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## European regional employment and exposure to labour-saving technical change: results from a direct text similarity measure

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# European regional employment and exposure to labour-saving technical change: results from a direct text similarity measure

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**Abstract**

Does labour-saving technological change pose a threat to European employment, and if so, to what extent? This study investigates the degree of employment exposure to labour-saving technological change across NUTS-2 regions in Europe. We construct a cross-walked metric between the SOC and ISCO classification systems to adapt the direct measure of occupational exposure developed by Montobbio et al. (2024) for the US economy and apply it to the European context. This methodology enables us to generate detailed insights into the exposure of European occupations by leveraging the similarity rankings between technological classifications in the USPTO (CPCs) and task descriptions. To evaluate the transmission from occupational exposure to employment outcomes, we utilise data from the European Structure of Earnings Survey (EU-SES), thereby constructing exposure indices at both sectoral and regional levels. Finally, we examine the industrial and geographical diffusion of labour-saving technological change in recent years and provide robust econometric evidence indicating that low-wage regions, as well as deindustrialising areas heavily integrated into global value chains, are disproportionately vulnerable to the threat of substitution.

**JEL CODES: O33, R10, O14**

**KEYWORDS: regional disparities, manufacturing downgrading, automation, global value chains**

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## 1. Introduction

The relationship between automation and the labour market has been a central theme in economic thought since the onset of the First Industrial Revolution in the 18th century. The progressive mechanisation of production processes has continually altered the structure of work, displacing many manual occupations. Initially, concerns arose that automation would lead to widespread unemployment, as machines replaced human labour across a range of tasks (Fernández-Macías and Bisello, 2020). However, while automation did result in the displacement of certain jobs, it also gave rise to new forms of employment, often in sectors that had not previously existed (Calvino and Virgillito, 2018). The capacity of economies to adapt through innovation, the creation of new markets, and the reallocation of labour, has been a defining characteristic of industrial societies.

While much of the early discourse centred on the direct substitution effect, where machines take over specific human tasks, other indirect consequences have also shaped labour markets in significant ways. Compensation mechanisms, such as increased productivity driving down costs and prices and consequently boosting demand, the creation of entirely new industries, and the emergence of complementary jobs requiring advanced skills, have historically mitigated job displacement (for a detailed discussion of compensation mechanism proposed across different school of thought see Calvino and Virgillito, 2018, and Vivarelli, 2014).

As technological advancements continue to accelerate, particularly in the realms of robotics, artificial intelligence, and machine learning, a new debate has emerged: is the current wave of automation different from previous industrial revolutions (Brynjolfsson and McAfee, 2011)? Some proponents of the so-called "Fourth Industrial Revolution" argue that the rapid pace and breadth of innovations, signal a fundamental departure from earlier forms of technological change. Unlike past revolutions, which involved incremental changes to established processes, the current wave of automation could fundamentally reshape the nature of work, displacing large portions of the workforce in ways that previous technologies did not (Schwab, 2016). However, others view this new wave of automation as an extension of the trends already set in motion by the ICT revolution (Cetrulo and Nuvolari, 2019).

The debate remains unresolved. While some scholars caution that we may be underestimating the potential for technology to disrupt labour markets in unforeseen ways (Frey and Osborne, 2017), others contend that, as in the past, markets will adapt by creating new forms of employment; consequently, evidence on the overall impact remains elusive (Mondolo, 2022).

The relationship between technological change and employment outcomes is complex and difficult to generalise. While it is clear that technological innovations, particularly automation, have a direct impact on the demand for labour in certain occupations, the overall effects are shaped by a range of factors, including industry-specific technological and innovation regimes (Pavitt, 1984), institutional contexts (Giuliodori and Stucchi, 2012), and the type of innovation being introduced (Dosi et al., 2022). For instance, process innovations, which affect production methods, may result in labour-saving (hereafter, LS) effects in specific sectors, particularly in routine-based tasks that machines can easily perform. In contrast, product innovations, involving the creation of new goods or services, may generate new employment opportunities that often require higher skill levels and offer improved wages (Harrison et al., 2014). However, it is important to note, as highlighted by Dosi (1984, p. 104), that "in practice, the product innovations of one sector frequently function as process innovations for the sectors that adopt them."

Moreover, the impact of automation on labour demand is not uniform across different sectors (Pavitt, 1984) and occupations (Author et al., 2011; Goose and Manning, 2014). Studies have shown that high-tech industries and knowledge-intensive services are more likely to benefit from automation, as they often lead to new product innovations and higher demand for skilled workers (Van Roy et al., 2015; Lucchese and Pianta, 2012; Evangelista and Savona, 2003). In contrast, industries reliant on routine tasks, such as low- and medium-tech manufacturing, may experience a more pronounced LS effect (Bartelsman et al., 2009).

An aspect still relatively understudied in the literature is the relationship between the labour market effects of automation and the country-region specialisation pattern. The outcomes vary significantly depending on whether the economy is focused on manufacturing or services, and within manufacturing, whether the focus is on high-tech or low-tech productions. In fact, a region's mode of participation and position within Global Value Chains (GVCs), whether upstream or downstream, plays a key role in determining how it can leverage automation for competitive advantage and eventually employment gains (Marcolin et al., 2016). For instance, countries or regions that are positioned at the high end of GVCs, typically involved in research and development, high-value manufacturing, or advanced services, are more likely to experience positive labour market outcomes from automation. In contrast, regions that are primarily involved in lower-value-added activities, such as basic manufacturing or low-tech services, or bet on cost reduction strategies may face job losses as automation reduces the need for routine labour (Fontagnè et al., 2024). Indeed, GVCs deeply shape the occupational structure of insourced/outsourced occupations (Cresti et al., 2025).

Technical change continuously drives the reallocation of labour not only across sectors, occupations, and firms, but also across regions. This geographical reshuffling is particularly pronounced within the European Union, where the single market increases the potential for offshoring and for localised disparities in technological adaptation. Prior regional studies investigate critical aspects of this dynamic. Wirkelman et al. (2025), focussing on the trade dimension, identify a fractal core–periphery structure within high-tech EU networks, where employment outcomes depend on the balance between trade centrality along global value chains and technological autonomy. Their findings suggest that uneven technological diffusion across EU regions has adverse effects, as innovation tends to be cumulative and reinforces regional inequalities, contributing to imbalanced trade relations. Jaccoud et al. (2024) emphasise that the employment impacts of automation fluctuate across the phases of technology life cycles, which aligns with our findings on the temporal scaling of exposure effects. In particular, in the case of robotic technologies, which are the primary focus of this article, they find that life cycle phases are more influential than regional characteristics in explaining employment outcomes.

Other regional studies examine the spatial dimensions of technological change while highlighting persistent regional disparities. Buerger et al. (2010) demonstrate how sectoral innovation dynamics, particularly in high-tech industries such as medical equipment and electronics, drive employment growth through the linkages between patents, research and development, and employment. However, their focus on German industries leaves open questions regarding broader European heterogeneity. Capello et al. (2012) extend this analysis to all EU regions, showing how regional structural characteristics, including functional specialisation and metropolitan settlement patterns, mediate the employment effects of different types of innovation. Product innovation tends to boost employment in production-oriented regions, whereas process innovation is associated with employment reductions in urban hubs. Moroc et al. (2019) add further complexity by linking job quality and intellectual assets to labour market performance. Nonetheless, their emphasis on cross-sectional job attributes overlooks the role of occupational composition. Collectively, these studies underscore the heterogeneous regional impacts of technological change but leave underexplored how workforce *structures*, particularly the task-specific composition of regional labour markets, interact with automation pressures within an integrated economic space. Similarly, although sectoral specialisation and innovation inputs are well studied, the role of occupational exposure in mediating the spatial inequalities of automation remains unclear.

Other important confounding factors, such as trade dynamics, labour market institutions, and cyclical demand fluctuations (Peters et al., 2014), complicate the task of isolating the specific effects of automation. For example, the rise of trade liberalisation and globalisation has led to a transformation in the structure of global labour markets, influencing both the supply and demand for labour in ways that are difficult to disentangle from the effects of technological change (Vivarelli and Meschi, 2008).

