

Technological Change and the Upskilling of European Workers

Seamus McGuinness, Paul Redmond, Lorcan Kelly, Luke Brosnan

ESRI

Konstantinos Pouliakas

CEDEFOP



Introduction

- Literature on impact of technological change has been expanding over recent years.
- However, little is known about the extent to which technological change has impacted the task content of jobs.
- Changes in skill composition will likely be associated with increased employer-based training requirements, and understanding these requirements is important for policymakers and employers.
- We use data from the second wave of the European Skills and Jobs Survey (ESJS2) to address these gaps in the literature.

Existing research

- **Job Displacement vs Task Creation:**

- Frey and Osborne (2013) Widely cited for predicting that nearly 47% of jobs in advanced economies could be replaced by automation and AI. However, this study does not account for the heterogeneity of tasks within occupations.
- Arntzet al. (2016) Refines the estimates from Frey and Osborne by accounting for task heterogeneity, finding only 914% of jobs at high risk of automation in developed economies.

- **Task Augmentation and Rebalancing:**

- Acemoglu and Restrepo (2018) Argue that automation leads to task displacement but is often counterbalanced by the creation of new, labour-intensive tasks within jobs, increasing productivity and overall labour demand.
- Autor (2024): Suggests that generative AI tools can complement human workers by enabling skilled workers to perform higher level tasks, particularly in roles involving decision making and communication.

Existing research

- **Training Needs for Task Disruption:**
 - OECD (2023) Finds that over 50% of employees in industries adopting AI (e.g., finance and manufacturing) received training on new technologies. Employers favored reskilling over hiring/firing.
 - McGuinness et al. (2023) Highlights the relationship between task displacement caused by technology and increased job complexity, which drives the need for targeted training programs.
- **Shifts in Skills Demand:**
 - Huang et al. (2019) Demonstrates the increasing importance of social and emotional intelligence in the workforce as AI automates technical and analytical tasks.
 - Alekseeva et al. (2021) Finds a growing demand for AI-related skills across occupations, with significant wage premiums in AI-intensive roles.

Motivation

- Most studies explore prospective risk, little is known about ‘actual’ effects of technological change.
- Mixed predictions of technological based task disruption.
- No Europeanwide estimates.
- Most research focuses solely on the impact of new technologies e.g. AI/robotics. This only makes up a subset of digital technologies used at work by European adult workers.
- Changes in tasks will likely lead to increased training requirements. Understanding the extent of these requirements and how they vary depending on degree of task change is important for policymakers and employers to prepare for the future.

Research Questions

1. How does technological change alter job task composition across Europe?
2. Which workers are most affected by these changes?
3. What is the relationship between task disruption and the need for job-related training?

Data

- Use data for 29 countries from ESJS2 (46,083 responses).
- Variables include:
 - Technological adoption in current jobs.
 - Task composition changes (creation, displacement, both or neither).
 - Receipt of employer-provided training.
 - Worker demographics and job characteristics.

Empirical strategy

- Separate workers into five categories:

Table 1: Definitions of Technological Change Categories

Technological Change Category	<i>There has been a change in the use of technology used at work for the main job (digital or machines).</i>	<i>You now do not do some tasks you did before.</i>	<i>You now do some different or new tasks.</i>
1. No Technological Change	NO	NO	NO
2. Technological Change, No Task Change	YES	NO	NO
3. Displacement Only	YES	YES	NO
4. Creation Only	YES	NO	YES
5. Displacement & Creation	YES	YES	YES

Technological change categories are derived from variables D_CHTECH, D_CHJOBNEW and D_CHJOBDISP

- Identify job characteristics of employees in categories 2., 3., 4. & 5. relative to 1.:

$$\Pr(\text{Task}\Delta_i = 1 | X_i) = \phi(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \sum_{\tau=2}^{29} \theta_{\tau} C_i^{\tau}) \quad (1)$$

- $\text{Task}\Delta_i$ is a binary variable indicating the direction in which worker i 's tasks have been changed owing to new technologies. (creation, destruction, both, neither)
- X_1 is a vector of individual characteristics, X_2 are employment characteristics, X_3 are sector FEs, C^{τ} are country dummies.

Empirical strategy

- Assessing the extent to which training participation varies depending on direction of technological change's effects on task composition

$$\Pr(\text{Train}_i = 1|X_i) = \phi(\beta_0 + \beta_1 \text{Task}\Delta_i + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \sum_{\tau=2}^{29} \theta_{\tau} C_i^{\tau}) \quad (2)$$

- Train_i is a binary variable indicating if worker i has received work-based training in the 12 months prior to the survey. X_2, X_3, X_4, C are individual characteristics, employment characteristics, sector and country FE respectively.
- Implement PSM for equation 2 to account for potential selection bias:

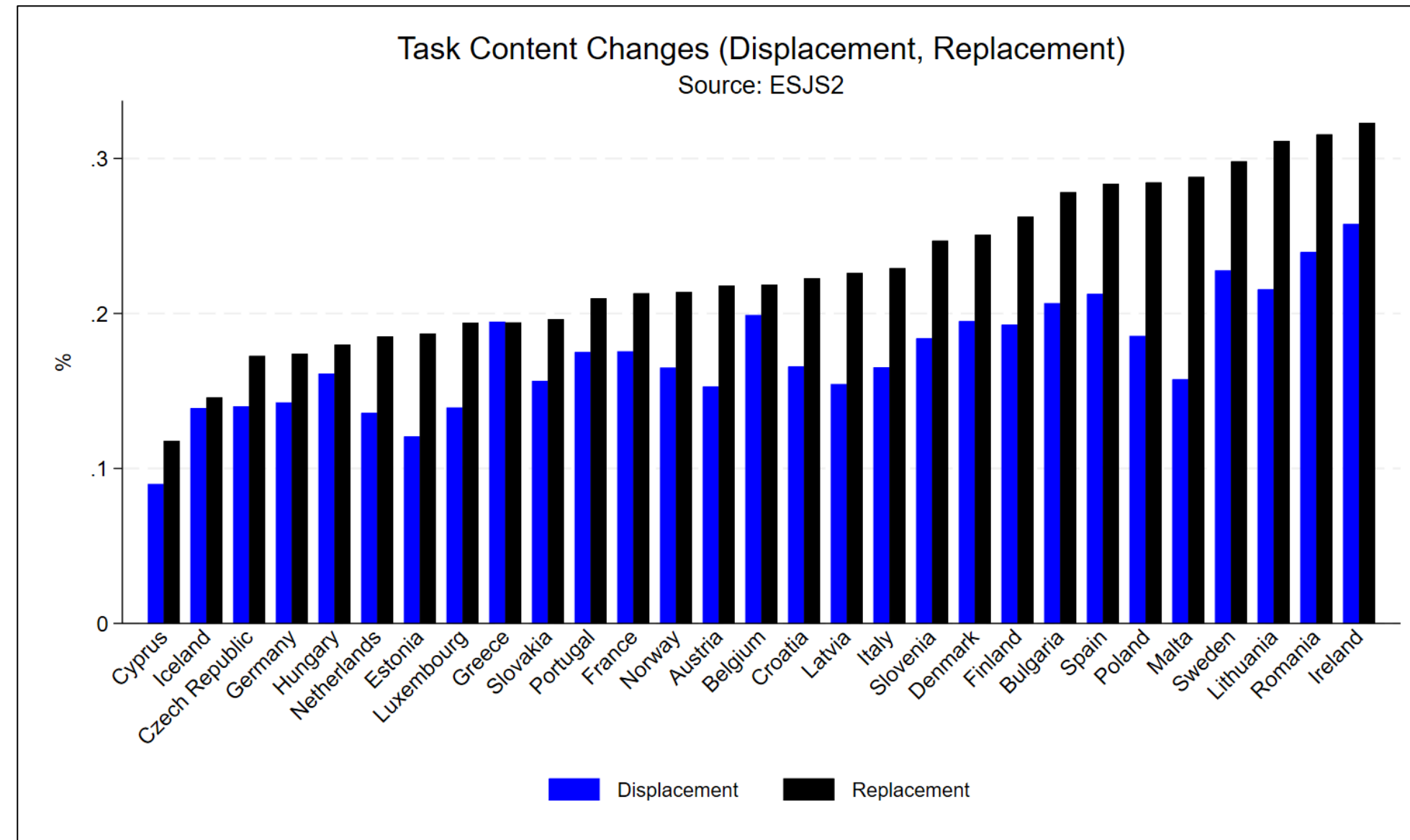
$$p(X) = \Pr\{D = 1|X\} = E\{D|X\} \quad (3)$$

- D is the treatment dummy. 4 specifications: In each specification, $D=1$ indicates that a person experiences technological change and the corresponding task disruption (creation, destruction, both or neither) and $D=0$ indicates that an employee does not experience technological change.
- Step 1: $p(X)$ is estimated using a probit model to predict the likelihood of D based on the characteristics X .
- Step 2: compare the outcomes of treated ($D = 1$) and untreated ($D = 0$) individuals with similar propensity scores.

Results

- 58% of employees report that they have experienced no change in the use of new technologies within their main jobs.
- As a result of technological change:
 - 14% report no task change.
 - 13% report both task displacement and task creation.
 - 10% report task creation only.
 - 5% report task displacement only.
- Notable variation between countries, with no obvious geographical patterns emerging.
- Task creation correlated with task displacement within countries.

Figure 1



Results

- Females are less likely to be in jobs impacted by technological change.
- Employees with third level qualifications are more likely to be in jobs impacted by technology.
- Workers on parttime hours and those with lower tenure are generally less likely to be employed in jobs impacted by technological change
- Contrary to the predictions of previous research, workers in three of the four categories impacted by new technologies are less likely to undertake repetitive tasks
- Employees in jobs impacted by new technologies are more likely to routinely have to react to unpredictable situations.

