# Hours of work polarization?

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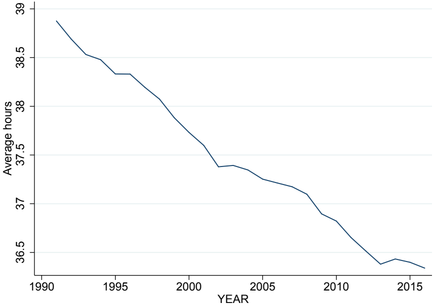
# Motivation: large decline in hours-per-worker

**Figure 1:** Trend in hours worked in EU-15 countries, 1992-2016

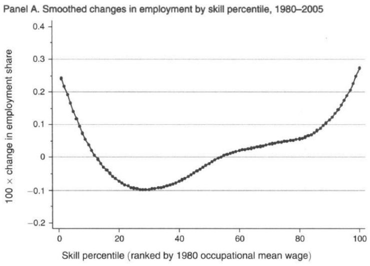



Source: EU Labour Force Survey, authors' own calculations.

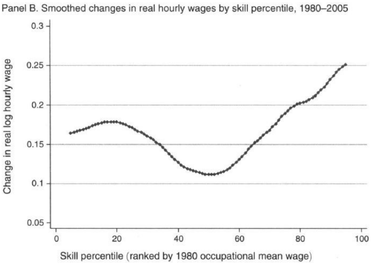
- Long term, widespread trend in EU countries. Primarily driven by shift from full time to part time work. ▸ Shift-share

# Motivation: employment and wage polarization

**Figure 2:** Job polarisation from Autor and Dorn (2013): Smoothed changes in employment share and wages by skill percentile, 1980-2005




**(a)** Employment




**(b)** Wages

Source: Autor and Dorn (2013) for the USA. The same patterns have been found for the EU in Goos et al. (2014)

# Background: relevant literature

- Hours per worker literature:
  - Well documented long-term declining trend with heterogeneity by skill group e.g. Cahuc et al. (2014); Aguiar and Hurst (2007).
  - Various explanations put forward including taxation systems, unionisation, labour laws, technology e.g. Prescott (2004); Alesina et al. (2005); Faggio and Nickell (2007); Bick et al. (2018); Vandenbroucke (2009).
- Polarization literature:
  - Well documented polarization in wages and employment (full-time-equivalent and headcount) e.g. Goos et al. (2009, 2014); Goos and Manning (2007); Autor and Dorn (2013); Acemoglu and Autor (2011).
  - Routine-biased technology change: task content of jobs is key e.g. Autor et al. (2003); Acemoglu and Autor (2011). ▸ Framework

This paper: links the intensive margin (hours per worker) to the polarization literature.

# Piecing the trends together

**Key question:**
Are hours per worker trends associated with similar routinisation phenomenon as job polarization?

- Are hours per worker trends a mitigating or exacerbating force for job polarization?
- How does this intensive margin impact the distributional consequences of polarization? Total income $Y = E \times W \times H$
- Implications for labour market earnings, consumption, monetary policy, welfare, political considerations etc.

# Approach of the paper

- Construct Acemoglu and Autor (2011)'s five routinisation task indices + sixth for the service sector using O*NET task data.
- Find a large relative reduction in hours-per-worker in highly routine manual jobs, increasing relative hours in high skilled cognitive jobs, and heterogeneity by tasks in low skilled jobs.
- Hours-per-worker patterns are occupational: do not appear to be driven by demographic shifts, industrial composition changes or offshoreability.
- Widespread across EU-15 countries, but the reverse for the USA. A sign of reliance on intensive margin employment adjustment.

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# Data and O*NET task indices

# Data sources

**Main data source:** European Union Labour Force Survey (EU-LFS)

- Harmonised microdataset (individual level) across European countries
- Labour information (employment status, hours of work etc) and demographic information (age, sex).
- 3 digit occupation and 1 digit industry.
- Our core sample is EU-15 countries from 1992-2016.

