Exposure to Automation and Augmentation and Wage Inequality in Europe

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Motivation

Automation hits subgroups differently, and the sign depends on the data: aggregated indices find more negative, individual and experimental data more positive employment effects. Acemoglu & Restrepo (2020); Brynjolfsson, Li & Raymond (2025) Dauth et al. (2021) vs. Ghodsi et al. (2025); Noy & Zhang (2023)

Wage and income inequality: mixed results, some regularities

- technology goes with a declining labour share
  Karabarbounis & Neiman (2014); Minniti, Prettner & Venturini (2025); Prettner & Strulik (2020)
- robots: reducing the middle, skill premium ↑
  Barth et al. (2026); Lankisch, Prettner & Prskawetz (2019); Bloom et al. (2025)
- AI: *high-skill automation*, skill premium ↓, more dispersion at the top
  Webb (2020); Bloom et al. (2025); Jaccoud (2025)
- high-wage countries are more exposed
  Gmyrek et al. (2023); Ribeiro & Prettner (2025)

Question: how much of this comes from the exposure measure itself?

What is an exposure measure?

How much of the work in a unit u **a technology can take over or complement**, weighted by the time spent on each task.

- $u =$ **occupation**: tasks and weights of a job title, identical for all workers
- $u =$ **worker**: tasks and weights of the actual job, *varies within occupations*

Technology

robots, software, AI

Direction

automation: takes over tasks
augmentation: new or faster tasks

How exposure is measured in the literature

Approach	Variant	Examples	Within occ.
Aggregated cells	▪ expert assessments	Frey & Osborne (2017); Brynjolfsson et al. (2018); Felten et al. (2021)	none
	▪ shift-share of deployed capital	Acemoglu & Restrepo (2020); Dauth et al. (2021)	
	▪ deployed tools by occupation	Handa et al. (2025)	
	▪ patent- and LLM-based scores	Webb (2020); Eloundou et al. (2024); Oleš & Lábaj (2026)	
Microdata	▪ ICT and tool-use surveys	Nedelkoska & Quintini (2018); Ghodsi et al. (2025); ESJS (this paper)	full
	▪ administrative adoption data	Genz et al. (2019)	
Experiments	▪ randomised access to a tool	Noy & Zhang (2023); Brynjolfsson, Li & Raymond (2025)	exogenous
Simulations	▪ automation growth models	Lankisch, Prettner & Prskawetz (2019); Prettner & Strulik (2020)	n.a.
	▪ calibrated simulations	Acemoglu & Restrepo (2022); Bloom et al. (2025); Ribeiro & Prettner (2025)	

The measurement-dependence hypothesis

Aggregated, externally assigned

- capture technological *potential*, not what a worker does
- no within-occupation variation by construction
- ignore the worker's scope for adaptation

→ tend towards **negative** effects

Close to the individual job

- capture genuine adaptation and re-skilling
- but also selection and self-assessment

→ tend towards **zero or positive** effects (software and AI, not robots)

Research Questions

How does exposure to automation and augmentation relate to the wage distribution in Europe? And does the answer depend on the exposure measure?

Internal test: same sample, same workers, same controls, same outcome; only the exposure measure varies.

Two ways to measure exposure

Worker-level job-task indices (JT)

- Cedefop ESJS 2021: 24 EU countries, 37,849 employees
- unit: worker, tasks *actually performed*
- **varies within occupations**
- items: task requirements, tool use, realised task change (last 12 months)
- polychoric PCA, task frequency as time weight; first component = index ▸ rules

Patent-based indices (PB)

- Google Patents (31 million, 1960–2015), ISCO-08 task descriptions
- unit: ISCO-3 occupation
- **constant within occupations**
- patent text similarity to ISCO task descriptions (Oleš & Lábaj, 2026)
- PatentSBERTa: A Deep NLP based Hybrid Model for Patent Distance and Classification ▸ pairing patents

both: robots, software, AI × automation, augmentation

What enters each JT index

Robots

Automation (RAut)

- works with robots, CNC, PLC
- repetitive, physical or hazardous work
- dexterity in routine tasks
- task lost to new machinery

