Italian Labour Law e-Journal
Issue 2, Vol. 17 (2024)
ISSN 1561-8048
https://doi.org/10.6092/issn.1561-8048/20803

The Geography of New Technology: Exposure to AI, Software and Robots in European Regional Labour Markets

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Abstract

This research examines the differentiated regional exposure to new technologies across Europe. Over the past 40 years, biased technological change, particularly the rise of computer technologies, has led to declining employment in routine occupations, with varying local impacts; some regions benefit, while other struggle. Recent adoption of AI-technologies will likely bring equally significant and regionally varied employment effects. With this as a backdrop, we assess regional exposure to AI, software, and robots by linking occupation-level exposure measures to NUTS-2 regions. Using data from the European Union Labour Force Survey, we show that i) AI exposure is particularly high in high-skilled regions and Robots and Software exposure in low- and middle educated areas and ii) that there are stark differences between Western/Northern regions and Eastern/Southern regions in the EU with the latter typically showing greater exposure to technology.

Keywords: Technological Change; EU-LFS; Regional Labour Markets; Artificial Intelligence; Robots; Software; Inequality.

1. Introduction.

Technological change has been extensively documented to alter the production of goods and services. Activities where technology has a comparative advantage over humans are

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[β] The article has been amended in date 2025-01-09. The amendment regarded the Table no. 3 that was graphically incorrect. *See* the Erratum: https://doi.org/10.6092/issn.1561-8048/21074.

increasingly automated, leading to a decreased demand for workers traditionally performing these tasks. Simultaneously, it has increased demand for those who are able to work with technology and become more productive. This shift has exacerbated inequality among workers. Those in jobs with tasks where technology excels have experienced declining real wages and reduced employment opportunities, while individuals whose tasks are complemented by technology have seen growth in both wages and employment.

Research on biased technological change has shown that the rise of computer technologies over the past 40 years has led to declining employment in routine and repetitive occupations that have larger overlap with automation capabilities of machines in the 80s until the early 2000s.[1] The impact has varied locally, with some regions more affected than others.[2] This can be partly explained by regional differences in exposure to automation technology.[3] That is, regional differences in the occurrence of jobs that are influenced by the adoption of the new technologies. Regions that heavily relied on manufacturing, for example, have seen a significant shift in employment in response to the adoption of automated processes (robots) in production. Employment in regions that relied more on service employment has remained more stable.[4]

With the rapid advancement of Artificial Intelligence (AI) and its integration into daily work environments, similar regionally differentiated employment impacts can be expected. It is unclear though whether this will unfold along similar lines as for earlier technological changes. AI is increasingly able to undertake tasks requiring creativity, innovation, and problem-solving – areas historically dominated by humans – and as a result the employment advantages of workers in these roles may diminish. AI may then impact other jobs and tasks than earlier advancements and with that, the regions most affected may also be different. Therefore, understanding exposure to AI-related technologies, also in relation to other technologies, is crucial for anticipating future inequalities. This is especially relevant since previous waves of task-replacing technologies, such as computer software and robots, have led to growing inequalities between those workers whose tasks can be replaced, and those who still hold a comparative advantage over technology.[5]

This paper investigates the geographical distribution of exposure to various emerging technologies, including robots, software, and artificial intelligence. Specifically, it seeks to identify regions in Europe where exposure to these technologies is most pronounced. To do

[1] Acemoglu D., Autor D.H., *Skills, Tasks and Technologies: Implications for Employment and Earnings*, in *Handbook of Labor Economics*, 4, 2011, 1043–1171; Autor D.H., Dorn D., *The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market*, in *American Economic Review*, 103, 5, 2013, 1553–1597; Goos M., Manning A., Salomons A., *Explaining Job Polarization: Routine-Biased Technological Change and Offshoring*, in *American Economic Review*, 104, 8, 2014, 2509–2526.

[2] Terzidis N., Ortega-Argilés R., *Employment polarization in regional labor markets: Evidence from the Netherlands*, in *Journal of Regional Science*, 2021, 1–31.

[3] Crowley F., Doran J., McCann P., *The vulnerability of European regional labour markets to job automation: the role of agglomeration externalities*, in *Regional Studies*, 55, 10/11, 2021, 1711–1723.

[4] Dauth W., Findeisen S., Sedum J., Woessner N., *The Adjustment of Labor Markets to Robots*, in *Journal of the European Economic Association*, 19, 6, 2021, 3104–3153; Gregory T., Salomons A., Zierahn U., *Racing with or Against the Machine? Evidence from Europe*, in *Journal of the European Economic Association*, 2021.

[5] Autor D.H., Dorn D., nt. (1); Autor D.H., Levy F., Murnane R.J., *The Skill Content of Recent Technological Change: An Empirical Exploration*, in *The Quarterly Journal of Economics*, 118, 4, 2003, 1279–1333; Webb M., *The Impact of Artificial Intelligence on the Labor Market,* in *SSRN Electronic Journal*, 2019.

so, we use data on technology-exposure on the occupation-level for three different types of labour-replacing technology: Software, Robots and AI. We merge this data to regional statistics to observe where exposure to these three types of technology is strongest.

2. Literature review.

2.1. Background.

The technological changes of the past decades have undeniably had a significant impact on the organization of work, with some workplaces, workers, and tasks being more subject to change than others. Within labour economics, several attempts have been made to investigate the dimensions along which technological change creates wage inequalities and inequalities in employment opportunities. Generally, two main hypotheses are dominant: that technology is either predominantly skill-biased, or routine-biased.

The skill-biased technological change hypothesis posits that technology primarily benefits highly educated and skilled workers.[6] They are able to keep up with modern technologies, utilize them, and increase their productivity. A good example of this is the rapid adoption of computers in the workplace in the 1980s and 1990s, as described in Autor, Katz and Krueger.[7] These enabled many to perform tasks that were previously impossible, such as big data analysis, sending emails, or searching for information on the internet, or to carry out existing tasks more quickly, for instance scanning documents, writing text, or making calculations in spreadsheets. It was primarily college-educated workers who began using computers intensively.[8] People who were unable to use such technologies fell behind in the labour market. Evidence for this hypothesis was provided by the growing wage premium for employees with a university degree.[9]

A later strand of literature argued that skill-biased technological change could not fully explain *why* college-educated workers received a premium.[10] It could, for example not account for job polarization: the phenomenon of growing employment at the tails of the wage distribution and a relative decline in middle-paying occupations in the US[11]and Europe.[12] For example, between 1980 and 2016, there has been a stark increase in the number of employed managers and professionals, typically positions filled by higher-educated workers, and a

[6] Katz L.F., Murphy K.M., *Changes in Relative Wages, 1963-1987: Supply and Demand Factors*, in *The Quarterly Journal of Economics*, 107, 1, 1992, 35–78; Autor D.H., Katz L.F., Krueger A.B., *Computing Inequality: Have Computers Changed the Labor Market?*, in *The Quarterly Journal of Economics*, 113, 4, 1998, 1169–1213; Caroli E., Van Reenen J., *Skill-Biased Organizational Change? Evidence from A Panel of British and French Establishments*, in *The Quarterly Journal of Economics*, 116, 4, 2001, 1449–1492; Autor D.H., Levy F., Murnane R.J., nt. (5); Goldin C., Katz L.F., *The Race between Education and Technology: The Evolution of U.S. Educational Wage Differentials, 1890 to 2005*, in *NBER – National Bureau of Economic Research*, 2007, available at: https://www.nber.org/papers/w12984 (accessed 11 October 2021).

