Tommaso Ciarli, Florencia Jaccoud and *Fabien Petit*

Heterogeneous Adjustments of Employment to Automation Technologies: Evidence from Manufacturing Industries in European Regions*

KEY MESSAGES

- **Employment adjustments to automation vary across industries, regions, technologies, and time**
- **Technological penetration of robots is related to higher employment within the industry in low-tech regions in the short run**
- **Robots are negatively correlated to employment in knowledge-intensive regions**
- **Regional heterogeneity in employment adjustment to robots is not driven by industry composition**
- **High-tech industries adjust employment to ICT penetration faster than low-tech industries**

Automation of activities changes the demand for labor across industries, regions, and occupations (Acemoglu and Restrepo 2019). However, the net effect of investment in different digital and automation technologies on employment in local labor markets remains unclear (see Aghion et al. 2022 for a survey), especially among European regions that differ in their industry composition, labor force characteristics, and technological endowments. These differences raise questions for policymakers about how to best deal with the varying effects of automation technologies across regions and industries, and over time. How do employment adjustments differ in structurally diverse regions such as Inner London (a knowledge- and service-intensive region), Stuttgart (a high-tech and manufacturing-intensive region), and Calabria (a low-tech tourist-driven region) in the wake of increased investment in a given automation technology?

This paper provides evidence on the relation between investment in digital and automation technologies and employment in different manufacturing industries in Europe and the extent to which this relation varies over time across technologies, industries, and regions. We find that in the short run the technological penetration of robots is associated with higher employment in low-tech regions, while service-intensive regions and cities experience decreased employment. Our heterogenous results suggest the need for different but coordinated policies at the European, national, and sub-national levels.

We distinguish four digital and automation technologies: robots, communication technology, information technology, and software-database (see Box below for definitions). By combining data from several sources, we build a measure of the penetration of these technologies at the industry-region level. We include 144 NUTS-2 regions from seven European countries between 1996 and 2017. Our three-step analysis includes, first, estimation of the employment adjustments in a given region and industry to a change in technology penetration in the same year, and up to 15 years later. Second, we cluster regions into knowl-

* We are grateful to Teresa Farinha and Maria Savona for research inputs and to participants at the GeoInno conference and the PILLARS EconPol conference for useful comments and suggestions. We also thank EUROSTAT for data on employment at NUTS 2 and 2-digit industry levels provided under a special extraction from its User Support department. This work was supported by the European Union Horizon 2020 Research and Innovation Programme under Grant Agreement No. 101004703 (PIL- LARS), the "France 2030" initiative (French National Research Agency grant ANR-17-EURE-0020), the ANR-18-CE41-0003-01 grant, and the Excellence Initiative of Aix-Marseille University - A*MIDEX. All errors remain the responsibility of the authors.

Tommaso Ciarli

is Senior Researcher at UNU-MERIT and SPRU, University of Sussex Business School. He leads several projects on the impact of science, technology, and innovation on societies.

Florencia Jaccoud

is a Ph.D. Fellow at UNU-MERIT. Her research interests focus primarily on labor market, technological change, and economic development.

Fabien Petit

is a Research Fellow at SPRU at the University of Sussex. His research interests lie in labor, behavioral, and macroeconomics.

edge-intensive, high-tech, and low-tech, and cluster industries into high-tech and low-tech. Third, we examine heterogeneity in employment changes across region and industry clusters.

We obtain two main empirical results. First, the relation between investment in digital and automation technologies and employment differs in the short (less than 5 years) and medium (between 6 and 15 years) runs, adopting a pattern specific to each technology. Second, the adjustment of employment to technological penetration differs substantially across industries and regions.

Our paper contributes to several literature strands. We extend the literature on the effects of digital technologies on labor markets (e.g. Autor et al. 2003; Goos et al. 2009; Michaels et al. 2014) by showing the existence of large differences across regions and industries in regarding the consequences of information and communication technology (ICT) for employment.

