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Technology and Skill Demand: Labor Market Polarization in European Countries

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Abstract
This paper adds new evidence on labor market polarization in Europe driven by technological change. In particular, it studies the relationship between displacement and reinstatement effects associated with automation and new tasks on the one hand and the demand for skills on the other. The analysis focuses on a group of advanced European countries and provides robust empirical evidence that technological progress leads to labor market polarization, as the tasks created by new technologies seem to be more suitable for high- and low-skilled workers. In addition to this novel finding of the reinstatement-driven hollowing out of the middle class, we confirm that automation contributes to top-bottom inequality. We also document that men and women are disproportionately affected by displacement and reinstatement technologies, and show that the labor market polarization is strongly associated with middle-aged cohorts of workers.

1. Introduction

The phenomenon of labor market polarization is well documented in the literature. In the United States, it began in the 1980s (Autor, 2011, 2019), and there have been similar trends in European countries since at least the mid-1990s (Goos et al., 2009, 2014; Bachmann et al., 2019; Breemersch et al., 2017; Bekhtiar et al., 2021). This paper adds new empirical evidence on the role played by technological change in these trends since the end of 2000s. Previous studies have focused almost exclusively on the role of automation in the rise of polarization and have not considered the creation of new tasks in which labor has a comparative advantage. In this paper, we fill this gap and analyze the distinct effects of both automation and the creation of new tasks. In particular, our research builds on the empirical strategy of Acemoglu and Restrepo (2020) and uses regression analysis to study the effects of automation (displacement effect) and creation of new tasks (reinstatement effect) on the demand for skills. Displacement effects measure the shift in task content of production driven by automation towards a capital. On the other side, reinstatement effects reflect the creation of new tasks in which humans have a comparative advantage that leads to a higher demand for labor (a more detailed definition is provided in Section 2). Acemoglu and Restrepo (2020) use industry-level estimates of displacement and reinstatement effects to investigate whether automation and new

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tasks are associated with changes in the relative demand for skills in the United States. It turns out that over the last 30 year, both automation and new tasks have been associated with increases in the relative demand for skills of the industry. Our analysis, which focuses on European countries and the period 2008–2020, finds that the technology-driven demand for high skills is due only to the reinstatement effect, rather than a combination of both displacement and reinstatement. In addition, we focus on three groups of workers (compared to two groups in Acemoglu and Restrepo (2020)). This allows us to study the phenomenon of the labor market polarization and provide new evidence on the distinctive effects of automation and the creation of new tasks in this trend.

The paper is divided into four sections. The first section reviews the literature on demand for skills and labor market polarization. The decomposition of changes in the economy-wide wage bill that leads to industry-level estimates of displacement and reinstatement effects is described in the Methodology section. This section also describes the regression model and variables used in the empirical analysis. This is followed by details of the data used in the empirical analysis, the results of which are presented in the last section. Finally, we summarize the main findings and conclude.

2. Literature Review

Long-term shifts in labor demand have led to a significant polarization of job opportunities across occupations in the United States since the late 1980s, with employment and wage growth concentrated in high- and low-skill jobs (Autor, 2011). Between 1980 and 2016, the fraction of college workers in high-skill occupations rose from 57.2% to 60.7%, the share in middle-skill occupations fell from 27.1% to 20.2%, and the share in low-skill occupations increased from 15.6% to 19%. Moreover, the share of non-college employment in middle-skill occupations fell by 14 percentage points, with almost 90% of this decline being explained by the movement into traditionally low-skill work. Autor (2019) attributes this to the transformational and deskilling[1] nature of technological change. Goos et al. (2009, 2014), Breemersch et al. (2017), Antonczyk et al. (2018), Bachmann et al. (2019) and Bekhtiar et al. (2021), among others, show that European and other advanced countries have experienced very similar trends. As in the case of the United States, technological change seems to be the main driving force behind these labor market changes. In addition to automation of middle-skill routine tasks previously performed primarily by workers with moderate education, alternative explanations of the observed patterns focus on offshoring, Chinese import competition, wage inequality, shifts/differences in labor market institutions and cohort effects (Autor et al., 2003; Blinder, 2007; Goos et al., 2009; Autor, 2011; Breemersch et al., 2017; Antonczyk et al., 2018). For the UK, Salvatori (2018) finds a distinctive polarization pattern and explains it by changes in the skill mix (increasing educational attainment of the workforce) rather than technological change. As all job growth in the United States and other advanced economies is predicted to be in high- and low-wage occupations (Manyika et al., 2017), job and income polarization is likely to continue in the coming years.

