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Diverging paths: AI exposure and employment across European regions

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ABSTRACT

This study explores exposure to artificial intelligence (AI) technologies and employment patterns in Europe. First, we provide a thorough mapping of European regions focusing on the structural factors—such as sectoral specialisation, R&D capacity, productivity and workforce skills—that may shape diffusion as well as economic and employment effects of AI. To capture these differences, we conduct a cluster analysis which group EU regions in four distinct clusters: high-tech service and capital centres, advanced manufacturing core, southern and eastern periphery. We then discuss potential employment implications of AI in these regions, arguing that while regions with strong innovation systems may experience employment gains as AI complements existing capabilities and production systems, others are likely to face structural barriers that could eventually exacerbate regional disparities in the EU, with peripheral areas losing further ground.

1. Introduction

The rapid advancement of artificial intelligence (AI) technologies has sparked a lively debate regarding its potential impact on economies and, in particular, on labour markets. This debate is not new: the ‘man vs. machine’ race has been a recurring theme since the times of Smith, Ricardo and Marx. Concerns over a new wave of AI-driven technological unemployment are bringing back to the fore the same fears that surrounded previous waves of automation and digitalisation (Frank et al., 2019; Autor, 2022).[1]

When it comes to the disruptive effects of AI, there are at least three discontinuities that are worth mentioning. First, AI technologies are, for the first time, putting man and machine in competition over tasks so far unattainable for non-human devices, particularly in the service sector. Generative AIs —e.g., OpenAI’s Chat-GPT or Google’s Bard— are already demonstrating their potential to replicate and, in some cases, outperform humans in carrying out activities requiring complex reasoning and judgements, such as legal or medical advice (Felten et al., 2023). For instance, the interpretation of x-ray images and other medical imaging diagnostics, typically a non-routine cognitive task requiring a lot of knowledge and experience, is now within AI’s scope. In other words, workers now face competition in their core competencies, which explains the ‘this time could be different’ attitude with regards to the labour market effects of technology. Second, AI is expected to magnify the potential of key automation technologies (e.g., robots), paving the way for job disruption also in manufacturing. Third, as AI-related technologies, knowledge and capabilities are not homogeneously distributed, this technological wave may exacerbate regional inequalities both across and within countries, with peripheral areas losing further ground as new forms of techno-economic dependency begin to emerge (Korinek and Stiglitz, 2021). On the other hand, AI promises to complement and assist workers in carrying out a number of tasks, in services and manufacturing alike (Gmyrek et al., 2023). Increasing productivity may spur labour demand, potentially compensating AI-induced job disruptions, should the latter take place. By the same token, organisational efficiency–including managerial tasks aimed at monitoring, coordinating and directing workers–will take a leap forward, resulting in potential labour-saving effects as well as changes in the composition of occupational profiles and their relative position within organisations (Chowdhury et al., 2023). New sectors and market niches are also about to emerge. Thus, it is hard to predict how many jobs this will create, as a significant share of disruptive AI applications are in their initial stage of development (Mondolo, 2022).

In this context, empirical research is struggling to provide policy-makers with robust evidence that could prove useful in tailoring AI-related policies and regulations (Autor, 2022). As the diffusion of AI

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[1] The ‘man vs machine’ race is already found in the writings of Keynes on the future of work (Keynes, 2010[1931]).

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gains momentum and its potential applications flourish across sectors (e.g., education, finance, legal counselling, insurance), attempts to assess its employment impact multiply (among others, see Brynjolfsson et al., 2018; Felten et al., 2021; Webb, 2020; Acemoglu et al., 2022; Albanesi et al., 2023).[2] Most existing research has focused on the US, largely converging towards a positive relationship between AI and employment, particularly concerning high-skill occupations. However, given that most of the available evidence relies on 'potential' measures of AI exposure, different outcomes may arise once data on actual adoption in sectors and firms are available, especially due to the early stage of the AI diffusion process.

An important role could also be played by heterogeneously distributed supply, demand and structural factors that are likely to influence the AI-employment nexus (Reljic et al., 2021; Xiao and Boschma, 2023). Countries and regions characterised by a larger share of knowledge intensive services are those where deployment of new technologies could be most rapid, especially with regard to AI applications capable of complementing human tasks. In contrast, where medium-technology sectors prevail and firms are predominantly adopters of technologies provided by external suppliers, labour substitution could prevail (Calvino and Fontanelli, 2023). Furthermore, the presence of labour market institutions aimed at protecting workers against dismissal could slow down the eventual process of AI-driven destruction of occupations (Pianta and Reljic, 2022). These are all elements which may ultimately contribute to determining the net (direct and indirect) employment impact of AI, as well as its distribution in space and time.

Given its complex multi-purpose nature, measuring AI and, even more so, the impact it may have on employment is a challenging endeavour. Despite the rapid diffusion of AI technologies across Europe, studies analysing their employment effects—particularly in light of significant structural heterogeneity across regions—remain limited. To address this research gap, we first conduct a cluster analysis to group European regions according to their readiness to adopt (and benefit) from AI technologies. This analysis incorporates multiple dimensions, including AI exposure, robot adoption, R&D investment, sectoral composition, labour productivity and workforce skills. Second, building on the cluster analysis results, we discuss potential scenarios of how AI could affect employment dynamics within these regional clusters.

Our analysis reveals not only the uneven exposure to AI technologies across regions but also the asymmetric distribution of capabilities and absorptive capacity needed to fully exploit AI's potential. We argue that the interplay of structural factors—sectoral specialisation, skills and innovation capacity—will likely determine whether regions emerge as early adopters (and developers) of AI, with varying impacts on employment.