In addition, labour market institutions, including trade unions and employment protections, can significantly shape how workers experience the impact of automation (Giuliodori and Stucchi, 2012; Cirillo et al., 2023). The most concerning aspect of these combined automation and trade dynamics is that their negative effects, namely reduced labour demand, downward pressure on wages, and deteriorating working conditions, tend to concentrate on the same vulnerable groups. These include fabrication workers in manufacturing and, increasingly, workers in logistics and transportation (Riccio et al., 2024). The literature on the so-called “smile curve” highlights this uneven distribution of occupations across global value chains (Meng et al., 2020), linking it to profit-driven offshoring of labour-intensive production to lower-wage countries (Riccio et al., 2024). This trend places European manufacturing sectors, which are already facing intense deindustrialisation pressures, in a difficult competitive position relative to low-wage Asian economies such as China. As a result, regional responses have diverged. Southern and Eastern EU countries have largely adopted strategies of wage suppression, while higher-wage economies, e.g. Germany, have pursued innovation and specialisation in high value-added production (Cresti et al., 2025).

In spite of a growing body of literature on the effects of automation on labour markets, measuring the transmission from technology to labour remains challenging. To better understand the impacts of automation, there is an increasing need for more fine-grained measures that capture the occupation-specific effects of each innovation (Montobbio et al., 2024). Traditional aggregate sectoral proxies, such as the number of robots, R&D investments, or patent counts, often fall short of capturing the intricate ways in which automation reshapes occupational structures and sectoral dynamics (Staccioli and Virgillito, 2021). Recent advancements in data availability and computational power allow for the matching, through text analysis, of detailed descriptions of occupations and information on patents and their technological classifications. This enables a better understanding of the idiosyncratic impact of new technologies on labour demand (see Webb, 2020; Felten et al., 2021; Kogan et al., 2021; Montobbio et al., 2024).

This article explores the heterogeneous relationship between automation and European regions by adapting the measure of US occupational exposure to LS technologies proposed by Montobbio et al. (2024) to the European labour market. Montobbio et al. (2024), through a detailed text analysis of patent CPC codes and O*NET task descriptions, developed a measure to quantify the exposure of each 8-digit US-SOC occupation to the LS technologies identified by Montobbio et al. (2022). According to their analysis, LS technical change specifically targets the most rapidly growing low-wage occupations, particularly in the logistics industry, while also continuing to affect declining production occupations in manufacturing. When transitioning from occupations to the regional dimension, higher exposure rates to LS technical change are recorded in the deindustrialising Rust Belt area and the South. This is not coincidental, as these are the two regions predominantly characterised by declining blue-collar manufacturing jobs in the former case, and growing blue-collar logistics jobs in the latter. The South, in particular, is marked by a larger incidence of states with Right to Work laws, which reduce labour costs. Indeed, the process of deindustrialisation in the American North has been accompanied by partial reindustrialisation and servitisation in the South in recent years.

Given such evidence from the US, does LS technical change threaten European employment? If so, to what extent? This contribution assesses the degree of exposure of employment in NUTS-2 European regions to LS technical change. We develop a cross-walked measure from SOC to ISCO in order to link the direct measure of occupational exposure presented by Montobbio et al. (2024) for the US economy and apply it to Europe. This approach enables us to obtain fine-grained information on the exposure of European occupations, utilising the information from the similarity ranking between the technological definitions of the USPTO (CPCs) and task descriptions. To assess the propagation from occupational exposure to employment, we employ the European Structure of Earnings (EU-SES), thereby producing indices of exposure at sectoral and regional levels. In this respect, our contribution specifically links the literature on automation and the labour market to that on global value chains (GVCs) and regional specialisation.

We construct industry and geographical penetration indices of LS technical change in recent years and identify robust econometric evidence that low-wage regions and declining industrial regions are those most exposed to the threat of substitution. More specifically, we find that adapting the measure of exposure to LS technologies for European labour markets reveals a clear hierarchical distribution in terms of occupational, sectoral, and regional vulnerability, broadly mirroring patterns observed in the US. Occupations in manufacturing, logistics, and construction are the most exposed to automation, with a concentration in Eastern and Southern Europe. Econometric analysis shows that higher exposure to LS technologies is associated with lower regional employment and wage levels, highlighting the dual impact of automation on both job availability and earnings. However, these effects are mediated by regional specialisation patterns and the mode of participation in GVCs (Riccio et al., 2024). In fact, negative substitution effects are particularly pronounced in regions specialised in declining manufacturing sectors, such as deindustrialising areas characterised by low wage levels, or regions deeply integrated into GVCs as outsourcing hubs, where the LS effects of automation are most acute.

The paper is organised as follows. Section 2 briefly discusses measures of labour-saving technologies; Section 3 presents the data and methodology; Section 4 outlines descriptive statistics; Section 5 details the econometric analysis; our conclusions are presented in Section 6.

## 2. Measures of labour-saving technologies

While measures of technological adoption at the regional, sectoral or firm-level provide valuable insights, they are often limited in capturing the heterogeneous effects of technology on specific groups of workers. Sectoral measures, for instance the adoption of robots provided by the International Federation of Robotics (IFR), focus on broad industry trends, making it challenging to discern how technology impacts different occupational groups within the same sector. For example, studies such as those by Acemoglu and Restrepo (2020) highlight sector-wide decreases in wages and employment for low-skilled workers but do not provide details on most exposed occupations. Furthermore, sectoral measures fail to capture the dynamics of task reallocation within firms, where automation might reduce demand for routine tasks but simultaneously create demand for high-skill complementary tasks.

Similarly, studies that rely on firm-level data may fail to account for the heterogeneity within firms, as employment impacts might vary significantly across tasks (Cirillo et al., 2021). These aggregated measures also face challenges in distinguishing between LS and labour-augmenting technologies. Moreover, firm-level measures, such as those using robotic adoption or imported capital equipment, are influenced by the so-called “business-stealing effect”, which might exaggerate the positive employment impacts at innovative firms while ignoring the negative effects on non-adopters (Calvino and Virgillito, 2018; Dosi and Mohnen, 2019).

Occupation-level measures of technological exposure address many of the limitations of sectoral or firm-level analyses by focussing on the direct relationship between technology and the specific tasks or activities that characterise each occupation. Frey and Osborne (2017) were among the first to employ this approach, using expert judgments to estimate the automation probability of various occupations. Their method assessed the likelihood of automating particular human functions, finding that in the US 47% of existing jobs are at high risk of being automated. Subsequent studies by Arntz et al. (2016), refined these estimates by focussing on tasks rather than occupations, providing a less dramatic estimate of 9% of the workforce being at risk of automation. Meanwhile, Nedelkoska and Quintini (2018) find that this impact is highly heterogeneous across countries.

Recent methodological advances in measuring technological exposure highlight the growing sophistication of linking innovation data to occupation specific characteristics. For instance, Webb (2020) developed a measure of exposure based on the co-occurrence of verb-noun pairs in AI patent titles and O*NET occupational tasks. While innovative, this method relies on patent titles alone, which may lack sufficient detail about the underlying functions of the technology, and for its focus on verb-noun pairs, which risks generating false positives. Similarly, Kogan et al. (2021) introduced a text-similarity measure linking breakthrough innovations to occupational descriptions. Though this approach allows for time-variant analyses, it primarily reflects long-term trends in "technological revolutions" rather than capturing immediate impacts on occupations.

Other studies, such as those by Felten et al. (2021) and Meindl et al. (2021), have sought to refine these methods by incorporating advanced natural language processing techniques and broader data sources. For instance, Felten et al. (2021) connected the most relevant and recent AI applications to O*NET abilities by using a crowdsourced questionnaire. In this survey, participants were asked whether they believed AI applications were related to or could potentially be utilised for each of the 52 abilities specified in the O*NET database. Meanwhile, Meindl et al. (2021) matched patent texts to detailed work activities in the O*NET database.

Prytkova et al. (2024) propose a methodology closely aligned with Montobbio et al. (2024) in its use of semantic natural language processing techniques to measure occupational exposure to digital technologies. Their approach begins by embedding patent titles and occupation descriptors (titles and task descriptions) using sentence transformers, then calculates cosine similarity scores to link patents to 4-digit ISCO-08 occupations. For each occupation, they derive two similarity metrics: one between the patent title and the occupation title, and another between the patent title and the most semantically aligned task description within the occupation. This dual-layer matching aims to capture both broad occupational alignment and task-specific technological relevance. While this framework shares conceptual ground with Montobbio et al. (2024) in leveraging textual similarity to connect innovation and labour markets, critical distinctions emerge. First, Prytkova et al. (2024) rely on patent titles rather than underlying textual definitions of their full technological classification (namely, CPC codes). Second, their task data draws from ISCO-08's task descriptions, which provide concise occupation-specific task lists, in contrast to more granular task databases like O*NET, which distinguish between core and supplemental activities.