Our work is also related to work on the impact of robots on employment, which despite using similar data and methods provides mixed evidence. Some suggest that robots have a negative impact on local or regional labor markets (Acemoglu and Restrepo 2020; Benmelech and Zator 2022), while others find no impact or even a positive association at the country and industry levels (Graetz and Michaels 2018; Dauth et al. 2021). We show that these differences are related to how employment adjusts in regions and industries. The heterogeneity in the relationship between robots and employment might be due to different occupational structures, investment patterns, and technological features of different regions and industries.

DATA AND METHODOLOGY

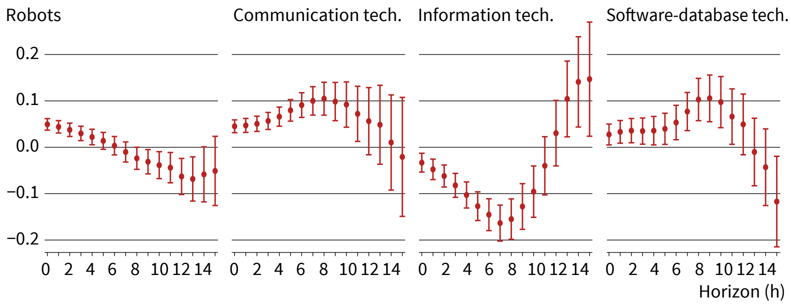
We observe data for 144 NUTS-2 regions from seven European countries (Austria, France, Germany, Italy, Netherlands, Spain, and the UK) between 1996 and 2017. Since more than 90 percent of industrial robots are used in manufacturing (Klenert et al. 2022), we focus on industries within this sector (International Standard Industrial Classification (ISIC Rev. 4) divisions 10-33). Since our data come from several sources which employ different industrial classifications, we aggregate divisions into eight groups that we define as industries (see Box on next page).

For each technology, we build a measure of its region-industry level penetration. First, we measure region-industry level of capital for each technology as the product of three components: (i) the national level of capital in a given industry; (ii) the within-country share of the gross fixed capital formation in manufacturing at the regional level assuming that in all industries more capital-intensive regions are likely to attract more digital and automation capital; and (iii) regional share of employment in the industry, relative to the national share of employment in this same industry (before the period of analysis), assuming that in all regions some industries are more exposed than others to digital and automation technologies. We then obtain a measure of penetration by dividing the level of capital by the number of employees in the region-industry before the period of analysis. We smooth our measure of technology penetration with a five-year moving average to account for investment cycles.

Figure 1

Employment Adjustments over Time

Change in employment (in %)



Note: Employment adjustments over time are expressed as the percentage changes to employment following a 1%-change in technology penetration. Each panel represents an individual technology. Point estimates and their confidence levels are depicted for each period up to 15 years.
Source: EU-LFS for employment; technology penetration based on authors' calculations using IFR, EU-KLEMS, ARDECO, and IPUMS data.

DIGITAL AND AUTOMATION TECHNOLOGIES

We consider four different but related automation technologies:

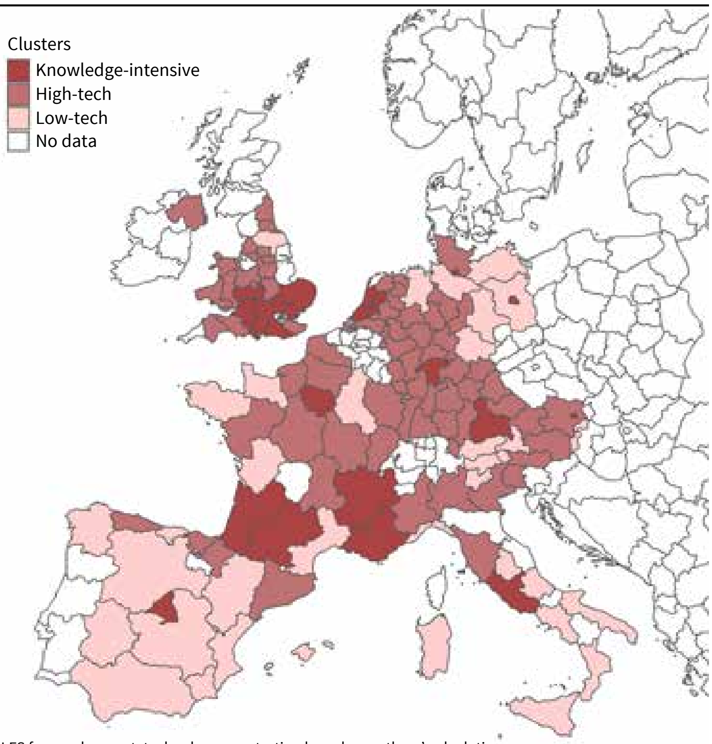
1. Robot: programmed actuated mechanism with a degree of autonomy to perform locomotion, manipulation, or positioning (ISO 8373:2021).
2. Communication technology: specific tools, systems, computer programs, etc., used to transfer information (ISO 24765:2017).
3. Information technology: resources required to acquire, process, store, and disseminate information (ISO 24765:2017).

4a. Software: computer programs, procedures, and possibly associated documentation and data pertaining to the operation of a computer system (ISO 24765:2017).

4b. Database: collection of interrelated data stored together in one or more computerized files (ISO 24765:2017).

For reasons of data availability, we consider Software (4a) and Database (4b) to be a unique software-database technology.

Figure 2
Cluster Distribution



Source: EU-LFS for employment; technology penetration based on authors' calculations using IFR, EU-KLEMS, ARDECO, and IPUMS data.

© ifo Institute

DATA SOURCES AND INDUSTRY CLASSIFICATION

For robots, we use the number of industrial robots reported by the International Federation of Robots (IFR). For ICT and software-database, we use the capital stock in constant 2010 USD from the EU-KLEMS database. Employment data are from the European Labour Force Survey (EU-LFS), which measure annual employment. Census data from IPUMS International or national statistical offices are used to build our measure of technology penetration (see also below). Data on gross fixed capital formation in manufacturing are from the ARDECO database. Imports from China and the consumption index are taken, respectively, from the OECD Trade in Value Added (TiVA) 2021 and Inter-Country Input-Output (ICIO) tables.

Division	Description of industry
10–12	Food products, beverages, tobacco products
13–15	Textiles, wearing apparel, leather products
16–18	Wood, wood products, paper, paper products, publishing, printing
19–23	Chemicals, pharmaceuticals, plastic, non-metallic mineral products
24–25	Basic metals, metal products
26–27	Computer, electronic, optical products, electrical equipment
28	Machinery and equipment not elsewhere classified
29–30	Motor vehicles, trailers, transport equipment
31–33	Furniture, other manufacturing, repair, and installation (not included)

In our baseline specification, we regress level of employment in year $t + h$ on the four technology penetration levels in year t, where h corresponds to the horizon, which we allow to vary between 0 and 15 years. Both variables are expressed in indices with respect to 1996. For short horizons, we examine the short-run technology penetration and employment co-movements. For long horizons, we estimate medium-term adjustments to employment in the region-industry. Both variables of interest are expressed as logarithms, so the coefficients can be interpreted as elasticities.

We include relevant control variables and fixed effects. The former includes imports from China (in billion USD) and the regional-level consumption index to account for the influence of foreign competition and demand cycles on employment. We consider region-industry and year-fixed effects.

EMPLOYMENT ADJUSTMENT OVER TIME

The baseline results suggest that increased penetration of different digital and automation technologies is related to different adjustments to employment in the short and medium terms (Figure 1). The panels correspond to individual technologies and show the average employment change for a 1 percent change in the penetration of the focal technology at the region-industry level. We provide confidence intervals for these employment responses over a 0 to 15-year horizon after the technology's penetration. A longer time horizon leads to wider confidence intervals as the sample shrinks.