**Wage analysis:** EU Statistics of Income and Living Conditions (EU-SILC).

**Key variable of interest: intensive margin hours**

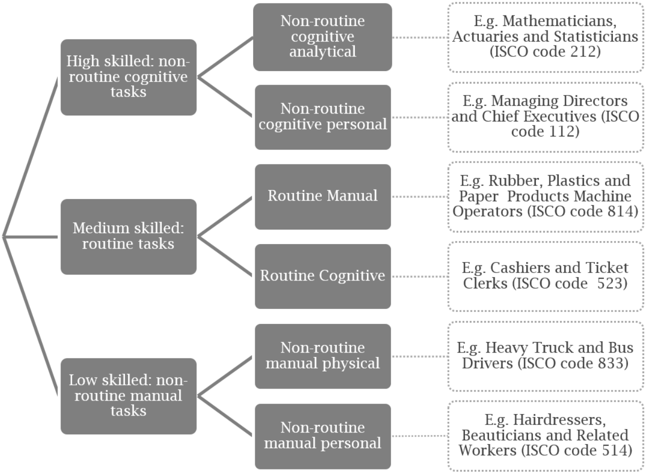
Two hours measures in EU-LFS: usual hours worked and actual hours work.

# Job task content

- Occupational task content explain increasingly more about employment patterns, vs education, occupation titles etc (Acemoglu and Autor (2011)).
- Each occupation involves a mix of tasks, and O*NET scores the degree to which each occupation uses each task.
- Interested in types of routine tasks.
- Increasing evidence that gradation needs to be finer (Acemoglu and Autor (2011)): separate tasks into physical and non-physical too. Separates routine tasks for accountancy from production line workers, service workers from truck drivers.
- We use Autor and Acemoglu’s (2011) five task measures plus a sixth to capture in-person service tasks.

# Task groupings

**Figure 3:** Occupation skill indices, tasks and example occupations




Wage correlations ONET tasks

# Six occupation skill indices

- The six indices are constructed with O*NET task data. Each occupation involves some task content of each, so receives a score for each.
- The indices are matched to the ISCO88 and ISCO08 occupation classifications in the EU-LFS.
- For ease of interpretation, the indices are discretised: an occupation is classified as having a ‘high index X score’ if it is above the 66th percentile for index X in a given year.

# Six occupation skill indices and hours

**Table 1:** The six indices predict employment polarization

| | – NR Cognitive – | | —— Routine —— | | —— NR Manual —— | |
|---|---|---|---|---|---|---|
| | analytical | personal | cognitive | manual | physical | personal |
| | Share of total employment in jobs with high content of each task | | | | | |
| 1992 | 31.5 | 33.0 | 30.6 | 32.6 | 33.6 | 30.4 |
| 1998 | 34.9 | 37.1 | 30.2 | 31.1 | 32.4 | 32.9 |
| 2007 | 39.2 | 41.2 | 28.7 | 27.8 | 29.3 | 33.9 |
| 2016 | 38.7 | 43.0 | 30.2 | 23.1 | 24.6 | 38.3 |
| 2010-1992 | 8.9 | 10.2 | -2.7 | -6.9 | -6.1 | 5.1 |
| 2016-1992 | 7.2 | 10.0 | -0.4 | -9.5 | -9.0 | 8.0 |

**Key idea**

These six job task indexes predict employment (and wage) polarization. Do they also predict hours per worker changes?

# Baseline analysis

# Empirical strategy

Do these indices predict hours per worker trends?

**Baseline regression equation**

$$H_{ikct} = \alpha_0 + \alpha_1 I_i + \alpha_2 t + \boldsymbol{\alpha_3 I_i * t} + \beta X_{ict} + c_c + c_k + \epsilon_{ikct}$$

- Individual, industry k, country c, time t.
- Errors clustered at the industry-country level.
- $I_i$ the index for individual i's occupation. We use a dummy variable that equals one if the individual's occupation has a high task content for that index (above the 66th percentile in each year).
- Baseline controls: gender, age, educational attainment, marital status, interview type, firm size, industry.

# Non-routine cognitive occupations

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Hours per worker | | | | | |
| | ——— Analytical ——— | | | ——— Personal ——— | | |
| High Index | 2.5290*** | 1.6728* | 2.8131*** | 2.2450*** | 1.760** | 3.2863*** |
| | (0.8698) | (0.9325) | (0.7629) | (0.8324) | (0.8496) | (0.6071) |
| t | -0.1182*** | -0.0945*** | -0.0793*** | -0.1006** | -0.0833*** | -0.0758*** |
| | (0.0154) | (0.0139) | (0.0137) | (0.0159) | (0.0120) | (0.0118) |
| **High Index*t** | **0.0500*** | **0.0884**** | **0.0430** | **-0.0089** | **0.0360** | **0.0141** |
| | **(0.0272)** | **(0.0363)** | **(0.0289)** | **(0.0275)** | **(0.0315)** | **(0.0269)** |
| Constant | 37.92*** | 39.60*** | 41.74*** | 38.05*** | 39.08*** | 41.15*** |
| | (0.5777) | (1.2558) | (0.5725) | (0.57) | (1.2748) | (0.842) |
| Observations | 2156515 | 16754427 | 16754427 | 2156515 | 16754427 | 16754427 |
| R-squared | 0.0193 | 0.1574 | 0.2086 | 0.0103 | 0.1529 | 0.2085 |
| Controls | No | Yes | Yes | No | Yes | Yes |
| Country FEs | No | Yes | No | No | Yes | No |
| County-Sector FEs | No | No | Yes | No | No | Yes |