[7] Autor D.H., Katz L.F., Krueger A.B., *ibidem*.

[8] Autor D.H., Katz L.F., Krueger A.B., *ibidem*.

[9] Autor D.H., Katz L.F., Krueger A.B., *ibidem*; Katz L.F., Murphy K.M., nt. (6).

[10] Autor D.H., Levy F., Murnane R.J., nt. (5).

[11] Autor D.H., Katz L.F., Kearney M.S., *The Polarization of the U.S. Labor Market*, in *American Economic Review*, 96, 2, 2006, 189–194.

[12] Goos M., Manning A., Salomons A., *Job Polarization in Europe*, in *American Economic Review*, 99, 2, 2009, 58–63.

relative decline in jobs that require fewer skills. Yet, at the same time, there has also been an increase in low-skilled work, such as servers and guards. This uptick in low-skilled work does not align with the monotonic increase in employment by skill level predicted by the skill-biased technological change hypothesis, leading to the emergence of a new hypothesis: Routine-Biased Technological Change – RBTC.[13]

In contrast to skill-biased change, the RBTC hypothesis explains the characteristic U-shape of employment changes over the previous decades by highlighting the fact that most technologies have a specific comparative advantage in executing routine tasks, and not necessarily in low-skilled tasks.[14] Routine tasks historically took place in the lower to middle part of the wage distribution, with jobs such as machine operators, craft workers and clerks. These occupations share a common feature: a large part of the activities in these occupations can be classified as being routine-intensive. Such tasks are either repetitive in nature from a manual perspective, such as making repetitive movements typical of assembly line work, or from a cognitive perspective, such as performing the same activity repeatedly, like filling out forms.

Yet, despite the widespread presence of computers and other automation technologies in today's workplace and subsequent predictions that up to 47% of occupations could be replaced by automation[15] there has not been a significant increase in joblessness, not even for workers that used to execute routine tasks.[16] One explanation for this is that workers have adapted their work activities, either by shifting *within* occupations, increasing the non-routine content of their jobs towards tasks requiring social interaction or cognitive abilities,[17] or by transitioning *across* occupations. In the latter case, workers have moved either towards lower-paying, low-skilled occupations or, if feasible, to higher-paying occupations that experienced increased demand due to technological change.[18]

One other explanation is that as technology complements work (such as nonroutine abstract tasks) and replaces work (such as routine tasks), it also creates new work.[19] The majority of new employment opportunities are concentrated in either high-paid professional roles or low-paid service positions.[20] This trend suggests that as technological advancements diminish opportunities for middle-paid production and clerical occupations, they

[13] Autor D.H., Dorn D., nt. (1); Goos M., Manning A., Salomons A., nt. (1).
[14] Acemoglu D., Autor D., nt. (1).
[15] Frey C.B., Osborne M.A., *The future of employment: How susceptible are jobs to computerisation?,* in *Technological Forecasting and Social Change*, 114, 2017, 254–280.
[16] Autor D.H., *Why Are There Still So Many Jobs? The History and Future of Workplace Automation*, in *Journal of Economic Perspectives*, 29, 3, 2015, 3–30; Autor, D. H., Salomons A., *Robocalypse Now–Does Productivity Growth Threaten Employment?*, in *ECB Forum on Central Banking Proceedings*, 2017.
[17] Spitz-Oener A., T*echnical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure*, in *Journal of Labor Economics*, 24, 2, 2006, 235–270; Arntz M., Gregory T., Zierahn U., *Revisiting the risk of automation*, in *Economics Letters*, 159, Supplement C, 2017, 157–160.
[18] Cortes G.M., *Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data*, in *Journal of Labor Economics*, 34, 1, 2015, 63–105; Cortes G.M., Jaimovich N., Siu H.E., *Disappearing routine jobs: Who, how, and why?*, in *Journal of Monetary Economics*, 91, 2017, 69–87.
[19] Acemoglu D., Restrepo P., *Automation and New Tasks: How Technology Displaces and Reinstates Labor*, in *Journal of Economic Perspectives*, 33, 2, 2019, 3–30.
[20] Autor D., *New Frontiers: The Origins and Content of New Work, 1940–2018**, in *The Quarterly Journal of Economics*, 2024.

concurrently create new employment prospects in other areas. Hence, technology also facilitates the potential for movements across occupations, as evidenced in studies by Cortes and others.[21] High overlap between human capabilities and technological capabilities therefore do not need to imply that humans will be replaced by technology necessarily, as technology can also create new tasks and enable shifts to other existing tasks.

2.2. Differentiated effects of technologies.

In the early studies on the effects of technology on the labour market, the primary focus was on the rapid computerization of the workplace. In recent years, there has been growing interest in various types of technologies and how each uniquely shapes labour market inequalities. For example, Webb analyses patent texts of robot, software, and AI technologies to examine the exposure of different occupations to various forms of automation technology.[22] His research shows that robots, which are primarily capable of repetitive, manual movements, strongly correlate with low-income jobs that involve both routine and nonroutine manual tasks, a finding empirically corroborated in European countries.[23] In contrast, software technologies overlap more with jobs in the middle of the wage distribution, encompassing a wide range of tasks except for social tasks.[24] Thus, both software and robots demonstrate the capabilities of technology underlying the skill-biased and routine-biased technological change hypothesis: these technologies predominantly affect low- to medium-skilled jobs and overlap mostly with routine and manual tasks, leaving nonroutine cognitive tasks for high-skilled workers.

Interestingly, patents related to artificial intelligence suggest that this specific technology might be capable of taking over an entirely different type of job, specifically those that have not yet been threatened by technological change. Webb's analysis clearly shows that the overlap between the tasks performed by humans and the capabilities of AI is greatest in high-skilled occupations and nonroutine cognitive analytical tasks.[25] This contradicts both the routine-biased technological change (RBTC) and skill-biased technological change (SBTC) hypotheses that would predict technology replaces either i) routine-intensive work or ii) low-skilled work. AI may not be biased against low- and middle-skilled jobs, but rather, it could pose a threat to high-skilled professions.

In that sense, AI offers a unique opportunity to extend the importance of human expertise, allowing a broader range of workers with complementary knowledge to perform higher-stakes decision-making tasks. This has the potential to restore the middle-skill, middle-class segment of the labour market that has been hollowed out by automation.[26]

[21] Cortes G.M., nt. (18); Cortes G.M., Jaimovich N., Siu H.E., nt. (18).
[22] Webb M., nt. (5).
[23] Nikolova M., Lepinteur A., Cnossen F., *Just Another Cog in the Machine? A Worker-Level View of Robotization and Tasks*, in *GLO Discussion Paper Series*.
[24] Webb M., nt. (5).
[25] Webb M., *ibid.*
[26] Autor D., *Applying AI to Rebuild Middle Class Jobs*, in *NBER - National Bureau of Economic Research*, 2024, available at: https://www.nber.org/papers/w32140 (accessed 22 May 2024).

Indeed, some argue that AI could decrease the relative return to high-skilled labour, to the benefit of lower skilled workers.[27] Early empirical evidence on the impact of AI on wage inequality suggests that this phenomenon may be occurring: the wage premium for performing nonroutine analytical tasks in AI-intensive industries is less substantial compared to that in robot- or other computer-intensive industries.[28]

Of specific interest to economic geographers and regional economists are the spatial differences in the labour market effects of technological change. The evidence on this is relatively sparse,[29] as most labour economics papers focus on economy-wide phenomena. One key paper that bears strong similarity to ours in methods is that of Crowley et al,[30] who analyse the vulnerability of European regional labour markets to 'Industry 4.0', based on automation exposure measures – that is the susceptibility of jobs to being substituted by automated processes – constructed by Frey and Osborne.[31] They show that workers in more diversified regions with higher population densities and higher shares of knowledge and creative workers have a greater ability to adapt to automation shocks. Such regions are less vulnerable to job replacement by automation.