Augmentation (RAug)

- programs, sets up, repairs machines
- 3D printing, specialised equipment
- varied tasks; dexterity in non-routine work
- new or faster tasks with machinery

Software

Automation (SAut)

- runs rule-based tools: text, spreadsheets, ERP
- basic arithmetic, document reading
- task lost to new software

Augmentation (SAug)

- extends tools: macros, databases
- develops or maintains IT systems
- creates new methods and products
- new or faster tasks with software

Artificial intelligence

Automation (AIAut) after Webb (2020)

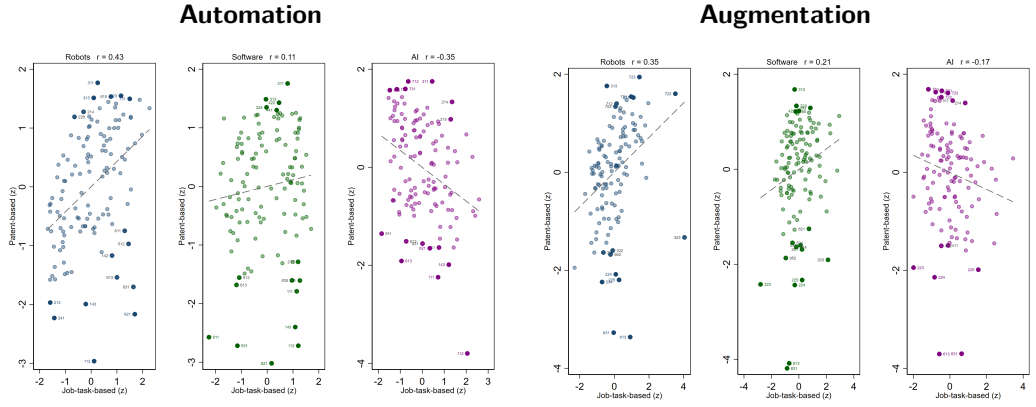
- stable, learnable data pattern
- measurable, evaluable output
- bounded digital action space
- task lost to AI (AI users)

Augmentation (AIAug)

- uses AI and programming
- retrieves, interprets information, generates ideas
- learning intensity
- new or faster tasks with AI

Same item, opposite sign: dexterity on an assembly line is substitutable, dexterity in robot-assisted surgery is complemented. Task variability decides, not the occupation title.

Validation against patent-based exposure



Job-task-based (JT) indices collapsed to weighted ISCO-3 means ($n = 127$) vs. patent-based (PB) indices of Oleš & Lábaj (2026); both z-standardised at the cell level.

Predictive validity: which measure anticipates changes in skill demand?

Skill type	Job-task indices (JT)	Patent-based indices (PB)
Digital	↑ RAug 5 · AIAug 5 · SAug 4	–
Analytical	↑ SAug 6m · AIAug 6m · AIAut 5m · RAug 4	↑ robots aut. 6m · software aut. 5 · AI aut. 4
Social	–	↑ robots aut. 5m
People mgmt	↑ RAug 4	–
Language	↓ SAut 6m	–
Manual	–	↓ software aut. 5 · AI aut. 5 · robots aut. 4 · AI aug. 4
Interpersonal	↓ SAug, AIAut, AIAug 5 (not in skill mix: shorter ads)	↓ robots aut. 4m · AI aut. 4m

Augmentation net of automation: JT predicts rising digital (+0.63 to +0.85 pp) and analytical (+0.45 to +0.80 pp) requirements per SD; PB ≈ 0.

Core vs. periphery: JT stronger in CEE and the South (AIAug → digital 1.62 vs. 0.72 pp); PB works mainly in the core.

