Implications of Technology on Wages, Factor Shares and Inequalities across Demographic Groups in the European Labor Market

Tomáš Oleš

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Labor share decline

Two compelling hypotheses:

- Automation (Acemoglu and Restrepo, 2018a, 2022)
- Increasing market concentration (Autor et al., 2017, 2020)

Other hypotheses:

- Offshoring (Feenstra and Hanson, 1999)
- Compositional factors (Fortin and Lemieux, 1997)
- Extensive capital accumulation (Piketty and Zucman, 2014)

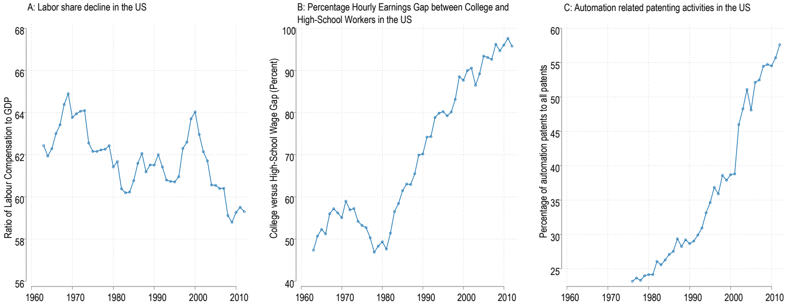

Figure displays labor share decline, increase in the skill premium of college to high school workers, and the increase of patents share that are classified as automation ones. The US economy 1960-2012. Source: Authors' illustration based on Feenstra et al. (2015)'s (Panel A); Autor (2014)'s (Panel B); Mann and Püttmann (2018)'s (Panel C) data.

Aims of the dissertation

- **First Aim:** Empirically investigate the impact of automation within the task-based framework in France and Germany, building on the framework created by Acemoglu and Restrepo (2022).
- **Second Aim:** Explore both effects of labor-automation and labor-augmentation technologies simultaneously in the European labor market, filling the gap left by existing research predominantly centered around the US (Autor et al., 2022).
- **Third Aim:** Examine the implications of increasing market concentration on labor share, productivity, and wages, particularly focusing on 'old' European countries and superstar firms (Autor et al., 2017, 2020).

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Structure of the dissertation

Tasks, Automation, and Inequalities in France and Germany

Impact of Automation and Augmentation Technologies on Employment

Digitalization, Superstar Firms, and Labor Dynamics

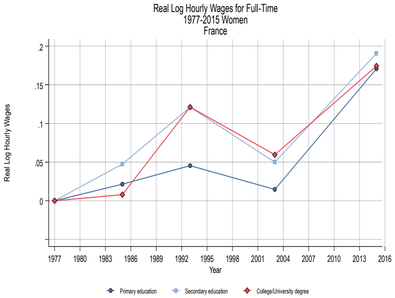

Reviewer 2 Must Be Stopped!
Adnan Ali · 1 h ·
That one Chapter in Thesis.
127
8 shares

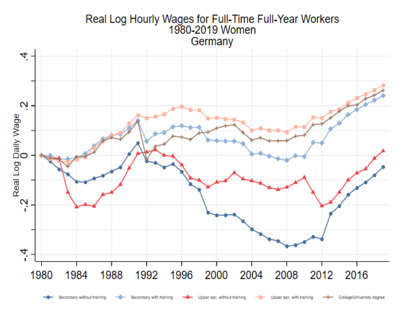
Tasks, Automation, and Inequalities in France and Germany

Motivation

- Inequalities over last five decades surged, predominantly caused by negative shift towards labor (Acemoglu and Restrepo, 2022)
- Technological change is the most plausible explanation:
  - Skill-biased technological change (Goldin and Katz, 2009)
  - Task-polarization model (Acemoglu and Restrepo, 2022)
- In the US, the changes in automation technologies can explain 50-70% of the change in wage structure (Acemoglu and Restrepo, 2022)
- Have automation technologies in Europe caused labor market polarization as in the US?

Some consequences for wages

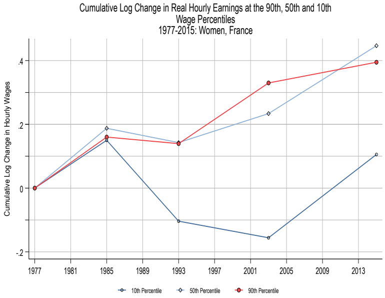


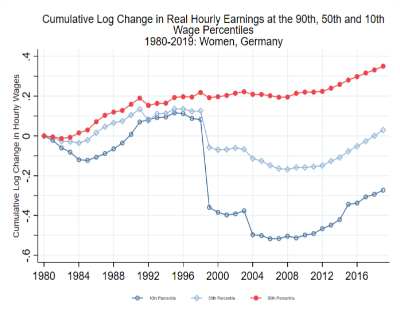


Composition adjusted real wages for full-time workers, women, in France and Germany, Source: FQP survey (wave 1977, 1985, 1993, 2003, 2015) and SIAB (Version 7521 v1).

▸ Wages for men.

Some consequences for wage distributions



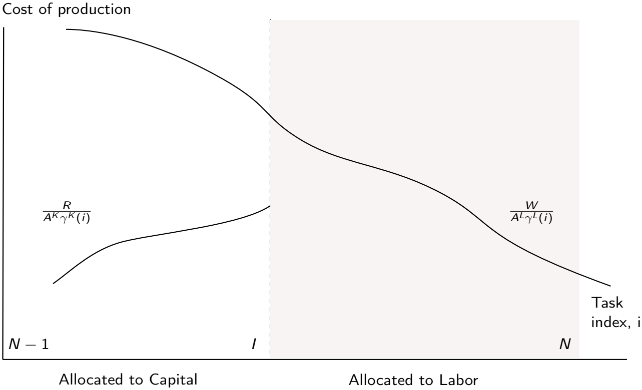


Composition adjusted real wages for full-time workers, women, in France and Germany, Source: FQP survey (wave 1977, 1985, 1993, 2003, 2015) and SIAB (Version 7521 v1).

Distributions for men.

Task-polarization model

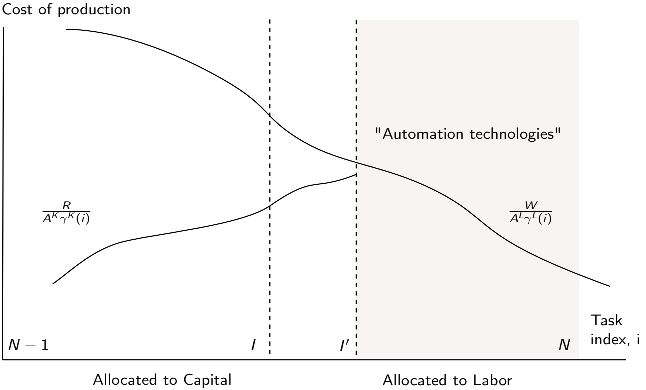
$$Y = \left(\int_{N-1}^{N} y(i)^{\frac{\lambda-1}{\lambda}} di \right)^{\frac{\lambda}{\lambda-1}}$$



Equilibrium allocation of tasks to capital and labor in production based on the Acemoglu and Restrepo (2018b) and Acemoglu and Restrepo (2020).