A study using Webb's measures, although not focused on European regions, shows variation in the exposure to AI, software, and robot technologies across European countries.[32] It reveals that AI exposure impacts employment differently across regions. In the Netherlands, for example, employment in AI-exposed occupations has increased, while in Greece there is a decline in AI-exposed occupations. This suggests that the Dutch labour market is more susceptible to the impact of AI than the Greek one. Regarding wages, the overall effect across countries is insignificant, but individual countries show varying results. For example, the return to AI is negative in the Netherlands, France, and Belgium, but positive in Lithuania, Ireland, and Austria.[33] This underscores that various technologies can affect workers in diverse ways:[34] they may reduce employment in AI-exposed occupations by automating tasks (task replacement), yet simultaneously increase demand for these occupations if AI complements human activities (task creation or task augmentation). Both this study as well as that by Crowley et al.[35] highlight that the impacts of technology may differ strongly across space, and that those impacts are shaped by local institutions and labour market characteristics.

[27] Bloom D.E., Prettner K., Saadaoui J., Veruete M., *Artificial Intelligence and the Skill Premium*, in *NBER - National Bureau of Economic Research*, 2024, available at: https://www.nber.org/papers/w32430 (accessed 22 May 2024).
[28] Cnossen F., *Tasks, Wages and Technologies*, in *Industrial Relations*, 2024, e-pub ahead of print, available at: https://doi.org/10.1111/irel.12380 (accessed on 30 October 2024).
[29] Ciffolilli A., Muscio A., *Industry 4.0: national and regional comparative advantages in key enabling technologies*, in *European Planning Studies*, 26, 12, 2018, 2323–2343.
[30] Crowley F., Doran J., McCann P., nt. (3).
[31] Frey C.B., Osborne M.A., nt. (15).
[32] Albanesi, S., Dias da Silva A., Jimeno J. F., Lamo A., Wabitsch A., *New Technologies and Jobs in Europe*, 2023.
[33] Albanesi, S., Dias da Silva A., Jimeno J. F., Lamo A., Wabitsch A., *ibidem*.
[34] Acemoglu D., Restrepo P., nt. (19).
[35] Crowley F., Doran J., McCann P., nt. (3).

2.3. Hypotheses.

Technological progress around AI, computer use and robotics each have their unique impact on task and, by extension, jobs. Building on this logic, regions can be expected to be exposed to the effects of AI, computer use and robotics in varied ways following the regional job structure as well as regional features that may be more or less conducive to the implementation of the different technologies. Our expectations regarding the regional pattern of exposure are divided in two categories: related to the regional production structure and agglomeration benefits.

Technology exposure indicators overlap with specific types of production processes, with some industries benefiting more from AI technologies than other industries. This suggests that the regional exposure to different technologies unfolds along the lines of the regional industrial composition. For instance, firm-level evidence from the Netherlands suggests that AI is predominantly adopted in industries such as IT and information services, research, and telecommunications.[36] In contrast, robots are more commonly utilized in manufacturing sectors like the metal, machine, and plastics industries.[37] Software, being a general-purpose technology, shows less distinct adoption patterns across industries. Nonetheless, its adoption is highest in insurance, banking, and telecommunications, and relatively low in food and accommodation services, industry, and retail.[38] Ex ante, the following hypotheses are less grounded in existing literature and serve primarily as a guide for our empirical analysis. Our primary interest lies in understanding how relative specialization in various industries shapes exposure scores and explains geographical variation.

H1a: Exposure to AI is higher in regions that are relatively specialized in knowledge-intensive service industries
H1b: Exposure to Software is not related to industrial specialization
H1c: Exposure to Robots is higher in regions with higher shares of employment in manufacturing

Furthermore, based on empirical evidence by Webb and the conceptual model by Bloom et al.,[39] artificial intelligence is predicted to substitute for high-skilled labour, implying that exposure scores to AI are higher for high-skilled jobs relative to low- and middle-skilled jobs. Conversely, robot tasks overlap more strongly with lower skilled jobs, and is predicted to substitute more for those jobs[40] implying increased exposure to robots in lower skilled jobs. Software, or computerization, overlaps with middle-skilled employment.[41] Therefore, our second set of hypotheses is as follows:

[36] Centraal Bureau voor de Statistiek, *StatLine - ICT-gebruik bij bedrijven; bedrijfstak, 2023*, 2023, available at: https://opendata.cbs.nl/statline/#/CBS/nl/dataset/85736NED/table?ts=1721998972558 (accessed 26 July 2024).
[37] Nikolova M., Cnossen F., Nikolaev B., *Robots, meaning, and self-determination*, in *Research Policy*, 53, 5, 2024, 104987.
[38] Centraal Bureau voor de Statistiek, nt. (36).
[39] Webb M., nt. (5). *See* also: Bloom D.E., Prettner K., Saadaoui J., Veruete M., nt. (27).
[40] Nikolova M., Lepinteur A., Cnossen F., nt. (23); Webb M., nt. (5).
[41] Autor D.H., Dorn D., nt. (1).

H2a: Exposure to AI is higher in regions that employ more high-skilled (i.e. tertiary educated) workers
H2b: Exposure to Software is higher in regions that employ more middle-skilled (i.e. higher secondary educated) workers
H2c: Exposure to Robots is higher in regions that employ more low-skilled (i.e. primary and lower secondary educated) workers

In our hypotheses, we refrain from using the task-approach to labour markets that is common in the literature.[42] It posits that technology's capabilities are strongly related to the tasks executed within each occupation. AI commonly refers to systems that exhibit intelligent behaviour by analysing their environment and taking actions to achieve specific goals with a degree of autonomy, whether software-based (e.g., speech and facial recognition systems) or embedded in devices (e.g., autonomous robots like self-driving cars and drones). Conceptually, therefore, these types of activities overlap most with nonroutine cognitive analytical tasks: they have the potential to replace tasks that require problem-solving, creativity and discretion or autonomy. Also, in Webb's analysis,[43] AI overlaps most strongly with these tasks. Software should overlap more with routine tasks, as following from the RBTC literature that is mostly based on the computerization of the labour market.[44] Lastly, robots are machines able to "manipulate" its environment by grasping or moving objects around it. Most of the activities that industrial robots perform are reaching and handling tasks. As such, its capabilities align most with manual tasks, be they routine or nonroutine.[45] However, as both tasks and technology are measured on the occupation-level, the correlation on the region-level is based on the same occupational structure and thus creates too strong correlations.