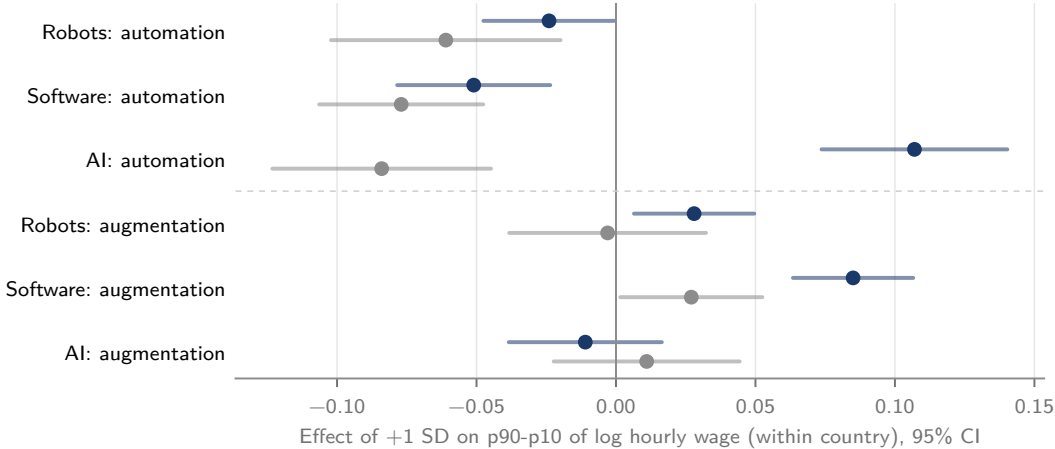
Change in the share of online job ads (Eurostat WIH) requiring each ESCO skill type, 2020–22 to 2023–25; 3,002 country × ISCO-3 cells, EU-27; country FE, pre-period share, weights = pre-period ads, SE clustered at ISCO-3. Number = specifications (of 6) with $p < 0.05$ and the same sign; m = also holds for the skill mix (not driven by ad length). ↑ / ↓ relative to other occupations in the same country.

Methods

- **Unconditional quantile regressions** (RIF) on the within-country distribution of log hourly wages: quantiles, p90–p10, p90–p50, p50–p10, Gini (Firpo et al., 2009)
- automation and augmentation of a technology in one model; pre-determined controls; SE clustered at ISCO-3
- **between vs. within occupations:** index split into country × ISCO-3 mean and deviation (Mundlak, 1978)
- **checks:** distribution regression (DR) (Chernozhukov et al., 2013), static indices, monthly wage, CAWI only, Oster δ (Oster, 2019), bootstrap SE, wage non-response, and asses the wage non-response

24 EU countries; multiply imputed wages (N = 35,257), complete cases (N = 27,791).

AI automation: the two measures point in opposite directions



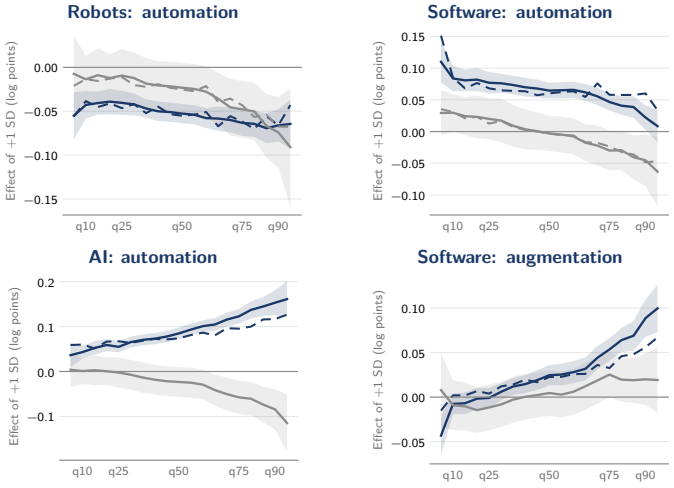
Effect of +1 SD of each index on p90-p10, multiply imputed wages. ● Job-task ● Patent-based.