[1] In the sense that it has narrowed the set of jobs in which non-college workers perform specialized work that has historically commanded higher pay levels.

Other authors point to a closely related phenomenon of the technology-driven growth in the demand for skills. Autor and Katz (1999) argue that strong secular increases in the relative demand for skills are likely to be the reason for the great expansion of overall wage inequality and educational wage differentials in the United States since 1950. Acemoglu and Restrepo (2020) use industry-level estimates of displacement (due to automation) and reinstatement (due to new tasks) in the US economy to investigate whether automation and new tasks are associated with these changes in the relative demand for skills. During both 1947–1987 and 1987–2016, displacement is associated with increases in the relative demand for skills of the industry. On the contrary, greater reinstatement is associated with lower relative demand for skills during 1947–1987. However, as in the case of displacement, during the last three decades, reinstatement goes hand in hand with greater demand for skills. In other words, unlike in the past when technological progress was associated with new job opportunities primarily for less-skilled workers, new tasks are now being allocated mainly to those with college education. Recent data from the first European Skills and Jobs Survey suggest that this trend also applies to European countries. McGuinness et al. (2021) show that it is high-skill jobs/occupations rather than medium- and low-skill ones that are associated with reinstatement (increasing within-job task variety as a result of technological change). This relationship between technological change and demand for skills is unlikely to change in the near or distant future. It is estimated that automation and AI will increase the demand for technological and higher cognitive skills. In contrast, basic cognitive skills and physical and manual skills are predicted to be less in demand (Bughin et al., 2018). However, medium-skilled workers may be less disproportionately affected by technological displacement (Brynjolfsson et al., 2018).

The race between technological progress increasing the demand for skills and education increasing the supply of skills has been studied in canonical skill-biased technological change models (Katz and Murphy, 1992; Goldin and Katz, 2009). However, as argued in Acemoglu and Autor (2011) and Acemoglu and Restrepo (2019), these models cannot account for recent occupational trends observed in most advanced countries. They cannot account for stagnant or declining wages of unskilled workers and the disappearance of middle-skill occupations. Acemoglu and Autor (2011) and Acemoglu and Restrepo (2019, 2020) propose a task-based model in which the effects of technological change on productivity and wages are decoupled and not mediated by the elasticity of substitution. This framework is explained in more detail in the following section. It is then applied to study recent trends in the demand for skills in a European context. In this way, we provide new empirical evidence on the role of automation and new tasks in the labor market polarization in Europe over the period 2008–2020.

3. Methodology

Following Acemoglu and Restrepo (2019), our aim is to decompose changes in the economy-wide wage bill (which captures the total amount employers pay for labor) into productivity, composition and substitution effects, and changes in the task content of production.[2]

[2] See Acemoglu and Restrepo (2019) for more details.

Because the economy-wide wage bill is the sum of wage bills across industries, the following applies:

$$ln(W_t L_t) = ln\left(Y_t \sum_i \chi_{i,t} s_{i,t}^L\right).$$

Here, $W_t L_t$ is the economy-wide wage bill in year t, Y_t is total value added in year t, $\chi_{i,t}$ is the share of industry i in total value added in year t, and $s_{i,t}^L$ is the corresponding labor share.

If the base year is indexed with the subscript t_0, the percent change in wage bill normalized by population, N, between t_0 and t can be expressed as:

$$\begin{aligned}
\ln\left(\frac{W_t L_t}{N_t}\right) - \ln\left(\frac{W_{t_0} L_{t_0}}{N_{t_0}}\right) &= \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t_0}}{N_{t_0}}\right)\left[\text{Productivity effect}_{t_0,t}\right] \\
&+ \ln\left(\sum_i x_{i,t} s_{i,t}^L\right) - \ln\left(\sum_i x_{i,t_0} s_{i,t}^L\right)\left[\text{Composition effect}_{t_0,t}\right] \\
&+ \ln\left(\sum_i x_{i,t_0} s_{i,t}^L\right) - \ln\left(\sum_i x_{i,t_0} s_{i,t_0}^L\right)\left[\text{Change in labor shares}_{t_0,t}\right],
\end{aligned}$$

where the first term on the right-hand side represents changes in the total value added per capita, which directly corresponds to the productivity effect. The productivity effect arises from the fact that automation increases value added and the demand for labor from non-automated tasks, and also captures the positive effect of factor-augmenting technologies.