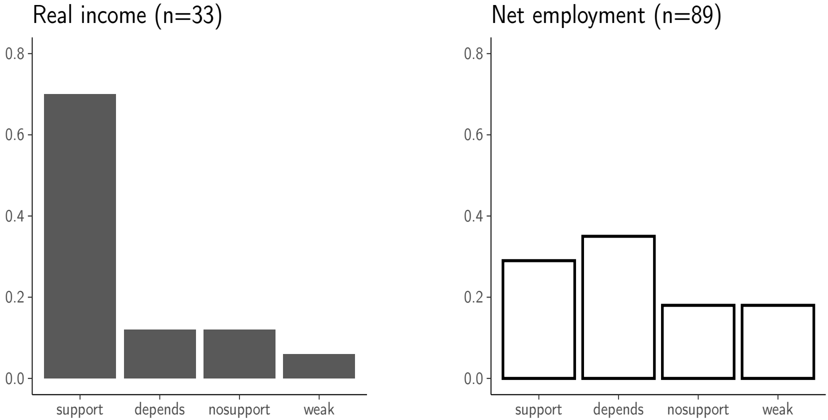
Automation in task-polarization model

$$d\ln w_g = \frac{1}{\lambda} d\ln y + \frac{1}{\lambda}\sum_{i\in\mathcal{I}} \omega_g^i \cdot d\ln\zeta_i + \frac{\lambda-1}{\lambda} d\ln\tilde{A}_g - \frac{1}{\lambda}\sum_{i\in\mathcal{I}} \omega_g^i \cdot d\ln\Gamma_{gi}^{auto}$$



Equilibrium allocation of tasks to capital and labor in production based on the Acemoglu and Restrepo (2018b) and Acemoglu and Restrepo (2020).

Empirical evidence on the race between the man and machine



Authors' illustration based on Hötte et al. (2022)'s meta-analysis

Results systematically differ at firm-level and industry-level (Guarascio et al., 2024; Jurkat et al., 2023).

Data technology side and labor share

- EU-KLEMS database:
  - Covers 33 industries from 1985 to 2015.
  - Includes labor share, value added, and employment data.
- Complemented with US industry-level technology proxies from Acemoglu and Restrepo (2022):
  - Average change in dedicated machinery and software (orig. BEA).
  - Adjusted penetration of robots (orig IFR).

Data workers side: France

- Institut National de la Statistique et des Études Économiques (INSEE)
- (i.) Formation Qualification Professionnelle (FQP) and (ii.) Survey and Enquête Emploi (EE, EEC):
  - Period (i.): 1977, 1985, 2003, 2014-2015.
  - Period (ii.): 1977-2015.
  - Demographic Groups: 60.
- Demographic groups characteristics:
  - Gender.
  - Age: Three age cells.
  - Education: Four education cells.
  - Nationality: Four consistent nationality cells (French, European, African, and others).
- Occupational routine task intensities (RTI) are taken from Mihaylov and Tijdens (2019).

Data workers side: Germany

- Institut für Arbeitsmarkt und Berufsforschung (IAB)
- Sample of Integrated Market Biographies (SIAB) and auxiliary Employment History Data (BEH):
  - Period (ii.): 1985-2016.
  - Demographic Groups: 132.
- Demographic groups characteristics:
  - Gender.
  - Grouped education into five education cells.
  - Grouped nationality into four groups (Germans, Western Europeans, Eastern Europeans, and others).
  - Grouped age into five age cells.
- Occupational routine task intensities (RTI) are taken from Dengler et al. (2014).

Acemoglu and Restrepo (2022)'s link of automation to wage changes

$$d \ln w_g = \frac{1}{\lambda} d \ln y + \frac{1}{\lambda} \sum_{i \in \mathcal{I}} \omega_g^i \cdot d \ln \zeta_i + \frac{\lambda - 1}{\lambda} d \ln \tilde{A}_g - \frac{1}{\lambda} \sum_{i \in \mathcal{I}} \omega_g^i \cdot d \ln \Gamma_{gi}^{auto}$$

Empirical mapping:

- The common expansion of output, $d \ln y$, will be absorbed by the constant term.
- The industry shifters term $\sum_{i \in \mathcal{I}} \omega_g^i \cdot d \ln \zeta_i$ will be parametrized by group g's exposure to changes in industry (log) value added shares.
- The third term, $d \ln \tilde{A}_g$, will be parametrized as in the SBTC literature. Assuming:

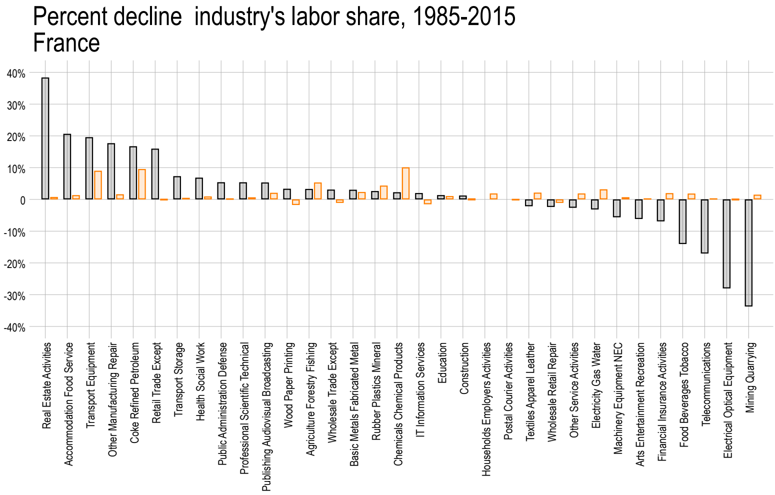
$$\frac{\lambda - 1}{\lambda} d \ln \tilde{A}_g = \alpha_{edu(g)} + \gamma_{gender(g)} + \upsilon_g$$

  where υ_g is an unobserved component, and $\alpha_{edu(g)}$ and $\gamma_{gender(g)}$ will be absorbed by the dummies for education levels and gender.
- The key explanatory variable is a measure of direct task displacement driven by the advances in automation technologies, $\sum_{i \in \mathcal{I}} \omega_g^i \cdot d \ln \Gamma_{gi}^{auto}$.

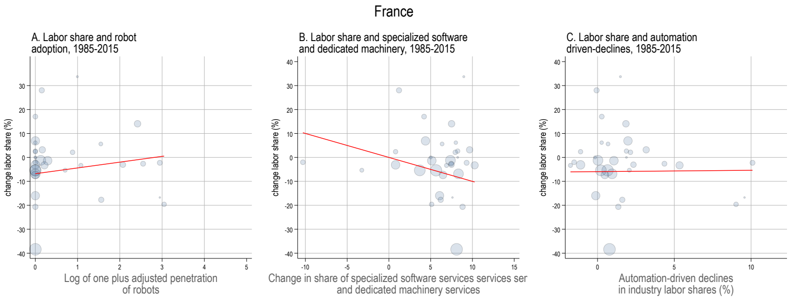
Task displacement parametrization

$$\text{Task displacement}_g^{c,\text{direct}} = \sum_{i \in \mathcal{I}} \omega_{gic} \cdot \frac{\omega_{gic}^R}{\omega_{ic}^R} \cdot \left(-d \ln s_i^{L,\text{auto}} \right)$$

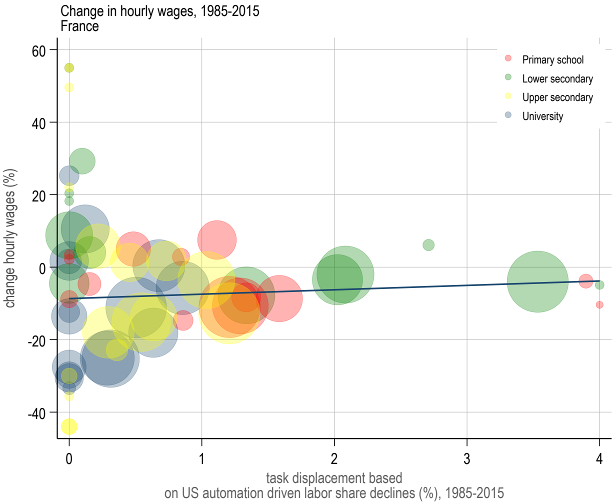
- ω_{gic}, is the share of wages earned by group g workers in industry i and country c relative to their total earnings.
- $\frac{\omega_{gic}^R}{\omega_{ic}^R}$ is the share of wages earned in routine occupations by group g, industry i, and country c relative to all wages earned in routine occupations in industry i and country c.
- $-d \ln s_i^{L,\text{auto}}$ is the automation drive labor share decline



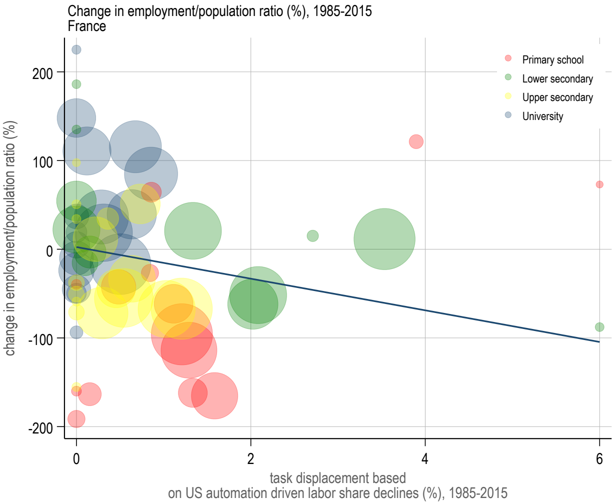
Percent decline in industry labor shares (in blue/dark) and automation-driven labor share decline (in orange/light), 1985-2015. Source: Author's elaboration based on data from the EU-KLEMS and Acemoglu and Restrepo (2022) databases.



