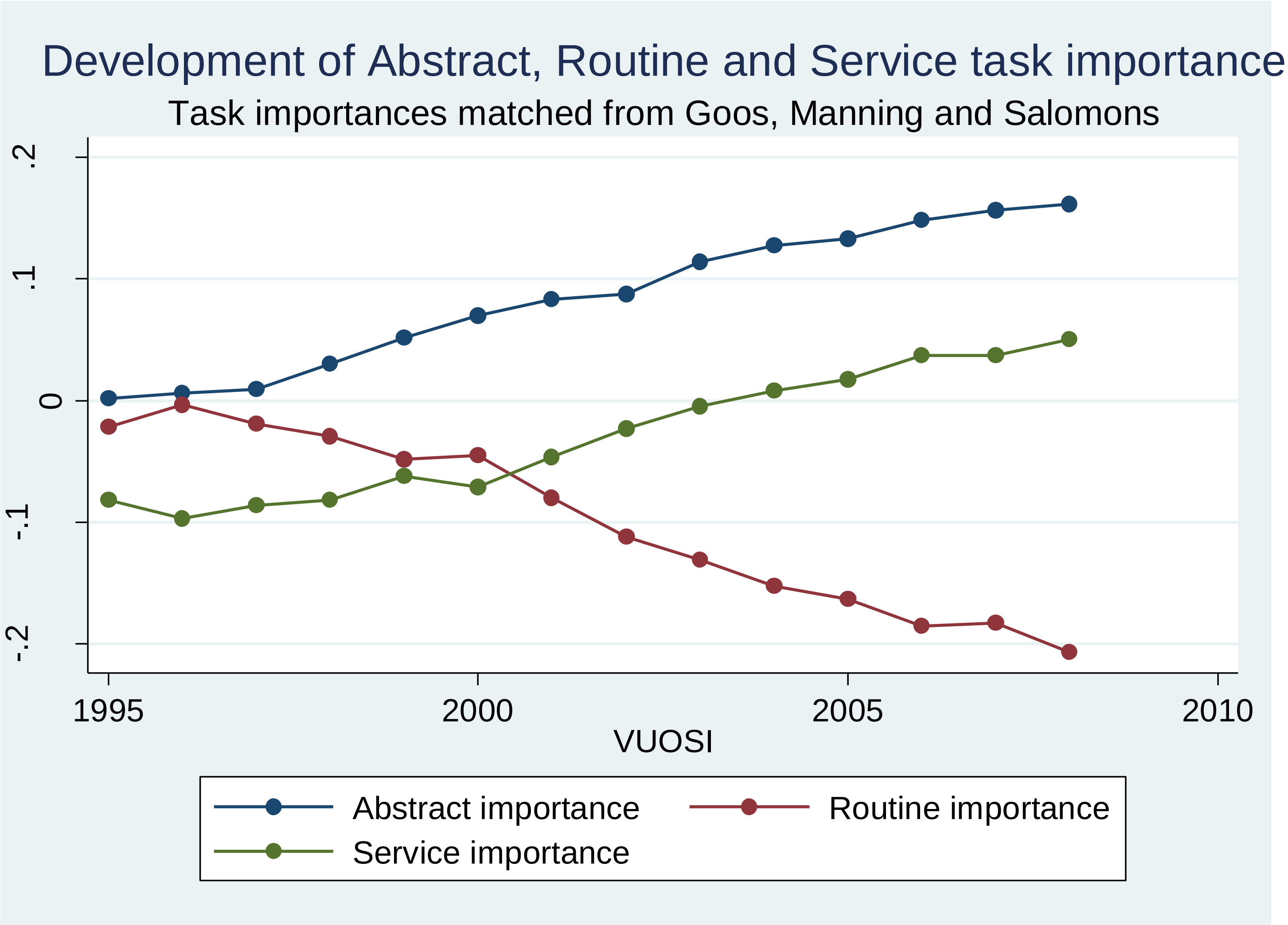
- Match in task variables and offshorability from Goos, Manning and Salomons (2011) at 2-digit ISCO occupation level.
- Look at aggregate trends in task variables over time
- Do task variables and offshorability explain the changes in occupational employment shares?