The second term on the right-hand side captures the impact of shifts in industry shares (changes in $\chi_{i,t}$ over time) on labor demand holding the labor share within each industry, $s_{i,t}^L$, constant. This corresponds to the composition effect. The composition effect arises from the reallocation of activity across industries with different labor intensities and captures the implications of changes in the share of value-added across industries.

The last term on the right-hand side captures the role of changes in labor shares within industries (changes in $s_{i,t}^L$ over time) on labor demand holding industry shares, $\chi_{i,t}$, constant at their initial value, $\chi_{i,t}$. The change in labor shares corresponds to the combined effect of substitution and changes in the task content of production. This is because with competitive factor and product markets, the change in task content and the substitution effect are the only forces affecting the labor share of an industry.

The substitution effect captures the substitution between labor- and capital-intensive tasks within an industry in response to a change in task prices, which may be caused, for example, by factor-augmenting technologies making labor or capital more productive at tasks they currently perform. Changes in the task content of production are estimated from residual changes in industry-level labor shares (beyond what can be explained by substitution effects).

Acemoglu and Restrepo (2019) show that the substitution effect in industry i between t_0 and t can be computed as:

$$\text{Substitution effect}_{i,t_0,t} = (1-\sigma)\left(1-s^L_{i,t_0}\right)\left(ln\frac{W_{i,t}}{W_{i,t_0}} - ln\frac{R_{i,t}}{R_{i,t_0}} - g^A_{i,t_0,t}\right),$$

where W denotes the price of labor (wage), R denotes the price of capital (rental rate), σ denotes the elasticity of substitution between capital and labor, and g^A stands for the growth rate of factor-augmenting technologies.

The change in task content in industry i between t_0 and t is then calculated as a residual part of the change in labor share in industry i:

$$\begin{aligned} &[\text{ Change in labor share}_{t_0,t}] \\ &\ln s^L_{i,t} - \ln s^L_{i,t_0} = \quad (1-\sigma)(1-s^L_{i,t_0})(\ln\frac{W_{i,t}}{W_{i,t_0}} - \ln\frac{R_{i,t}}{R_{i,t_0}} - g^A_{i,t_0,t})[\text{Substitution effect}_{t_0,t}] \\ &\qquad + [\text{Change in task content}_{t_0,t}]. \end{aligned}$$

Besides industry-level changes in effective factor prices, the substitution effect also depends on the elasticity of substitution σ. Similarly to Acemoglu and Restrepo (2019), in order to estimate the substitution effect in an industry, the estimate of Oberfield and Raval (2021), $\sigma = 0.8$, was chosen as the baseline estimate of the elasticity of substitution between capital and labor. Our robustness checks show that the results are not sensitive to different values around this estimate. To convert observed factor prices into effective ones, it is supposed that A^L_i/A^K_i grows at a common rate equal to average labor productivity—if all technological progress were labor-augmenting, this would be the rate of growth in A^L_i required to match the behavior of labor productivity.

Changes in the task content of production can be further decomposed into displacement and reinstatement effects. To do so, following Acemoglu and Restrepo (2019), it is assumed that over five-year windows, an industry engages in either automation or the creation of new tasks but not in both activities.

Thus, if the average change in the task content of production in industry i over the five-year period (five-year moving average) is negative, it is considered that the industry experiences a displacement effect. If it is positive, a reinstatement effect is assumed to take place in the industry. The total contribution of displacement and reinstatement effects can be computed by cumulating the changes over time. Displacement effects are caused by automation that replaces labor, while reinstatement effects are driven by the creation of new tasks in which labor has a comparative advantage. We show that our main results are robust to shorter, 3-year and 4-year time windows as well.