Our man results show that, in high-tech service and capital regions (e.g., Berlin, Île-de-France, Prague, Vienna), preexisting local capabilities are likely to facilitate AI diffusion and enable AI technologies to complement existing knowledge-intensive economic activities, potentially resulting in positive employment outcomes. Conversely, regions in southern Europe (e.g., the Greek islands, southern Italy, Andalusia) seem to be trapped in a vicious circle of low growth, weak R&D investment, limited skills and low productivity. Their economic structure—still heavily reliant on agriculture and tourism—is likely to hinder the initial adoption of AI and limit their ability to capitalise on its benefits later, potentially exacerbating existing economic disparities within the EU.

The advanced manufacturing core regions— predominantly located in Germany, though there are some notable exceptions, such as Italian Piedmont, Spanish Navarra and French Alsace —with their strong industrial base, high robot density, substantial R&D investment and high-skilled workforce, are well-positioned to benefit from both diversifying into emerging AI-related areas and integrating AI into their existing capital-intensive production systems. As AI enhances automation technologies, including robots (Agrawal et al., 2019), these regions are poised to seize new opportunities for process automation. However, this also brings the risk of AI-driven job displacement, unless efficiency gains translate into new employment opportunities. While the final employment outcome remains uncertain, the positive correlation between AI exposure and employment growth in these regions provides some grounds for optimism.

Meanwhile, eastern European peripheral regions, despite facing similar challenges to southern Europe in terms of skills and innovation capacity, recorded the highest employment growth during the observed period, largely driven by manufacturing. However, their reliance on low-skill and labour-intensive activities (such as fabrication) makes them more susceptible to the negative employment effects of AI-driven automation. Without significant structural upgrading, eastern peripheral regions are likely to face greater difficulties in integrating AI in ways that complement workers, compared to the more advanced manufacturing core regions.

This paper is organised as follows. Section 2 provides a review of the literature, highlighting key issues and systematising the available empirical evidence. Section 3 spells out our main research question, while data and descriptive evidence are provided in Section 4. Cluster analysis and main results are reported in Section 5, while Section 6 concludes by discussing policy implications, limitations of the analysis and avenues for future research.

2. The diffusion of AI and its economic implications: a literature review

Stimulated by the proliferation of potentially disruptive applications (e.g., autonomous machines, next-gen recommender systems, high-performance image recognition technologies), the literature analysing the diffusion of AI and its economic implications is rapidly growing. In what follows, we provide a brief review of the extant literature focusing on two major streams. The first group of contributions analyses AI's diffusion patterns, highlighting their asymmetric nature and identifying the structural elements (e.g., technological capabilities, infrastructures, institutions) shaping diffusion at the sectoral and territorial level. The second group includes contributions that, building on different indicators to capture relative exposure to and/or actual use of such technologies (for a review, see Guarascio and Reljic, 2024), investigate the employment impact of AI. Indeed, these two literature streams are conceptually intertwined, although rather separated within the broad corpus of contributions focusing on AI. In fact, an appropriate assessment of the economic and employment implications of AI cannot disregard the structural elements that may favour convergence/divergence in the diffusion process, including the asymmetric distribution of AI-related gains/costs.

2.1. The geography of AI: structural drivers and diffusion patterns

The diffusion of new technologies is never homogeneous across sectors, regions and countries. Rather, these are more likely to emerge and concentrate in areas where certain enabling conditions are present, highlighting the local and path-dependent nature of technological diffusion (Boschma, 2017). The literature identified a range of factors explaining why the adoption of new technologies emerge in certain areas rather than others (Rigby, 2015). Key elements include absorptive capacity, cognitive proximity, relative strength of the national and regional systems of innovation (Cohen and Levinthal, 1990). Concerning path-dependency, what matters is the positive correlation between size and quality of technological capabilities, on the one hand, and the capacity to capture new technological opportunities, on the other. Where capabilities are large and rich absorptive capacity is expected to increase, giving rise to reinforcement mechanisms which may lead to

[2] For an earlier review of the literature on the AI-employment nexus, see Barbieri et al. (2020) and Mondolo (2022).

divergence between the most dynamic sectors/areas and those lagging behind. Relatedly, many authors underlined the correlation between macroeconomic (i.e., intensity and composition of demand flows) and structural conditions (e.g., skills, size and quality of relevant infrastructures) that heterogeneously characterise sectors and geographical areas and their propensity to adopt and develop innovations (Bogliacino and Pianta, 2010; Dosi et al., 2021; Guarascio et al., 2017; Pianta and Reljic, 2022; Reljic et al., 2021). Countries, industries and regions facing relatively more intense demand flows and endowed with the appropriate skills and infrastructures are expected to be faster in developing, adopting as well as in seizing the economic opportunities associated to new technologies. Technological capabilities and diffusion processes are also related to the hierarchical structure of Global Value Chains (GVCs).[3] Far from being evenly distributed, strategic functions related to, among other things, development, control and management of innovations (e.g., R&D, product design), are concentrated near the headquarters of the companies dominating GVCs. This may further contribute to the uneven distribution of technological capabilities and, related to that, of the value (extra profits, rents) that can be extracted from innovations. Sectoral specialisation matters too. Automation technologies (e.g., robots) tend to be concentrated in areas where manufacturing activities prevail. On the contrary, IT and digitalisation technologies are to a significant extent concentrated where services, and, particularly, 'knowledge-intensive' ones (Evangelista et al., 2013), are prevalent (Bontadini et al., 2022).