All regression weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66th percentile for the index in that year. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016, hours variable is 'usual' hours of work.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# Routine occupations

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Hours per worker | | | | | |
| | ——— Cognitive ——— | | | ——— Manual ——— | | |
| High Index | -2.2284*** | -0.3114 | -0.9555*** | 4.9924*** | 2.6676*** | 0.9829*** |
| | (0.4875) | (0.4790) | (0.2678) | (0.7305) | (0.4886) | (0.3143) |
| t | -0.1254*** | -0.0834*** | -0.0836*** | -0.0328** | -0.0172 | -0.0309** |
| | (0.0144) | (0.0158) | (0.0129) | (0.0137) | (0.0136) | (0.0118) |
| **High Index*t** | **0.0769*** ** | **0.0226** | **0.0203** | **-0.2083*** ** | **-0.1828*** ** | **-0.1282*** ** |
| | **(0.0176)** | **(0.0172)** | **(0.0131)** | **(0.0390)** | **(0.0265)** | **(0.0194)** |
| Constant | 39.47*** | 39.22*** | 41.10*** | 37.11*** | 38.34*** | 41.20*** |
| | (0.5409) | (1.1470) | (0.5656) | (0.4864) | (1.1674) | (0.5616) |
| Observations | 2156515 | 16754427 | 16754427 | 2156515 | 16754427 | 16754427 |
| R-squared | 0.0061 | 0.1457 | 0.1944 | 0.0139 | 0.1483 | 0.1960 |
| Controls | No | Yes | Yes | No | Yes | Yes |
| Country FEs | No | Yes | No | No | Yes | No |
| County-Sector FEs | No | No | Yes | No | No | Yes |

All regression weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66th percentile for the index in that year. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016, hours variable is 'usual' hours of work.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# Non-routine manual occupations

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Hours per worker | | | | | |
| | Personal | | | Physical | | |
| High Index | -1.3067** | -0.1414 | 1.6622*** | 4.1315*** | 1.7090*** | 0.5487 |
| | (0.6306) | (0.6699) | (0.4563) | (0.6982) | (0.4912) | (0.3416) |
| t | -0.1137*** | -0.0931*** | -0.0858*** | -0.0763*** | -0.0562*** | -0.0608*** |
| | (0.0149) | (0.0110) | (0.0106) | (0.0139) | (0.0150) | (0.0126) |
| **High Index*t** | **0.0398*** | **0.0572**** | **0.0482***** | **-0.0679**** | **-0.0684***** | **-0.0479***** |
| | **(0.0219)** | **(0.0225)** | **(0.0191)** | **(0.0287)** | **(0.0236)** | **(0.0178)** |
| Constant | 39.19*** | 39.22*** | 40.93*** | 37.32*** | 38.38*** | 41.11*** |
| | (0.4068) | (1.2286) | (0.5182) | (0.4992) | (1.1837) | (0.6086) |
| Observations | 2156515 | 16754427 | 16754427 | 2156515 | 16754427 | 16754427 |
| R-squared | 0.0045 | 0.1467 | 0.2006 | 0.0197 | 0.1467 | 0.1939 |
| Controls | No | Yes | Yes | No | Yes | Yes |
| Country | No | Yes | No | No | Yes | No |
| County-Sector FEs | No | No | Yes | No | No | Yes |

All regression weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Index is a dummy that takes value 1 if the occupation is above the 66th percentile for the index in that year. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016, hours variable is 'usual' hours of work.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