Regional exposure to technological change can thus be understood as the result of non-random spatial sorting of activities, tasks and jobs. A second underlying mechanisms can be regional features that are more or less conducive to the uptake of new technologies and the speed in which this is done. Agglomeration benefits are particularly relevant in this respect, since they describe the economic advantages that dense places (cities) offer over less dense places (rural areas). They pertain to the sharing of costs, for example for infrastructure and public transport, across many users (Urbanization Economies) and specific advantages for certain activities (Localization Economies). Localization economies emerge in three specific domains; labour markets, input and output relationships between producers and knowledge spill-overs.[46] Knowledge spill-overs are facilitated in dense places as people, firms and economic actors can easily meet both intendedly and unintendedly. This is particularly relevant for the uptake of new technologies. Not only do new technologies emerge relatively often in cities, they are also adopted more quickly in cities as the new knowledge on the technology becomes available more easily. With this in mind, it can be expected that cities

[42] Autor D.H., *The 'task approach' to labor markets : an overview*, in *Journal for Labour Market Research*, 46, 3, 2013, 185–199.
[43] Webb M., nt. (5).
[44] Autor D.H., Levy F., Murnane R.J., nt. (5).
[45] Autor D.H., Levy F., Murnane R.J., *ibid*; Nikolova M., Cnossen F., Nikolaev B., nt. (37); Webb M., nt. (5).
[46] Glaeser E. and others, *Growth in Cities*, in *Journal of Political Economy*, 100, 6, 1992, 1126–1152.

https://doi.org/10.6092/issn.1561-8048/20803

experience a phase-difference when it comes to the exposure to new technologies over and beyond the industrial composition of the places. AI, being the most recent technology is then expected to be particularly relevant for cities compared to less dense areas. In contrast, the employment effects of robots – being the more mature technology – may have already taken place in cities leaving them relatively less exposed currently to the use of robots in production.

H3a: Exposure to AI is higher in dense regions
H3b: Exposure to Software is not related to density
H3c: Exposure to Robots is higher in less dense regions

Table 1 summarizes the expectations regarding the spatial patterns of exposure to the new technologies considered.

Table 1 Hypotheses based on literature framework

	AI	Software	Robots
Regional production structure: industries			
Exposure should be higher in regions with more employment in:	H1a. Knowledge-intensive services	H1b. Unclear ex ante: more General Purpose Technology	H1c. Manufacturing
Regional production structure: skills			
Exposure should be higher in regions with:	H2a. High-skilled employment	H2b. Middle-skilled employment	H2c. Low-skilled employment
Agglomeration benefits			
Exposure should be higher in regions with	H3a. Higher population density	H3b. Unclear ex ante: more General Purpose Technology	H3c. Lower population density

3. Data and methods.

The empirical approach relies on three consecutive steps. In the first step, we establish to what extent task profiles of jobs are exposed to technology by using a measure of the overlap of tasks with the capabilities of the three technologies, following Webb.[47] If there is a strong overlap between the tasks a technology can fulfil and the tasks that together constitute a job, the job is said to be exposed to this technology. That is, the job may be taken over by an automated process rather than performed by a human. We focus on AI, software use and

[47] Webb M., nt. (5).

https://doi.org/10.6092/issn.1561-8048/20803

Robotics technologies. In the second step, these job-level exposure measures are aggregated to the regional level to arrive at a region-level exposure measure, again pertaining to the three different technologies. This then, in effect, measures the relative regional occurrence of jobs that could be taken over by the technology. In the third and final step, regional level information is collected and correlated with the exposure measures to unveil regularities in the spatial patterns of exposure. For this, we use three distinct data sources:

3.1. European Labour Force Survey.

For our main data source, we use the European Union Labour Force Survey (EU-LFS) data for the year 2016, similar to Webb.[48] Our analysis includes all countries for which both International Standard Classification of Occupations (ISCO) data at the 3-digit level and Nomenclature of Territorial Units for Statistics (NUTS2) regional classification data are available. This comprehensive dataset allows us to explore detailed occupational structures and regional variations across Europe, providing valuable insights into labour market dynamics and regional economic disparities.

3.2. Technology exposure data.

For our technology exposure data, we rely on the study by Webb (2019) that collected exposure scores in 2016. For each occupation, he calculates the exposure to AI,[49] robots and software by observing the patent texts of each technology and links it to occupational descriptions. If the texts of the descriptions have strong overlap with the texts of the patents, an occupation will receive a high score on the exposure index of that specific technology.

The definitions for the specific types of technologies are as follows. First, software consists of computer programs that follow manually-specified "if-then" rules. It is considered software, rather than AI, if all actions are predefined by human programmers, who must anticipate every potential scenario and describe the steps required to complete tasks. Common examples include word processing and spreadsheet software, web browsers, and business applications like enterprise resource planning and reservation systems.[50]

When defining robots, the study focuses specifically on *industrial* robots, which are widely adopted in manufacturing and are defined as automatically controlled, reprogrammable manipulators with multiple axes for industrial automation applications. Unlike service sector robots (such as surgical robots or robotic waiters), industrial robots have a standardized definition (ISO 8373). They include examples such as welding or painting car manipulators, material movers, and CNC machine tool tenders, but exclude equipment like assembly line conveyor belts.[51]

[48] Webb M., nt. (5).
[49] Webb M., *ibid.*
[50] Webb M., *ibid.*
[51] Webb M., *ibid.*

https://doi.org/10.6092/issn.1561-8048/20803

Artificial Intelligence refers specifically to machine learning algorithms, focusing on i) supervised learning and ii) reinforcement learning. Supervised learning involves algorithms learning functions that map inputs to outputs from training data pairs, allowing for flexible relationships and diverse data types, such as text or images. For instance, these algorithms can convert images into textual descriptions or predict loan repayment likelihoods from financial histories. Reinforcement learning teaches algorithms to take actions in dynamic environments to achieve objectives, similar to optimal control but applicable to more complex scenarios like robotic manipulation or factory machinery operation. These algorithms learn through trial and error, requiring experimental interaction with the environment or accurate simulations and performance evaluations.

AI is different from robots and software in the types of tasks it can replace. Conceptually, software overlaps with routine-tasks, that are based on 'if-then' clauses, following specific sequences.[52] AI, on the other hand, though also a specific form of software, allows for the possibility of coming up with new solutions, that have not been pre-programmed by a human programmer. There is no clear if-then, and as a result, its tasks have stronger overlap with non-routine elements of work.

The Webb data is available on the eight-digit SOC level, a US-biased occupational classification, which we need to map to three-digit ISCO occupations that are available in the EU-LFS. We use correspondence tables from SOC to ISCO from Hardy, Keister, and Lewandowski.[53] We create occupation-weighted wage percentiles for the full EU population and create occupation-weighted averages of these percentiles for each NUTS2 region. As a result, our final regional measures capture the average percentile exposure score of workers in each specific region, where the local occupational composition is taken into account.

3.3. Eurostat, Regional data.

We have incorporated additional 2016 data from Eurostat[54] with information on the regional socio-economic characteristics relevant to gauge regional differences in exposure to technology. This includes employment indicators such as the unemployment rate and female participation rate, as well as educational metrics like the share of tertiary-educated individuals and rates of primary and middle education completion. Demography variables consist of population change, population density (to proxy for agglomeration benefits), and total population. GDP data is included, both per capita and total GDP by NUTS2 regions, measured in 2020 EU27 Purchasing Power Standards. Occupational structure is analysed using shares from EU-LFS at the ISCO 1-digit level, alongside average routine and nonroutine task components. Finally, technology indicators encompass investment in

[52] Autor D.H., Levy F., Murnane R.J., nt. (5).

[53] Hardy, Keister, and Lewandowski *Educational upgrading, structural change and the task composition of jobs in Europe*, in *Economics of Transition*, 26, 2, 2018, 201–231.

[54] With thanks to Sébastien Fontenay and Sem Vandekerkhove from KU Leuven for making EUROSTATUSE available as STATA code.

https://doi.org/10.6092/issn.1561-8048/20803

research and development, the presence of science and technology personnel, and the share of households with internet access.