When it comes to the diffusion of AI technologies, the available evidence displays a rather polarised landscape. Focusing on AI-related patents, Fanti et al. (2022) show how the diffusion of this set of technologies (e.g., machine learning, neural networks, sound and image recognition systems) is reinforcing the overall trend towards market concentration traditionally characterising the ICT techno-economic paradigm (Dosi and Virgillito 2019). Building on their strong capabilities and acquiring most of the more promising AI start-ups, few transnational corporations (i.e., Big-Tech) are consolidating their dominant positions also in this 'new' technological domain/market segment (for a discussion on the long-term evolution of the AI technological trajectory and related discontinuities, see Fanti et al. 2022). Along these lines, Maslej et al. (2024) have recently provided a more in-depth and updated analysis of the global distribution of AI-related patents and R&D activities. Regarding patents, the authors document significant polarisation both geographically and at the corporate level. Of all AI patents granted between 2010 and 2022, approximately 62 % originated from China, 20 % from the US, and only 3 % from applications submitted by the EU and the UK. A similar pattern is detected in what Maslej et al. (2024) define as 'notable machine learning models' and the 'foundational models' that are behind generative AIs (e.g., Bard, ChatGPT, Gemini). In both cases, the US and China hold the lion's share: between 2003 and 2023, around the 76 % of these models have been developed in the two countries (61 % in the US and 15 % in China) with few followers (France, Germany, Canada) lagging far behind. As for corporations owning the leading foundational models, the usual suspects come to the fore: Alphabet, Meta, Microsoft and OpenAI dominate the ranking.

These trends are confirmed when looking at investments in AI-related ventures (about 65 % of total investments are located in the US) while around two-thirds of newly funded AI companies were established in the US and China (the data refer to 2023, for more details, see Maslej et al., 2024). Distinguishing between different technological trajectories of AI patents (short-range, academic, technical, broad view), Hötte et al. (2023) highlight, again, that AI inventions are highly concentrated within a few firms. Among the top patentees, companies such as Amazon, IBM, Intel, Microsoft and Samsung stand out. Indeed, although these authors provide further confirmation of the powerful position of a few Big Tech companies in the AI technological domain, no clear empirical evidence is provided regarding a generalised concentration in AI patenting (to conduct their analysis, Hötte et al. (2023) analyse the evolution of the Herfindal-Hirschman index between 1990 and 2019). Dibiaggio et al. (2024) provide further evidence regarding the geographical polarisation of AI-related technological capabilities. Relying on three major patents classifications (International Patent Classification, Cooperative Patent Classification and the File Index / File forming terms) to analyse EPO PATSTAT data, they confirm the polarisation documented by previous contributions yet reporting a stronger position of China vis-à-vis the US: in absolute terms, China records a larger number of AI related patents, while the number of EU27 patents is almost a third that of US ones. A rather different picture emerges regarding AI-related scientific publications as reported by the Scopus database. In this case, the US and the EU27 report the highest number of publications, while China ranks third (Dibiaggio et al., 2024).

The asymmetric diffusion of AI technologies, heterogeneous distribution of capabilities and structural drivers and resulting polarisation dynamics are detected also at the regional level. This is not surprising, though, as agglomeration dynamics and innovation patterns are closely related to the relative strength of local innovation systems (Balland et al., 2015). In this context, Xiao and Boschma (2023) rely on patent data to investigate the knowledge production of AI technologies in 233 European regions observed from 1994 to 2017. Their analysis reveals that regions displaying the highest share of AI patents are those characterised by a strong pre-existing ICT knowledge base, confirming the importance of cumulative and path-dependent dynamics in explaining diffusion processes. These findings are in line with previous evidence provided by Buarque et al. (2020). Through a similar geographical mapping of AI technologies in European regions, these authors show that the most successful AI regions are those where AI technologies are most embedded in their knowledge space.

In fact, as argued before, the ability to absorb and, even more so, to develop digital technologies, including AI, is strongly related to the availability of an appropriate skill-base. Regarding AI technologies, what matters is the relative endowment of digital skill, particularly the most advanced ones. In this respect, Caravella et al. (2023) propose a new regional 'digital skill index', distinguishing between users, practitioners and developers, to explore the diffusion of digital skills in Europe. As expected, they document a polarisation dynamic similar to the one highlighted by Xiao and Boschma (2023) regarding AI-related knowledge. In particular, they report that the factors shaping the distribution of digital skills at the regional level are: i) the concentration of large and high-tech/knowledge intensive corporations; ii) the presence of a qualified workforce that magnifies complementarity with digital technologies; and iii) sustained aggregate demand.

In a nutshell, virtually all the elements (e.g., knowledge base proxied by patents and publications, investments, competences, share of high-tech-firms, sustained demand flows) that, from a theoretical viewpoint, are expected to explain the asymmetric and often polarised distribution of frontier technologies emerge as key drivers of diffusion, also in the case of AI.

2.2. The AI-employment nexus

Although it is relatively recent, the corpus of empirical literature focusing on the AI-employment nexus is large enough to be distinguished according to the adopted unit of analysis and related approach to measure the potential/actual penetration of such technologies.

A significant group of contributions relies on occupation and ability-based indicators to assess the relative 'AI exposure' (Felten et al., 2018), i.e., the likelihood that an occupation will come into contact with, be assisted or replaced by AI, given the characteristics of the tasks performed and the underlying abilities. In line with the literature studying the employment impact of ICTs distinguishing occupations according to the degree of 'routineness' of their tasks (Autor et al., 2003) or

[3] For a thorough discussion, see Stollinger (2021) and Coveri and Zanfei (2023).

automation probabilities (Frey and Osborne, 2017), this stream of works starts by ranking jobs considering the importance and prevalence of abilities that occupations 'share' with AI (Tolan et al., 2021). Brynjolfsson et al. (2018) focus on advancements in machine learning (ML) technologies, which are at the basis of virtually all AI applications. Relying on the rubric evaluating task potential for ML proposed in Brynjolfsson and Mitchell (2017), the authors introduce a task-based measure of 'Suitability for Machine Learning' (SML) linking it to 18, 156 tasks included in the O*NET[4] database. Their key results are summarised as follows: i) most of the occupations included in O*NET display at least some SML tasks; ii) only few of them turn out to be fully replaceable by AI technologies; and iii) redesign of job task content is often required to employ such technologies. Another occupation-based measure is proposed by Felten et al. (2018, 2021), who link the ten most promising AI applications (e.g., image recognition, language modelling, translation, among others) to human abilities included in O*NET. Felten et al. (2021)'s AI Occupational Exposure (AIOE) scores identify white-collar workers as the most exposed occupational group. However, the measure remains silent on the likelihood of AI having a complementary or substitutive effect.