## 3. Data and Methodology

### Quantifying the occupation exposure to labour-saving technologies

To quantify the relationship between LS technologies and occupational exposure, Montobbio et al., (2024) develop a novel measure of textual similarity that bridges technological definitions of CPC codes with occupational tasks described in the O*NET database. Their procedure entails three major steps: identifying LS patents, calculating task-level similarity, and aggregating this similarity at the occupation level.

1. **Identifying Labour-Saving Patents:** building on the work of Montobbio et al. (2022), the author first identify patents related to robotics in the period 2011-2019. Then, they further classify those that explicitly involve LS heuristics. This classification yields a set of CPC codes to which LS patents belongs. To capture the technological essence of these patents, they rely on CPC definitions rather than raw patent text, ensuring a standardised representation of technological content.

2. **Calculating Task-Level Similarity:** using the *bag-of-words* model, they compute the cosine similarity between the textual definitions of CPC codes and the tasks listed in the O*NET database. This approach represents each text as a multiset of words, disregarding syntax but retaining word frequencies. The result is a similarity matrix, where each cell represents the similarity score between a CPC code and an O*NET task. They further refine the matrix by weighting rows, i.e. CPC codes, based on their frequency in LS patents. Aggregating these scores across all CPC codes yields a task similarity vector that ranks tasks by their proximity to LS technological functions.

3. **Aggregating at the Occupation Level:** to map task-level exposure to occupations, they leverage O*NET's classification, which categorises tasks as core or supplemental based on importance, relevance, and frequency. Core tasks are critical to the occupation, while supplemental tasks have lower relevance or importance. Exposure scores are weighted accordingly: core tasks contribute two-thirds and supplemental tasks one-third to the occupationss overall score. Adjustments are made for the varying number of tasks across occupations to ensure a robust representation.

In this paper, we adapt the measure to the European labour market by leveraging and assuming similarity in the overall tasks distribution across occupations and their task content, between the US and EU labour markets. Using a crosswalk provided directly by O*NET, we first transition from the 8-digit SOC classification to the 6-digit level, aligning with data from the US Bureau of Labour

Statistics (BLS). Next, we apply US employment statistics to weight the crosswalk from the 6-digit SOC categories to the 3-digit ISCO categories, which correspond to the classification used in the Labour Force Statistics provided by Eurostat (LFS).

The primary data source for this analysis is the European Labour Force Survey (LFS) provided by Eurostat, which offers detailed insights into labour force participation for individuals aged 15 and over across 28 EU member states, the United Kingdom, Norway, and Switzerland. From the LFS we extract occupation-specific employment levels at the 3-digit ISCO classification for NUTS-2 EU regions. Additionally, we obtain occupation-specific employment statistics for 1-digit NACE sectors, along with data on educational attainment, broadly categorised into three groups: primary, secondary, and tertiary education.

Taking into account the coverage of the variables extracted and the changes in their respective classifications, our analysis focusses on the period 2011–2023. This reduced sample size results from the interplay of three distinct taxonomies, namely NACE, NUTS, and ISCO, that underwent several reclassifications within the European Labour Force Survey (LFS). While the NACE 1-digit classification has remained unchanged since 2000, the introduction of ISCO-08 in 2011, which replaced the earlier ISCO-88, limits our analysis to the years following this transition. In the case of the geographic scope, changes have varied across countries, necessitating a reclassification of regions to align with the 2016 version of the NUTS classification. This step ensures a consistent and uniform regional framework, mitigating discrepancies caused by national-level variations in earlier classifications.

Ultimately, from the available data series, we had to exclude Norway due to the inability to consistently reclassify its regions into a harmonised framework. Similarly, Bulgaria was excluded because it reports occupations only at the 2-digit ISCO level, making it incompatible with the required level of granularity for our analysis. We retained the United Kingdom up to 2018 and the Netherlands, despite limitations in their regional classifications. In the case of the UK, regional data are recorded at the 1-digit level, and for the Netherlands, regions are reported at the 0-digit (i.e., country-wide) level. These exceptions were made to maintain a broader dataset; however, we provide results also for a restricted sample which assures complete consistency across classifications.

## 4. Descriptive statistics and validation

The analysis of Table 1 reveals a clear distinction between the most and least exposed occupations to LS technologies. The top 3-digit ISCO occupations identified as most exposed are highly aligned with the findings of Montobbio et al. (2024) for the US labour market, lending validity to our methodology and the conversion procedure employed for adapting the analysis to the European context. From the top panel of Table 1, we observe that workers engaged in transportation and logistics, such as “Stationary Plant and Machine Operators” and “Heavy Truck and Bus Drivers”, are among the most exposed. Similarly, production-related roles, such as “Machinery Mechanics and Repairers” and “Chemical and Photographic Products Plant and Machine Operators”, as well as construction-related workers like “Blacksmiths, Toolmakers and Related Trades Workers”, also rank high in exposure. This pattern underscores the strong focus of LS technological advancements on automating tasks within industries that rely on manual or mechanical precision, heavy equipment handling, and machine operation. These occupations heavily involve standardised tasks, which are particularly susceptible to automation, but also tasks performed in unstructured workplaces, like construction.

| **Occupation** | **Occupation Exposure** |
|---|---|
| Manufacturing Labourers | 1,00 |
| Stationary Plant and Machine Operators | 0,95 |
| Machinery Mechanics and Repairers | 0,77 |
| Electrical Equipment Installers and Repairers | 0,77 |
| Heavy Truck and Bus Drivers | 0,75 |
| Chemical and Photographic Products Plant and Machine Operators | 0,71 |
| Blacksmiths, Toolmakers and Related Trades Workers | 0,69 |
| Vehicle, Window, Laundry and Other Hand Cleaning Workers | 0,64 |
| Building Finishers and Related Trades Workers | 0,62 |
| Sheet and Structural Metal Workers, Moulders and Welders, | 0,60 |
| Material Recording and Transport Clerks | 0,60 |
| **…** | **…** |
| Teaching Professionals | 0,10 |
| Finance Professionals | 0,09 |
| Legal, Social and Religious Associate Professionals | 0,09 |
| Cooks | 0,08 |
| Cashiers and Ticket Clerks | 0,07 |
| Financial and Mathematical Associate Professionals | 0,06 |
| Child Care Workers and Teachers’ Aids | 0,05 |

| | |
|---|---|
| Service Managers | 0,03 |
| Business Services and Administration Managers | 0,01 |
| Legal Professionals | 0,00 |

**Table 1.** Top (bottom) panel presents the 10 most (least) exposed 3-digit occupations in the EU labour force market measured using the Occupation Exposure Measure presented in Staccioli et al., (2023). Data source: EU-LFS.

The bottom panel of Table 1, conversely, highlights occupations least exposed to LS technologies. These roles, such as “Legal Professionals”, “Business Services and Administration Managers”, and “Service Managers”, are typically characterised by tasks that are either cognitive, interpersonal, or require complex decision-making and strategic planning, making them less amenable to automation. Similarly, occupations in education and care, such as “Child Care Workers and Teachers’ Aids”, exhibit low exposure, reflecting the inherently human-centric nature of these professions that demand adaptability, and a high degree of personal interaction.

A recurring pattern evident from Table 1 is the polarisation of exposure along occupational macro-groups. On the one hand, “Plant and Machine Operators and Assemblers” and “Transport and Storage Workers” consistently rank high in exposure, mirroring the targeted automation efforts in logistics and manufacturing. On the other hand, “Professionals” and “Managers”, particularly those in fields like legal, financial, and social services, are least affected, demonstrating that these areas still rely heavily on non-routine, judgment-intensive tasks.