Task variables and Offshorability 1

- Task measures derived using 2006 version of US Occupational Information Network (ONET) database.
- Use 96 ONET variables related to worker characteristics, worker requirements and work activities of occupations to create measures for task importance for each occupation; variables divided into 3 groups for:
  - **Abstract** task importance: critical thinking, complex problem solving
  - **Routine** task importance: manual and finger dexterity, operation monitoring and control, repetitive/computerizable
  - **Service** task importance: assisting and caring for others, service orientation, interpersonal relations
- Job incumbents, occupational analysts and occupational experts evaluate how important each task variable is in each occupation on a scale from 1 (not important at all) to 5 (extremely important)
- Task importance measures are the principal components of the task variables in each of the three task categories above (Abstact, Routine, Service) for SOC occupations in ONET. Then converted to ISCO occupations using US SOC employment weights. Then rescaled to mean 0, standard deviation 1.
- **Routine task intensity**: one dimensional measure defined as Routine importance divided by sum of Abstract and Service importance.

Task variables and Offshorability 2

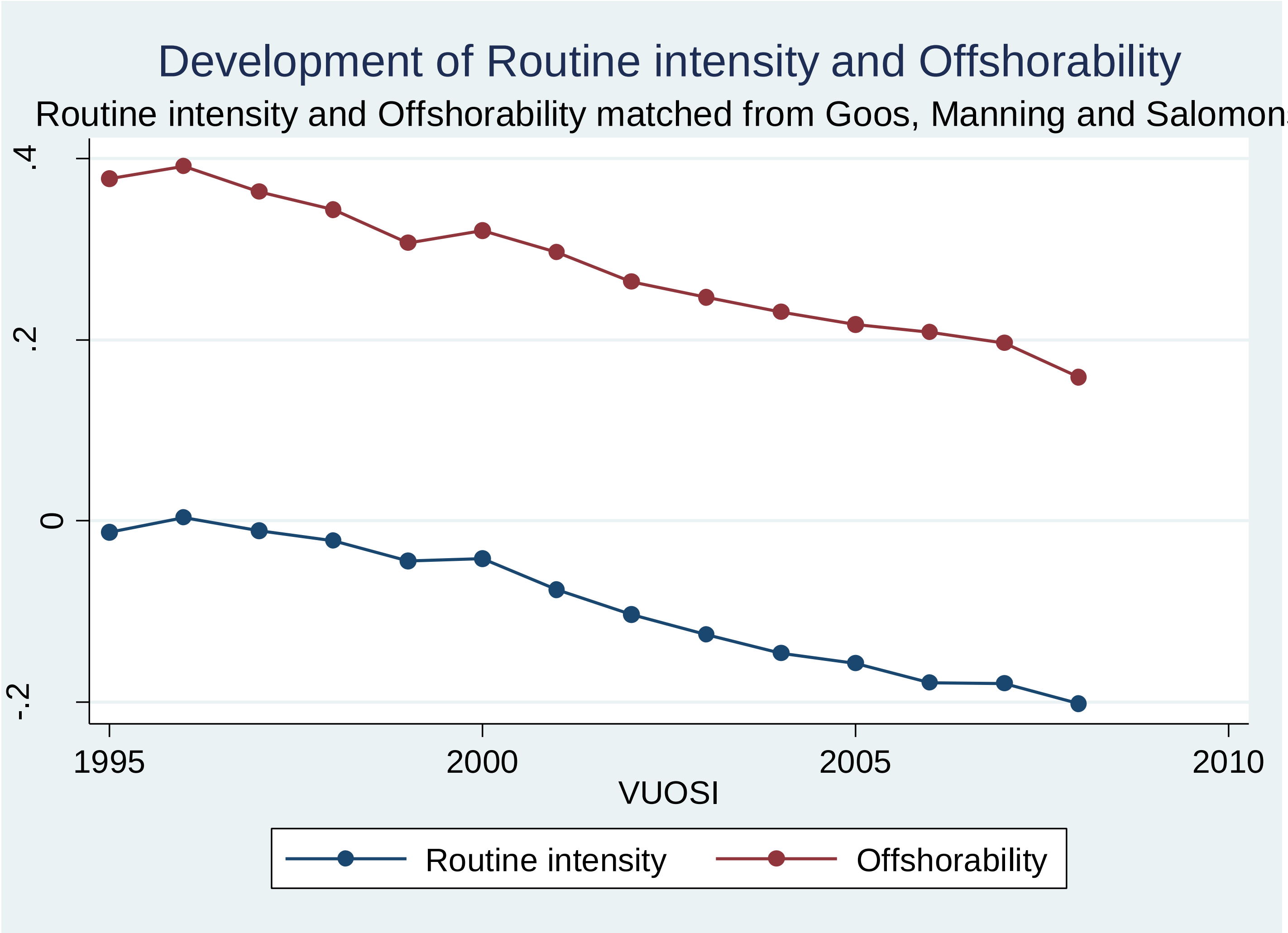
- **Offshorability** measure derived from the information in European Restructuring Monitor (ERM) of the European Monitoring Centre on Change.
- Fact sheets of actual offshoring cases with information on kind of jobs (occupations) offshored.
- Goos, Manning and Salomons (2011) construct an index of offshorability of different occupations (2-digit ISCO level). Rescaled to have mean 0 and standard deviation of 1.
- We match 2-digit values of task variables and offshorability to each 3-digit occupation belonging to a 2-digit group.
- These variables are constant over time: development over time of average values of task variables and offshorability reflect changes in occupational employment structure (extensive margin), not changes in task content of occupations (intensive margin).