Relationship between automation technologies and changes in industry labor shares, France, 1985-2015. Source: Author's elaboration based on data from the EU-KLEMS and Acemoglu and Restrepo (2022) databases.



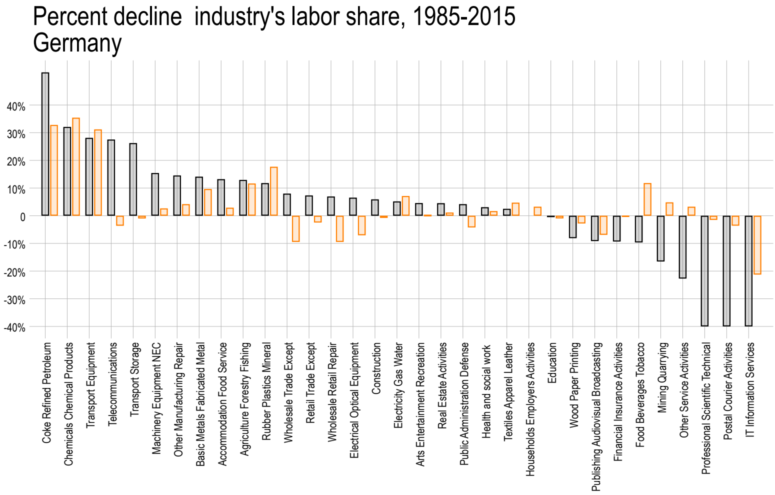
Change in hourly wages and task displacement measure, constructed base on the US automation frontier, 1985-2015. Source: Authors' elaboration based on EE, EEC, FQP, EU-KLEMS, Acemoglu and Restrepo (2022)'s databases.



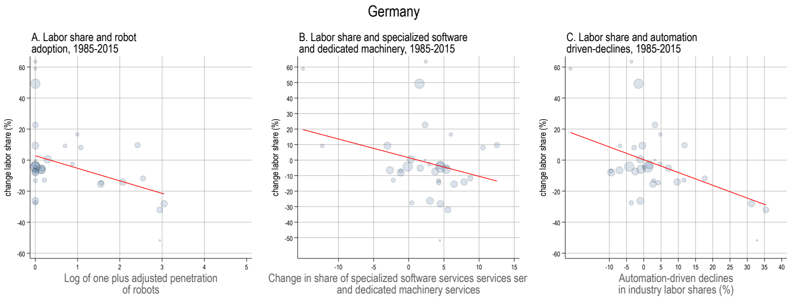
Change in employment-to-population ratio and task displacement measure, constructed base on the US automation frontier, 1985-2015. Source: Authors' elaboration based on EE, EEC, FQP, EU-KLEMS, Acemoglu and Restrepo (2022)'s databases.

	Change in hourly wages 1985-2015	Change in employment-to-population 1985-2015
Panel A		
Task displacement	-0.001	-0.072
	(0.005)	(0.045)
Exposure to industry change in value added	0.047	0.124
	(0.071)	(0.212)
Industry shifters	-25.089***	3.439
	(8.658)	(29.094)
Education, gender dummies	✓	✓
N	60	60
R^2	0.288	0.271
Panel B		
Task displacement	-0.031	-1.368*
	(0.105)	(0.787)
Exposure to industry change in value added	0.047	0.129
	(0.071)	(0.212)
Industry shifters	-25.089***	3.317
	(8.658)	(29.12)
Education, gender dummies	✓	✓
N	60	60
R^2	0.288	0.272

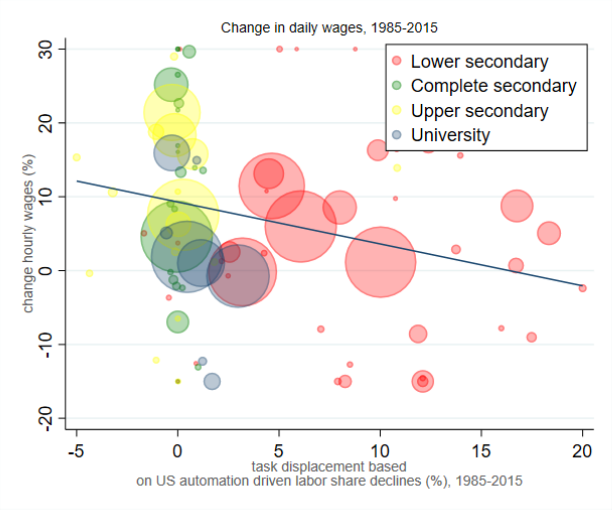
Task displacement and changes in real hourly wages and employment-to-population ratio, France, 1985-2015. Panel A reports results for parametrized measure of task displacement based on observed labor share declines. Panel B reports results for parametrized measure of task displacement based on automation-driven labor share declines based on the US' technological frontier.



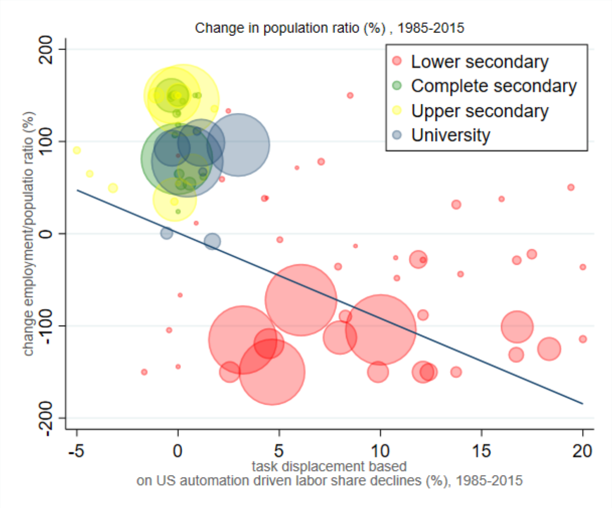
Percent decline in industry labor shares (in blue/dark) and automation-driven labor share decline (in orange/light), 1985-2015. Source: Authors' elaboration based on data from the EU-KLEMS and Acemoglu and Restrepo (2022) databases.



Relationship between automation technologies and changes in industry labor shares, Germany, 1985-2015. Source: Authors' elaboration based on data from the EU-KLEMS and Acemoglu and Restrepo (2022) databases.



Change in hourly wages and task displacement measure, constructed base on the US automation frontier, 1985-2015. Source: Authors' elaboration based on SIAB (Version 7521 v1), EU-KLEMS, Acemoglu and Restrepo (2022)'s databases.



Change in employment-to-population ratio and task displacement measure, constructed base on the US automation frontier, 1985-2015. Source: Authors' elaboration based on SIAB (Version 7521 v1), EU-KLEMS, Acemoglu and Restrepo (2022)'s databases.