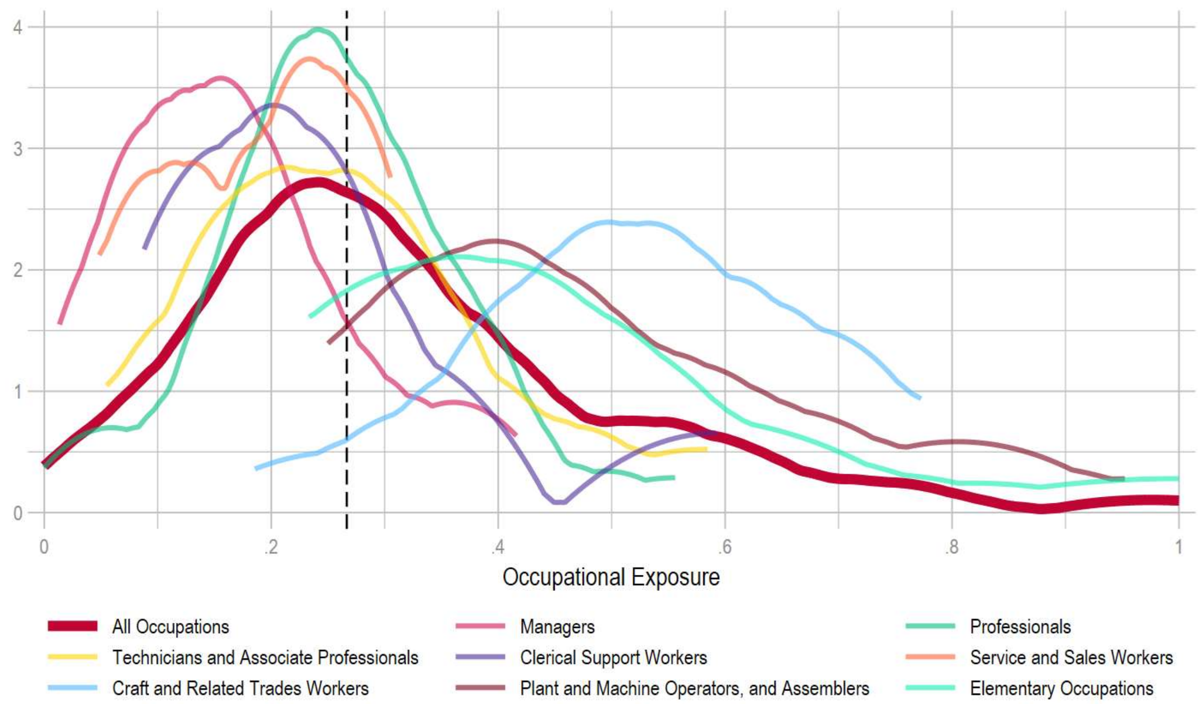


**Figure 1.** Unweighted distribution of Occupation Exposure. The red-thick line represent the distribution of exposure across all occupations; the others across 1-digit ISCO occupations. Data source: EU-LFS.

Figure 1 displays the unweighted distribution of occupation exposure for the whole employment and by 1-digit ISCO classes. The aggregate unweighted distribution is left skewed with median and mean values not too dissimilar. When dividing by occupational categories, we see that "Managers", "Service and Sales Workers", "Clerical Support Workers", "Technicians and Associate Professionals" are the most left skewed (i.e. less exposed); "Clerical Support Workers" and "Technicians and Associate Professionals" especially show wide distribution support. On the other hand, "Craft and Related Trades Workers", "Plant and Machine Operators and Assemblers", and "Elementary Occupations" are the most exposed (and with great difference), broadly in line with the findings of Montobbio et al. (2024) for the US.

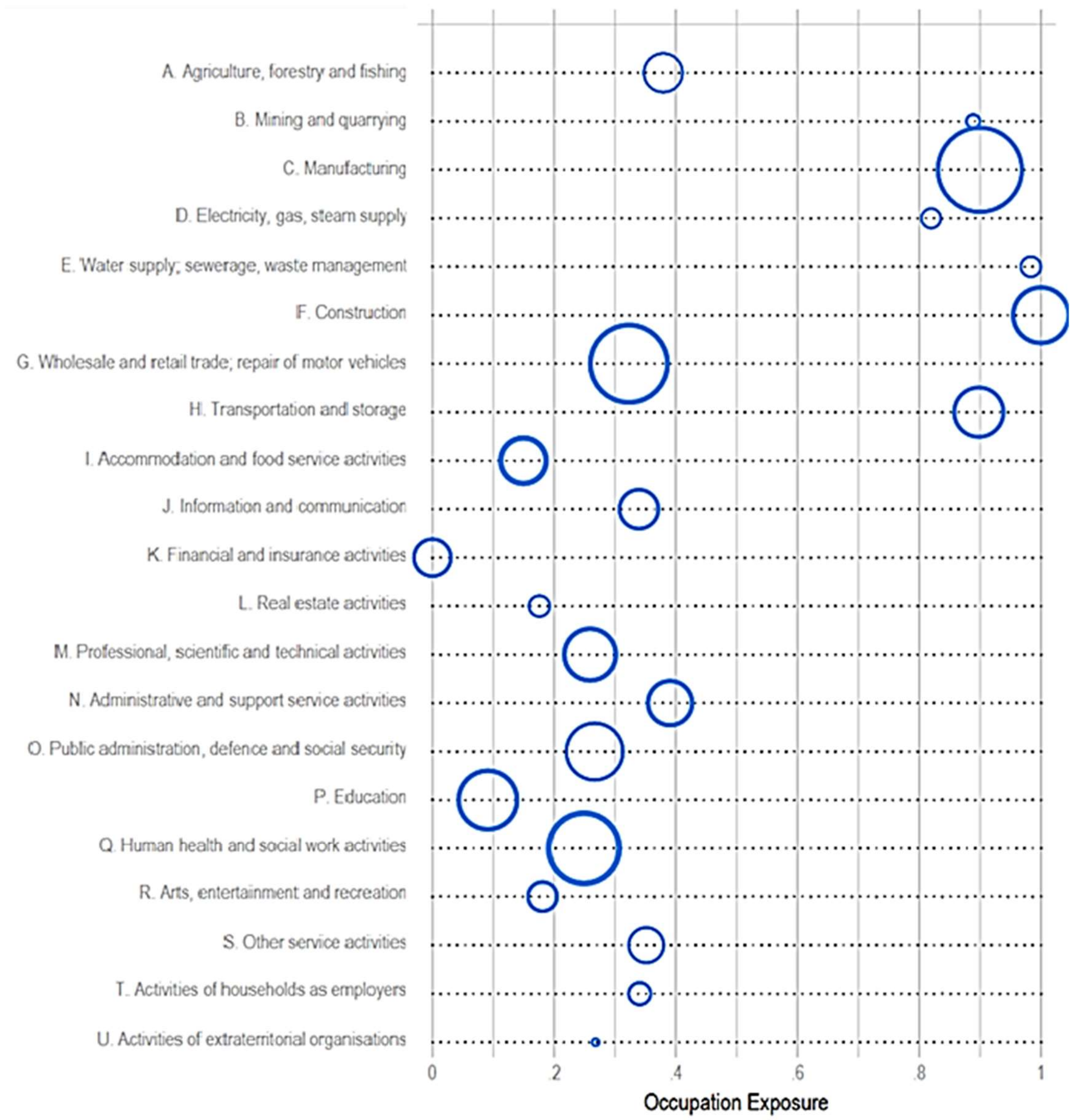


**Figure 2.** Ranking of most exposed 1-digit NACE sectors, averaged across the whole time span. The size of the circles are proportional to the employment share. Data source: EU-LFS.

Overall, the picture reinforces the well-documented polarisation of exposure risks across occupational categories, with cognitive, interpersonal, and high-skilled tasks remaining less exposed, while operational, manual, and routine-intensive roles face higher susceptibility to LS technologies.

Figure 2 ranks sectors by their average occupational exposure to LS technologies. Additionally, the size of the circle is proportional to the workforce employed in each sector to gauge its relevance. At the lower end of the spectrum, “Financial and Insurance Activities” (0.00), “Education” (0.09), and “Accommodation and Food Service Activities” (0.15) emerge as the least exposed sectors. These findings align with Montobbio et al. (2024), where similarly human-centric sectors, relying heavily on interpersonal, cognitive, and creative tasks that are difficult to automate, also ranked among the least exposed. Similarly, other low-exposure sectors such as “Arts, Entertainment and Recreation” (0.18) and “Real Estate Activities” (0.18) highlight the limited penetration of LS technologies into fields dominated by creativity and client interaction. These findings are consistent with the US labour market results. However, a notable difference is observed within the healthcare sector: while in the US it appears as one of the most exposed, in Europe it is instead classified among the least exposed.