The only attempt to apply Felten et al. (2021)'s occupation-based methodology to assess the employment impact of AI on the European economy is the one by Albanesi et al. (2023) and Guarascio and Reljic (2024). Using a crosswalk, analogous to the one upon which our analysis is based, to link the O*NET-based AIOE to European 3-digit occupations,[5] Albanesi et al. (2023) find that, in Europe, employment shares tend to increase in occupations more exposed to AI. The evidence is particularly significant for those occupations characterised by a relatively higher proportion of younger and skilled workers. Focusing on 16 European countries over the period 2011- 2019, these authors argue that, although country-level heterogeneities do matter, particularly concerning differences in terms of pace of technological diffusion, education levels, product market regulation and employment protection laws, there is no EU country where the share of the most AI-exposed occupations tends to decline.

On the other hand, Guarascio and Reljic (2024) report that occupations more exposed to AI technologies display stronger employment growth compared to the rest of the workforce. Yet, even in this case, heterogeneous patterns are in order. Positive employment outcomes tend to be concentrated in Innovation Leaders[6] (Belgium, Denmark, Finland, the Netherlands and Sweden) and Strong Innovators (Austria, Cyprus, France, Germany, Ireland and Luxembourg), while no effects are observed in Moderate (Czechia, Estonia, Greece, Hungary, Italy, Lithuania, Portugal and Spain) and Emerging Innovators (Croatia, Latvia, Poland, Romania and Slovakia). In line with the literature studying the distribution of AI-related technological capabilities (as noted above), these findings confirm that a country's innovation system relative strength and, relatedly, its 'absorptive capacity' play a key role in explaining the distribution of AI-related (potential) employment (and economic) gains.

Recently, Felten et al. (2023) updated their indicator to isolate advances in Language Modelling (LM) – i.e., the AI technology which is key for the development of frontier 'generative' applications such as GPT-4 – to determine if and to what extent such a specific technological development could have a peculiar impact on employment. To do so, the AIOE undergoes a weighting procedure, allowing it to order occupations according to the number of abilities that are related to LM, disregarding the other AI-related abilities included in the original indicator. Although most of the top-exposed occupations appear in the list provided in Felten et al. (2021), some relevant 'new entries' are worth mentioning. Among the top occupations exposed to LM AI are telemarketers and various post-secondary teachers in fields such as English language and literature, foreign language and literature and history. Concerning the distribution of the LM AI indicator across industries, the sectors displaying the highest values include legal services and securities, commodities and investments.

Focusing on occupations but adopting a different approach, Gmyrek et al. (2023) assess the employment impact of Generative Pre-Trained Transformers (GPTs). Unlike Felten et al. (2021, 2023), these authors use Chat GPT-4 to estimate task-level scores of occupation exposure to AI. This ranking is then used to quantify the impact of AI on employment and job quality, by country and income group. According to their estimations, only occupations related to clerical work are highly exposed to AI, with 24 % of clerical tasks considered highly exposed and an additional 58 % with medium-level exposure. Concerning other occupational groups, the greatest share of highly exposed tasks ranges between 1 % and 4 %, and medium exposed tasks do not exceed 25 %. As a result, they reject the hypothesis of massive substitution, pointing instead to complementary effects that are concentrated among white collars and high-skilled occupations. A similar analysis is carried out by Elondou et al. (2023), who combine experts' opinion and GPT-4 classifications to quantify the impact of GPTs on the US labour market. Merging task-level information stemming from O*NET and employment data drawn from the Bureau of Labour Statistics (BLS) referring to the years 2020 and 2021, these authors reveal that around 80 % of the US workforce could have at least 10 % of their work tasks affected by GPTs, while almost one fifth of occupations could have up to 50 % of their tasks impacted. Confirming previous evidence, the highest level of exposure is concentrated at the top of the occupational distribution, among high-skilled and high-income workers.

Despite being very useful for characterising occupations according to their relative AI exposure, occupation and task-based measures have notable limitations. First, this type of indicator provides a proxy of 'potential' AI exposure, remaining silent on whether such technologies are actually employed – along with the 'how, when and where'. Second, and relatedly, these indicators lack any information about industry- and firm-level technological heterogeneities which, as discussed above, may play a key role in shaping the impact of such technologies. In an attempt to account, jointly, for technological and occupational heterogeneities, Webb (2020) developed an indicator tracking the co-occurrence of verb-noun pairs in the title of AI patents and O*NET tasks. In this way, he obtains a measure which considers, at the same time, technological choices of firms (and fine-grained characteristics of specific AI technologies) as illustrated in patents and task-related characteristics of occupations, as reported in O*NET. According to Webb (2020)'s results, AI is more likely to affect skilled and older workers than previous innovation waves, such as robots or software. However, the robustness of this mixed patent-occupation AI exposure measure is partly undermined by the fact that patent titles do not fully describe the underlying technology. No less relevant, restricting co-occurrence to verb-noun pairs risks increasing false positives.