We also consider industrial structure, which details relative employment across different sectors and sums to one. Services are divided into knowledge-intensive services (KIS) and less knowledge-intensive services (LKIS), which is based on the share of tertiary educated person at the NACE-2 level. These are constructed by Eurostat. Examples of knowledge-intensive services are telecommunications (NACE code 61), scientific research and development (72), publishing (58), education (85) and human health activities (86).[55] Examples of less knowledge-intensive services are retail (47), postal services (53), accommodation services (55) or food and beverage related services (56).

3.4. Empirical strategy.

Our empirical model is as follows

$$E_r = \alpha + \sum_k \delta_k K_{kr} + \sum_s \beta_s S_{sr} + \gamma P_r + X_r \chi + \mu_c + \varepsilon_r$$

The dependent variable is E_{rt}, the exposure score in region r in 2016, which can refer to AI, Software or Robots, measured as the occupation-weighted average percentile score of all workers in each region. K_{krt} refers to specialization in sector K, where K is the full set of sectors available. S_{srt} is the share of the population with a certain level of education, where s can refer to tertiary, secondary or primary education. Lastly, P_{rt} are region-level measures of population density, to capture agglomeration benefits. X_{rt} refers to other region-specific controls, such as GDP, GDP per capita, population, population growth, unemployment rate, female participation rate. μ_c refers to country-fixed effects, and ε_{rt} is the error term. We only use regions for which we have the full set of controls, and after cleaning our sample consists of 227 NUTS 2 regions.

4. Results.
4.1. Spatial variation in technology exposure.

In this section, we present descriptive statistics of regional variation in technology exposure, our main variable of interest. Figure 1 displays three maps of European NUTS2 regions in our sample, each showing the relative exposure to each of the three automation technologies. The scores reflect regional averages of percentile scores of occupational exposure. The robot exposure scores range from 27.5 to 82.8, indicating that the region with the lowest score has an occupational structure significantly less exposed to robotic automation compared to other regions. For software technologies, the scores range from

[55] Eurostat, *Glossary: Knowledge-intensive services (KIS),* available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Knowledge-intensive_services_(KIS) (accessed on 30 October 2024).

31.5 to 91.4, while for AI, the range spans from 28.2 to 95.2. These are the main dependent variables in the regression analysis later on.

A few notable patterns emerge when we observe the regional variation in the exposure of jobs to automation. First, for all three types of technologies it is clear that some Eastern and Southern European countries (Romania, Poland, Greece) have much stronger exposure scores on average than other countries. One potential explanation for these differences is presented in Appendix Figure A **1**: regions in Nordic and Western countries typically have a higher educated population than in Eastern and Southern regions. In terms of industrial structure, there are also some key differences. Nordic/West regions employ more workers in knowledge-intensive sectors, and especially Eastern regions have higher shares of workers working in manufacturing.

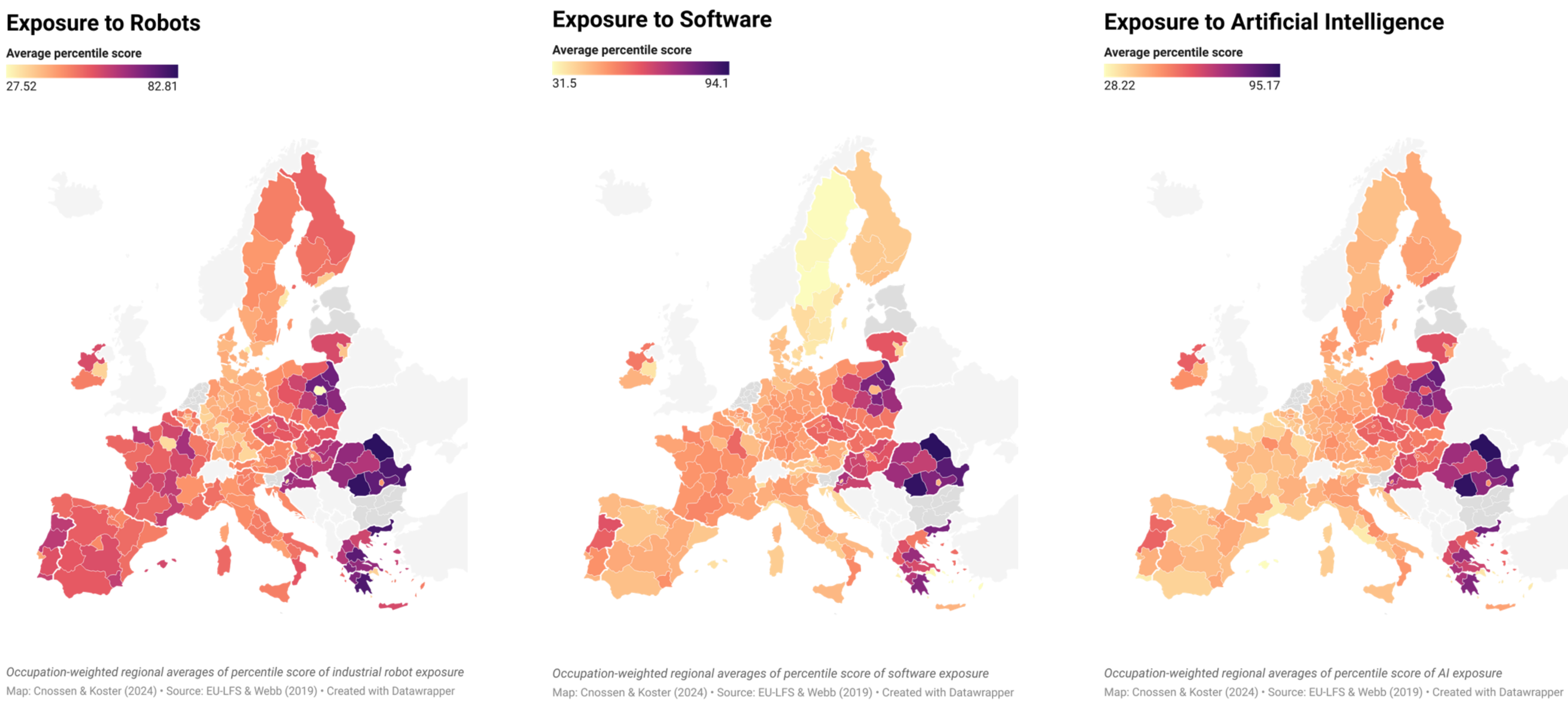
Second, the spatial variation in robot software exposure seems to play out on the rural versus urban dynamic: capital regions such as Paris, Warsaw, Berlin, Prague, Vienna and Bucharest have lower exposure scores than the other regions in their countries. Though NUTS2 data is not fine-grained enough to make claims about the actual city versus hinterland dynamic, the differences between the capital cities do seem to suggest such, which is why we explicitly control for population density in our later estimations.

Third, the patterns seem to correlate geographically to an extent: many regions with high percentile scores on Robots also have high scores for Software and AI exposure. To further explore this, Figure 2 and Table 2 show how the technology exposure measures correlate between one and other across the regions. First, the correlations between all technology exposures measures are positive when observing all regions in Europe. This implies that regions that are exposed to e.g. AI are also exposed to software or robots. The correlation is strongest for software and AI, that are both software-related, but whereas AI focuses on learning algorithms, software patents focus on if-then clauses.