Main specification: p90-p10 and Gini

	p90-p10		Gini	
	JT	PB	JT	PB
Robots: automation	-0.024^{**}	-0.061^{***}	-0.004	-0.011^{*}
Software: automation	-0.051^{***}	-0.077^{***}	-0.019^{***}	-0.014^{**}
AI: automation	0.107^{***}	-0.084^{***}	0.021^{***}	-0.016^{**}
Robots: augmentation	0.028^{**}	-0.003	0.010	0.000
Software: augmentation	0.085^{***}	0.027^{**}	0.022^{***}	0.005
AI: augmentation	-0.011	0.011	-0.000	-0.000

Coefficient per 1 SD, multiply imputed wages, RIF within country. Gini on wage levels. * p<0.10, ** p<0.05, *** p<0.01.

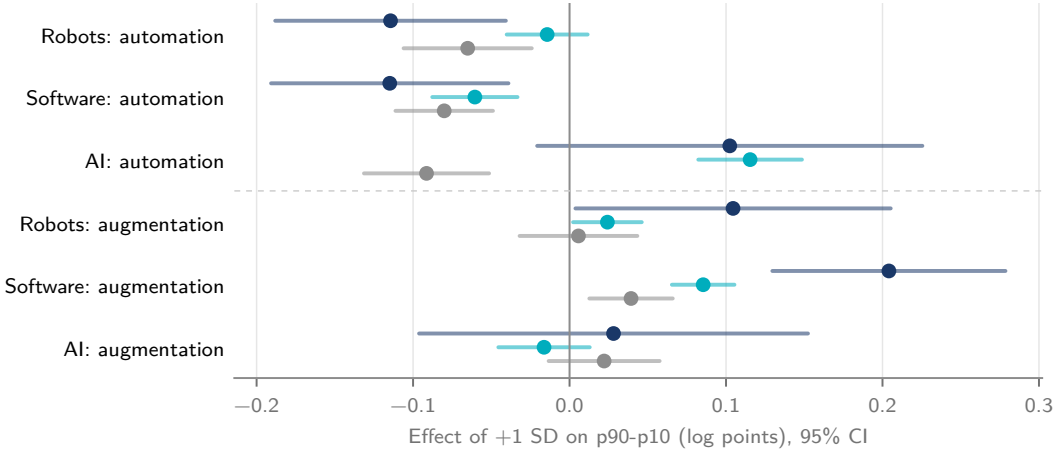
Where in the distribution



- **AI automation, software augmentation:** JT effects rise along the distribution, PB effects fall or stay flat
- **Robots and software automation:** PB effects fall towards the top; JT flat (robots) or falling (software)
- Distribution regression: same sign, about half the RIF size for AI

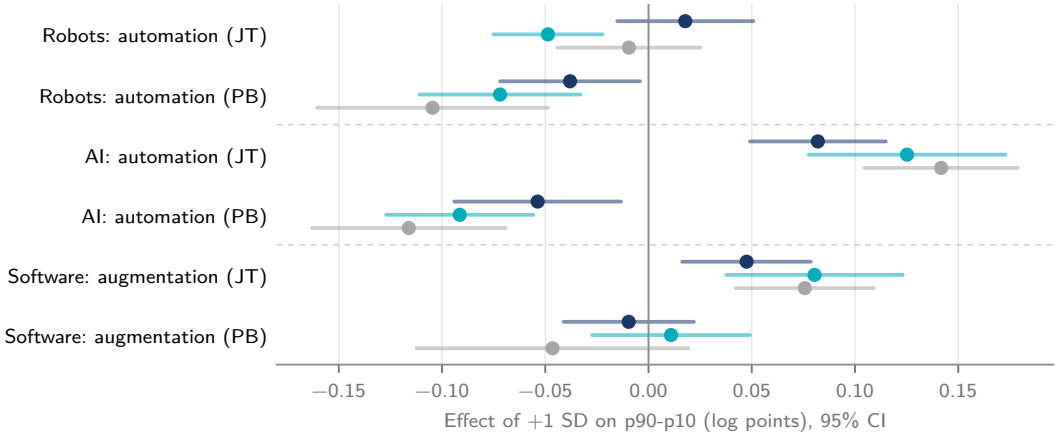
Effect of +1 SD on log hourly wage at quantiles 5 to 95, complete cases.