Acemoglu and Restrepo (2020) developed a task-based model for skilled and unskilled labor that maps into this decomposition they proposed in Acemoglu and Restrepo (2019). In order to investigate whether automation and new tasks are associated with changes in the relative demand for skills, the following model is estimated:

$$\Delta\text{Skill demand}_{c,i} = \beta_0 + \beta_1\text{Displacement}_{c,i} + \beta_2\text{Reinstatement}_{c,i} + \gamma_c + \varepsilon_{c,i},$$

where γ_c captures country fixed effects.

Acemoglu and Restrepo (2020) document empirical estimates of this regression based on two groups of workers (skilled and unskilled) for the United States. To provide new empirical evidence on labor market polarization in Europe, we estimate the demand for skills for three groups of workers (low-, medium- and high-skilled) for a rich sample of European countries.

The primary outcome variable ($\Delta\text{Skill demand}_{c,i}$) is the change in the log of the labor compensation share of one group of workers relative to another one in each country-industry pair. $\text{Displacement}_{c,i}$ ($\text{Reinstatement}_{c,i}$) captures the strength of the displacement (reinstatement) effect (expressed as decimals rather than percentages). When analyzing whether the identified effects are driven mainly by employment or wage gap changes, change in the log of the employment share of one group of workers relative to that of another in each country-industry pair is used as an additional outcome variable.

4. Data

To decompose changes in labor demand into productivity, composition and substitution effects, and changes in the task content of production (displacement and reinstatement effects), this paper uses data from the EU KLEMS database: industry-level data on capital compensation and services, labor compensation and services, gross value added, and employment, which we use to normalize the change in the wage bill. We work with the latest 2023 release of EU KLEMS database (Bontadini et al., 2023) provided by the Luiss Lab of European Economics at Luiss University.

To study the impact of automation and new tasks on the demand for skills, we use the labor accounts data available in this database. They include the shares of employment and compensation by type of worker, cross-classified by gender, age and educational attainment. Eighteen worker types are distinguished within each country, industry and year. Workers are classified by gender (male, female), age (15–29 years, 30–49 years, 50 years and over) and education (high, medium, low). This information is not available in other public data sources. It has been estimated for the EU KLEMS database from the Eurostat Labour Force Survey and the Structure of Earnings Survey to take into account that an hour worked by a young unskilled person usually does not have the same economic value as an hour worked by a highly qualified, highly experienced person (Bontadini et al., 2023). Low-skilled workers are defined by the International Standard Classification of Education (ISCED 2011) as workers with educational levels 0–2, i.e. up to lower secondary education. Medium-skilled workers are those with ISCED levels 3–4 and high-skilled workers are those with ISCED levels 5–8.

Industry-level data on the shares of labor compensation and employment by educational attainment are available from 2008 onwards. Moreover, the EU KLEMS database contains this information only at the level of broad NACE Rev. 2 sections. The analysis is based on data for 15 industries that are part of the market economy: A, B, C, D, E, F, G, H, I, J, K, M, N, R and S.

The full sample consists of 23 countries, namely: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Ireland, Latvia, Lithuania, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and the United Kingdom. As the literature documents that the polarization of the labor market driven by new technologies is predominantly present in the most advanced countries, we divide these countries into two groups: the 12 highest income European countries[3] and the catching-up EU countries. We use GDP per capita in 2020 as a measure of income. The group of the 12 highest income EU countries is used as the base sample for a more disaggregated analysis by gender and age, as the main results hold only for this group of countries. The analysis for this base sample is therefore based on a total of 180 country-industry pairs (12 countries times 15 industries). The number of observations is also 180, as we explain the change between 2008 and 2020 (cross-sectional data).

Table 1 Descriptive Statistics for Employment and Labor Compensation Share Changes by Skill Levels for the 12 Highest Income European Countries between 2008 and 2020

Variable	*Obs.*	*Mean*	*Std. Dev.*	*Min*	*Max*
Change in low-skilled employment shares	180	0.74	0.18	0.29	1.24
Change in medium-skilled employment shares	180	0.93	0.17	0.48	1.53
Change in high-skilled employment shares	180	1.43	0.27	0.90	2.63
Change in low-skilled labor compensation shares	180	0.71	0.20	0.27	1.30
Change in medium-skilled labor compensation shares	180	0.96	0.18	0.51	1.56
Change in high-skilled labor compensation shares	180	1.27	0.25	0.73	2.25

Source: Authors' elaboration based on data from the EU KLEMS database.