	Change in hourly wages 1985-2015	Change in employment-to-population 1985-2015
	Panel A	
Task displacement	0.774	1.046
	(0.629)	(5.723)
Exposure to industry change in value added	-0.825	417.531
	(86.979)	(528.861)
Industry shifters	2.461	2.992
	(4.889)	(26.630)
Education, gender dummies	✓	✓
N	132	132
R^2	0.486	0.617
	Panel B	
Task displacement	0.336	-3.020
	(0.528)	(3.491)
Exposure to industry change in value added	-44.979	148.951
	(67.997)	(495.223)
Industry shifters	0.571	(0.615)
	(4.216)	(26.487)
Education, gender dummies	✓	✓
N	132	132
R^2	0.482	0.622

Task displacement and changes in real hourly wages and employment-to-population ratio, Germany, 1985-2015. Panel A reports results for parametrized measure of task displacement based on observed labor share declines. Panel B reports results for parametrized measure of task displacement based on automation-driven labor share declines based on the US technological frontier.

Impact of Automation and Augmentation Technologies on Employment in Europe

Motivation

- Automation may disrupt labor markets:
  - Displacement (*automation*) effect
  - Reinstatement (*augmentation*) effect
- The net effect on employment is an empirical question (Arntz et al. (2019))
- We stand on the shoulders of giants (literally):
  - Literature considering both effects simultaneously is scarce (Autor et al. (2022))
  - Europe is not in the scope of interest. Why?

...by applying existing ideas not transferring previous results to the European context.

The ideas

- Automation (displacing) technologies are those that replace input of job tasks (Autor et al. (2022)).
- Augmentation (reinstating) technologies are those that improve the capabilities, quality, or utility of the output of occupations (Autor et al. (2022)).
- Different technologies (robots, software, and AI) have a different impact on employment caused by different exposure caused by the different nature of these technologies (Webb (2019)). Lebelling keywords.

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Implementation

- We identify what tasks humans and technology perform ...and measure to what extent these input tasks overlap (*automation*).
- We identify what is the final output that technology potentially complements
  ... and measure how the final output and technology are 'close' to each other (*augmentation*).

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  ... and measure how the final output and technology are 'close' to each other (*augmentation*).

What labor is actually doing?

Weawing and Kitting Machine Operators - Unit Group 8152 ISCO 08: Setting up and operating batteries of automatic, link-type knitting machines to knit garments of specified pattern and design, Threading yarn, thread and fabric through guides, needles and rollers of machines for weaving, knitting or other processing...

Electrical Engineers - Unit Group 2151 ISCO 08: Advising on and designing power stations and systems which generate, transmit and distribute electrical power, Supervising, controlling and monitoring the operation of electrical generation, transmission and distribution systems, Advising on and designing systems for electrical motors, electrical traction...

Data

- *On the technology side:* Google Patents Public database
- *On the workers side:* Description of task in the cleaned description of tasks based on ISCO-08 by Mihaylov and Tijdens (2019) and occupational microtitles by Tijdens (2023) and merged EU-LFS since 1993 to 2017 for Germany, the United Kingdom, France, Italy, and Spain

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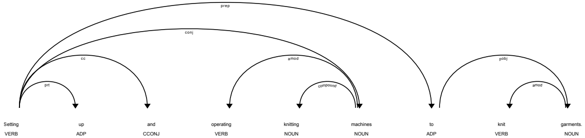
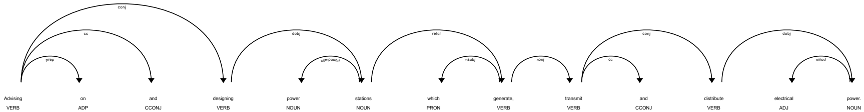
Occupational tasks of Weawing and Kitting Machine Operators

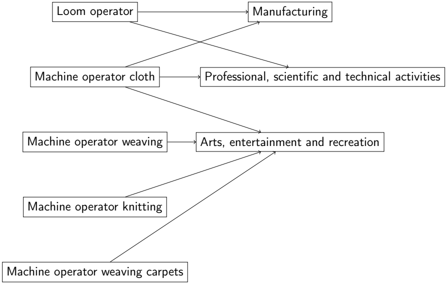


Occupational tasks of Electrical Engineers



Example of process of extracting tasks from the description of occupational tasks in Mihaylov and Tijdens (2019) database by Honnibal and Montani (2017) dependency parsing algorithm.

But what is the output of an occupation that technology could complement?



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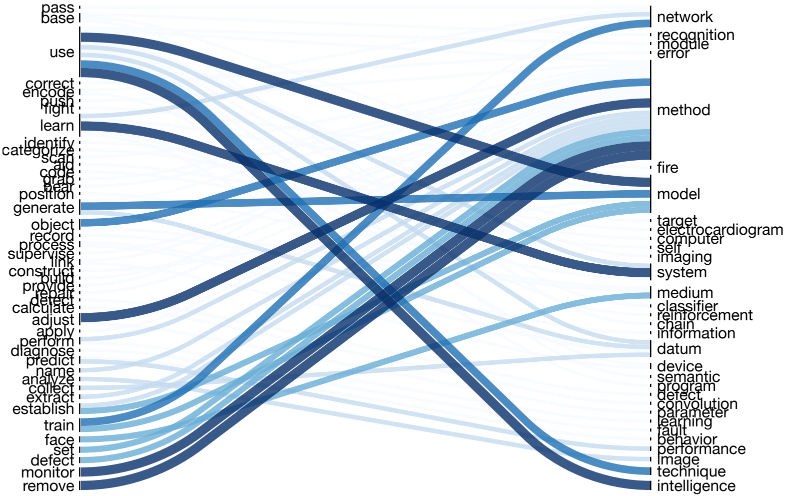
JP-H05140844-A Prediction system and control unit for malweaving in loom: AI
JP-2005095696-A Computerized sewing machine: software
CN-104420075-A Electro-pattern-sewing machine: robots
CN-101177848-A Direct-driving single needle industrial sewing machine control system: software
JP-2020195650-A Sewing system: robots
CN-104345689-A Self-calibration control device of warp knitting machine yarn guide bar: software
CN-111401629-A Production management algorithm and production management method for warp knitting workshop of intelligent knitting factory: software
JP-H05245283-A Needle thread feed quantity control device for sewing machine: robots

Scheme of micro-occupational titles obtained from Tijdens (2023) database - for Weaving and Knitting Machine Operators - Unit Group 8151, that with industries (NACE Rev. 2 one-digit) could form these combinations of occupation-industry pairs. An example of patents' titles and respective technology that could augment these occupation-industry pairs.

What technology is capable of substituting and complementing?

- Technological advances is measured by patents (Mann and Püttmann (2018); Webb (2019); Dechezleprêtre et al. (2021); Autor et al. (2022)).
- Dictionary-based labels of a broad technological category of each technology to robots, software, and AI (not exclusively distinct subset).
- Extracting the meaning of description in patent titles and abstracts for each technology.



Most common tasks of the artificial intelligence (AI) technology, 1980-2020. Source: Authors' elaboration based on Google Patents Public Database 3000 patents random sample

» Tasks of robot and software tech.