AI works within occupations, robots between them



JT index split into its country × ISCO-3 mean and the deviation from it, both in one RIF regression (Mundlak, 1978); complete cases. ● between (JT) ● within (JT) ● PB.

Regions



Each index alone, slope by region, complete cases. ● Core ● CEE ● South.

Takeaways: exposure and wage inequality

- **The measure decides the AI result.** Worker-level AI automation exposure widens p90-p10 (0.107), patent-based exposure narrows it (-0.084). Joint test of equal effects: $\chi^2(6) = 85$, $p < 0.001$; opposite signs in 100% of bootstrap draws
- **Not only aggregation.** The AI gap of 0.21 splits into 0.09 from within-occupation variation and 0.12 from what the indices measure: even averaged to the occupation, JT and PB differ
- **Where the measures agree:** robot and software automation compress wage gaps under both; software augmentation widens them (JT)
- **AI works inside occupations.** Among comparable workers in the same country $\times$ ISCO-3 cell, AI automation raises q90$-$q10 by 0.085; patent-based effects vanish once major occupation groups are absorbed, so they reflect composition between occupations

Takeaways: regions and education

- **Core vs. periphery.** The JT/PB divergence for AI holds in every region and is largest in the South and CEE. Robot automation compresses wages only on the periphery
- **Education.** Tertiary-educated workers drive the country-level effect. Within education groups, AI automation spreads wages most among the low-educated

Conclusion. Exposure to AI automation raises wage inequality, mostly between workers in the same occupation. Occupation-level measures cannot see this and reverse the sign.

Thank you for your attention

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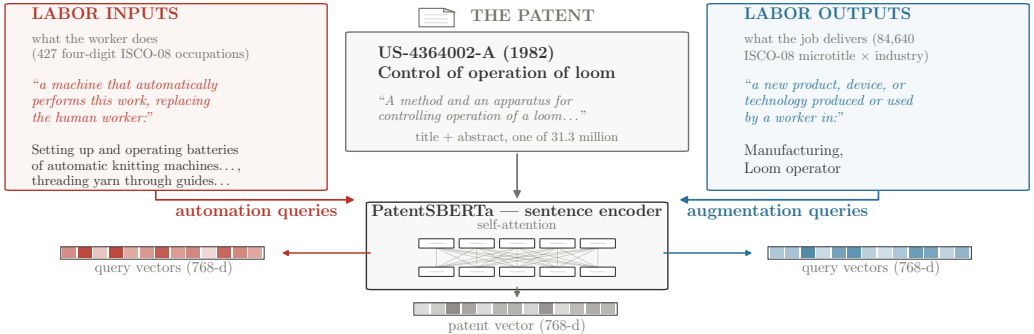
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Appendix: Patent similarity to occupations

a Three kinds of text, one encoder



b Score every patent–text pair; one global cut keeps the top 15% of all pairs, so matches per patent vary



Appendix: item retention and index diagnostics

Retention rules

1. all items point in the theoretically expected direction
2. strong correlation within the block, but no collinearity
3. first eigenvalue dominates; PC1 explains $> 30\,\%$ of variance
4. internal consistency: Cronbach's $\alpha > 0.60$
5. face validity: RAut highest for welders, plant operators, assemblers; SAut for clerical and managerial work; AI indices peak in ICT
6. convergence with perceived displacement risk ($r = 0.18$–0.30) and future skill needs (0.22–0.31) (not an input)

back

Diagnostics

	Items	PC1 %	e_1/e_2	α
RAut	10	54.2	3.24	0.69
RAug	9	65.8	4.45	0.71
SAut	6	58.6	4.37	0.69
SAug	8	51.5	3.48	0.73
AIAut	14	38.6	3.68	0.73
AIAug	10	50.6	3.07	0.78

Polychoric PCA, country panel weights.