Zooming in further, the scatterplots reveal noticeable differences across groups of countries suggesting that these country groups operate in variegated regimes on interplay between the technologies. The correlation (see Table 2) between AI and Robots is *positive* in East and South European regions, but *negative* in Western and Nordic regions. In other words, while Eastern and Southern regions are more likely to face "double exposure" of both AI and robots, the other regions are more likely to be either relatively more exposed to AI or to robots, but not necessarily at the same time. This is an important finding, as it shows that there could be specific regional characteristics that provide ground for a workforce being more exposed to certain technologies. It is also consistent with the idea that the supra-national country groups are in different phases of the technology life-cycle. This is most salient for software that has spread evenly across regions in the West-group and which is at quite low levels throughout. In short, the labour market seems to have adapted across the entire area. In Eastern European countries, in contrast, there are still quite large differences in the exposure and the level of exposure is relatively high throughout. Both are consistent with the idea that the labour market is still adjusting to software use in production. The regionally specific regimes suggest that policies aimed at addressing the transition challenges that come with new technologies should be region-specific as well.

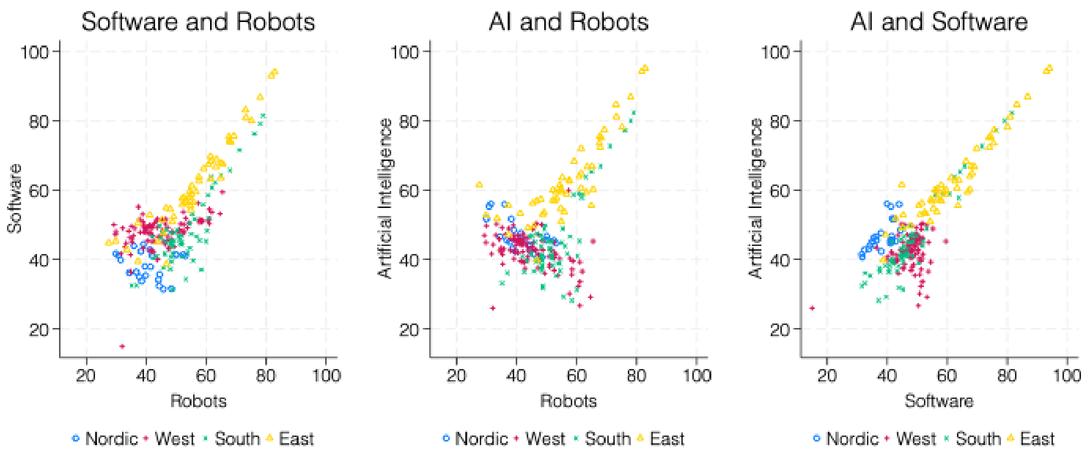
In contrast to AI and robots, AI and Software technologies, correlate positively in all European regions. This suggests there are some characteristics of regions that drive exposure to software, either more complex artificial intelligence taking over nonroutine cognitive tasks as well as simpler software technologies replacing routine (cognitive and manual) tasks.

Figure 1 Spatial variation in Exposure to Robots, Software and Technology



Source: Authors' calculations using data from Webb (2019) and EU-LFS

Figure 2 Scatterplots of technology exposure indicators, split by country block



Source: Authors' calculations using data from Webb (2019) and EU-LFS

Table 2 Correlations between technology exposure measures, split by country block

	N	AI/Robot	AI/Software	Robot/Software
Total EU	227	0,54	0,85	0,75
Split samples:				
Nordic	24	-0,64	0,64	-0,13
West	92	-0,53	0,30	0,42
East	60	0,77	0,85	0,95
South	51	0,82	0,95	0,94

Source: Authors' calculations using data from Webb (2019) and EU-LFS

4.2. What explains technology exposure in regional labour markets?

In the next step of the analysis, we explore, by means of the regression analysis introduced in the methods section, how exposure to technology aligns with regional socio-economic characteristics including skill composition of the work force, industry composition and agglomeration.

presents the results. Columns (1) to (3) show the results for the regional industrial composition. The reference category is manufacturing, and since all other sectors are included and add up to 100, the coefficient can be interpreted as the effect of a percent employment increase in one sector compared to manufacturing. All regressions contain the full set of controls, including country dummies.

Regions with more employment in manufacturing are more exposed to all types of technologies, suggesting that manufacturing jobs align closely with technological capabilities. However, the extent of this exposure varies across different technologies. For example, a one percent increase in knowledge-intensive sectors relative to manufacturing results in a 0.35 percent decrease in exposure to robots and a 0.17 percent decrease in exposure to AI. This indicates that while higher manufacturing employment leads to greater exposure to both robots and AI, the effect is stronger for robots.

In columns (4) to (6), we divide the manufacturing industry into low-tech and high-tech manufacturing to reflect the complexity of tasks performed in these sectors. We find no significant differences in exposure between these manufacturing sectors.

In columns (7) to (9), we include skills-related indicators measured at the population level in a specific region. It is important to note that the knowledge intensity of an industry is determined based on the average share of tertiary employment at the sector level across Europe. However, there may be geographical variation in the skill intensity of these sectors, depending on the local population's skills. Therefore, the skill composition variables capture this additional variation based on skills, which is also evident in the differences between knowledge-intensive and less knowledge-intensive industries.

The inclusion of additional skill measures changes our results. Starting with AI, we see that regions with a higher share of tertiary education (compared to secondary education) are more exposed to AI. This aligns with Webb's (2019) analysis, which also finds that AI overlaps more with jobs held by workers with higher education levels. Conversely, exposure to robots and software is higher in regions where a larger portion of the population has lower education levels. Additionally, we observe that the skill composition correlates with the knowledge intensity of sectors, as the coefficient for knowledge-intensive sectors becomes more strongly negative when education levels are included.

In columns (10) to (12) we complement the skill composition with the detailed industrial sectors, by splitting the different manufacturing sectors. Again, these are insignificant.

Lastly, we observe the role of agglomeration benefits, as proxied by the log of population density. Here we find strong robust results for the fact that AI exposure is higher in denser, more urban regions. In contrast, the association is negative for robots, indicating rural jobs are more exposed to robots. This coefficient is, however, not consistently significantly different from zero, especially not when including skill composition variables.

The spatial patterns across European countries discussed earlier justify an additional regression analysis by country block to determine if the dynamics influencing exposure differ between the regions. Given the correlations in Table 2, we split the sample into Nordic and Western versus Eastern and Southern regions. The results are presented in Table 3.

The findings suggest that the dynamics between Western/Northern regions and Eastern/Southern regions are quite similar. In both groups, regions with a higher share of tertiary-educated workers show greater exposure to AI and lower exposure to robots. Manufacturing is also more closely associated with all technology measures in both groups, with coefficient sizes and signs being roughly the same. Combining this with the results in bi-variate plots in Figure 2, it suggests that the associations between socio-economic regional characteristics and technology exposure are similar across Europe. The East and Southern part of Europe, however, is positioned in a different part of the distribution, experiencing higher exposure levels throughout.

However, there are some notable differences as well. First, population density is insignificant in Western/Northern regions but positive for AI exposure in Eastern/Southern regions, indicating that agglomeration effects are more significant in the latter. This could indeed indicate a phase difference between the supra-national groups with even the newest technologies (AI) impacting evenly across territories in the West and North, while employment associated with AI still concentrates in cities more in Eastern and Southern European countries.

Second, while regions with a larger proportion of lower-educated workers are more exposed to robots and software in the North/West, there is no significant difference in exposure between regions with secondary or primary-educated workforces in the East/South.