At the higher end of the ranking, “Manufacturing” (0.90), “Transportation and Storage” (0.90), and “Construction” (1.00) stand out as the most exposed sectors. This is consistent with Montobbio et al. (2024), where manufacturing was identified as the most exposed sector due to its concentration of standardised and logistics-related tasks that are highly susceptible to automation. A key difference, however, lies in the utilities sector. In the US labour market, utilities occupy a mid-ranking position in terms of occupational exposure, whereas in the European labour market, they stand out among the most exposed. Specifically, “Water Supply; Sewerage, Waste Management” (0.98) and “Electricity, Gas, Steam and Air Conditioning Supply” (0.82) exhibit high exposure, reflecting the increasing focus of LS technologies on automating tasks related to system monitoring and maintenance.

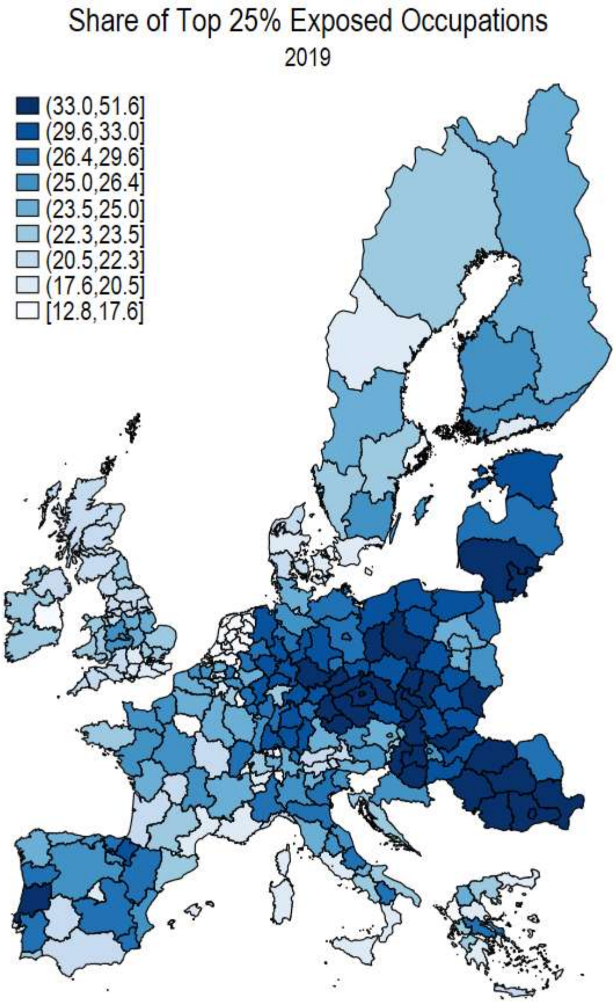

**Figure 3.** Map showing the share of 25% top exposed occupations in EU NUTS-2 regions plus UK and Switzerland. First, we identify the 25% most exposed occupation pooling all EU workers. Then we plot the share of these workers as a percentage of the regional workforce. Darker regions are those where the share of 25% top exposed occupation is greater than 25% (most exposed regions).

Figure 3 presents the geographical distribution of the most exposed jobs across NUTS-2 European regions. First, we aggregate all European workers and identify the top 25% employed in the most exposed occupations. The choice of the top 25% reflects the high skewness of the distribution, indicating that focussing on the right tail provides more informative insights than examining the entire distribution. We then analyse how these workers are distributed across European regions. Darker regions are those with a relatively higher concentration of top-exposed workers. A clear distinction emerges between Eastern and south-western Europe. Germany, together with parts of the Eastern European periphery and northern Italy, forms a cluster of regions that are relatively more exposed to LS technologies. Notably, this largely coincides with the manufacturing hub linking Germany, the Czech Republic, western Poland, northern Italy, and Bulgaria[3].

Conversely, southern Italy appears to be among the least exposed regions. While this may seem surprising at first, it can be attributed to the deindustrialisation trends that have already impacted these areas, leading to a reduced presence of manufacturing activities, which are highly correlated with LS exposure at the regional level. Indeed, this area is currently specialised in low-end service-oriented activities. Similarly, but looking at high-end service-oriented regions, capital cities and most of the United Kingdom, historically the first European deindustrialising country, are less exposed, reflecting their focus on sectors like finance and professional services, which rely more heavily on cognitive tasks and human interactions that are less susceptible to automation.

## 5. Econometric Analysis

We analyse the relationship between occupational exposure to LS technologies and employment dynamics across European NUTS-2 regions using a weighted least squares (WLS) estimator. Employment changes ($\Delta Emp_{i,t}$), measured as logarithmic differences over 3-, 5-, and 10-year horizons, are regressed on a lagged occupational exposure index ($Exposure_{i,t-1}$), offshorability measures ($Offshorability_{i,t-1}$), and regional controls. Initial employment levels at the NUTS-2 level serve as weights to address heteroskedasticity, with unweighted specifications confirming robustness.

[3] Due to data limitations, Bulgaria is excluded from the econometric analysis because it reports occupational flows only at 2-digit level. However, we retain Bulgaria in the graphical representation (Figure 3) for illustrative purposes.

All variables enter in logarithmic form to interpret coefficients as elasticities and mitigate outlier effects. Standard errors are clustered at the regional level to account for serial correlation. The baseline econometric specification is as follows:

$$\Delta Emp_{i,t} = \beta_0 + \beta_1 Exposure_{i,t-1} + \beta_2 Offshorability_{i,t-1} + \beta_3 PriEdu_{i,t-1} + \beta_4\, GFCF/w_{i,t-1} + \beta_5 ManSh_{i,t-1} + \gamma_t + \delta_c + \epsilon_{i,t}$$

Eq. 1

The occupational exposure index $Exposure_{i,t}$ aggregates 3-digit ISCO occupation-level exposure scores, derived from US O*NET task data, weighted by regional occupations shares. This construction ensures dynamic regional variation through shifting occupational compositions while minimising endogeneity concerns, as US task measures are exogenous to European labour market trends. The specification is as follows:

$$Exposure_{i,t} = \frac{\sum_k Exposure_k \times Emp_{k,i}}{\sum_k Emp_{k,i}}$$

Eq.2

where $k$ represents 3-digit ISCO occupations, $i$ the NUTS-2 region, and $t$ the underlying time period. Note that the exposure measure is based on O*NET tasks from the US labour market, and therefore concerns on the endogeneity of the results are minor. Further, although the exposure measure is constant within each occupation in the period considered, the measure is dynamic at the regional level since it accounts for changes in the occupation structure.

Similarly, the offshorability index $Offshorability_{i,t-1}$, is computed at the occupation level and aggregated at the NUTS-2 level, capturing the probability that a specific occupation can be offshored, as developed by Autor and Dorn (2013). This index serves as a proxy for the impact of globalisation on regional labour markets. The share of the population with primary education $PriEdu_{i,t-1}$ is included to control for the educational composition of the regional labour force, as this proves to be more significant than primary education to our analysis. Gross fixed capital formation per worker $GFCF/w_{i,t-1}$ proxies regional investment levels, which is a loose proxy for adoption of new technologies. The share of employment in manufacturing $ManSh_{i,t-1}$ accounts for regional specialisation, with manufacturing-intensive regions potentially experiencing stronger LS effects due to the higher prevalence of standardised tasks. Year-fixed effects $\gamma_t$ and country-fixed effects $\delta_c$ are included to account for time-specific shocks and unobserved heterogeneity at the regional level, respectively. The error term $\epsilon_{i,t}$ captures residual variation.

To explore the heterogeneous relationship of occupational exposure across regions and the link with regional specialisation, we split the sample based on key regional characteristics. In the first sample, regions are divided into two groups based on the median share of manufacturing employment, allowing us to test whether the penetration of automation is more pronounced in manufacturing-intensive regions. Similarly, regions are split into high- and low-wage groups based on the median wage level, allowing us to examine whether the effects of automation vary with regional wage structures. GVC participation of the region, computed as the sum of foreign backward and forward linkages relative to overall final demand, serves as the GVC-adapted version of openness. The specification is as follows:

$$GVCpart_{i,t} = \frac{\sum_{k\in i} frw_{i,k,t}^{for} + bkw_{i,k,t}^{for}}{\sum_{k\in i} fd_{i,k}} \qquad \text{Eq.3}$$

where $i$ represents EU NUTS2 regions, $k$ the industry, and $t$ the underlying time period; $frw_{i,k,t}^{for}$ and $bkw_{i,k,t}^{for}$ denote the foreign forward and backward linkages respectively. The index is constructed as a weighted average of industry-region-specific foreign GVC participation level. Then, regions are classified as high or low GVC participation based on the median value.