Robustness: p90-p10

	Main	Static indices	Equal weights	Monthly wage	CAWI only	Oster δ	SE ratio bootstrap
AI: automation (JT)	0.112^{***}	0.105^{***}	0.106^{***}	0.155^{***}	0.114^{***}	8.3	1.03
AI: automation (PB)	-0.086^{***}	–	-0.090^{***}	-0.113^{***}	-0.096^{***}	17.9	1.09
Software: automation (JT)	-0.061^{***}	-0.067^{***}	-0.060^{***}	-0.041^{**}	-0.058^{***}	−2.4	1.20
Software: automation (PB)	-0.075^{***}	–	-0.077^{***}	-0.082^{**}	-0.088^{***}	28.9	1.15
Software: augmentation (JT)	0.097^{***}	0.108^{***}	0.098^{***}	0.099^{***}	0.096^{***}	−30.2	1.10
Robots: automation (JT)	-0.024^{*}	-0.024^{**}	−0.017	-0.066^{***}	-0.025^{*}	1.1	1.01
Robots: automation (PB)	-0.061^{***}	–	-0.070^{***}	-0.101^{***}	-0.070^{***}	13.0	1.08

Complete cases. Static: indices without realised task-change items. Oster δ (Oster, 2019), $R_{max} = 1.3R^2$: $|\delta| > 1$ means unobservables would have to matter more than observables; negative: controls strengthen the effect. SE ratio: bootstrap (ISCO-3 clusters) over analytic.

Appendix: adding controls, worker-level job-task indices (JT)

	(1)	(2)	(3)	(4)	(5)	(6)
Robots: automation	−0.046***	−0.047***	−0.020	−0.020	−0.017	−0.002
	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)	(0.013)
Software: automation	−0.029*	−0.028*	−0.061***	−0.056***	−0.054***	−0.049***
	(0.015)	(0.016)	(0.014)	(0.014)	(0.014)	(0.014)
AI: automation	0.123***	0.122***	0.103***	0.113***	0.113***	0.114***
	(0.020)	(0.020)	(0.018)	(0.017)	(0.015)	(0.016)
Robots: augmentation	0.043***	0.042***	0.029***	0.029***	0.030***	0.021*
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Software: augmentation	0.093***	0.097***	0.096***	0.097***	0.087***	0.082***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
AI: augmentation	−0.009	−0.003	−0.004	−0.007	−0.008	−0.012
	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)

p90-p10, complete cases. Coefficient per 1 SD, SE in parentheses (clustered at ISCO-3). (1) country + survey mode; (2) + gender, age, age^2; (3) + education; (4) + tenure, firm size, contract type (main set); (5) + country × ISCO-1; (6) country × ISCO-3 absorbed. * p<0.10, ** p<0.05, *** p<0.01.

Appendix: adding controls, patent-based indices (PB)

	(1)	(2)	(3)	(4)	(5)
Robots: automation	−0.067***	−0.073***	−0.060***	−0.061***	−0.026
	(0.022)	(0.021)	(0.020)	(0.020)	(0.018)
Software: automation	−0.079***	−0.078***	−0.077***	−0.075***	−0.027
	(0.018)	(0.018)	(0.016)	(0.016)	(0.019)
AI: automation	−0.092***	−0.096***	−0.085***	−0.086***	−0.038*
	(0.024)	(0.023)	(0.020)	(0.020)	(0.020)
Robots: augmentation	0.005	−0.008	0.000	0.001	−0.001
	(0.020)	(0.020)	(0.019)	(0.019)	(0.014)
Software: augmentation	0.038**	0.030*	0.029**	0.029**	0.011
	(0.016)	(0.016)	(0.014)	(0.014)	(0.014)
AI: augmentation	0.025	0.012	0.014	0.015	−0.003
	(0.020)	(0.020)	(0.019)	(0.019)	(0.016)

p90-p10, complete cases. Columns as for JT. Patent-based indices are constant within ISCO-3, so column (6) is not identified. * p<0.10, ** p<0.05, *** p<0.01.