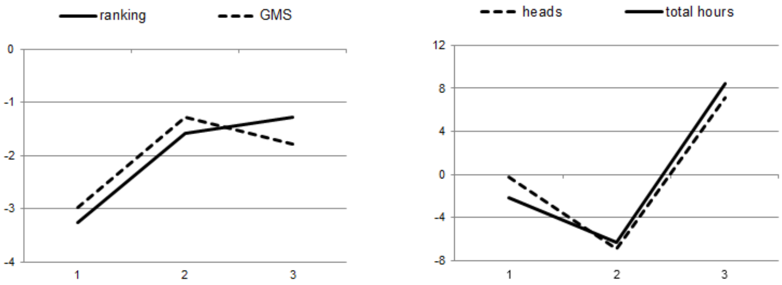
# Summary of baseline results

- A large and very significant reduction in hours per worker in highly routine manual occupations (e.g. factory production workers).
- A decrease in hours in non-routine manual physical occupations.
- An increase in hours per worker in highly non-routine cognitive occupations.
- Results robust to a variety of different specifications e.g. measure of hours, including zero hours, various fixed effects, time trend specifications.

▸ Robustness

# Intensive margin contribution to polarization

**Figure 4:** Hours-per-worker and headcount polarization by wage category, 1992-2016




**(a)** Hours-per-worker **(b)** Contribution to polarization

# Potential contributing factors

# Contributing factors: Offshoreability

## Increasing offshoreability and international supply chains?

Much of the employment polarization literature investigates whether globalisation is hollowing out routine jobs. Consensus seems to be that it is a small, second order contributer. Is the case the same for hours per worker?

Approach:

- use Acemoglu and Autor (2011)'s measure of offshoreability, also created with ONET task data.
- Repeat the same core regressions: does offshoreability predict trend in hours per worker.
- Short answer: yes, but second order. Highly offshoreable occupations have decreased hours per worker.

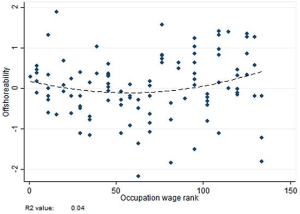



Fig: Offshore index versus wage

# Contributing factors: Offshoreability

| | (1) | (2) | (3) |
|---|---|---|---|
| | Hours per worker | | |
| High Offshoreability | -0.5940 | 1.2772** | 0.6140* |
| | (0.4917) | (0.4658) | (0.3360) |
| t | -0.0966*** | -0.0563*** | -0.0630*** |
| | (0.0132) | (0.0144) | (0.0111) |
| **High Offshoreability*t** | **-0.0119** | **-0.0533*** ** | **-0.0410*** ** |
| | **(0.0230)** | **(0.0208)** | **(0.0142)** |
| Constant | 38.9422*** | 38.81*** | 40.8686*** |
| | (0.5107) | (1.1294) | (0.5348) |
| Observations | 21561515 | 16754427 | 16754427 |
| R-squared | 0.0044 | 0.1463 | 0.1938 |
| Controls | No | Yes | Yes |
| Country FE | No | Yes | No |
| Country-Sector FE | No | No | Yes |

All regression weighted with EU-LFS weights, and standard errors clustered at country-sector level. Demographic controls: age, educational level, sex, size of firm, proxy interview, marital status. Industry controls are 1 digit NACE. High Offshorability is a dummy that takes value 1 if the occupation is above the 66th percentile for the offshorability index in that year. Sample is individuals working non-zero hours in EU-15 countries from 1992-2016, hours variable is ‘usual’ hours of work.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# Contributing factors: changing gender patterns in workforce

**Increased female labour force participation driving the results?**

More women entered the labour market over the period, often working part time.

Approach:

- Segment the sample by gender and find both men and women experiencing hours polarization. (Within group)
- Investigate whether the gender composition of different occupations is changing overtime. (Reallocation across groups)
- Formally undertook a shift share comparison: within effect dominates.
- Country specific: polarization patterns widespread, not just in countries with large increases in female participation.

In short: while increase female participation important for aggregate hours trends, it does not appear to be driving hours-per-worker patterns along routinisation lines.

▸ Gender results ▸ Gender shift-share

# Contributing factors: Ageing workforce

## An ageing workforce driving the results?

As individuals age, and work fewer hours, does this drive the hours polarization? Existing work has found shrinking industries have higher average ages.

Approach:

- Segment the sample along age lines – all age groups experiencing similar hours polarization. (Within group)
- Segment sample along cohort/date of birth lines, and find younger and older cohorts experiencing similar hours polarization. (Within group)
- Check whether age groups reallocated across different occupations. (Reallocation across groups). Routine manual jobs have an increasing relative age of workers (reverse for non-routine cognitive jobs)

In short: routinisation hours trends affects all age groups and cohorts, but shrinking routinized occupations have an increasing share of older workers. ▸ Age results

# Contributing factors: educational attainment

## Increased educational attainment driving the results?

Educational attainment has risen over the timeframe perhaps – as per a classic Tinbergen education-technology race – this has driven part of the routine hours patterns.