### 5.1 Employment Growth Regressions

The results from the weighted least squares regressions, in Table 2, reveal a robust and consistent negative relationship between exposure to LS technologies and employment changes across European NUTS-2 regions. The exposure coefficient remains statistically significant and stable across specifications, varying narrowly between –0.043 and –0.057 for 3-year horizons, despite incremental control additions. This consistency suggests minimal omitted variable bias, reinforcing confidence in the exposure measure's distinct explanatory power. Note that coefficient magnitudes scale approximately proportionally with the employment change window: a 10% increase in exposure reduces employment by 0.4–0.6 percentage points over three years, increasing to –0.07 for the 5-year windows and to –0.120 for the 10-year span (cf. column 7 and 8, respectively). This pattern suggests that prolonged exposure amplifies labour market adjustments.

Turning the attention to the other regressors, offshorability exhibits instability, with coefficients statistically insignificant in most specifications. Gross fixed capital formation per worker positively and significantly associates with employment growth (0.036–0.100), suggesting investment mitigates automation-driven declines. Primary education shares show similar positive effects while manufacturing specialisation yields null results, challenging the presumption that industrial regions went through deindustrialisation diminishing regional employment in the period under analysis. Finally, model fit improves markedly with fixed effects, rising to 0.72 for 10-year horizons, as longer intervals better capture structural adjustments. These results underscore the value of accounting for both temporal shocks and cross-country institutional differences.

Table 3 presents the results of the WLS regressions, that split the sample into two quantiles to explore heterogeneity across regions based on manufacturing employment share, wage levels, and GVC participation. Regions with high manufacturing specialisation exhibit stronger negative exposure coefficients (–0.061 vs. –0.051 in low-manufacturing regions), aligning with expectations that industrial sectors face heightened automation risks due to routinised tasks. However, the lack of statistical significance between subgroups suggests that the role of manufacturing may be mediated by unobserved factors, such as sectoral heterogeneity or firm-level technology adoption strategies.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Baseline – Employment Growth *Weighted Least Squared* | | | | | | | |
| | 3-year log-changes | | | | | | 5-year | 10-year |
| $Exposure_{i,t-1}$ | –0.043*** | –0.047*** | –0.047*** | –0.057*** | –0.036*** | -0.054** | –0.077*** | –0.120** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.022) | (0.030) | (0.050) |
| $Offshorability_i$ | | | 0.008 | 0.015** | -0.001 | -0.005 | -0.005 | -0.001 |
| | | | (0.006) | (0.006) | (0.006) | (0.008) | (0.012) | (0.019) |
| $PriEdu_{i,t-1}$ | | | | 0.017*** | 0.019*** | 0.018*** | 0.032*** | 0.064*** |
| | | | | (0.005) | (0.004) | (0.005) | (0.006) | (0.015) |
| $GFCF/w_{i,t-1}$ | | | | | 0.036*** | 0.036*** | 0.063*** | 0.100*** |
| | | | | | (0.006) | (0.006) | (0.008) | (0.015) |
| $ManSh_{i,t-1}$ | | | | | | 0.007 | 0.005 | 0.001 |
| | | | | | | (0.007) | (0.010) | (0.015) |
| Observations | 2,204 | 2,204 | 2,203 | 2,203 | 2,203 | 2,199 | 1,749 | 636 |
| R-squared | 0.019 | 0.306 | 0.307 | 0.310 | 0.326 | 0.327 | 0.458 | 0.718 |
| Year FE | NO | YES | YES | YES | YES | YES | YES | YES |
| Country FE | NO | YES | YES | YES | YES | YES | YES | YES |

**Table 2.** Baseline WLS regression results following Eq. 1. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Interestingly, low-wage regions appear to be more susceptible to automation exposure than high-wage regions (–0.084** vs. 0.004 in high-wage areas), suggesting that automation disproportionately affects regions with lower wage structures. Contrary to conventional wisdom about automation incentives being strongest in high-wage environments, these results demonstrate that regions with relatively lower wages within the European context suffer more pronounced employment declines. This pattern likely reflects the concentration of automatable occupations in these areas, where standardised manual tasks remain prevalent despite generally higher wage floors compared to global standards. The findings sound a cautionary note for development strategies predicated on labour cost competitiveness, suggesting that within integrated markets like the EU, wage differentials may fail to protect against automation-driven displacement when occupational structures remain anchored in standardised work.

| | (1) High Man. Share | (2) Low Man. Share | (3) High Wage | (4) Low Wage | (5) High GVC part. | (6) Low GVC part. | (7) Low ISCO | (8) High ISCO |
|---|---|---|---|---|---|---|---|---|
| $Exposure_{i,t-1}$ | –0.061* | -0.051* | 0.004 | –0.084** | -0.104*** | –0.029 | -0.098** | –0.038 |
| | (0.036) | (0.028) | (0.029) | (0.036) | (0.035) | (0.025) | (0.042) | (0.027) |
| $Offshorability$ | –0.013 | –0.004 | 0.025** | –0.029** | –0.006 | –0.013 | -0.035** | –0.007 |
| | (0.016) | (0.011) | (0.012) | (0.013) | (0.012) | (0.011) | (0.017) | (0.011) |
| $PriEdu_{i,t-1}$ | 0.021*** | 0.012 | 0.003 | 0.023** | 0.024*** | 0.015** | 0.017*** | 0.002 |
| | (0.006) | (0.008) | (0.007) | (0.009) | (0.007) | (0.007) | (0.005) | (0.013) |
| $GFCF/w_{i,t-1}$ | 0.041*** | 0.027** | 0.044*** | 0.035*** | 0.024*** | 0.073*** | 0.048*** | 0.039*** |
| | (0.011) | (0.011) | (0.009) | (0.008) | (0.008) | (0.010) | (0.010) | (0.008) |
| $ManSh_{i,t-1}$ | 0.034* | 0.005 | –0.016* | 0.029*** | 0.024** | 0.004 | 0.020 | 0.005 |
| | (0.019) | (0.010) | (0.009) | (0.011) | (0.012) | (0.009) | (0.014) | (0.009) |
| Obs. | 1,068 | 1,106 | 1,103 | 1,072 | 1,256 | 924 | 1,035 | 1,138 |
| R-squared | 0.353 | 0.344 | 0.408 | 0.338 | 0.324 | 0.344 | 0.289 | 0.382 |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Country FE | YES | YES | YES | YES | YES | YES | YES | YES |

**Table 3.** WLS Regression Results following Eq. 1. Split-sample analysis dividing regions by above and below median Manufacturing Share (1, 2), Wage (1, 2) and GVC participation. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Global value chain participation emerges as another critical mediating factor of automation impacts, with highly integrated regions showing particularly strong negative employment effects from technological exposure. This heightened sensitivity likely reflects the competitive pressures inherent to export-oriented sectors, where firms face strong incentives to adopt LS technologies to maintain international competitiveness. The differential role of investment across subgroups further underscores these divergent trajectories. While gross fixed capital formation consistently supports employment across all regions, its positive effect is markedly stronger in less GVC-integrated areas, potentially indicating greater capacity for investment to offset automation pressures where technological adoption proceeds more gradually.

The control variables paint a complementary picture of regional dynamics. Offshorability measures produce divergent effects depending on regional context, potentially benefiting higher-wage regions through skill-biased opportunities while exacerbating displacement pressures in lower-wage areas. Educational attainment appears most protective in manufacturing and GVC-intensive regions, where even primary education may provide sufficient skills to navigate technological transitions in predominantly middle-skill environments. Manufacturing specialisation itself shows context-dependent effects, supporting employment in some industrial regions while correlating with decline in high-wage contexts where deindustrialisation pressures dominate. Overall, the results underscore the heterogeneous effects of automation across regions, with manufacturing-intensive, low-wage, and high-GVC regions experiencing the most pronounced employment declines. These regions represent the so-called left-behind places of Europe (Bez and Virgillito, 2024).