Table 2: Determinants of Technological Change (Probit Estimates, dY/dX)

VARIABLES	Technological Change (No Task Changes)	Technological Change (Displacement Only)	Technological Change (Replacement Only)	Technological Change (Displacement & Replacement)
Female	-0.013** (0.005)	-0.025*** (0.004)	-0.012* (0.007)	-0.042*** (0.005)
Repetitive	-0.030*** (0.006)	-0.008** (0.003)	-0.010** (0.005)	0.003 (0.006)
Uncertain	0.033*** (0.005)	0.018*** (0.004)	0.035*** (0.004)	0.067*** (0.005)
Tenure (Years)	-0.001*** (0.000)	-0.0004** (0.000)	-0.002*** (0.000)	-0.003*** (0.000)
Part Time	-0.022*** (0.007)	-0.006 (0.005)	-0.025*** (0.006)	-0.005 (0.009)
Education				
Low (ISCED-2)	Ref.	Ref.	Ref.	Ref.
Medium (ISCED-3)	0.035*** (0.009)	0.012** (0.005)	0.037*** (0.008)	0.003 (0.009)
High (ISCED-5)	0.121*** (0.010)	0.047*** (0.005)	0.099*** (0.007)	0.077*** (0.010)
Observations	32,790	28,403	30,891	32,217

Results

- Across entire sample, 64% of employees report undertaking some ~~related~~ **relevant** training in the previous 12 months.
- This varies greatly by degree of technological change:

Table 3: training by degree of technological change

Category	% of Total Sample	Training Rate
No Technological Change	57.9%	51.4%
Tech Change, No Task Change	14.3%	74.4%
Task Displacement Only	4.7%	81.0%
Task Creation Only	10.1%	84.2%
Task Displacement & Creation	13.1%	87.8%

Results

- Results confirm the results of descriptive analysis of job related training.
- Strict positive monotonic relationship between job related training and degree of technological change.
- Relative to workers in jobs not impacted by new technologies, employees in jobs with new technologies are:
 - 18 ppmore likely to receive job related training (no task changes).
 - 26 ppmore likely to receive job related training (task displacement only).
 - 29 ppmore likely to receive job related training (task creation only).
 - 33 ppmore likely to receive job related training (both task displacement and creation).

Table 4: Marginal Effects of Probit Models Predicting Likelihood of Training (Joint)

VARIABLES	(1) Training	(2) Training
<u>Technological Change</u>		
No Technological Change	Ref.	Ref.
Technological Change (No Task Changes)	0.231*** (0.012)	0.184*** (0.009)
Technological Change (Displacement Only)	0.296*** (0.015)	0.256*** (0.013)
Technological Change (Replacement Only)	0.328*** (0.012)	0.285*** (0.007)
Technological Change (Displacement & Replacement)	0.364*** (0.014)	0.330*** (0.010)
Female		-0.017*** (0.006)
Repetitive		-0.022*** (0.006)
Uncertain		0.057*** (0.006)
Employment Duration (Years)		-0.001*** (0.000)
Part Time		-0.041*** (0.009)
<u>Education</u>		
Low (ISCED 0-2)		Ref.
Medium (ISCED 3-4)		0.016 (0.013)
High (ISCED 5-8)		0.117*** (0.016)
Country Included	NO	YES
Industry Included	NO	YES
Observations	45,986	45,430

Results

- Strong monotonic relationship persists when Propensity Score matching is applied.

Table 5: ATEs (Propensity Score Matching Estimates)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Training (Default)				Training Caliper, 25% of σ_{PS}			
Technological Change (no task change)	0.179*** (0.000)				0.181*** (0.009)			
Displacement Only		0.246*** (0.015)				0.268*** (0.012)		
Replacement Only			0.265*** (0.010)				0.298*** (0.009)	
Displacement & Replacement				0.334*** (0.000)				0.336*** (0.008)
Caliper	--	--	--	--	0.023391	0.010307	0.018698	0.023071
Nearest Neighbour Min.	1	1	1	1	1	1	1	1
Observations	32,770	28,403	30,875	32,200	32,768	28,400	30,871	32,198

Robust standard errors in parentheses. Calipers are specified as 25% of the standard deviation of propensity scores.

Unmatched observations are dropped from caliper estimations and calipers are re-estimated until all observations are matched.

Final Thoughts and Call to Action

- **Nuanced Impact of Technology:**
 - Technology's role in both creating and displacing tasks highlights a complex labour market transformation.
- **Importance of Proactive Measures:**
 - Emphasise the need for education and training to support workforce resilience.
- **Collaboration Among Stakeholders:**
 - Encourage policymakers, employers, and educational institutions to work together in fostering a balanced technological transformation.
- **Directions for Future Research:**
 - Investigate long-term career outcomes for workers experiencing task displacement vs. creation.
 - Explore the role of specific types of training in facilitating technological adaptation.
 - Examine sector-specific impacts of technological change within European countries.

Thank you



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