In Appendix Table A1 we perform the same analyses as in

, with one key difference. Whereas the baseline regressions omit manufacturing industry's employment, these regressions have knowledge-intensive sectors as omitted categories. This allows us to also compare knowledge-intensive sectors with less knowledge-intensive sectors, to see whether they affect technology exposure differently. The results are in line with the theoretical predictions. AI exposure is higher in regions with relatively more employment in complex services compared to less complex services. The same holds for software technologies. The converse applies to industrial robots, where exposure is higher in regions that employ relatively more workers in less knowledge-intensive sectors. These results are robust for the inclusion of skill and detailed manufacturing covariates.

Table 3 Baseline results: OLS regression of exposure to three types of technology on industries, skills and agglomeration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Industry composition			Split manufacturing			Add education			Split manufacturing		
	AI	Software	Robots	AI	Software	Robots	AI	Software	Robots	AI	Software	Robots
Industrial composition												
Ref. cat.: Manufacturing					*Ref. cat: Low-tech manufacturing*						*Ref. cat: Low-tech manufacturing*	
Knowledge-intensive sectors	-0.17**	-0.21**	-0.35***	-0.19	-0.18	-0.35**	-0.41***	-0.31***	-0.24***	-0.44**	-0.22	-0.18
	(0.09)	(0.10)	(0.08)	(0.19)	(0.21)	(0.17)	(0.10)	(0.10)	(0.09)	(0.18)	(0.20)	(0.16)
Less knowledge-intensive sectors	-0.69***	-0.48***	0.06	-0.69***	-0.43**	0.06	-0.67***	-0.54***	-0.04	-0.68***	-0.45**	0.02
	(0.09)	(0.11)	(0.10)	(0.18)	(0.21)	(0.18)	(0.08)	(0.10)	(0.09)	(0.16)	(0.19)	(0.16)
High-tech manufacturing				0.17	0.14	-0.28				-0.00	0.19	-0.07
				(0.41)	(0.46)	(0.41)				(0.40)	(0.49)	(0.41)
Medium-high tech manufacturing				-0.02	0.18	0.08				-0.05	0.24	0.16
				(0.21)	(0.24)	(0.20)				(0.20)	(0.22)	(0.18)
Medium-low tech manufacturing				-0.10	-0.18	-0.06				-0.04	-0.07	0.02
				(0.32)	(0.33)	(0.28)				(0.30)	(0.31)	(0.26)
Skill composition												
Ref. cat.: Secondary education												
Tertiary education share							0.49***	0.17	-0.25***	0.14**	0.16*	0.03
							(0.10)	(0.12)	(0.09)	(0.07)	(0.08)	(0.04)
Primary education share							0.10	0.26**	0.20**	-0.01	-0.00	-0.02
							(0.08)	(0.11)	(0.08)	(0.05)	(0.06)	(0.02)
Agglomeration benefits												
Population density (log)	1.37**	0.48	-0.93*	1.34**	0.50	-0.93*	1.39**	0.75	-0.66	1.34**	0.74	-0.66
	(0.57)	(0.75)	(0.50)	(0.59)	(0.78)	(0.52)	(0.54)	(0.61)	(0.51)	(0.55)	(0.63)	(0.53)
Constant	62.90**	75.88**	69.73**	66.46**	71.09**	67.62**	66.95**	64.32**	53.38**	70.61**	53.72*	44.99*
	(19.02)	(20.47)	(17.14)	(24.88)	(28.01)	(23.75)	(18.95)	(21.64)	(18.25)	(24.23)	(28.48)	(23.86)
Observations	227	227	227	227	227	227	227	227	227	227	227	227
R-squared	0.897	0.871	0.896	0.898	0.872	0.896	0.908	0.879	0.911	0.909	0.880	0.911

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

https://doi.org/10.6092/issn.1561-8048/20803

Table 4 OLS regressions by country blocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Nordic, West and Ireland			South and East		
	AI	Software	Robots	AI	Software	Robots	AI	Software	Robots
Industrial composition									
Ref. cat.: Manufacturing									
Knowledge-intensive sectors	-0.41***	-0.31***	-0.24***	-0.36***	-0.29**	-0.17*	-0.56***	-0.35*	-0.25
	(0.10)	(0.10)	(0.09)	(0.12)	(0.12)	(0.10)	(0.18)	(0.18)	(0.16)
Less knowledge-intensive sectors	-0.67***	-0.54***	-0.04	-0.16	-0.19	-0.19*	-0.89***	-0.68***	-0.01
	(0.08)	(0.10)	(0.09)	(0.12)	(0.15)	(0.11)	(0.10)	(0.12)	(0.10)
Skill composition									
Ref. cat.: Secondary education									
Tertiary education share	0.48***	0.17	-0.24***	0.48***	0.33*	-0.22**	0.35**	-0.23	-0.39***
	(0.10)	(0.12)	(0.09)	(0.16)	(0.17)	(0.11)	(0.16)	(0.16)	(0.15)
Primary education share	0.11	0.27**	0.20**	0.07	0.45***	0.35***	0.16	-0.24	-0.23
	(0.09)	(0.12)	(0.08)	(0.09)	(0.09)	(0.06)	(0.19)	(0.18)	(0.16)
Agglomeration benefits									
Population density (log)	1.39**	0.75	-0.66	0.69	1.01	0.56	1.75**	0.64	-1.32
	(0.54)	(0.61)	(0.51)	(0.66)	(0.68)	(0.42)	(0.80)	(0.88)	(0.89)
Constant	67.66***	64.60***	52.95***	29.51	28.74	47.66**	103.15**	65.39	17.69
	(19.57)	(21.55)	(17.97)	(19.93)	(22.03)	(18.32)	(51.62)	(54.01)	(41.63)
Observations	227	227	227	119	119	119	108	108	108
R-squared	0.906	0.877	0.911	0.754	0.805	0.922	0.932	0.909	0.888

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

https://doi.org/10.6092/issn.1561-8048/20803

5. Discussion and conclusion.

Research on biased technological change highlights that the rise of computer technologies over the past 40 years has led to reduced employment in routine occupations, particularly from the 1980s to the early 2000s. The impact varies by region, partially because of local differences in the exposure to automation technology; that is the local share of occupations that are influenced by automation. With the rapid advancement of artificial intelligence (AI), this dynamic is expected to shift further. As AI increasingly undertakes tasks requiring creativity and problem-solving – traditionally human domains – the employment advantages of workers in these roles may diminish. Even though the impact of AI on the work force has not yet fully materialized, there are early signs that a different group of workers will be impacted. With that, the regional diverse impact of AI-technologies may therefore also shift and understanding regional exposure to AI is therefore crucial for anticipating future wage and employment inequalities between workers as well as between regions.

This study examines the geographical distribution of exposure to emerging technologies – robots, software, and AI – in Europe. Using data from the European Union Labour Force Survey (EU-LFS) in 2016, we analysed differences in exposure based on differences in industrial structure, skill composition and population density. We used technology exposure data based on Webb's study, which links patent texts of various technologies to occupational descriptions, creating an exposure index for each technology.[56] This exposure is collapsed to the NUTS2 level for over 200 regions in the EU.