Our measure of European-specific automation and augmentation exposure

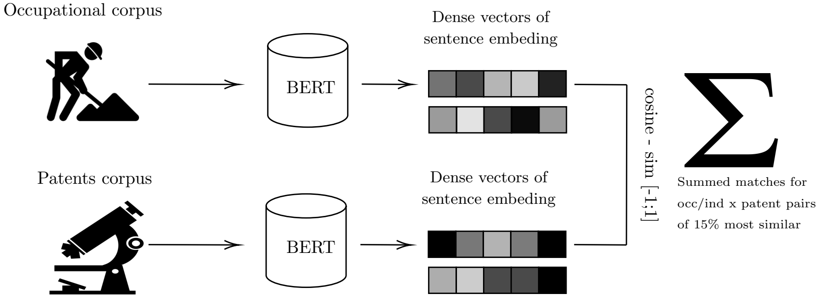
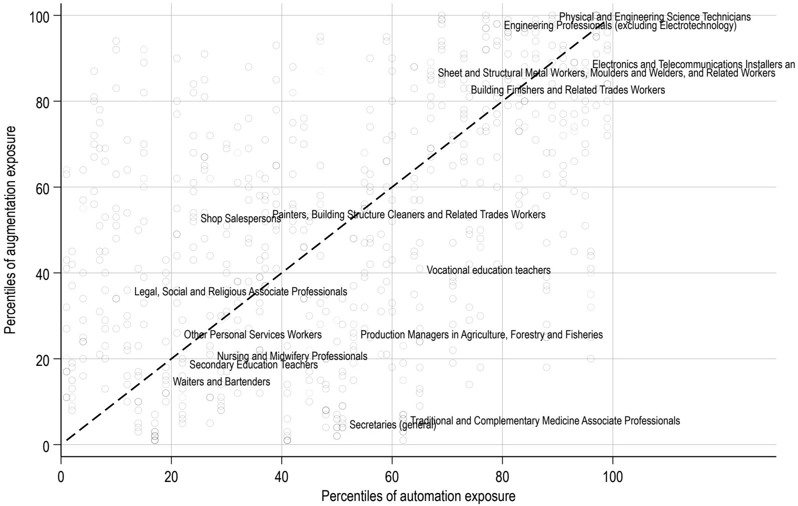


Figure: Adapted process of creation augmentation/automation exposure of occupational tasks in ISCO-08 from Autor et al. (2022). Sentence embeddings are obtained by BERT-for-patents model, fine-tuned on the entire Google patent database by Srebrovic and Yonamine (2020).

$$I^{\tau}_{p,j} = 1 \text{ if } X^{\tau}_{p,j} \geq \lambda^{\tau}_{t} \text{ and zero otherwise;}$$

$$Aut^{\tau}_{t} = \sum_{p \in \mathcal{P}^{\tau}} \sum_{j \in \mathcal{O}} I^{\tau}_{p,j}$$

Average exposure to automation and augmentation technologies in Europe (1990-2020)



Empirical specification

$$100 \times \ln(\Delta E_{ij,t}) = \beta_1^{\tau} AugX_{ij}^{\tau} + \beta_2^{\tau} AutX_{j,t}^{\tau} + \gamma_{i,t} + \delta_{j,t} + \varepsilon_{ij,t}$$

$100 \times \ln(\Delta E_{ij,t})$: five-year stacked long-run difference in the total full-time equivalent employment in the consistent* one-digit NACE r.2 industry i by three-digit ISCO-08 occupation j cell

$AugX_{ij,t}^{\tau}$: IHS transformed augmentation exposure in the industry-by-occupation cells

$AutX_{j,t}^{\tau}$ IHS transformed automation exposure in the occupation cells by each technology (robots, software, and AI), represented by τ

$\gamma_{i,t}; \delta_{j,t}$: fixed effects

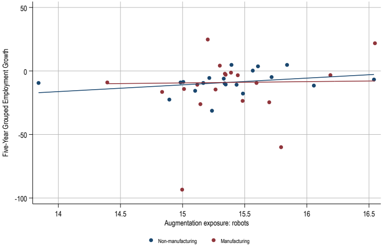
Testable hypotheses: $\beta_1^{\tau} > 0$ $\beta_2^{\tau} < 0$

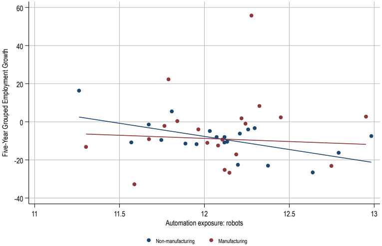
The size of reinstatement and replacement of labor in Europe by each technology

	Robot		Software		AI	
	(1)	(2)	(3)	(4)	(5)	(6)
	100 × Five-year grouped Δ(Employment)					
Augmentation exposure	6.45**	4.21†	8.70***	6.16†	7.75***	6.55*
	(2.99)	(3.03)	(3.04)	(3.76)	(2.85)	(3.81)
Automation exposure	-2.84	-11.81**	-2.95	-13.04**	-6.97*	-15.73***
	(4.16)	(5.61)	(4.30)	(6.62)	(4.03)	(5.66)
Constant	-73.62*	69.19	-106.59*	57.83	-42.39	69.03
	(44.58)	(57.99)	(56.57)	(68.29)	(43.52)	(51.07)
N	2389	2389	2389	2389	2389	2389
R^2	0.34	0.65	0.35	0.65	0.35	0.66
Industry × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Broad Occupations × Time FE	No	Yes	No	Yes	No	Yes

$p^{\dagger} < 0.20,\ p^{*} < 0.10,\ p^{**} < 0.05,\ p^{***} < 0.01.$

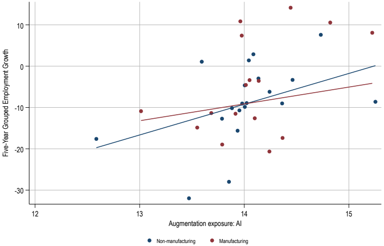
Manufacturing and non-manufacturing decomposition of reinstatement and replacement effect of robots technology

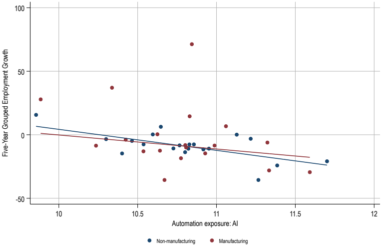




Conditional Correlations between Automation, Augmentations by Robot Tech. and Employment Growth, (based on Column (2)), 1993-2018

Manufacturing and non-manufacturing decomposition of reinstatement and replacement effect of AI technology





Conditional Correlations between Automation, Augmentations by AI Tech. and Employment Growth (based on Column (6)), 1993-2018

Correlations for the software technology

Digitalization, Superstar Firms, and Labor Dynamics: evidence from France, Germany, Italy, and Spain

Motivation and aim

- Rising market concentration serves as an independent explanation for the observed decline in aggregate labor share (Autor et al., 2017).
- Superstar firms are large firms dominating product market shares (Autor et al., 2020).
- Superstar firms:
  - they have higher productivity (Autor et al., 2017; Ferschli et al., 2021; Autor et al., 2020; Mertens, 2022)
  - they pay higher wages (Autor et al., 2020; Mertens, 2022)
  - they have lower labor share (Autor et al., 2017, 2020)
  - they employ new (digital) technologies, that accelerate above trends (Calvino et al., 2018; Calligaris et al., 2018; Ferschli et al., 2021)
- Do these predictions hold in the 'old' European countries?

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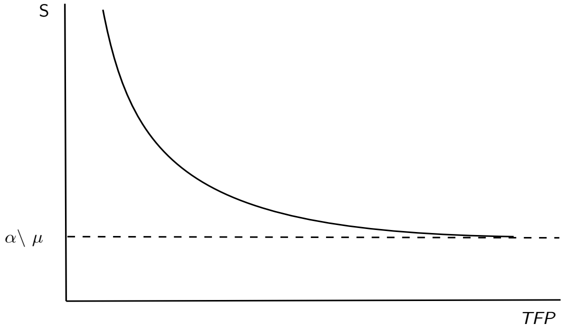
  - they employ new (digital) technologies, that accelerate above trends (Calvino et al., 2018; Calligaris et al., 2018; Ferschli et al., 2021)
- Do these predictions hold in the 'old' European countries?

Labor share: firm level

$$S_i = \left(\frac{wL}{PY}\right)_i = \frac{\alpha_L}{\mu_i} + \frac{wF}{(PY)_i}$$

- α_L is labor elasticity of substitution, μ_i is the markup, w is wage rate, L is total labor, F is fixed labor, and PY is nominal value added (Autor et al., 2017, 2020).



Relationship between the labor share and total factor productivity in the superstar model based on Stiel and Schiersch (2022).