Weighted means of task variables across 3-digit occupations:

Declining Routine importance = declining employment in routine intensive occupations

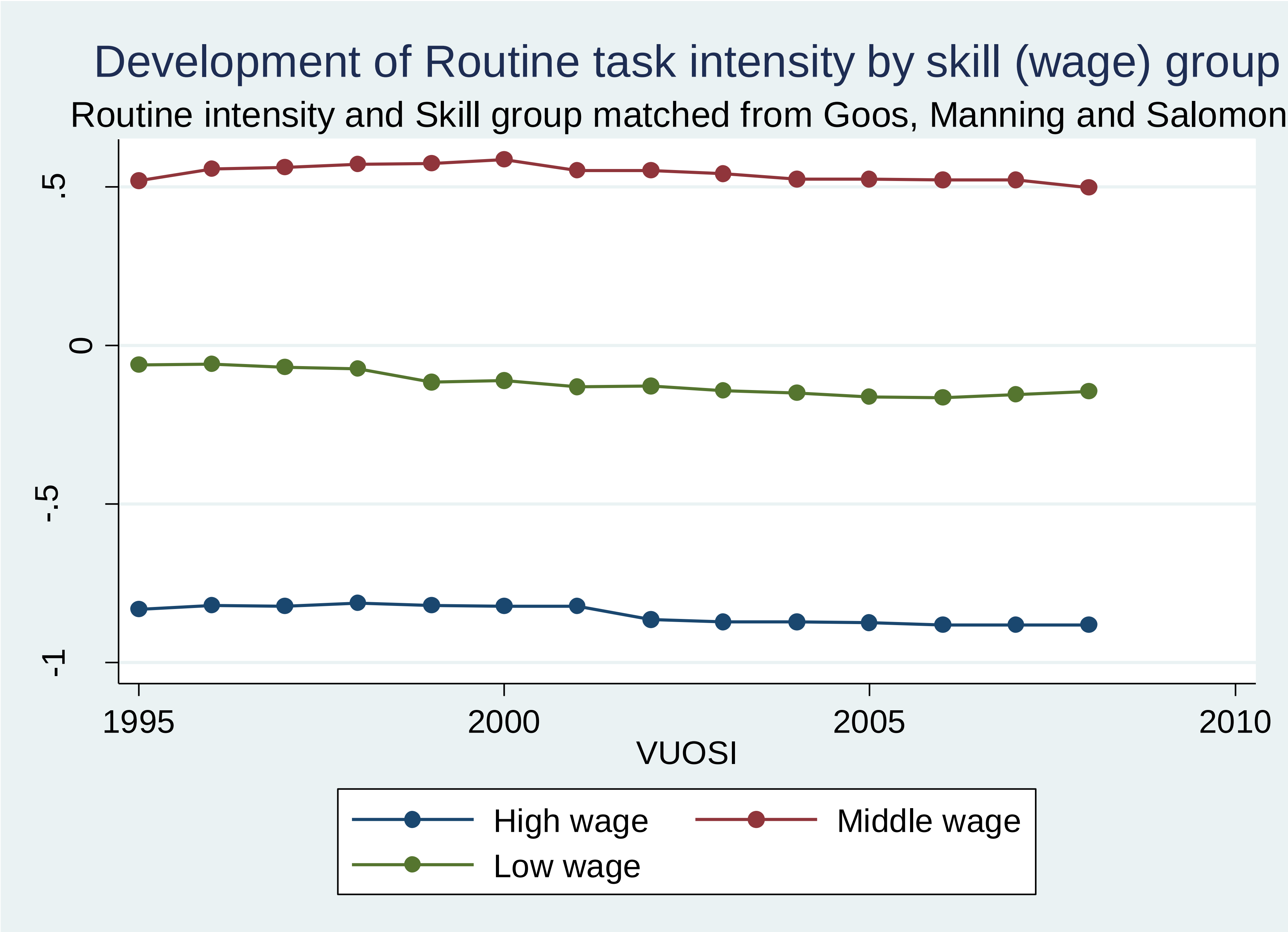
Increasing Abstract and Service importance = increasing employment in abstract and service intensive occupations