Among the few firm-level studies analysing the employment implications of AI, there is a contribution by Damioli et al. (2023). These authors rely on a sample of 3.500 front-runner companies, stemming from the Orbis BvD database, which patented AI-related inventions over the period 2000–2016 (data are drawn from the PATSTAT database). The coefficient associated with AI patents is always positive and significant, despite being relatively small in terms of size, which points to a

[4] The O*NET program is the US primary source of occupational information. Central to the project is the O*NET database, containing information on hundreds of standardized and occupation-specific descriptors. The database is continually updated by surveying a broad range of workers from each occupation.

[5] The O*NET repository uses SOC occupational codes used in the US, while EU member states follow the International Standard Classification of Occupations (ISCO) to classify occupations. 3-digit ISCO codes are referred to as subminor groups. See also Section 4.

[6] To capture the role of country-specific technological capabilities, Guarascio and Reljic (2024) rely on the classification stemming from the European Innovation Scoreboard.

moderate positive employment impact of AI patenting (with a short-term elasticity of about 3–4 %). Such a 'labour-friendly' effect is paralleled by an analogously positive and significant effect of other (non-AI) firm innovation activities. These findings confirm the employment-friendly nature of product innovation in general and provide novel firm-specific evidence on emerging AI technologies. However, it's important to note that patents serve as a partial measure of product innovation, as not all innovation activities are patented, rather than direct AI adoption. Additionally, as the study focuses solely on patenting companies, it remains silent on the net aggregate effect, failing to account for aspects such as 'business stealing' (see Calvino and Virgillito, 2018).

Another way to look at the relationship between AI technologies and employment is to use job-posting data. In a seminal work, Acemoglu et al. (2022) rely on Burning Glass Technologies data, which provide wide coverage of firm-level online job postings, linked to SOC occupational codes to assess the relative penetration of AI technologies at the establishment level in the US. To quantify the degree of firm-level AI exposure, they employ three definitions, namely those proposed by Brynjolfsson et al. (2018), Felten et al. (2021) and Webb (2020). The authors do not find any clear employment effect of AI at the industry or occupation-level. Instead, some evidence of a re-composition effect towards more AI-intensive jobs emerges. This lack of effects is attributed to the relatively limited diffusion of AI technologies and the niche-level nature of adoption. In addition, no evidence of direct complementarity between AI job posts and non-AI jobs arises, hinting at a prevalent substitution effect and workforce re-composition, rather than productivity enhancement after AI adoption. While online job vacancies offer a rich data source, caution is necessary when assessing their representativeness of overall labour demand, as they tend to be biased toward specific occupations, industries and countries. A systematic overview of different AI proxies, along with the main findings and their limitations, is available in Table A1 in Appendix.

It is not only about cognitive activities and services, however. AI is poised to enhance the capabilities and scope of a number of automation technologies, including robots (Agrawal et al. 2019). This connection between AI and digital technologies is also more broadly in line with the claim by CIIP (2022) that digitalisation, particularly in the industrial domain, is less about new tangible technologies and more about the integration of existing technologies stemming from the 'physical' and 'ICT' worlds. As robots and other machines become 'smarter'–that is, capable of learning and adjusting their 'behaviour' in ever more complex productive contexts–opportunities for process automation and related efficiency gains grow (Barbieri et al. 2020). If this is the case, a wave of AI-induced job destruction in manufacturing could be on the way (Autor, 2022)–unless the same efficiency gains translate into compensation mechanisms capable of offsetting the not so remote possibilities of job destruction (for a discussion on these mechanisms, see Calvino and Virgillito, 2018). It is hard to say, at present, which is the most likely scenario, as no robust empirical evidence on the impact of AI on manufacturing seems to be available.

Four main takeaway messages emerge from this brief literature review. First, much remains to be understood about the employment impact of AI, as AI is still in its early stage of diffusion and novelties in terms of applications and potential impact on job quality and quantity continuing to emerge. Second, although the available indicators represent a very useful base to assess exposure and (potential) employment impact of AI, further refinements, considering both the characteristics of occupations and actual business decisions, as well as the specifics of industries regarding the adoption process, would be of great advantage. Third, spatial specificities (e.g., characteristics of regions, provinces, cities or local labour markets) must be adequately taken into account, given the weight that these elements may have in determining the diffusion of AI and its impact on the labour market. Fourth, more evidence is needed regarding the intertwining of AI and automation technologies in manufacturing (e.g., robots). This is particularly relevant in the European case, where manufacturing still plays an important role and the diffusion of AI could intertwine with transformative trends such as the transition toward electrification in the energy and automotive sectors.

We have now reviewed the relevant literature and highlighted the key issues concerning the AI-employment nexus. In what follows, we spell out our research questions, which aim to address some of the abovementioned gaps in the literature.

3. AI exposure and employment in european regions: research questions and contribution

As one of the world's largest markets, Europe has seen a growing diffusion of AI technologies, driven by its knowledge-intensive business services and high-tech manufacturing industries (European Commission, 2018). Yet, a major technological gap vis-à-vis the US and China has also been documented, particularly in the realm of digital technologies (Maslej et al., 2024). Therefore, at least for now, European economies and regions are regarded more as potential adopters (and, to a certain extent, 'regulators' of AI) rather than developers of such technologies. It is too early to determine how this peculiar status of the European economy will affect AI diffusion patterns and their economic (and labour) implications. Yet, this must be taken seriously into account when interpreting the available empirical evidence and, even more so, in predicting technological, economic and employment dynamics related to the unfolding of AI.