Approach:

- Same as before: segmented sample along education lines. Slightly more heterogeneity, but overall the pattern is still pretty consistent within groups.

In short: the hours patterns go beyond simple demographic trends, by affecting all groups approximately equally. ▸ Education results

# Contributing factors: industrial restructuring

**Industrial change driving the results?**

Common argument: a changing economy shifts employment to industries with lower hours, reducing aggregate average hours.

Approach:

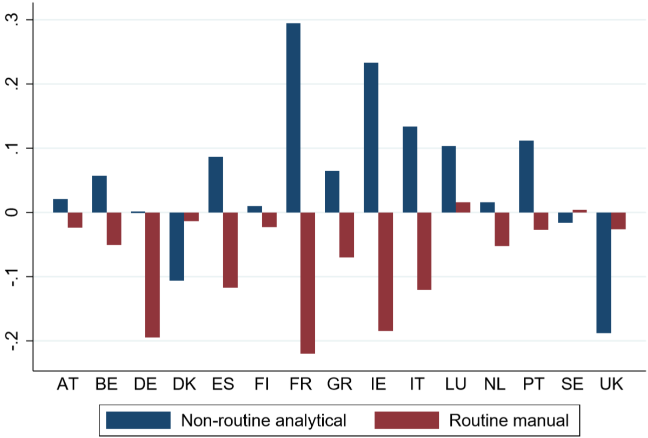
- Shift-share analysis to break down the reduction of aggregate hours into within (fall in hours within industries) versus between (shift of employment to low average hours industries) factors.
- Preliminary evidence: at least 75% of the aggregate reduction comes from the within effect. This suggests that the occupational/task effect was stronger.

In short: Industrial restructuring only appears to be a small fraction of the effect.

# Country comparisons

# Individual EU-15 results

The full set of results were calculated for each EU-15 country, and were broadly the same. Graph shows the country coefficients (on the time interaction term) for non-routine analytical – almost always positive – and routine manual – almost always negative.




Note: all results statistially significant, with exception of DE and FI for non-routine and LU for routine

# USA baseline results

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Non-routine cognitive | | | | | |
| | Analytical | | | Personal | | |
| High Index*t | -0.0296** | -0.0241** | -0.0430*** | -0.0230 | -0.0186 | -0.0287** |
| | (0.0141) | (0.0104) | (0.0090) | (0.0170) | (0.0141) | (0.0127) |
| | Routine | | | | | |
| | Cognitive | | | Manual | | |
| High Index*t | 0.0723*** | 0.0606*** | 0.0387*** | 0.0115 | 0.0181 | 0.0390*** |
| | (0.0101) | (0.0101) | (0.0083) | (0.0167) | (0.0132) | (0.0114) |
| | Non-routine manual | | | | | |
| | Personal | | | Physical | | |
| High Index*t | -0.1323*** | -0.0676*** | -0.0357*** | -0.0264** | -0.0177* | -0.0130 |
| | (0.0114) | (0.0100) | (0.0097) | (0.0128) | (0.0103) | (0.0088) |
| Controls | No | Yes | Yes | No | Yes | Yes |
| State FEs | No | Yes | Yes | No | Yes | Yes |
| Sector FEs | No | No | Yes | No | No | Yes |

All regression weighted with CPS weights, and standard errors clustered at state-sector level. Demographic controls: age, educational level, sex, size of firm, marital status. High Index is a dummy that takes value 1 if the occupation is above the 66th percentile for the index in that year. Sample is individuals working non-zero hours in the CPS sample from 1995-2016..

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

# Conclusion

# Concluding remarks

- Large decreases in hours of work for routine manual jobs. Increased hours of work for non-routine cognitive analytical jobs (high skilled) and non-routine manual personal (lower skilled).
- The intensive margin exacerbates high skill employment-wage polarization, and mitigates the growth for low skill occupations.
- The patterns appear to impact a broad range of demographics, and only 1/4 can be explained by industrial restructuring.
- Intensive margin (hours) another adjustment margin for labour – particularly in EU versus US. Hypothesis: tighter labour laws in EU.
- Going forward: further investigate divergence in EU vs USA trends. Idea: an Autor-Dorn model with firing costs to explain this.