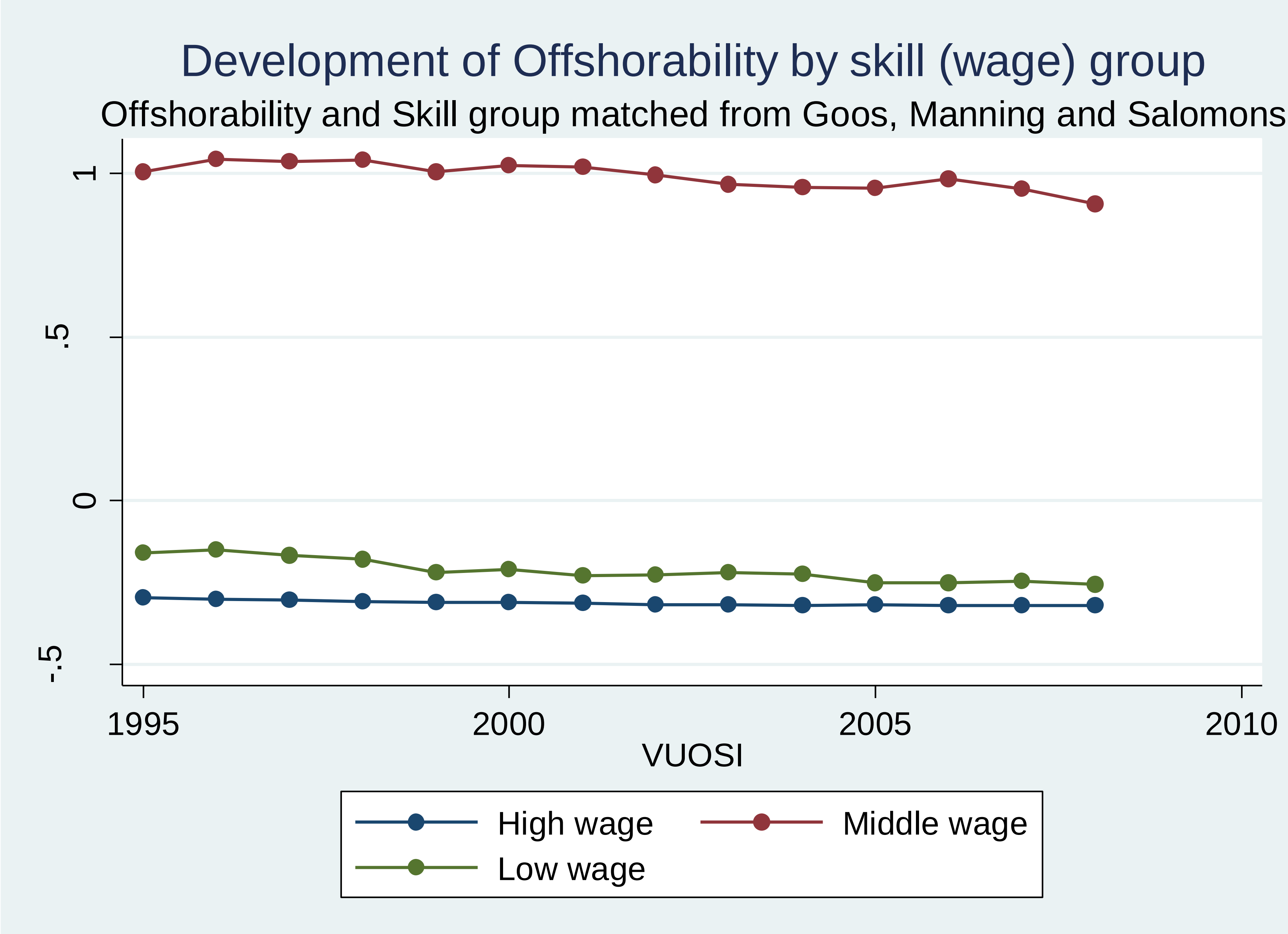


Weighted means of variables across 3-digit occupations:

Declining Routine intensity = declining employment in routine intensive occupations

Declining offshorability = declining employment in high offshorability occupations (offshored?)


Development of Routine task intensity by skill (wage) group
Routine intensity and Skill group matched from Goos, Manning and Salomons
.5
0
-.5
-1
1995
2000
2005
2010
VUOSI
High wage
Middle wage
Low wage


Development of Offshorability by skill (wage) group
Offshorability and Skill group matched from Goos, Manning and Salomons
1
.5
0
-.5
1995
2000
2005
2010
VUOSI
High wage
Middle wage
Low wage

Change in occupational employment share not significantly related to separate task importance variables or offshorability

	Dependent variable: Change in occupational employment share			
VARIABLES	(1)	(2)	(3)	(4)
Abstract_importance	0.00158	0.00166	0.00158*	0.00166*
	(0.00122)	(0.00120)	(0.000892)	(0.000866)
Routine_importance	-0.00124	-0.00106	-0.00124	-0.00106
	(0.00125)	(0.00131)	(0.000891)	(0.000899)
Service_importance	-0.000335	0.000541	-0.000335	0.000541
	(0.00167)	(0.00157)	(0.00129)	(0.00112)
Offshorability	-0.000862		-0.000862	
	(0.000790)		(0.000610)	
Year-dummy (2008)	0.000946	0.000992	0.000946	0.000992
	(0.00102)	(0.00102)	(0.00132)	(0.00133)
Constant	-0.000237	-0.000454	-0.000237	-0.000454
	(0.00117)	(0.00113)	(0.000992)	(0.000965)
Observations	171	171	171	171
R-squared	0.219	0.201	0.219	0.201

Three digit occupations weighted by working hours and survey weights. Columns (1)-(2) robust standard errors clustered by 2-digit occupation in parentheses. Columns (3)-(4) heteroscedasticity robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Explanatory variables from Goos, Manning and Salomons (2011). Standardised as mean zero, unit standard deviation.