Against this background, we pursue two major analytical tasks. The first one concerns highlighting the role of technological and structural heterogeneities in shaping the potential impact of AI across European regions. To do so, we examine the co-evolution of AI exposure, on the one hand; and of a set of key factors (i.e., R&D intensity, share of high-skilled workers) likely to affect absorptive capacity as well as the distribution of AI-related gains/costs, on the other. Once different regional clusters are grouped in terms of productive, technological and labour market characteristics, on top of relative AI exposure, the second analytical task regards comparing their employment patterns.

In so doing, we provide a twofold contribution to the extant literature. First, we enrich the evidence regarding the geography of AI in Europe (Xiao and Boschma, 2023), highlighting the joint role of key dimensions affecting strength and characteristics of local innovation systems as well as shaping diffusion processes. This is particularly relevant in the European case, where structural heterogeneities and related divergence in economic and employment patterns across countries and regions constitute a major policy concern, as testified by the large chunk of EU funds devoted to structural/cohesion policies (Darvas et al., 2019; Landesmann and Stöllinger, 2020). Second, we contribute to the still limited body of research (Albanesi et al., 2023; Guarascio and Reljic, 2024) exploring the employment implications of AI in Europe, by revealing structural factors that may affect regional readiness for AI as well as susceptibility to labour-saving effects. Third, by linking structural factors with potential employment outcomes, we show how AI could reinforce regional inequalities in Europe.[7].

More specifically, two main research questions are addressed. How do European regions' structural characteristics influence their capacity to adopt and benefit from AI technologies? To explore this, we adapt Felten et al. (2021)'s AI Occupational Exposure Index to European occupations, aggregating it to the NUTS-2 regional level (see Section 4). Given that new technologies are more likely to emerge in regions where

[7] The empirical research quantifying AI's impact on the European labour markets remains limited compared to the US. This gap is especially pronounced when it comes to exploring AI's potentially heterogeneous impacts across countries and regions. While existing studies, such as Albanesi et al. (2023), hint at country disparities in AI exposure, they do not take into account strong inter- and intra-country structural heterogeneity characterising different areas.

they are related to the preexisting local capabilities (Boschma, 2017), we use a cluster analysis to examine how region-specific factors—such as sectoral specialisation, R&D investment and workforce skills—shape regional AI readiness. This clustering exercise allow us to identify regions with high AI adoption potential and those facing structural constraints. Building on these clusters, we then ask: What are the likely employment implications of AI, given these structural differences? This question considers how regional structures might shape AI's potential to either complement or substitute labour. In regions characterised by high levels of knowledge-intensive services, educational attainment and R&D investment, AI might complement high-skilled labour, boosting productivity and labour demand in sectors like ICT, finance and professional services. In contrast, regions dominated by labour-intensive industries, where low- to medium-technology sectors and limited R&D are prevalent, face structural barriers that may hinder AI adoption in the first place.

The following sections illustrate data used, offer a comprehensive assessment of AI occupational exposure across EU's occupations and regions, outline the empirical strategy and present the main results.

4. Data and descriptive evidence

4.1. Data

We combine data from several sources referring to the period 2011–2018.[8,9] Since the NUTS-2 classification has undergone changes in some countries over time due to a combination of administrative and statistical-related factors (Eurostat, 2020), we took specific steps to ensure data consistency throughout this period. For regions where only the NUTS labels changed (e.g., French regions), we simply recoded the labels. However, in cases where the classification involved more significant changes, such as the splitting or merging of regions, we aggregated NUTS-2 regions (e.g., LT00–02, IE01–06, DE40–42).[10]

Artificial Intelligence. Regarding AI, we draw on earlier works by Felten et al. (2018, 2021), who made available the indicator of AI occupational exposure. This indicator links various AI applications - abstract strategy games, real-time video games, image recognition, visual question answering, image generation, reading comprehension, language modelling, translation, speech recognition and instrumental track recognition - to 52 workplace abilities (e.g., mathematical reasoning, speech recognition, written comprehension, originality, body coordination) using the mTurk web service survey.[11] Occupational exposure to AI (AIOE) is constructed by weighting the ability-level exposure to AI with their prevalence and importance within each occupation:

$$AIOE_k = \frac{\sum_{j=1}^{52} A_{ij} * L_{jk} * I_{jk}}{\sum_{j=1}^{52} L_{jk} * \ I_{jk}} \tag{1}$$

where A_{ij} stands for the ability-level AI exposure, calculated as a sum of relatedness scores across ten AI applications for each of the 52 abilities; L_{jk} and I_{jk} represent prevalence and importance of each ability (j) within each occupation (k).

This means that occupations characterised by a higher prevalence and importance of abilities classified as highly exposed to AI exhibit a relatively higher exposure to AI, and vice versa. Under the assumption that AI-related workplace abilities of US occupations are similar to those characterising their EU counterparts[12] (Albanesi et al., 2023), we map Felten et al.'s AIOE available at the six-digit SOC occupations into the International Classification of occupations (ISCO-08) at the four-digit level, ultimately collapsing at the three-digit ISCO level (126) by calculating the mean exposure across occupations. As the focus of our analysis are European regions, we construct a regional AI exposure (AIRE) indicator following the approach suggested by Felten et al. (2021). To this end, we combine the occupational AI exposure (AIOE) with the occupational distribution (ISCO 3-digit) of employees within regions from the EU LFS, as follows:

$$AIRE_{ij} = \sum_{k=1}^{126} \frac{EMP_{kij}}{EMP_{ij}} * AIOE_k \tag{2}$$

where EMP_{kijt} denotes the number of employees in occupation k in region j in country i, while EMP_{ijt} stands for the total number of employees in region j in country i. Thus, the first term denotes the employment share of each of the 126 ISCO 3-digit occupations in region r in 2018, while $AIOE_k$ corresponds to occupational AI exposure, as defined in Equation 1.[13] The *AIRE* indicator is normalised to have a zero mean and unit standard deviation, representing relative AI exposure across regions.