Appendix: main specification, all measures

	Mean	q10	q50	q90	p90-p10	p90-p50	p50-p10	Gini
Robots: automation (JT)	−0.053***	−0.041***	−0.051***	−0.064***	−0.024**	−0.014*	−0.010	−0.004
	(0.006)	(0.008)	(0.005)	(0.009)	(0.012)	(0.008)	(0.008)	(0.005)
Robots: automation (PB)	−0.031**	−0.010	−0.020	−0.070***	−0.061***	−0.051***	−0.010	−0.011*
	(0.014)	(0.014)	(0.014)	(0.020)	(0.021)	(0.016)	(0.009)	(0.007)
Software: automation (JT)	0.065***	0.078***	0.062***	0.026***	−0.051***	−0.035***	−0.016*	−0.019***
	(0.008)	(0.011)	(0.006)	(0.009)	(0.014)	(0.009)	(0.010)	(0.005)
Software: automation (PB)	0.001	0.032**	0.001	−0.044**	−0.077***	−0.046***	−0.031***	−0.014**
	(0.017)	(0.015)	(0.014)	(0.020)	(0.015)	(0.013)	(0.008)	(0.006)
AI: automation (JT)	0.083***	0.036***	0.079***	0.142***	0.107***	0.065***	0.042***	0.021***
	(0.007)	(0.008)	(0.007)	(0.014)	(0.017)	(0.014)	(0.009)	(0.005)
AI: automation (PB)	−0.027	0.005	−0.018	−0.078***	−0.084***	−0.061***	−0.023**	−0.016**
	(0.017)	(0.014)	(0.016)	(0.022)	(0.020)	(0.014)	(0.010)	(0.007)
Robots: augmentation (JT)	0.047***	0.033***	0.051***	0.061***	0.028**	0.010	0.018**	0.010
	(0.006)	(0.008)	(0.005)	(0.009)	(0.011)	(0.009)	(0.007)	(0.007)
Robots: augmentation (PB)	−0.000	0.007	−0.008	0.004	−0.003	0.011	−0.014*	0.000
	(0.014)	(0.014)	(0.014)	(0.018)	(0.018)	(0.013)	(0.008)	(0.005)
Software: augmentation (JT)	0.019**	−0.009	0.023***	0.077***	0.085***	0.054***	0.032***	0.022***
	(0.008)	(0.006)	(0.006)	(0.010)	(0.011)	(0.009)	(0.006)	(0.004)
Software: augmentation (PB)	0.003	−0.008	0.001	0.018	0.027**	0.017*	0.010	0.005
	(0.013)	(0.013)	(0.012)	(0.014)	(0.013)	(0.010)	(0.008)	(0.004)
AI: augmentation (JT)	0.000	0.004	0.005	−0.007	−0.011	−0.012	0.001	−0.000
	(0.007)	(0.008)	(0.006)	(0.012)	(0.014)	(0.011)	(0.008)	(0.004)
AI: augmentation (PB)	0.010	0.008	0.006	0.019	0.011	0.012	−0.001	−0.000
	(0.014)	(0.013)	(0.014)	(0.017)	(0.017)	(0.011)	(0.010)	(0.004)

Multiply imputed wages (M = 20), N = 35,257. Coefficient per 1 SD, SE in parentheses, clustered at ISCO-3. * p<0.10, ** p<0.05, *** p<0.01.

Appendix: who does not report a wage

	Logit coefficient	SE	p
Robots: automation (JT)	−0.049	(0.033)	0.131
Software: automation (JT)	−0.224***	(0.034)	0.000
AI: automation (JT)	0.169***	(0.038)	0.000
Robots: augmentation (JT)	0.135***	(0.033)	0.000
Software: augmentation (JT)	−0.013	(0.045)	0.778
AI: augmentation (JT)	0.022	(0.035)	0.520
Robots: automation (PB)	−0.010	(0.052)	0.852
Software: automation (PB)	0.048	(0.041)	0.243
AI: automation (PB)	−0.025	(0.063)	0.691
Robots: augmentation (PB)	0.128**	(0.054)	0.018
Software: augmentation (PB)	−0.061	(0.045)	0.170
AI: augmentation (PB)	−0.110	(0.067)	0.102

Logit of a missing wage on all indices of one family, controls and country, common sample. Joint test: JT $\chi^2(6) = 87.9$, $p < 0.001$; PB $\chi^2(6) = 9.3$, $p = 0.16$.