But is significantly related to routine intensity and offshorability alone: routine intensity more significant in (3)

	Dependent variable: change in occupational employment share		
VARIABLES	(1)	(2)	(3)
Routine_intensity	-0.00228***		-0.00185*
	(0.000698)		(0.000987)
	(0.000616)		(0.000842)
Offshorability		-0.00152**	-0.000724
		(0.000593)	(0.000868)
		(0.000407)	(0.000592)
Year-dummy (2008)	0.00107	0.00108	0.00103
	(0.00103)	(0.00103)	(0.00103)
	(0.00137)	(0.00146)	(0.00136)
Constant	-0.000499	-3.93e-06	-0.000258
	(0.00116)	(0.00122)	(0.00123)
	(0.000982)	(0.00101)	(0.00104)
Observations	171	171	171
R-squared	0.167	0.106	0.182

Three digit occupations, weighted by working hours and survey weights. Robust standard errors clustered by two digit occupation groups in parentheses. Heteroscedasticity robust standard errors in second parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Explanatory variables from Goos, Manning and Salomons(2011). Standardised as mean zero, unit standard deviation.

Summary of aggregate results

- Aggregate trends consistent with ”routinization hypothesis” of Autor, Levy and Murnane (2003):
  - Structure of employment changing towards occupations intensive in Abstract and Service tasks, and away from occupations intensive in Routine tasks
  - Some indication of implied job polarization, but evidence not strong (not statistically significant)
- Are these trends (skill bias) related to technological change?

Acemoglu-Autor (2010) task based model

- Empirical illustration of model's implications:
  - Technological change that increases productivity of a skill group must raise its relative wage
  - Form skill groups by gender, education, age and region (indexed by s,e,j,k)
  - Group occupations into three groups on the basis of their task intensity: Abstract, Routine and Service task intensive occupations
  - Comparative advantage of a skill group in performing different tasks is indicated by its occupational specialization in the initial year of their sample (1959, precomputerization), i.e. by
  - $\gamma_{sejk}^{O} =$ employment share of occupation group O in total employment of skill group s,e,j,k
  - O = A, R S for Abstract, Routine, Service occupations

Acemoglu-Autor (2010) task based model

- Computerization implies that wages should rise for skill groups that have comparative advantage in Abstract and Service occupations and decline for skill groups that have comparative advantage in Routine occupations
- Estimate the following equation for decadal changes in wages allowing regression coefficients to vary over decades

$$\Delta \ln w_{sejk,t} = \sum_t \beta_t^A \cdot \gamma_{sejk}^A + \sum_t \beta_t^S \cdot \gamma_{sejk}^S + \delta_t + \phi_e + \lambda_j + \pi_k + e_{sejkt}$$

- expected that the regression coefficients β_t^A and β_t^S increase over the decades (t), decade dummies reflect wage development in routine tasks and they are expected to decline over time

Acemoglu-Autor results for Finland using aggregate data

- We have shorter data period, but estimate A-A regression as a background for firm level regressions:
  - We have only two 6-year periods
  - Skill groups similar to A-A, except region (national contracts dominate wage setting in Finland)
  - Define occupational specialization of skill groups in 1995
- Results:
  - Skill groups specializing in Abstract occupations experienced larger increases in employment and wage bill shares, but not higher wage growth
  - Somewhat higher wage growth in skill groups with service specialization, but no higher employment or wage bill growth
- Possible interpretation:
  - For skill groups with Abstact specialization, the effects of technological change are experienced more in employment than in wages in Finland, with more rigid wage setting compared to US
  - Higher wage growth in skill groups with (low wage) service specialization could be reflecting solidarity effects in wage setting (in the late 1990’s).