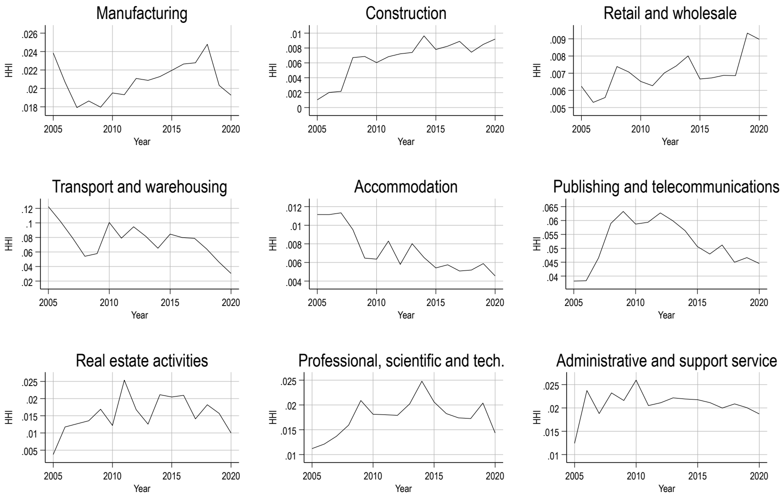
Data and empirical specification

- France, Germany, Italy, and Spain, 2005-2020
- *On the industry side:* EU-KLEMS (February 2023 release) by (Bontadini et al., 2023) to construct digitization indicators inspired by (Ferschli et al., 2021):
  - IT, CT, Software and R&D share on investments
  - IT and CT capital deepening
- *On the firms side:* The Competitiveness Research Network of the EU System of Central Banks (CompNet), 9th vintage (Joint Distributions)
  - Labor productivity, wages, and labor share and capital intensity
  - K/L ratio as control

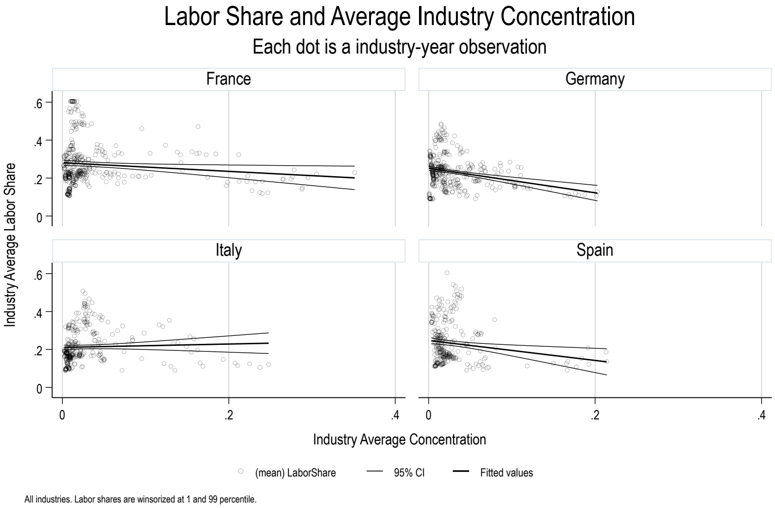
$$Y_{cit} = \beta_0 + \sum_{k=1}^{4} \beta_k Q_{k+1ci} + \beta_5 DI_{ci,t-1} + \sum_{k=1}^{5} \beta_{k+5}(Q_{k+1ci} \times DI_{ci,t-1}) +$$

$$\beta_{10} Capital\ intensity_{ci,t-1} + \alpha_c + \gamma_i + \rho_t + \varepsilon_{cit}$$

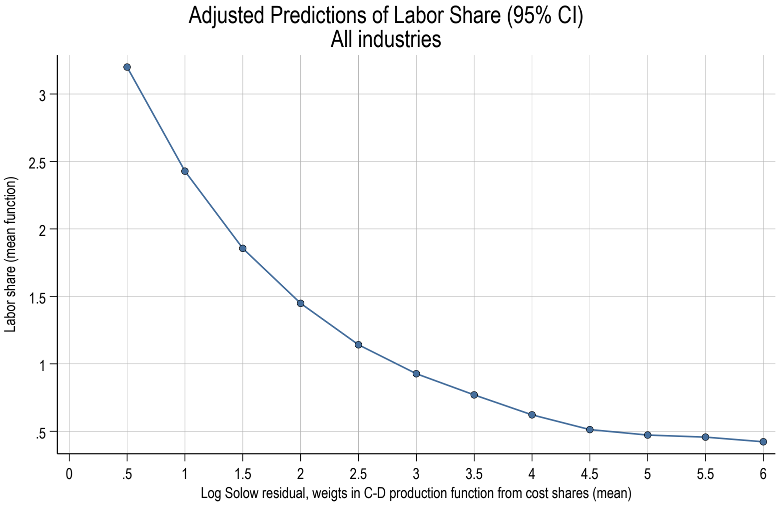
Industry concentraction



Average industrial concentration across aggregated industries in France, Germany, Italy, and Spain, 2005-2020. Aggregated as the weighted average of total employment.

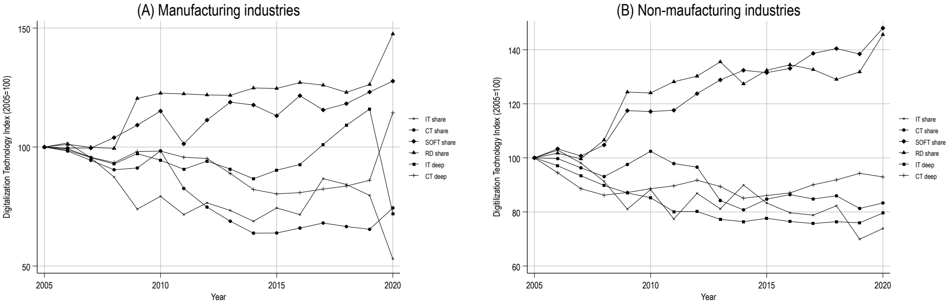


Average industrial concentration and labor share across all industries (C-N, NACE Rev. 2) in France, Germany, Italy, and Spain, 2000-2020.



Mean function of labor share and total factor productivity in France, Germany, Italy, and Spain, 2020. All variables are taken from CompNet 9th vintage. Labor share is measured as nominal labor cost over nominal value added (LR01_lc_va_mn). Total factor productivity is log transformed Solow residual from the Cobb-Douglas production function (PV05_lnsr_cs).

Digitalization indicators



The figure shows the evolution of the digitalization indices based on Ferschli et al. (2021) and the KLEMS database. Investment in information technology ("IT share"), investment in communication technology ("CT share"), investment in research and development ("RD share"), and software and databases ("SOFT share"), all measured as a share of non-residential gross fixed capital formation. The stock of IT capital ("IT deep") and the stock of software and databases ("SOFT deep") are both relative to hours worked.

	log (Labor productivity)					
	(1)	(2)	(3)	(4)	(5)	(6)
2. Quintile	0.346***	0.335***	0.296***	0.351***	0.443***	0.417***
	(0.031)	(0.056)	(0.033)	(0.031)	(0.017)	(0.024)
3. Quintile	0.518***	0.477**	0.424***	0.525***	0.616***	0.632***
	(0.054)	(0.089)	(0.055)	(0.060)	(0.038)	(0.050)
4. Quintile	0.662***	0.563***	0.501***	0.662***	0.790***	0.827***
	(0.075)	(0.094)	(0.060)	(0.084)	(0.072)	(0.096)
5. Quintile	0.849***	0.721***	0.657***	0.822***	1.035***	1.035***
	(0.084)	(0.085)	(0.057)	(0.101)	(0.113)	(0.108)
	IT share$_{t-1}$	CT share$_{t-1}$	Soft share$_{t-1}$	R&D share$_{t-1}$	IT deep $_{t-1}$	CT deep$_{t-1}$
1. Quintile	0.008*	-0.010	-0.044*	0.015	-0.019*	-0.030**
	(0.003)	0.011)	(0.015)	(0.010)	(0.007)	(0.007)
2. Quintile	0.006	-0.006	-0.020***	0.008	0.006	-0.008
	(0.005)	(0.013)	(0.003)	(0.009)	(0.003)	(0.010)
3. Quintile	0.003	0.005	-0.000	0.003	0.006	0.006
	(0.008)	(0.015)	(0.006)	(0.005)	(0.006)	(0.007)
4. Quintile	0.013	0.027*	0.031*	0.002	0.014	0.022**
	(0.007)	(0.010)	(0.013)	(0.005)	(0.006)	(0.004)
5. Quantile	0.026***	0.038***	0.046***	0.006	0.028	0.028**
	(0.003)	(0.006)	(0.007)	(0.011)	(0.014)	(0.009)
Capital intensity	0.001**	0.001**	0.001**	0.002***	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	4.022***	4.021***	4.093***	3.864***	3.945***	3.912***
	(0.039)	(0.018)	(0.050)	(0.075)	(0.035)	(0.056)
Industry, Country, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.785	0.786	0.788	0.799	0.785	0.786
N	13820	13839	13795	13275	13869	13869