Table 1 provides an overview of changes in the composition of employment and labor compensation shares by skill levels over the period 2008–2020. On average, employment and labor compensation shares of low-skilled workers decreased by almost 30%. Medium-skilled shares decreased slightly less, by 7% for employment shares and by 4% for compensation shares. Both employment and labor compensation shares increased significantly for high-skilled workers, with a higher increase in employment share. However, there is significant country-industry variation in the data. For example, changes in low-skilled compensation shares vary from 0.27 to 1.30. In the following analysis, we leverage this country-industry variation in the data to explore the linkages with the displacement and reinstatement effects of new technologies.

5. Results

We study the recent effects of automation and new tasks on the demand for skills in a wide sample of European countries and add new empirical evidence on the role of displacement and reinstatement effects by gender and age groups. The main results are presented in Table 2.

[3] Austria, Belgium, Denmark, Finland, France, Germany, Italy, Ireland, the Netherlands, Spain, Sweden and the United Kingdom.

Table 2 Changes in the Relative Demand for Skills of the Industry versus Displacement and Reinstatement in European Countries, 2008–2020

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
	HE/ME		*ME/LE*		*HE/LE*	
	LC	*EMP*	*LC*	*EMP*	*LC*	*EMP*
Panel A, full sample of 23 European countries:						
Displacement	0.0497	-0.0714	-0.00836	0.0191	0.0413	-0.0523
	(0.129)	(0.119)	(0.145)	(0.113)	(0.147)	(0.159)
Reinstatement	0.188	0.123	-0.262**	-0.314***	-0.0736	-0.191**
	(0.114)	(0.0883)	(0.110)	(0.0892)	(0.0886)	(0.0967)
Observations	345	345	345	345	345	345
R^2	0.323	0.371	0.493	0.438	0.406	0.236
Panel B, base sample of the 12 highest income European countries:						
Displacement	0.154	0.0825	0.150	0.223*	0.304**	0.305***
	(0.213)	(0.156)	(0.164)	(0.134)	(0.143)	(0.103)
Reinstatement	0.330***	0.185**	-0.292***	-0.283***	0.0373	-0.0977
	(0.104)	(0.0927)	(0.0981)	(0.0718)	(0.0593)	(0.0763)
Observations	180	180	180	180	180	180
R^2	0.401	0.370	0.404	0.483	0.466	0.294

Source: Authors' elaboration based on data from the EU KLEMS database.
Notes: HE denotes highly educated workers, ME medium-educated workers and LE low-educated workers, and LC stands for labor compensation and EMP for employment. Country dummies are included in all specifications. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

To examine the effects on the demand for skills, two measures of labor demand are used and presented in separate columns: labor compensation (LC) and employment (EMP). Columns 1 and 2 show the results for the change in the relative demand between high- and medium-skilled workers. Columns 3 and 4 report estimates for the change in the relative demand between medium- and low-skilled workers. Changes in the demand for high-skilled versus low-skilled workers are presented in columns 5 and 6. Table 2 is divided into two panels. Panel A presents the results for the full sample of 23 European countries. The estimates of the partial effects of displacement on skills demand are very close to zero across all specifications. On the other hand, reinstatement is much more strongly associated with the demand for skills measures, albeit not very precisely estimated in the case of high-skilled versus medium-skilled workers (columns 1 and 2). The results may be driven towards zero and less precisely estimated due to heterogeneity between advanced and catching-up countries. Our sample split confirms this hypothesis, as the estimates for the base sample of the 12 highest income European countries (Panel B in Table 2) provide much stronger and more robust evidence on the relationship between technological change and skills demand. In contrast, there are no significant effects for the group of catching-up countries (see Appendix, Table A1).