Our findings reveal several key patterns. Some Eastern and Southern European countries (e.g., Romania, Poland, Greece) have higher average exposure scores to all technologies. Urban regions, particularly capital cities, tend to have lower exposure scores compared to their rural counterparts, especially for robots and software. Regions with high exposure to one technology often have high exposure to others as well, with the strongest correlation between software and AI. However, the relationship between AI and robots varies geographically – positive in Eastern/Southern regions and negative in Western/Nordic regions – indicating region-specific factors influencing technology exposure.

Regions with more manufacturing employment show higher exposure to all technologies, although the extent of exposure varies across different technologies, with a stronger effect for robots compared to AI. High-tech and low-tech manufacturing sectors do not significantly differ in their exposure levels. Regions with a higher share of tertiary-educated workers are more exposed to AI, aligning with findings that AI overlaps with the tasks in higher-education jobs. Conversely, regions with a relatively lower-educated workforce are more exposed to robots and software. The knowledge intensity of sectors also correlates with skill composition, with stronger negative coefficients for knowledge-intensive sectors when education levels are included. Additionally, AI exposure is higher in denser, urban regions, while robot exposure tends to be higher in rural areas, suggesting that urban areas benefit more from AI, whereas rural areas rely more on jobs exposed to robots.

[56] Webb M., nt. (5).

Analysing regional blocks (Nordic/Western versus Eastern/Southern) reveals similar dynamics in technology exposure, with tertiary-educated regions showing higher AI exposure and lower robot exposure across both blocks. However, agglomeration effects are more significant in Eastern/Southern regions, and there is a notable difference in how lower-educated workers' exposure to robots and software varies between the two blocks.

Even though the analysis unveils distinct spatial patterns in the exposure to the different types of technology, interpretation should be done carefully. The reliance on patent texts to determine technology exposure may not capture all nuances of technology adoption and its impact on occupations. High exposure to a certain technology may imply a higher probability of task-replacement but could equally mean task augmentation. For instance, writing texts is a large part of many occupations, and even though AI can replace some of the writing work, it can also complement it in many occupations where writing is an important task. Similarly, exposure to technology does not necessarily imply the adoption of it, particularly in the short run. The eventual implementation of new technology into the production process also is influenced by labour costs and labour protection that is in place. Relatively low wages as well as strong labour protection may mitigate the (short term) employment effects of new technologies. Exposure to technology must then be interpreted as the potential impact it may have, not the actual take-up.

The data also lacks granularity at finer regional levels such as NUTS3, which could provide more detailed insights into urban versus rural dynamics, especially as our results highlight a pronounced role for population density in explaining variation in technology exposure.

The analysis highlights the complex interplay between technology, skills, and regional characteristics, emphasizing the need for tailored policies to address regional disparities in technology exposure and its socio-economic impacts. Understanding these dynamics is crucial for mitigating future wage and employment inequalities as technological advancements continue to reshape labour markets.

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Disclaimer

This study is based on microdata from Eurostat, EU-LFS 2016 under the project code RPP 292/2020-LFS. The conclusions drawn from the data lies entirely with the authors.

Appendix

A.1. Sector classification: KIS vs LKIS

KIS: Knowledge Intensive Services

High-tech knowledge-intensive services:

- Motion picture, video and television programme production, sound recording and music publishing activities (59);
- Programming and broadcasting activities (60);
- Telecommunications (61);
- Computer programming, consultancy and related activities (62);
- Information service activities (63);
- Scientific research and development (72)

Knowledge-intensive market services (excluding financial intermediation and high-tech services):

- Water transport (50);
- Air transport (51);
- Legal and accounting activities (69);
- Activities of head offices; management consultancy activities (70);
- Architectural and engineering activities; technical testing and analysis (71);
- Advertising and market research (73);
- Other professional, scientific and technical activities (74);
- Employment activities (78);
- Security and investigation activities (80)

Knowledge-intensive financial services:

- Financial service activities, except insurance and pension funding (64);
- Insurance, reinsurance and pension funding, except compulsory social security (65);
- Activities auxiliary to financial services and insurance activities (66)

Other knowledge-intensive services:

- Publishing activities (58);
- Veterinary activities (75);
- Public administration and defence; compulsory social security (84);
- Education (85);
- Human health activities (86);
- Residential care activities (87);
- Social work activities without accommodation (88);
- Creative, arts and entertainment activities (90);
- Libraries, archives, museums and other cultural activities (91);
- Gambling and betting activities (92);
- Sports activities and amusement and recreation activities (93)

LKIS: all other service sectors

https://doi.org/10.6092/issn.1561-8048/20803

Appendix Table A 1 OLS Regression with knowledge-intensive sectors as baseline category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Industry composition			Split manufacturing			Add education			Split manufacturing		
	AI	Software	Robots	AI	Software	Robots	AI	Software	Robots	AI	Software	Robots
Industrial composition												
Ref. cat.: Knowledge-intensive sectors				*Ref. cat: Low-tech manufacturing*						*Ref. cat: Low-tech manufacturing*		
Less knowledge-intensive sectors	-0.52***	-0.26**	0.41***	-0.50***	-0.25*	0.40***	-0.26**	-0.23*	0.21*	-0.24*	-0.23	0.20*
	(0.12)	(0.13)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.14)	(0.12)	(0.13)	(0.14)	(0.12)
Manufacturing	0.69***	0.48***	-0.06				0.67***	0.54***	0.04	-0.68***	-0.45**	0.02
	(0.09)	(0.11)	(0.10)				(0.08)	(0.10)	(0.09)	(0.16)	(0.19)	(0.16)
High-tech manufacturing				0.37	0.32	0.07				0.44	0.41	0.11
				(0.40)	(0.45)	(0.40)				(0.39)	(0.46)	(0.39)
Medium-high tech manufacturing				0.18	0.36**	0.43***				0.40***	0.45***	0.33***
				(0.14)	(0.14)	(0.12)				(0.15)	(0.15)	(0.11)
Medium-low tech manufacturing				0.10	-0.00	0.29				0.40*	0.15	0.19
				(0.22)	(0.24)	(0.20)				(0.23)	(0.23)	(0.20)
Low-tech manufacturing				0.19	0.18	0.35**				0.44**	0.22	0.18
				(0.19)	(0.21)	(0.17)				(0.18)	(0.20)	(0.16)
Skill composition												
Ref. cat.: Secondary education												
Tertiary education share							0.48***	0.17	-0.24***	0.48***	0.16	-0.24**
							(0.10)	(0.12)	(0.09)	(0.10)	(0.12)	(0.09)
Primary education share							0.11	0.27**	0.20**	0.11	0.28**	0.21**
							(0.09)	(0.12)	(0.08)	(0.08)	(0.12)	(0.08)
Agglomeration benefits												
Population density (log)	1.37**	0.48	-0.93*	1.34**	0.50	-0.93*	1.39**	0.75	-0.66	1.34**	0.74	-0.66
	(0.57)	(0.75)	(0.50)	(0.59)	(0.78)	(0.52)	(0.54)	(0.61)	(0.51)	(0.55)	(0.63)	(0.53)
Constant	45.69**	54.66**	34.46*	47.02***	53.38**	32.76*	25.50	33.29	29.09	26.47	32.05	27.32
	(17.65)	(21.02)	(18.01)	(17.76)	(21.11)	(18.30)	(19.40)	(21.18)	(18.52)	(19.35)	(21.40)	(18.78)
Observations	227	227	227	227	227	227	227	227	227	227	227	227
R-squared	0.897	0.871	0.896	0.898	0.872	0.896	0.908	0.879	0.911	0.909	0.880	0.911

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Figure A 1 Differences in skill composition and industrial composition across country blocks