The last two columns of Table 3 (Columns 7 and 8) distinguish between *High ISCO* occupations, encompassing managerial, professional, technical, clerical, and service/sales roles, and *Low ISCO* occupations, which include craft trades, machine operators, assemblers, and elementary positions. The significantly stronger negative effect of exposure on employment in Low ISCO occupations (–0.098** vs. –0.038) reveals a structural vulnerability: regions with larger shares of manual and routine-intensive roles experience disproportionately severe employment declines from automation.

The differential impacts of automation exposure across occupational groups underscore the critical role of workforce composition in mediating technological shocks. This divergence aligns with task-based theories of technological displacement, where occupations reliant on codifiable physical or procedural tasks face higher substitution risks. The muted effect in High ISCO occupations likely reflects the comparative resilience of cognitive, non-routine roles to LS technologies. Notably, the persistent significance of investment ($GFCF/w$) across both groups (0.048*** and 0.039***) suggests capital deepening mitigates displacement pressures, though its efficacy diminishes in skill-intensive contexts.

The results crystallise a key narrative: occupational structure, more than sectoral specialisation, dictates regional adaptability to automation. Regions anchored in Low ISCO occupations, often peripheral manufacturing hubs, face compounding risks from both technological exposure and limited skill buffers, whereas areas with diversified skill profiles exhibit greater labour market resilience.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Southern EU | Eastern EU | Core EU | Core EU + Anglo EU |
| $Exposure_{i,t-1}$ | –0.062* | –0.354*** | 0.040 | 0.009 |
| | (0.036) | (0.082) | (0.035) | (0.031) |
| $Offshorability_i$ | –0.001 | –0.096*** | 0.025* | 0.025* |
| | (0.013) | (0.032) | (0.015) | (0.014) |
| $PriEdu_{i,t-1}$ | 0.033** | 0.021 | 0.008 | 0.005 |
| | (0.014) | (0.018) | (0.005) | (0.005) |
| $GFCF/w_{i,t-1}$ | 0.062*** | 0.077*** | 0.060*** | 0.043*** |
| | (0.012) | (0.015) | (0.010) | (0.010) |
| $ManSh_{i,t-1}$ | 0.005 | 0.128*** | 0.040 | 0.009 |
| | (0.010) | (0.040) | (0.035) | (0.031) |
| Obs. | 797 | 422 | 927 | 1,020 |
| R-squared | 0.387 | 0.344 | 0.293 | 0.361 |
| Year FE | YES | YES | YES | YES |
| Country FE | YES | YES | YES | YES |

**Table 4.** WLS Regression Results following Eq. 1. Split-sample analysis dividing regions in four macro areas. Appendix A1 reports regions belonging to macro EU Areas. Robust standard errors in parenthesis *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To conclude the investigation on the relationship between exposure to LS technology and employment growth, Table 4 presents regression results stratified by European macro-regions. Among all the potential splits available across EU regions, we opted for country-wise region grouping. Southern EU covers Portugal, Spain, France, Italy, and Greece; Core EU encompasses Austria, Germany, Switzerland, Belgium, the Netherlands, Finland, Sweden, and Denmark, while Anglo EU accounts for the UK and Ireland. Finally Eastern EU groups ex-Soviet economies, namely Poland, Estonia Lithuania, Latvia, Bulgaria, Czechia, Slovenia, Slovakia, Romania, Hungary, and Croatia.

The regional analysis reveals striking geographical disparities in how automation exposure affects employment dynamics across Europe. The negative coefficients in South and East Europe (–0.062* and –0.354***, respectively) contrast sharply with the positive association in Core Europe (0.04), highlighting how production structures, specialisation patterns and GVC positioning fundamentally shape technological impacts. This divergence becomes particularly apparent when examining Eastern Europe, where extreme vulnerability to automation coincides with manufacturing specialisation. The 0.128*** coefficient on manufacturing share suggests that industrial concentration may be sustaining employment despite technological pressures, while the lack of statistical significance of Core and South Europe's manufacturing coefficients reflects deindustrialisation trends coupled with service-oriented specialisation.

The workforce composition emerges as a critical differentiator, with Core Europe's positive exposure effect likely stemming from its specialisation in high-value activities where technology complements rather than replaces labour. This pattern reverses dramatically in Eastern Europe, where the workforce structure anchored in routine manufacturing roles makes employment far more susceptible to automation. Educational attainment shows a positive correlation only in the South.

Investment, proxied by GFCF, demonstrates universal benefits except in Northern Europe, where its insignificant coefficient potentially indicates shift towards services where investments have a minor impact. The offshorability results further reinforce the core-periphery dynamics, with negative effects in Eastern Europe (–0.096***) contrasting with positive associations in Core Europe (0.025*). This pattern again suggests that globalisation impacts depend crucially on a region's position within European production networks.

Overall, the results underscore the uneven impact of automation across European regions, with Southern and Eastern Europe emerging as the most vulnerable and Core Europe showing greater resilience, despite high ex-ante exposure, particularly in Germany. Furthermore, the analysis reveals how regional economic trajectories are increasingly determined by underlying occupational structures, rather than sectoral composition alone.

## 6. Conclusions

This article represents a step forward in measuring occupational exposure to labour-saving technologies in European labour markets. By leveraging natural language processing techniques, Montobbio et al. (2024) identified labour-saving robotic patents and mapped their exposure to specific human tasks and occupations within the O*NET database. Their findings allowed us to construct a fine-grained measure of occupational exposure linked to European employment and wage data at the NUTS-2 level. Our analysis provides a comprehensive understanding of how labour-saving technical change influences labour markets across European regions. In addition, we link exposiure to automation with the role of sectoral specialisation, global value chain integration, and regional economic structures.

Our results reveal that occupations involving manual dexterity, object manipulation, and repetitive tasks, such as industrial truck operators, packaging machine operators, and medical appliance technicians, are the most exposed to labour-saving technologies. These occupations are predominantly clustered in manufacturing, logistics, and, to a lesser extent, healthcare and education. Econometric analysis confirms that higher exposure to labour-saving technologies is associated with lower regional employment levels and wage reductions. These effects are particularly pronounced in manufacturing-intensive regions, low-wage areas, and regions deeply integrated into global value chains. Interestingly, while Eastern Europe exhibits high exposure to automation, it demonstrates greater resilience in terms of employment outcomes compared to Southern Europe, where the negative effects are more severe. Core European regions, particularly those with a strong service orientation, appear less affected, reflecting the lower susceptibility of service sectors to automation.

The relationship between exposure to labour-saving technologies and employment dynamics is not uniform. For instance, some highly exposed occupations, such as those in transportation and material moving, have experienced positive employment growth, likely driven by demand-side factors that offset the labour-saving effects of automation. This highlights the importance of considering both technological and economic factors when assessing the impact of automation. Additionally, our measure of exposure is conservative, as the similarity matrix between Cooperative Patent Classification codes and occupational tasks is sparse (Montobbio et al., 2024), with high similarity values being relatively rare. This suggests that our estimates of occupational displacement are cautious and may even underestimate the overall effect.

The strengths of our approach lie in its objectivity and generality. By using a natural language processing procedure, we avoid subjective expert judgments and create a measure that applies to the entire spectrum of technological and occupational classifications. This allows for a robust and scalable analysis of automation impact across different contexts. The measure is exogenous and not affected by the current employment structure. Our study, however, presents some limitations. First, it assumes that the task intensity and distribution between the US and Europe is similar. Second, the measure represents a theoretical exposure rather than an effective estimate.

Nonetheless, the findings of the present study have important social and policy implications. The disproportionate impact of automation on manufacturing-intensive and low-wage regions underscores the need for targeted interventions to support vulnerable workers. Policymakers should prioritise reskilling and upskilling programmes, particularly in regions heavily reliant on standardised occupations, to facilitate transition towards less automatable roles. This highlights the potential for policies that strengthen regional cohesion and foster innovation in high-value-added activities. Finally, the relatively lower impact of automation in service-oriented regions points to the importance of economic diversification as a strategy to mitigate the disruptive effects of technological change.