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# References

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, volume 4, pages 1043–1171. Elsevier.

Aguiar, M. and Hurst, E. (2007). Measuring trends in leisure: the allocation of time over five decades. *The Quarterly Journal of Economics*, 122(3):969–1006.

Alesina, A., Glaeser, E., and Sacerdote, B. (2005). Work and leisure in the united states and europe: why so different? *NBER macroeconomics annual*, 20:1–64.

Autor, D. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, 103(5):1553–97.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4):1279–1333.

Bick, A., Fuchs-Schündeln, N., and Lagakos, D. (2018). How do hours worked vary with income? cross-country evidence and implications. *American Economic Review*, 108(1):170–99.

Cahuc, P., Carcillo, S., and Zylberberg, A. (2014). *Labor economics*. MIT press.

Faggio, G. and Nickell, S. (2007). Patterns of work across the oecd. *The Economic Journal*, 117(521):F416–F440.

Goos, M. and Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in britain. *The review of economics and statistics*, 89(1):118–133.

Goos, M., Manning, A., and Salomons, A. (2009). Job polarization in europe. *American economic review*, 99(2):58–63.

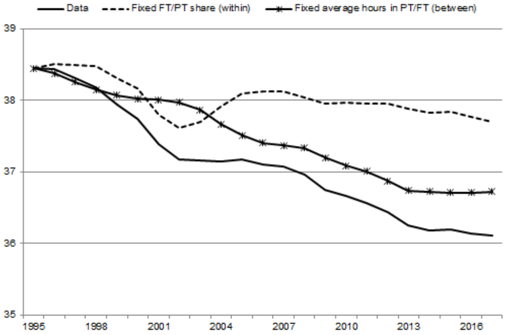
Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8):2509–26.

Prescott, E. C. (2004). Why do americans work so much more than europeans? Technical report, National Bureau of Economic Research.

Vandenbroucke, G. (2009). Trends in hours: The us from 1900 to 1950. *Journal of Economic Dynamics and Control*, 33(1):237–249.

# Full-time part-time shift share

**Figure 5:** Aggregate hours full-time part-time shift share decomposition




◂ Hours trend

# ONET tasks used to construct indices

Non-routine cognitive: Analytical

- 4.A.2.a.4 Analyzing data/information
- 4.A.2.b.2 Thinking creatively
- 4.A.4.a.1 Interpreting information for others

Routine cognitive

- 4.C.3.b.7 Importance of repeating the same tasks
- 4.C.3.b.4 Importance of being exact or accurate
- 4.A.4.b.5 4.C.3.b.8 Structured v. Unstructured work (reverse)

Non-routine cognitive: Interpersonal

- 4.A.4.a.4 Establishing and maintaining personal relationships
- 4.A.4.b.4 Guiding, directing and motivating subordinates
- 4.A.4.b.5 Coaching/developing others

Routine manual

- 4.C.3.d.3 Pace determined by speed of equipment
- 4.A.3.a.3 Controlling machines and processes
- 4.C.2.d.1.i Spend time making repetitive motions

◂ Task groupings

# ONET tasks used to construct indices

Non-routine manual physical

- 4.A.3.a.4 Operating vehicles, mechanized devices, or equipment
- 4.C.2.d.1.g Spend time using hands to handle, control or feel objects, tools or controls
- 1.A.2.a.2 Manual dexterity
- 1.A.1.f.1 Spatial orientation

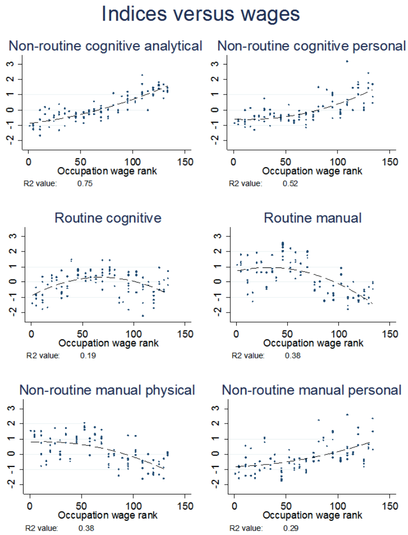
Non-routine manual interpersonal

- 2.B.1.a Social Perceptiveness
- 4.C.1.a.2.l Face to face discussions (Added by current authors)
- 4.A.4.a.5 Assisting and Caring for Others (Added by current authors)