Relationship between skill groups' occupational specialization and subsequent change in skill groups mean wage and employment and wage bill shares

(Six year changes for 1995-2001 and 2002-2008)

	(1) Wage	*(2) Employment*	*(3) Wage Bill*
VARIABLES	Change in mean log wage of skill group	Change in the share of total hours of skill group	Change in the share of total wage bill of skill group
Abstract occupation share x 1995_2001 dummy	-0.107	0.0123	0.0147*
	(0.0879)	(0.00914)	(0.00777)
Abstract occupation share x 2002_2008 dummy	-0.121	0.0172*	0.0198**
	(0.0846)	(0.00897)	(0.00758)
Service occupation share x 1995_2001 dummy	0.285**	-0.00953	-0.00929
	(0.132)	(0.0184)	(0.0159)
Service occupation share x 2002_2008 dummy	0.198	0.00513	0.00549
	(0.122)	(0.0171)	(0.0151)
Period 2002_2008 dummy	0.0314	-0.00410	-0.00425
	(0.0216)	(0.00314)	(0.00320)
Constant	0.0172	0.000294	0.000431
	(0.0262)	(0.00360)	(0.00328)
Observations	60	60	60
R-squared	0.356	0.521	0.554

Main effects for education, age and sex are included in all models. Weighted by the product of survey weights and hours worked at the skill group level. Heteroscedasticity robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Firm level regressions 1

- Estimate A-A type model at the firm level using technology indicators as explanatory variables instead of time trend
- Using wage bill share and employment share of skill groups as dependent variable in addition to wages
- Estimate following equations

$$\Delta y_{sej,it} = \beta_0 + \beta^A \cdot \Delta Tech_{it} \cdot \gamma^A_{sej,i(t-1)} + \beta^S \cdot \Delta Tech_{it} \cdot \gamma^S_{sej,i(t-1)} + \delta_t + \phi_e + \lambda_j + \pi_s + e_{sej,it}$$

- Where $\gamma^O_{sej,i(t-1)}$ is skill group’s employment share in occupation group O = A, S in the beginning of period and $\Delta Tech_{it}$ is an indicator for technological change in the firm during period (R&D intensity or change)
- Expect $\beta^A > 0, \beta^S \geq 0$ e.g. wage bill share of a skill group rises more in firms with rapid technological change and the skill group having initial specialization in abstract occupations
- Direct effects of technology and gamma’s also included

Firm level regressions 2

- Following Michaels, Natraj and Van Reenen's (2010) industry-country model we estimate at firm level equations for wage bill shares of education groups (E=Low, Middle, High) as follows

$$\Delta SHR_{it}^{E} = c^{E} + \beta_1^{E} \Delta \left(\frac{R\&D}{Q} \right)_{it} + \beta_2^{E} \Delta \left(\frac{K}{Q} \right)_{it} + \beta_3^{E} \Delta \ln Q_{it} + u_{it}^{E}$$

- K= capital, Q=output
- Polarization hypothesis: $\beta_1^{M} < 0$ $\beta_1^{H} > 0$

Future work

- Other technology indicators:
  - Investment in computer software and hardware from Financial Statement Statistics to measure computer intensity
  - ICT use from Survey for Information technology and electronic commerce in enterprises (ICT survey):
    - share of workers using computer at work,
    - or using laptop and broadband connections in work
    - other possibly relevant indicators that directly relate to organization of work using computers, like usage of EDI (Electronic Data Interchange) in commerce or in invoicing
  - Innovation survey includes indicators for activities like introduction of process innovations and organisational innovations, which are likely to affect the skill structure of firms labour force.
- Problem with other indicators: available sporadically and not for the whole data period
- Instrumental variable estimations
  - Lagged R&D as instrument, industry level instruments
  - Use task variables at industry level as instruments (c.f. Michaels, Natraj and Van Reenen, 2010): abstract and routine intensity of industries reflects the potential for firm’s investment in technology to be affected by falling price for computing

Future work

- Dynamic selection:
  - First differenced equations estimated only for continuing firms, which may be different from all firms in unobserved ways that correlate with both technology and skill demand
  - Estimate Probit for probability of selection and add Inverse Mill's ratio or polynomial in estimated probability as an explanatory variable in the estimated equations:
    - Survival explained by e.g. firm's labour productivity, firm size and age, foreign ownership, single/multi-plant status, indicator for industry demand

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