Panel B in Table 2 shows that in the 12 highest income European countries, new tasks increase the relative demand for high and low skills of the industry—the stronger the reinstatement effect, the higher the change in the demand for highly relative to medium-educated workers (columns 1 and 2), and at the same time there is a negative association between reinstatement and the change in the demand for medium- relative low-educated workers (columns 3 and 4). In other words, new tasks widen the wage and employment gaps between high- and medium-skilled workers, as well as between low- and medium-skilled workers, negatively affecting and hollowing out medium-educated workers. Automation, on the other hand, does not have this polarizing effect—displacement worsens the labor market outcomes of low-educated workers (columns 4 – 6) and benefits highly and medium-educated workers with no significant difference. Therefore, not all new technologies have the same effects. Some seem to polarize the labor market, while others lead to rather a uniform increase in inequality.

In the aggregate, technological progress mainly benefits highly educated workers. This overall finding is the same as in Acemoglu and Restrepo (2020). But our results are more nuanced. While displacement benefits high- and medium-skilled workers and contributes to top-bottom inequality, reinstatement contributes to labor market polarization and the hollowing out of the middle class, suggesting the deskilling nature of job-creating technologies on the one hand and their increasing demand for very high and specialized skills on the other.

Our main results for the group of 12 highest income European countries are robust to variations in the elasticity of substitution and to different time windows for identifying displacement and reinstatement effects. The results in Table 2 are based on the elasticity of substitution $\sigma = 0.8$, which is justified by the relevant literature. In Table A2 we provide estimates based on $\sigma = 0.7$, 0.9, and 1. The results remain the same. They point to a polarizing effect of reinstatement and the increase in inequality associated with the displacement of workers. Due to the relatively short time span of our data, we provide another robustness check in Table A3. We use three-year and four-year moving averages to calculate the displacement and reinstatement effects instead of the five-year moving average in our baseline specification. The regression results in Table A3 are robust to these changes.

Table 3 Changes in the Relative Demand for skills of the Industry versus Displacement and Reinstatement in the 12 Highest Income European Countries, 2008–2020 (by Gender)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		Male			***Female***	
	HE/ME	***ME/LE***	***HE/LE***	***HE/ME***	***ME/LE***	***HE/LE***
Displacement	0.314	0.240	0.554***	-0.0184	-0.305	-0.324
	(0.247)	(0.214)	(0.204)	(0.263)	(0.222)	(0.360)
Reinstatement	0.422***	-0.0534	0.368***	0.119	-0.631***	-0.512***
	(0.107)	(0.175)	(0.123)	(0.160)	(0.155)	(0.166)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	180	180	180	180	180	180
R^2	0.349	0.336	0.397	0.244	0.309	0.298

Source: Authors' elaboration based on data from the EU KLEMS database.
Notes: HE denotes highly educated workers, ME medium-educated workers and LE low-educated workers. Labor compensation is used as a measure of labor demand. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Next, we add new empirical evidence on the role of displacement and reinstatement effects by examining their effects by gender and age categories. Table 3 shows that the technology-driven increases in the relative demand for high skills identified in Table 2 are driven by the effect on male workers, and the reinstatement-driven increase in the relative demand for low skills is driven by the effect on female workers.

For men, displacement is strongly and significantly associated with an increase in the demand for high skills relative to low skills (column 3). Moreover, there is also likely to be a strong effect in favor of high skills when comparing high- and medium-skilled men (a one-sided test of the coefficient <= 0 rejects the null hypothesis with p-value = 0.103). In contrast, the coefficients for displacement effects for women are negative, although not statistically different from zero. However, a one-sided test of the coefficient in column 5 confirms that it is negative (p-value 0.085). These results suggest a deskilling effect for women as opposed to a high demand for skills for men associated with automation technologies. We see the same story with technologies creating new tasks: demand for high-skilled men (columns 1 and 3) and deskilling in the case of female workers (columns 5 and 6). Compared to displacement, the results for reinstatement are more precisely estimated.