Offshorability

- 4.A.4.a.8 Performing for or Working Directly with the Public (reverse)
- 4.A.4.a.5 Assisting and Caring for Others (reverse)
- 4.C.1.a.2.l Face to face discussions (reverse)
- 4.A.1.b.2 Inspecting Equipment, Structures, or Material (reverse)
- 4.A.3.a.2 Handling and Moving Objects (reverse)
- 4.A.3.b.4 0.5*Repairing and Maintaining Mechanical Equipment (reverse)
- 4.A.3.b.5 0.5*Repairing and Maintaining Electronic Equipment (reverse)

# Six occupation skill indices versus wages




Task groupings

# Theoretical framework from Autor and Dorn (2013)

Key mechanism: technological progress displaces routine labour with capital

- Goods (g) are produced using abstract labour ($L_a$), routine labour ($L_r$) and capital ($K$). K is a relative complement to $L_a$ and a relative substitute for $L_r$.

$$Y_g = L_a^{1-\beta}[(\alpha_r L_r)^{\mu} + (\alpha_k K)^{\mu}]^{\beta/\mu}$$

- The price of capital falls overtime, increasing demand for La and substituting $L_r$ with K.

$$p_k(t) = \theta e^{-\delta t}$$

Return

# Theoretical framework from Autor and Dorn (2013)

- Services are produced only with manual labour, $L_m$. There is no productivity impact of capital.

$$Y_s = \alpha_s L_m$$

- Consumers like to consume both goods and services, e.g. standard CES preferences

$$u = (c_s^{\rho} + c_g^{\rho})^{1/\rho}$$

◂ Return

# Robustness checks

A list of some robustness checks:

- Replacing usual hours of work with actual hours (differs due to holiday, sick leave, different shifts, overtime etc)
- Different samples of hours: include zeros, exclude zeros, include only those working >5 hours.
- Different fixed effects: none, country, industry, country-industry interaction.
- A variety of time trend specifications.
- Country level results provide an additional check of validity – the results are not driven but certain economies.
- Non-routine manual personal: focussed just on lower half of wage distribution, removed effect of occupations such as veterinary nurses etc.

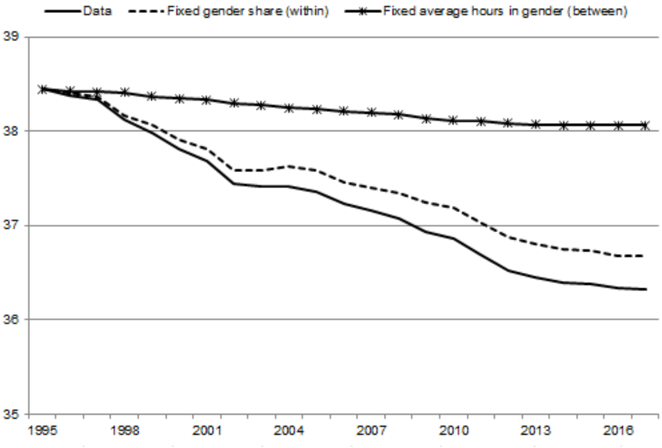
◂ Results summary

# Contributing factors: changing gender patterns

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Y variable | ------------------------------ Hours per worker ------------------------------ | | | | | |
| Gender included: | Female | Male | Female | Male | Female | Male |
| Index | NR Cog An. | NR Cog An. | NR Cog Per. | NR Cog Per. | R Cog. | R Cog. |
| **High Index*t** | **0.135***<br>(0.0397)** | **0.123***<br>(0.0299)** | **0.0789<br>(0.0496)** | **0.0780**<br>(0.0389)** | **-0.00192<br>(0.0243)** | **0.0478*<br>(0.0259)** |
| Observations | 4,768,634 | 5,447,758 | 4,768,634 | 5,447,758 | 4,768,634 | 5,447,758 |
| Standard controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Country & Sector FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| | (7) | (8) | (9) | (10) | (11) | (12) |
| Y variable | ------------------------------ Hours per worker ------------------------------ | | | | | |
| Gender | Female | Male | Female | Male | Female | Male |
| Index | R man. | R Man. | NR Man Ph. | NR Man Ph. | NR M Pers. | NR M Pers. |
| **High Index*t** | **-0.363***<br>(0.0431)** | **-0.105***<br>(0.0243)** | **-0.0409<br>(0.0358)** | **-0.0337<br>(0.0258)** | **0.130***<br>(0.0329)** | **0.0793***<br>(0.0299)** |
| Observations | 4,768,634 | 5,447,758 | 4,768,634 | 5,447,758 | 4,768,634 | 5,447,758 |
| Standard controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Country & Sector FEs | Yes | Yes | Yes | Yes | Yes | Yes |