Figure 1 provides two main results. First, an increase in the penetration of robots in the average European region-industry is associated with a short-run increase but a medium-run decrease in employment. On average, a 10 percent increase in robot penetration is associated with a 0.5 percent increase in employment in the same year, slowing down to a 0.1 percent increase after five years. This short-run relation may reflect co-movement of investments in capital and labor. However, the elasticity becomes negative for the average European region-industry over the medium run, with a 10 percent increase in robot penetration in a given region-industry being associated with a -0.7 percent decline in employment after 13 years. This implies that region-industries that invest more in robots do not absorb the workers replaced by robots.

Second, adjustment of employment to ICT and software-database penetration shows a hump-shaped relation over the time horizon analyzed. On the one hand, investment in communication and software-database technologies is associated with increased employment, whereby a 10 percent increase in the penetration of such investments is linked to a respective 0.5 percent and 0.3 percent increase in employment in the same year, on average across industries and regions. The highest elasticities (about 1 percent increase in employment for a 10 percent increase in penetration) are achieved between eight and nine years later. Although this positive relation with employment disappears in the medium run, in contrast to penetration by robots we found no evidence that investment in communication and software-database technologies reduces employment in the same region-industry over the same period. On the other hand, a 10 percent increase in the penetration of information technology dampens employment by -0.3 percent in the same year and by -1.6 percent after seven years. This relation is reversed in the medium run.

HETEROGENEITY ACROSS REGIONS AND INDUSTRIES

Despite the results identified above having important implications, heterogeneity in technologies and employment across European regions (Wirkierman et al. 2021) and industries (Dosi et al. 2021) raises questions for policy about the relevance of average region-industry employment behavior. For instance, it might be expected that a 10 percent change in use of robots in Inner London and Andalucía would be associated with different employment adjustment patterns. To investigate this, we used cluster analysis to examine both sources of heterogeneity by distinguishing regions and industries within more homogeneous groups.

REGIONAL CLUSTERS

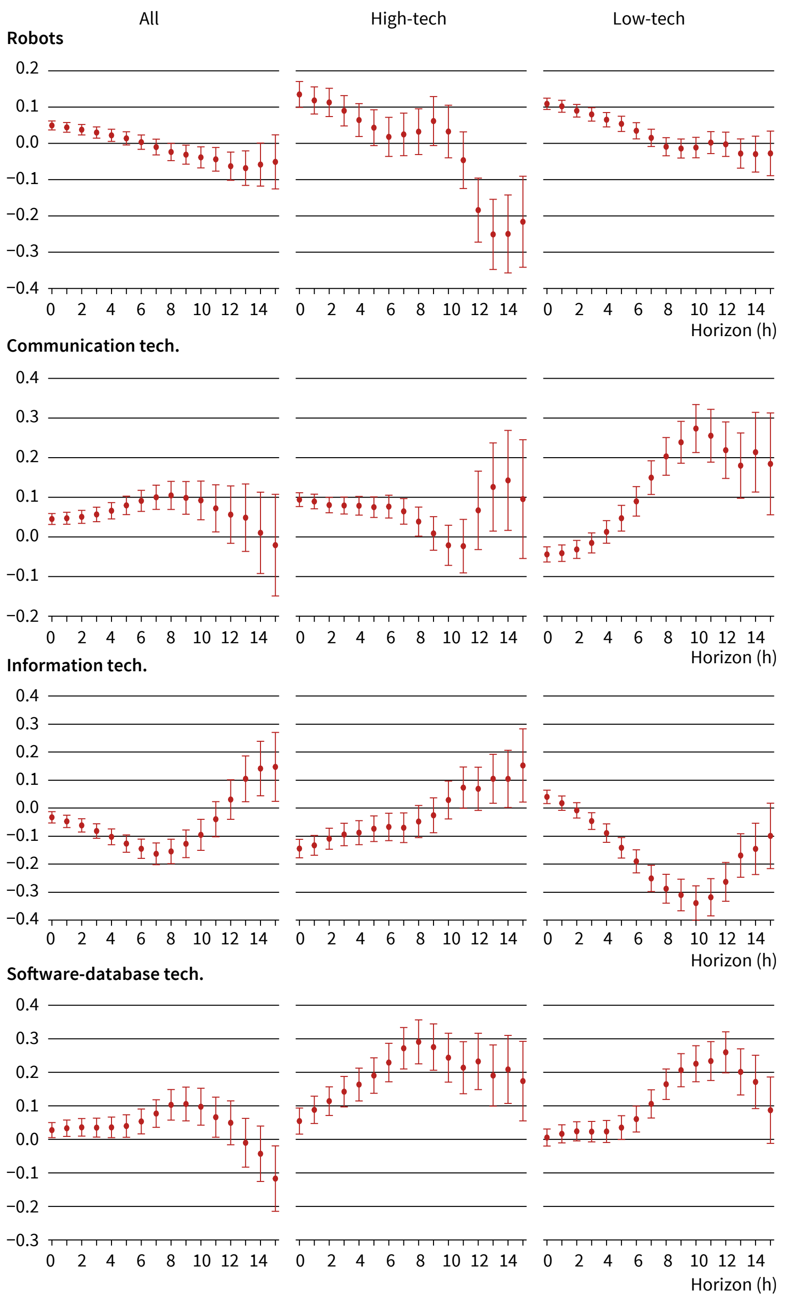
We identified three regional clusters, based on information on the share of highly educated workers, employment in knowledge-intensive activities, and gross value added (GVA) in manufacturing. The first (knowledge-intensive cluster) includes regions with the highest shares of employment in knowledge-intensive sectors and highly educated workers but the lowest share of GVA in manufacturing, as well as low levels of technology penetration in 1996, except for software-database. The second and third clusters are both less service-intensive but differ in the share of the manufacturing sector in the regions' value-added. The high-tech cluster includes regions with high shares of GVA and highly educated workers in high-tech industries, and high levels of technology penetration; the low-tech cluster includes all the remaining regions.