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Relationship between quintiles of firm size (defined by mean firms' revenues) labor productivity and digitalization indicator in France, Germany, Italy, and Spain, 2005-2020.

	log(Labor share)					
	(1)	(2)	(3)	(4)	(5)	(6)
2. Quintile	-0.115***	-0.132**	-0.077**	-0.111***	-0.132**	-0.124***
	(0.012)	(0.028)	(0.020)	(0.014)	(0.033)	(0.013)
3. Quintile	-0.163***	-0.178**	-0.114*	-0.159**	-0.165*	-0.183***
	(0.024)	(0.039)	(0.038)	(0.033)	(0.069)	(0.031)
4. Quintile	-0.201***	-0.222**	-0.146*	-0.198**	-0.222*	-0.219***
	(0.028)	(0.050)	(0.049)	(0.037)	(0.080)	(0.032)
5. Quintile	-0.237***	-0.239**	-0.162*	-0.233**	-0.296	-0.278**
	(0.038)	(0.049)	(0.060)	(0.055)	(0.128)	(0.071)
	IT share$_{t-1}$	CT share$_{t-1}$	Soft share$_{t-1}$	R&D share$_{t-1}$	IT deep $_{t-1}$	CT deep$_{t-1}$
1. Quintile	-0.010	-0.009	0.025	-0.001	0.001	0.002
	(0.006)	(0.007)	(0.012)	(0.005)	(0.009)	(0.003)
2. Quintile	-0.006*	-0.002	0.008	-0.004	-0.004	-0.001
	(0.002)	(0.001)	(0.008)	(0.004)	(0.003)	(0.003)
3.Quintile	0.002	-0.003	0.002	-0.003**	0.000	-0.004
	(0.003)	(0.002)	(0.007)	(0.001)	(0.004)	(0.003)
4.Quintile	-0.001	-0.001	-0.000	-0.002	-0.005	-0.004
	(0.002)	(0.004)	(0.010)	(0.002)	(0.007)	(0.002)
5.Quintile	-0.005	-0.008	-0.010	-0.002	-0.015	-0.011
	(0.006)	(0.007)	(0.009)	(0.005)	(0.016)	(0.011)
Capital intensity	-0.000**	-0.000*	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.560***	0.592***	0.514***	0.581***	0.561***	0.575***
	(0.015)	(0.015)	(0.031)	(0.017)	(0.038)	(0.019)
Industry, Country, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.534	0.533	0.536	0.515	0.534	0.533
N	13820	13839	13795	13275	13869	13869

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Relationship between quintiles of firm size (defined by mean firms' revenues) labor share and digitalization indicator in France, Germany, Italy, and Spain, 2005-2020.

Conclusions (a)

- In France tide lifts all boats (across education) but the wage distribution still witnessed a wage polarization between 10/90th percentile; in Germany wage polarization by both increase in educational differentials and significant wage declines for the least educated workers.
- Empirically parametrized the task-polarization model in a reduced form (wages, employment, task displacement) always significant (exemp. France wages).
- Fully specified task-polarization model (with productivity gains) documents insignificant relationship.
- *Future researchers*: assess robustness using French administrative data (e.g. DADS), expand study to include more countries, and construct a European-specific technological frontier, explore factors of wage rigities.

Conclusions (b)

- Contributed to the empirical literature by examining labor-complementing and labor-substituting effects of technology on employment changes simultaneously.
- Created an objective measure of exposure to automation and augmentation for ISCO-08 occupations using text analysis techniques.
- Revealed a moderate positive correlation between automation and augmentation exposure across occupations, similar to findings in the US.
- Occupations with higher exposure to automation than augmentation tended to experience declines in employment, while those with higher augmentation exposure saw higher employment growth.
- Results held true across different technologies (robots, software, AI) and sectors (manufacturing, non-manufacturing).
- *Future researchers*: explore impact on wages and more

Conclusions (c)

- Explored whether the mean function of labor share declines in a non-linear manner with increasing TFP towards superstar firms; found evidence supporting fixed-cost mechanism among firms, especially in non-manufacturing industries: good for EU antitrust.
- Between and with-in variation industries observed positive association between average industry concentration and labor productivity and wages, while negative association with labor share.
- Estimates of digitalization impact indicate significant acceleration of productivity and wages for firms in the fourth and fifth quintiles of firm size distribution; but no significant impact found on labor share declines.
- *Future researchers*: identify the fixed-costs mechanism by industry, explore the potential implications of emerging technologies, such as AI, focus on local labor market.

Thank you for your attention!

https://tomasoles.github.io/home/

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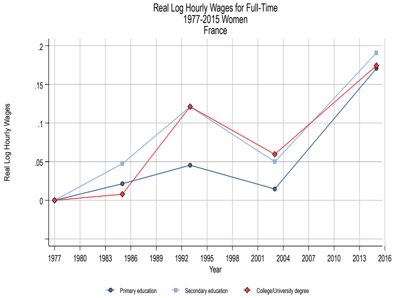
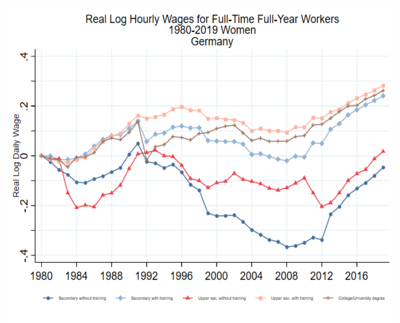
Appendix A

Some consequences for wages

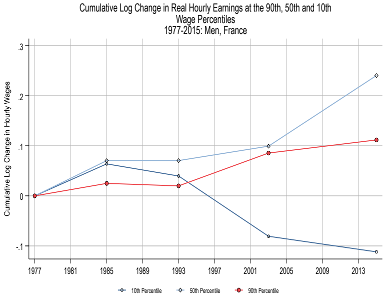


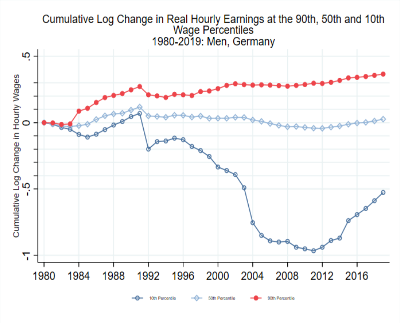


Composition adjusted real wages for full-time workers, men, in France and Germany, Source: FQP survey (wave 1977, 1985, 1993, 2003, 2015) and SIAB (Version 7521 v1).

» Back to women.