As argued before, the main limitation of Felten et al. (2021)'s indicator is that measures crowd-sourced opinions on relative exposure to AI technologies. It sheds light on which occupations, industries, countries and regions are most likely to be affected by advancements in AI rather than on its actual adoption. Recent work by Marguerit (2024) attempts to provide a proxy more similar to AI adoption constructing a measure of overlap between AI-related questions from Stack Overflow, reflecting the real-time problems developers are encountering and workplace abilities. Interestingly, the correlation with Felten et al.'s indicator is almost 1, providing reassurance about its robustness. Furthermore, we also check the degree of correlation with the data from Eurostat ICT business survey, reporting the percentage of enterprises employing AI technologies. To allow for comparison, we calculate AI exposure at the country level by combining the AIOE data with the occupational distribution (ISCO 3-digit) of employees within each country. Fig. 1 presents a scatter plot displaying the relationship between country level AI exposure and Eurostat's AI adoption indicator. Despite some noise, the positive correlation (correlation coefficient: 0.57) suggests that occupational AI exposure is fairly related to adoption, at least to a certain extent. Specifically, countries with higher degree of AI exposure tend to have a greater share of enterprises that adopt AI technologies.

While AI indicator appears effective in capturing the occupational exposure to AI technologies (and to some extent AI adoption, see Fig. 2), it falls short in accounting for AI's role in the realm of robotics. Indeed, Felten et al. (2019) explicitly acknowledge their focus on 'purely AI technologies,' intentionally omitting consideration of 'how the interaction between advanced AI and robotics technologies affects abilities or occupations.' Consequently, AI occupational exposure is inherently skewed toward cognitive abilities and tasks. While this is not necessarily a limitation, it is important to note that this indicator does not account for the fact that AI is also enhancing automation potential in manufacturing industries by making industrial robots more flexible, autonomous and intelligent (IFR, 2022; Soori et al., 2023).

[8] Our sample starts in 2011 due to a major revision of ISCO (International Standard Classification of Occupations), when ISCO-88 was succeeded by ISCO-08, which makes comparisons before and after 2011 impossible.

[9] Austria, Belgium, Bulgaria, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Greece, Hungary, Ireland, Italy, Lithuania, Latvia, Netherlands, Poland, Portugal, Romania, Sweden and Slovakia.

[10] For example, in the case of Lithuania, the change in classification in 2013 resulted in the separation of Lithuania into two NUTS-2 regions.

[11] The matching is realised by administering a questionnaire to 2,000 individuals, reached with Amazon's Mechanical Turk (mTurk) web service. Interviewees are asked whether AI applications are related to or could be used for each of the 52 abilities listed in the O*NET. A detailed methodology is provided in Felten et al. (2021).

[12] An analysis showing the US-EU within-occupation similarities in terms of digital task content has been recently provided by Gschwent et al. (2023).

[13] Note that we introduce dynamics by allowing our indicator AIRE to vary over time, reflecting the changes in the occupational distribution.

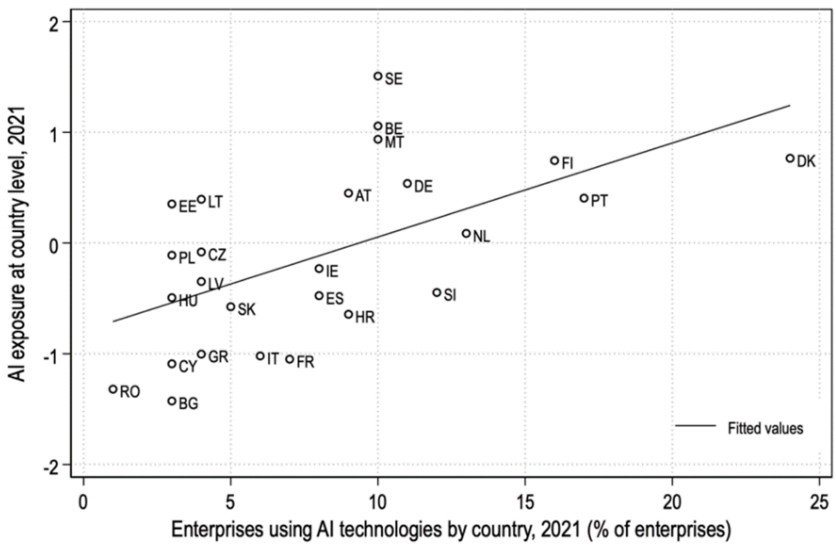

Fig. 1. AI exposure and share of enterprises using AI technologies by country.
Source: Authors' elaboration based on Felten et al. and Eurostat's ICT business survey