Table 4 Changes in the Relative Demand for Skills of the Industry versus Displacement and Reinstatement in the 12 Highest Income European Countries, 2008–2020 (by Age Categories)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
		15–29			*30–49*			*50+*	
	HE/ME	*ME/LE*	*HE/LE*	*HE/ME*	*ME/LE*	*HE/LE*	*HE/ME*	*ME/LE*	*HE/LE*
Displacement	0.189	0.106	0.295	0.0840	0.0951	0.179	0.529*	-0.0641	0.465*
	(0.355)	(0.255)	(0.409)	(0.277)	(0.211)	(0.232)	(0.272)	(0.256)	(0.242)
Reinstatement	-0.698***	-0.134	-0.832***	0.282*	-0.414***	-0.132	0.685***	-0.266	0.419***
	(0.216)	(0.269)	(0.255)	(0.149)	(0.122)	(0.196)	(0.169)	(0.212)	(0.145)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	180	180	180	180	180	180	180	180	180
R^2	0.153	0.063	0.145	0.382	0.403	0.495	0.327	0.388	0.348

Source: Authors' elaboration based on data from the EU KLEMS database.
Notes: HE denotes highly educated workers, ME medium-educated workers and LE low-educated workers. Labor compensation is used as a measure of labor demand. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 explores the impact of automation and new tasks on the demand for skills by age category. The identified displacement-driven increases in the relative demand for high skills are driven by the effect on older workers (50+), and the reinstatement-driven polarization of the labor market is driven by the effect on middle-aged workers (aged 30–49). A puzzling finding worthy of future research is the reinstatement-driven increase in the relative demand for middle-skilled workers among young workers (aged 15–29). Our evidence suggests that these workers fill the gap in demand for relatively low-paid jobs requiring low and medium skills, and that demand for high skills increases for older cohorts. In this respect, lifelong learning policies, training and re-skilling courses are at the forefront of active labor market policies that should help workers to remain attached to successful careers throughout their lifetimes.

6. Conclusion

This paper adds new and more detailed evidence on labor market polarization in Europe driven by technological change. It builds upon the empirical strategy of Acemoglu and Restrepo (2020) and uses industry-level estimates of displacement and reinstatement effects to investigate whether automation (displacement) and new tasks (reinstatement) are associated with changes in the relative demand for skills. The analysis focuses on European countries and the period 2008–2020. Our full sample covers 23 European countries. Given the heterogeneity between highest income and catching-up countries, we split the sample into two groups and provide robust evidence of displacement and reinstatement effects increasing skill demand and driving labor market polarization only for a subset of the 12 highest income European countries.

The finding that technological change increases the relative demand for high skills is the same as in Acemoglu and Restrepo (2020). Our focus on three groups of workers (compared to two groups in Acemoglu and Restrepo (2020)) also allows us to study the phenomenon of labor market polarization. We show that the demand for medium-educated workers relative to low-educated workers decreases with the creation of new tasks. This provides new evidence that technological progress leads to labor market polarization, as the tasks created by new technologies seem to be more suitable for high- and low-educated workers, while the medium-educated workers are the ones left behind. Automation contributes to top-bottom inequality, but does not seem to have this polarizing effect. We go even further by exploring the effects of automation and new tasks on the demand for skills by gender and age categories. The identified technology-driven increases in the relative demand for high skills are driven by the effect on male and older workers, and the reinstatement-driven labor market polarization is driven by the effect on female and middle-aged workers.

We are aware of several limitations of our study. Our results suggest a much weaker and less precisely estimated link between displacement effects and skill demand than in the original paper (Acemoglu and Restrepo, 2020) that studied the US economy. This could be due to the much shorter time period we analyzed and/or other and different forces at play in Europe that might be worth investigating in the future. Since both the displacement and reinstatement effects are very likely to occur simultaneously in industries, proxies that could disentangle these two effects might provide more accurate estimates of their differential effects on the demand for skills. Therefore, our results may be biased toward zero and future research could provide a stronger link between displacement/reinstatement and the demand for skills. Finally, it is important to keep in mind that these findings only apply to recent technologies. Although some authors expect these trends to continue (Manyika et al., 2017; Bughin et al., 2018), the analysis of Brynjolfsson et al. (2018), for example, suggests that machine learning technologies will affect very different parts of the workforce than previous waves of automation.