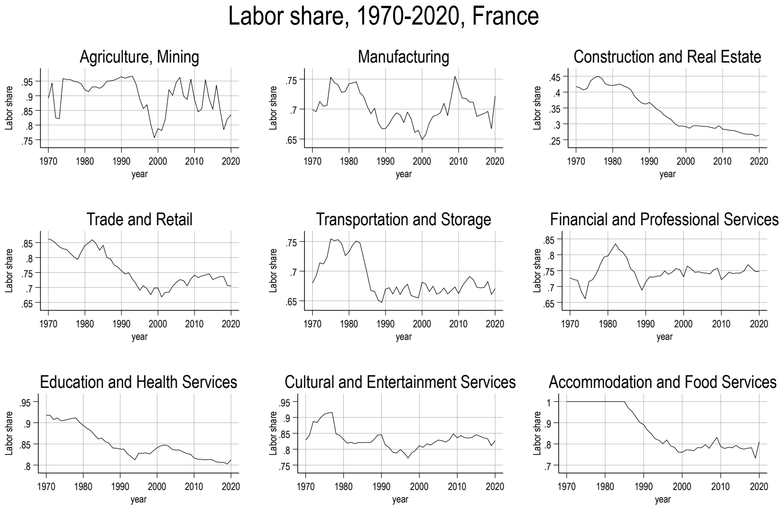
Some consequences for wage distributions



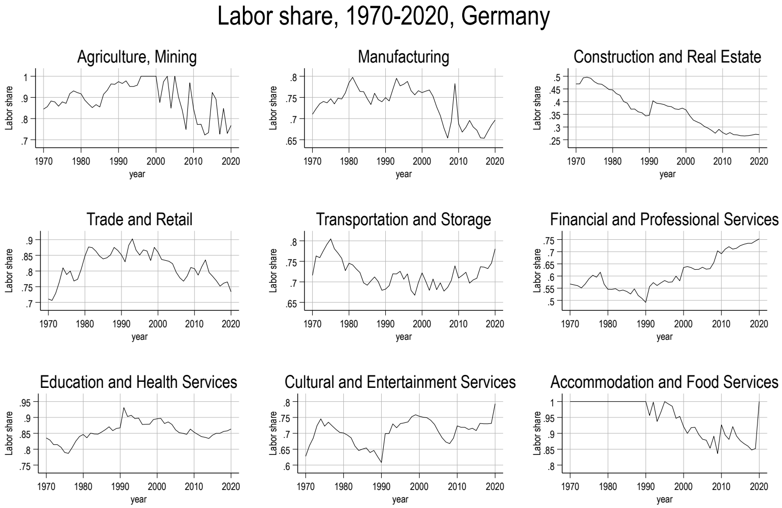


Composition adjusted real wages for full-time workers, men, in France and Germany, Source: FQP survey (wave 1977, 1985, 1993, 2003, 2015) and SIAB (Version 7521 v1).

Back to women.



Labor share, nine macro sectors, 1970-2020, France. Source: EU-KLEMS.



Labor share, nine macro sectors, 1970-2020, Germany. Source: EU-KLEMS.

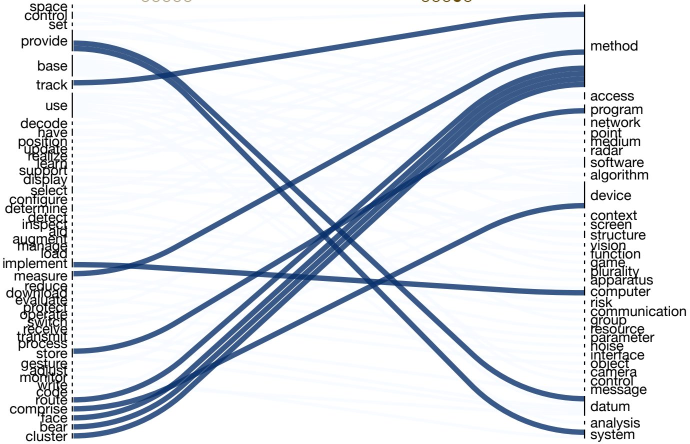
Appendix B

Labelling keywords of technology

- *Robots* [robot*$\vee$mechatroni(c|cs)$\vee$cyber-physical$\vee$system$\vee$computer$\vee$vision$\vee$control systems$\vee$sensor]
- *Software* [software$\vee$algorithm$\vee$computer program$\vee$data structure]
- *Artificial Intelligence* [artificial intelligence$\vee$machine learning$\vee$neural network$\vee$deep learning]

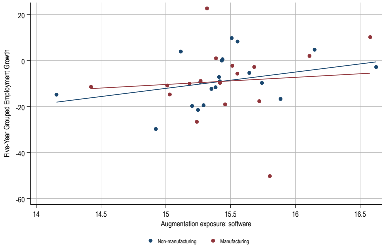
Back to ideas.

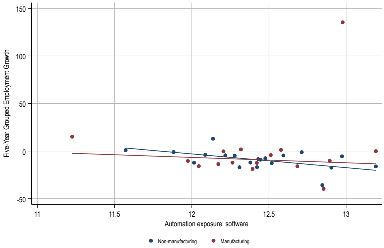
Most common tasks of the robot technology, 1980-2020. Source: Authors' elaboration based on Google Patents Public Database 3000 patents random sample



Most common tasks of the software technology, 1980-2020. Source: Authors' elaboration based on Google Patents Public Database 3000 patents random sample

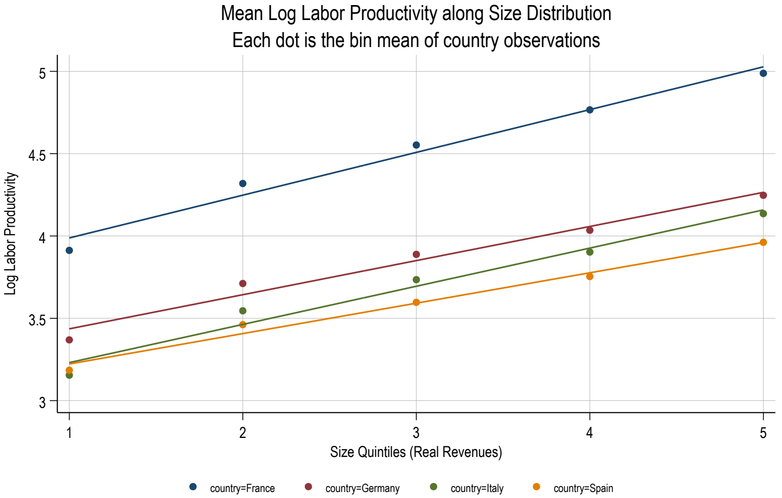
Manufacturing and non-manufacturing decomposition of reinstatement and replacement effect of software technology



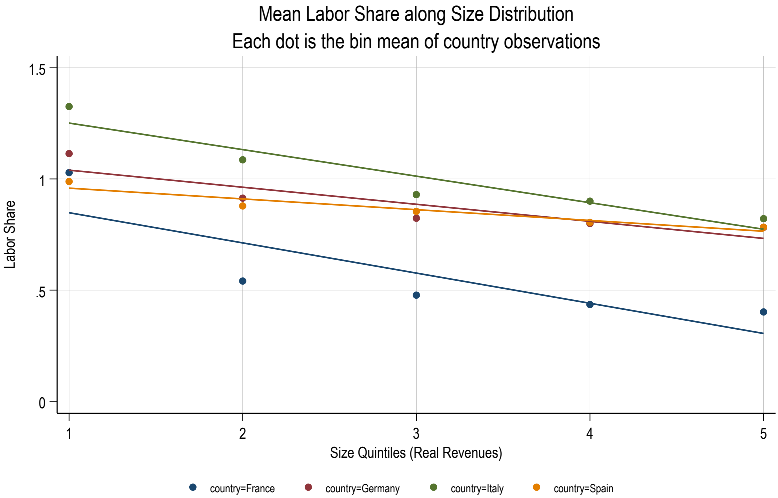


Conditional Correlations between Automation, Augmentations by Software Tech. and Employment Growth (based on Column (4)), 1993-2018

Appendix C



Unconditional bin scatter plot of labor productivity across size quintiles all industries (C-N, NACE Rev. 2) in France, Germany, Italy, and Spain, 2004-2020.



Unconditional bin scatter plot of labor shares across size quintiles all industries (C-N, NACE Rev. 2) in France, Germany, Italy, and Spain, 2004-2020.