In conclusion, this article contributes to the growing literature on the labour market effects of automation by providing a detailed, region-specific analysis of the European context. The results highlight an uneven distribution of automation impact across Europe, emphasising the need for tailored policy responses to address the unique challenges faced by different regions. As technological change continues to reshape labour markets, understanding these dynamics will be crucial for designing policies that promote inclusive growth and mitigate the disruptive effects of automation. Future research could extend the present analysis to other technologies, labour markets beyond Europe, and input-output data, offering even deeper insights into the complex relationship between automation, labour markets and productive specialisation.

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**Appendix**

**Appendix A**

**Region Coverage**

Countries are classified based on their region of belonging. Southern Europe comprises Italy, Spain, Portugal, and Greece. Eastern Europe includes Czechia, Croatia, Hungary, Finland, Lithuania, Latvia, Poland, Slovenia, and Romania. All remaining European countries are classified as Core Europe. Within Core Europe, we further distinguish regions by their manufacturing share of regional GDP. Regions with a manufacturing share below the European median are classified as *Core Service* that is, regions containing a national capital, irrespective of their manufacturing share. We make two exceptions to this broad country-based definition: Northern Italian regions are treated as part of Core Europe due to their strong economic linkages with German manufacturing, while southern France regions on the Mediterranean see are treated as Southern EU. In a series of robustness checks, we test that the aforementioned exceptions do not impact the main results.

| **MACRO-REGION** | **NUTS2 REGIONS INCLUDED** |
|---|---|
| SOUTHERN EU | EL41 EL42 EL43 EL51 EL52 EL53 EL54 EL61 EL62 EL63 EL64 EL65 ES11 ES12 ES13 ES21 ES22 ES23 ES24 ES41 ES42 ES43 ES51 ES52 ES53 ES61 ES62 ES63 ES64 ES70 FRJ1 FRL0 ITC3 ITF1 ITF2 ITF3 ITF4 ITF5 ITF6 ITG1 ITG2 ITI1 ITI2 ITI3 PT11 PT15 PT16 PT18 PT20 PT30 |
| CORE MANUFACTURING | AT22 AT31 AT34 BE22 DE11 DE12 DE13 DE14 DE21 DE22 DE23 DE24 DE25 DE26 DE27 DE40 DE50 DE60 DE71 DE72 DE73 DE80 DE91 DE92 DE93 DE94 DEA1 DEA2 DEA3 DEA4 DEA5 DEB1 DEB2 DEB3 DEC0 DED2 DED4 DED5 DEE0 DEF0 DEG0 FRC2 FRF1 FRF3 ITC1 ITC2 ITC4 ITH1 ITH2 ITH3 ITH4 ITH5 |
| CORE SERVICE | AT11 AT12 AT13 AT21 AT32 AT33 BE10 BE21 BE23 BE24 BE25 BE31 BE32 BE33 BE34 BE35 CH01 CH02 CH03 CH04 CH05 CH06 CH07 CZ01 DE30 DK01 DK02 DK03 DK04 DK05 EL30 ES30 FI1B FRB0 FRC1 FRD1 |

| | |
|---|---|
| | FRD2 FRE1 FRE2 FRF2 FRG0 FRH0 FRI1 FRI2 FRI3 FRJ2 FRK1 FRK2 FRM0 IE04 IE05 IE06 ITI4 LU00 NL00 PL90 PT17 RO32 SE11 SE12 SE21 SE22 SE23 SE31 SE32 SE33 SK01 UKC0 UKD0 UKE0 UKF0 UKG0 UKH0 UKI0 UKJ0 UKK0 UKL0 UKM0 UKN0 |
| EASTERN EU | CZ02 CZ03 CZ04 CZ05 CZ06 CZ07 CZ08 EE00 FI19 FI1C FI1D FI20 HR00 HR03 HR04 HU10 HU21 HU22 HU23 HU31 HU32 HU33 LT00 LV00 PL21 PL22 PL41 PL42 PL43 PL51 PL52 PL61 PL62 PL63 PL71 PL72 PL81 PL82 PL84 RO11 RO12 RO21 RO22 RO31 RO41 RO42 SK02 SK03 SK04 |

**Table A1.** Macro European Regions categorisation.

**Appendix B.**

Cross Correlation Matrix for the variables employed in regressions

| | ΔEmp | $Exposure$ | $Offshorabilit$ | $PriEdu$ | $GFCF/w$ | $ManSh$ |
|---|---|---|---|---|---|---|
| $\Delta Emp$ | 1.000 | | | | | |
| $Exposure$ | –0.008 | 1.000 | | | | |
| $Offshorabilit$ | –0.015 | 0.308 | 1.000 | | | |
| $PriEdu$ | 0.007 | –0.362 | –0.515 | 1.000 | | |
| $GFCF/w$ | 0.045 | –0.110 | 0.150 | –0.070 | 1.000 | |
| $ManSh$ | –0.013 | 0.792 | 0.592 | –0.342 | –0.108 | 1.000 |

**Table A2.** Cross correlation matrix. All variables are either log transformed or 3-year log-change.

Descriptive statistics for the variables employed in regressions

| | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| $\Delta Emp$ | 0.033 | 0.348 | –0.189 | 0.401 |
| $Exposure$ | 3.865 | 0.190 | 2.650 | 4.605 |
| $Offshorabilit$ | 3.658 | 0.361 | 0.758 | 4.605 |
| $Offshorabilit$ | –1.856 | 0.626 | –4.093 | –0.334 |
| $GFCF/w$ | 2.627 | 0.693 | 0.931 | 9.247 |
| $ManSh$ | –1.932 | 0.5290 | –5.079 | –1.009 |

**Table A3.** Descriptive statistics. All variables are either in log or 3-years log-changes.

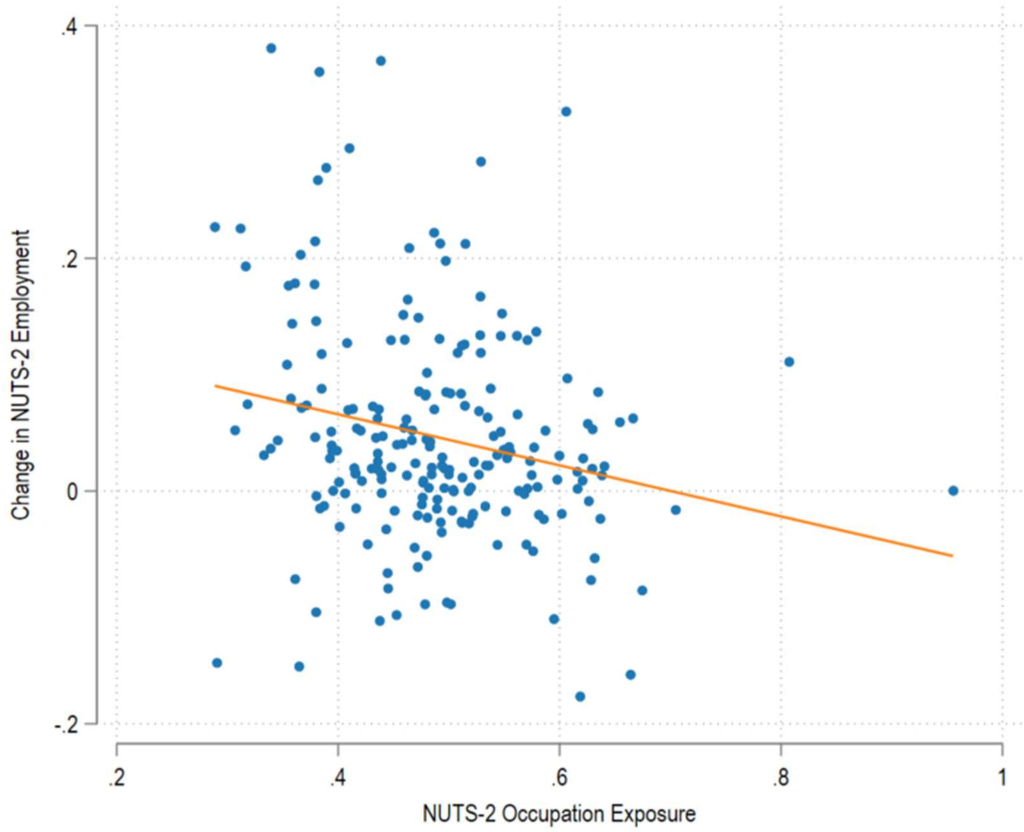


**Figure A1.** Average unconditional relation between occupation exposure and change in employment at the NUTS-2 Region Level.