APPENDIX

Table A1 Changes in the Relative Demand for Skills of the Industry versus Displacement and Reinstatement in 11 Catching-up European Countries, 2008–2020

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
	HE/ME		***ME/LE***		***HE/LE***	
	LC	***EMP***	***LC***	***EMP***	***LC***	***EMP***
Displacement	-0.0765	-0.189	-0.0850	-0.113	-0.162	-0.302
	(0.167)	(0.167)	(0.221)	(0.163)	(0.225)	(0.250)
Reinstatement	-0.158	-0.0384	-0.201	-0.404	-0.359	-0.443*
	(0.193)	(0.162)	(0.266)	(0.248)	(0.250)	(0.236)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	165	165	165	165	165	165
R^2	0.283	0.364	0.525	0.427	0.375	0.221

Source: Authors' elaboration based on data from the EU KLEMS database.
Notes: HE denotes highly educated workers, ME medium-educated workers and LE low-educated workers, and LC stands for labor compensation and EMP for employment. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2 Changes in the Relative Demand for Skills of the Industry versus Displacement and Reinstatement in the 12 Highest Income European Countries, 2008–2020

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
	HE/ME		***ME/LE***		***HE/LE***	
	LC	***EMP***	***LC***	***EMP***	***LC***	***EMP***
σ = 0.7:						
Displacement	0.179	0.0849	0.142	0.224	0.321**	0.309***
	(0.247)	(0.175)	(0.183)	(0.151)	(0.158)	(0.113)
Reinstatement	0.379***	0.207*	-0.331***	-0.332***	0.0478	-0.126
	(0.123)	(0.109)	(0.116)	(0.0822)	(0.0708)	(0.0919)
Observations	180	180	180	180	180	180
R^2	0.401	0.369	0.402	0.483	0.465	0.293
σ = 0.9:						
Displacement	0.131	0.0757	0.149	0.218*	0.280**	0.294***
	(0.183)	(0.139)	(0.148)	(0.120)	(0.129)	(0.0945)
Reinstatement	0.290***	0.166**	-0.261***	-0.244***	0.0284	-0.0784
	(0.0908)	(0.0809)	(0.0850)	(0.0636)	(0.0511)	(0.0649)
Observations	180	180	180	180	180	180
R^2	0.401	0.371	0.406	0.484	0.466	0.295
σ = 1:						
Displacement	0.113	0.0681	0.143	0.210*	0.256**	0.278***
	(0.160)	(0.126)	(0.135)	(0.109)	(0.116)	(0.0871)
Reinstatement	0.258***	0.149**	-0.236***	-0.214***	0.0219	-0.0651
	(0.0802)	(0.0718)	(0.0749)	(0.0570)	(0.0451)	(0.0565)
Observations	180	180	180	180	180	180
R^2	0.401	0.371	0.408	0.484	0.466	0.296

Source: Authors' elaboration based on data from the EU KLEMS database.
Notes: HE denotes highly educated workers, ME medium-educated workers and LE low-educated workers, and LC stands for labor compensation and EMP for employment. Country dummies are included in all specifications. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3 Changes in the Relative Demand for Skills of the Industry versus Displacement and Reinstatement in the 12 Highest Income European Countries, 2008–2020

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
	HE/ME		*ME/LE*		*HE/LE*	
	LC	*EMP*	*LC*	*EMP*	*LC*	*EMP*
Three-year moving average:						
Displacement	0.0931	0.0250	0.153	0.178	0.246**	0.203**
	(0.185)	(0.135)	(0.149)	(0.135)	(0.122)	(0.0948)
Reinstatement	0.224**	0.108	-0.198**	-0.203***	0.0261	-0.0953
	(0.0934)	(0.0843)	(0.0908)	(0.0663)	(0.0485)	(0.0671)
Observations	180	180	180	180	180	180
R^2	0.391	0.362	0.394	0.470	0.465	0.286
Four-year moving average:						
Displacement	0.0846	0.0293	0.203	0.247*	0.287*	0.276***
	(0.226)	(0.153)	(0.164)	(0.130)	(0.148)	(0.102)
Reinstatement	0.283***	0.152*	-0.259***	-0.258***	0.0242	-0.105
	(0.101)	(0.0888)	(0.0913)	(0.0688)	(0.0544)	(0.0741)
Observations	180	180	180	180	180	180
R^2	0.395	0.367	0.405	0.485	0.466	0.293

Source: Authors' elaboration based on data from the EU KLEMS database.
Notes: HE denotes high-educated workers, ME medium-educated workers and LE low-educated workers, and LC stands for labor compensation and EMP for employment. Country dummies are included in all specifications. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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