Return

# Contributing factors: gender shift-share analysis




Return

# Contributing factors: Ageing workforce

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Y variable | ------------------------------- | Hours per worker | ------------------------------- | | | |
| Age included: | Younger | Older | Younger | Older | Younger | Older |
| Index | NR Cog An. | NR Cog An. | NR Cog Per. | NR Cog Per. | R Cog. | R Cog. |
| **High Index*t** | **0.123*****<br>**(0.0252)** | **0.116*****<br>**(0.0354)** | **0.0670***<br>**(0.0342)** | **0.0847****<br>**(0.0421)** | **0.0333**<br>**(0.0232)** | **-0.00262**<br>**(0.0223)** |
| Observations | 3,571,625 | 3,560,155 | 3,571,625 | 3,560,155 | 3,571,625 | 3,560,155 |
| Standard controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Country & Sector FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| | (7) | (8) | (9) | (10) | (11) | (12) |
| Y variable | ------------------------------- | Hours per worker | ------------------------------- | | | |
| Gender | Younger | Older | Younger | Older | Younger | Older |
| Index | R man. | R Man. | NR Man Ph. | NR Man Ph. | NR M Pers. | NR M Pers. |
| **High Index*t** | **-0.140*****<br>**(0.0276)** | **-0.185*****<br>**(0.0310)** | **-0.0184**<br>**(0.0249)** | **-0.0354**<br>**(0.0248)** | **0.0726****<br>**(0.0300)** | **0.0889*****<br>**(0.0314)** |
| Observations | 3,571,625 | 3,560,155 | 3,571,625 | 3,560,155 | 3,571,625 | 3,560,155 |
| Standard controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Country & Sector FEs | Yes | Yes | Yes | Yes | Yes | Yes |

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# Contributing factors: Educational attainment

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Y variable | | | ---- Hours per worker ---- | | | |
| Education included: | Low | Middle | High | Low | Middle | High |
| Index | NR Cog An. | NR Cog An. | NR Cog An. | NR Cog Per. | NR Cog Per. | NR Cog Per. |
| **High Index*t** | **0.140***<br>(0.0405)** | **0.0709***<br>(0.0271)** | **0.0980***<br>(0.0347)** | **-0.0284<br>(0.0618)** | **-0.0312<br>(0.0490)** | **0.0785**<br>(0.0345)** |
| Observations | 2,757,104 | 4,757,345 | 2,701,943 | 2,757,104 | 4,757,345 | 2,701,943 |
| Standard controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Country & Sector FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| | (7) | (8) | (9) | (10) | (11) | (12) |
| Y variable | | | ---- Hours per worker ---- | | | |
| Education included: | Low | Middle | High | Low | Middle | High |
| Index | R Cog. | R Cog. | R Cog. | R Man. | R Man. | R Man. |
| **High Index*t** | **0.124***<br>(0.0293)** | **0.0471**<br>(0.0216)** | **-0.0378<br>(0.0288)** | **-0.162***<br>(0.0350)** | **-0.100***<br>(0.0289)** | **-0.145***<br>(0.0318)** |
| Observations | 2,757,104 | 4,757,345 | 2,701,943 | 2,757,104 | 4,757,345 | 2,701,943 |
| Standard controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Country & Sector FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| | (13) | (14) | (15) | (16) | (17) | (18) |
| Y variable | | | ---- Hours per worker ---- | | | |
| Education included: | Low | Middle | High | Low | Middle | High |
| Index | NR Man Ph. | NR Man Ph. | NR Man Ph. | NR M Pers. | NR M Pers. | NR M Pers. |
| **High Index*t** | **0.0848***<br>(0.0321)** | **0.0360<br>(0.0232)** | **-0.0574**<br>(0.0289)** | **0.0644<br>(0.0403)** | **0.0458*<br>(0.0254)** | **0.0853**<br>(0.0350)** |
| Observations | 2,757,104 | 4,757,345 | 2,701,943 | 2,757,104 | 4,757,345 | 2,701,943 |
| Standard controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Country & Sector FEs | Yes | Yes | Yes | Yes | Yes | Yes |

Return