Figure 2 depicts the geographical distribution of regions across the three clusters. Regions that include capital cities (e.g., Berlin, London, Paris, Vienna) and service-intensive regions (e.g., Essex, Hamburg, Provence-Alpes-Côte d'Azur, Utrecht) are in the knowledge-intensive cluster. The high-tech cluster includes traditional manufacturing core regions. The low-tech cluster (most of Spain, South Italy, East Germany) are

Figure3

Employment Adjustments over Time across Industries

Change in employment (in %)



Note: Employment adjustment over time are expressed as the percentage changes to employment following a 1%-change in technology penetration. Each row of panels represents an individual technology. The first panels in each row refer to the baseline estimates; the second and third panels report the results for each industry cluster. Point estimates and their confidence intervals are presented for each period up to 15 years.

Source: EU-LFS for employment; technology penetration based on authors' calculations based on IFR, EU-KLEMS, ARDECO, and IPUMS data.

areas where manufacturing and knowledge-intensive services are less prominent.

Adjustment of employment to technological penetration differs among the three clusters for all technologies. For instance, in the regions in the knowledge-intensive cluster, robots are associated with lower employment levels over the whole-time horizon. The pattern of employment in high-tech regions is similar to the average in Figure 1, i.e., positive in the short run and then turning negative. Low-tech regions exhibit large and stable positive employment adjustments following the penetration of robots, with elasticities stable at around 2 percent for a 10 percent increase in penetration up to year 6.

INDUSTRY CLUSTERS

Industries are clustered into a high-tech and low-tech cluster based on average technology penetration (across regions) for the four digital and automation technologies at the beginning of the period in 1996.

The high-tech cluster includes three industries: plastic, chemical products, glass, ceramic (19–23), electrical/electronics (26–27), and automobile and transport equipment (29–30). These industries are characterized by wide penetration of at least two of the four technologies considered. In the case of the automobile and transport equipment sector it is mainly robots and communications technologies; for the electrical/electronics sector it is information technologies and software-database, and all four technologies for the plastics/chemicals sector.

The low-tech cluster contains the five remaining industries (see list in the second Box). These industries have much lower initial levels of technology penetration compared to high-tech industries and differ less in terms of technology investments.

Figure 3 shows the employment response over time to technology penetration for the two industry clusters. The patterns differ significantly for different types of industries.

On average, high-tech industries experience earlier adjustments to employment in the same industry-region than low-tech industries following an increase in penetration of digital technologies. The last three panels show significant changes in employment in high-tech industries in the same year as the investment in the technology occurred, with this changed employment re-absorbed by the industry-region in the medium term. In low-tech industries, employment adjustments emerge only after the fourth year following increased technology penetration and persist in the medium term. These differences might be due to the different ability of workers in the industry to master the new technologies, positive impacts of the new technologies on final demand, or market competition. However, more research is needed on these aspects.

The top panel of Figure 3 emphasizes that the observed heterogeneity in short-term employment adjustments to robot penetration among the three clusters discussed above is not driven by industry composition. It also confirms that high-tech industries do not re-absorb employment in the medium run.

POLICY CONCLUSIONS

The findings suggest that employment adjustments within manufacturing industries in relation to increased investment in different digital and automation technologies differs across European regions, industries, and time horizons. This suggests the need for different policy instruments for regions with different labor force characteristics, technological endowments, and product specialization.

In terms of time, our findings indicate that in the short to medium run, policies should take account of different time horizons depending on the industries and regions. For instance, employment adjusts more rapidly in high-tech than in low-tech industries. In the medium to long run, compensation mechanisms seem to be in place for most technologies, regions, and industries, although robots in a high-tech region and industry context seem to be an exception, with employment separation persistent in the medium to long run. However, our analysis does not consider reallocation of jobs across industries or regions where more compensation mechanisms may be available.

With respect to regions, compared to low-tech and high-tech regions, knowledge-intensive regions are the least resilient to increased robot penetration. This result requires further scrutiny since it might affect regional industrialization and leveling-up policies. Note that this result is not driven by industry composition.

REFERENCES

Acemoglu, D. and P. Restrepo (2019), “Automation and New Tasks: How Technology Displaces and Reinstates Labor”, *Journal of Economic Perspectives* 33, 3–30.

Acemoglu, D. and P. Restrepo (2020), “Robots and Jobs: Evidence from US Labor Markets”, *Journal of Political Economy* 128, 2188–2244.

Aghion, P., C. Antonin, S. Bunel and X. Jaravel (2022), “The Effects of Automation on Labor Demand: A Survey of the Recent Literature”, *CEPR Discussion Paper* 16868.

Benmelech, E. and M. Zator (2022), “Robots and Firm Investment”, *NBER Working Paper* 29676.

Dauth, W., S. Findeisen, J. Suedekum and N. Woessner (2021), “The Adjustment of Labor Markets to Robots”, *Journal of the European Economic Association* 19, 3104–3153.

Dosi, G., M. Piva, M. E. Virgillito and M. Vivarelli (2021), “Embodied and Disembodied Technological Change: The Sectoral Patterns of Job-Creation and Job-Destruction”, *Research Policy* 50, 104199.

Goos, M., A. Manning and A. Salomons (2009), “Job Polarization in Europe”, *American Economic Review* 99, 58–63.

Graetz, G. and G. Michaels (2018), “Robots at Work”, *Review of Economics and Statistics* 100, 753–768.

Klenert, D., E. Fernández-Macías and J. Antón (2022), “Do Robots Really Destroy Jobs? Evidence from Europe”, *Economic and Industrial Democracy*, https://journals.sagepub.com/doi/10.1177/0143831X211068891.

Michaels, G., A. Natraj and J. V. van Reenen (2014), “Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years”, *Review of Economics and Statistics* 96, 60–77.

Wirkierman, A. L., T. Ciarli and M. Savona (2021), “A Map of the Fractal Structure of High-tech Dynamics across EU Regions”, *UNU-MERIT Working Papers Series* 2021-023.