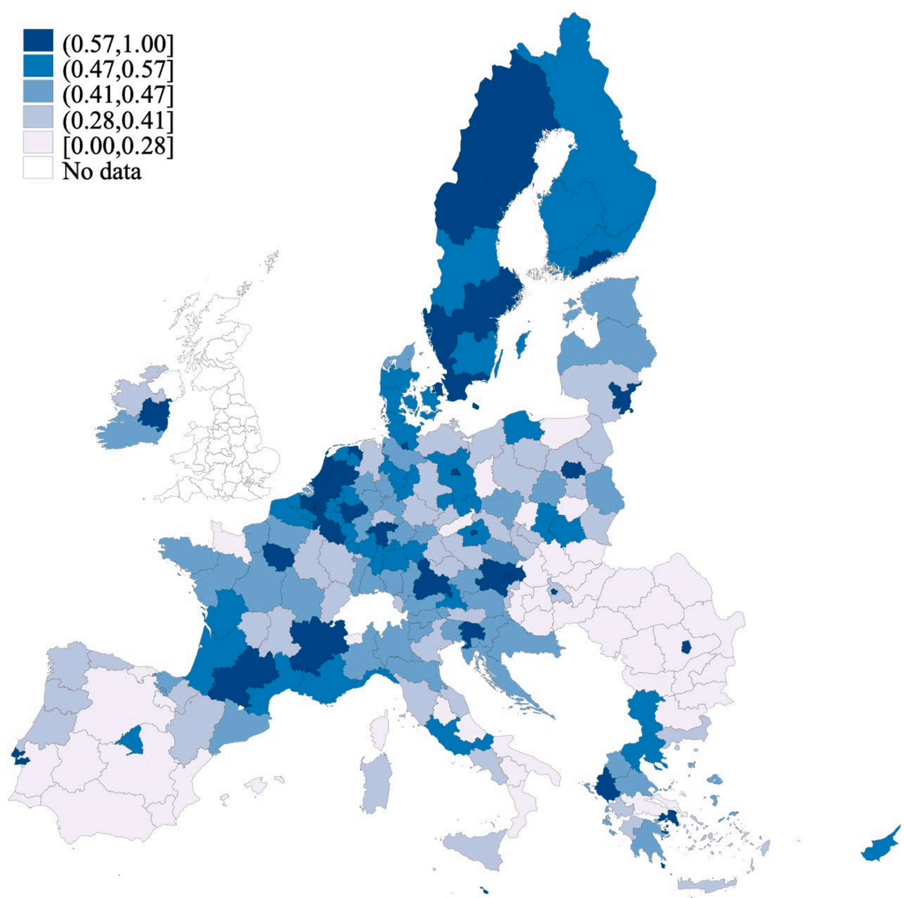

Fig. 2. AI exposure across European regions in 2018.
Source: Authors' elaboration based on Felten et al. (2021)

Robots. We rely on International Federation of Robotics (IFR) database, which provides information on the robot stock and new instalments at the country-industry level in manufacturing sector. As extensively discussed in Fernández-Macías et al. (2021), the IFR data comes with an important caveat: they do not account for variations in robot quality across different industries, countries and time periods. Nevertheless, the IFR remains the most reliable source of data upon which empirical literature on the employment effects of robots has flourished (see Acemoglu and Restrepo, 2020; Fernandez-Macias et al., 2021; Jestl, 2024; Petit et al., 2023; Reljic et al., 2023; Valentini et al., 2023, among others).

In line with earlier studies (Jestl, 2024; Petit et al., 2023, among others), to construct an indicator of robot density at the regional level we assume that the distribution of robots within an industry is uniform across regions within a country, conditional on the industry-region employment shares. To this end, we combine industry-level data on robot stock with employment distribution across the 2-digit NACE Rev.2 industries within regions, as follows:

$$Robot\ stock_{rt} = \sum_{j=1}^{J} \frac{EMP_{jrt}}{EMP_{rt}} * Robot\ stock_{jt} \quad (3)$$

where EMP_{jrt} denotes the number of employees in industry j in region r in year t, EMP_{rt} stands for the total number of employees in region r in year t and J represents the complete set of industries for which robot stock ($Robot\ stock_{jt}$) is available.

Structural variables. Given the significant role that structural heterogeneities play in shaping the labour market impacts of technological change (Reljic et al., 2023), we include several variables to capture sectoral specialisation, skills, labour market institutions and technological factors influencing the diffusion of new technologies in regions. First, regions with a highly educated workforce are more likely to benefit from new technologies, attract innovative firms and sustain positive employment trajectories. To proxy for skills, we use the percentage of employees with a tertiary degree, sourced from the EU LFS. Second, the strength of labour market institutions is proxied by the share of non-standard work (NSW), which includes all employment types other than full-time permanent contracts. A higher share of non-standard work suggests a greater level of labour market liberalisation. Additionally, firm size maybe an important determinant of AI adoption. Empirical evidence from Rammer et al. (2021) shows that in Germany, large firms (with at least 1000 employees) are nearly ten times more likely to adopt AI compared to small businesses (5 to 9 employees). Furthermore, AI adoption is also uneven across sectors, with the latest Eurostat ICT business survey indicating higher AI adoption rates in ICT services and professional business activities. To capture these structural differences, we consider the size of the manufacturing sector, the share of knowledge-intensive services and the share of firms with >50 employees. Finally, we also include regional levels of gross fixed capital formation, R&D investment and labour productivity, as these factors are critical for understanding the capacity of regions to adopt and benefit from new technologies, thereby influencing the employment impact of AI. All variables used in the empirical analysis and their sources are listed in Table A2 in Appendix.

4.2. Descriptive evidence

In order to get a first impression of the AI exposure index, we list the ten ISCO 3-digit occupations with the highest (Table 1) and the lowest scores (Table 2). The most striking feature of the top ten list is the dominance of high-skilled workers, predominantly stemming from the group of professionals (ISCO major group 2). The relatively high AI exposure of high-skilled workers is also in line with the wide-spread perception that labour market effects of digitalisation – or industry 4.0 – will affect not only, and maybe even not most strongly, blue-collar workers, as was the case with automation (Cirillo et al., 2021). In this context, it is noteworthy that the high score of professionals does not necessarily imply that these occupations will be substituted by AI technologies. Rather, they can also score high if they are complementary to AI, or as Felten et al. (2021) point out, the methodology for calculating the AI index is agnostic as to whether AI substitutes or complements occupations (respectively the abilities needed in occupations). This characteristic also explains why, along with various professionals, there are also some medium-skilled occupations present in the list of top-ranking occupations, such as numerical or general office clerks. In other words, the rationale of AI-exposure index is partly different from the one characterising other well-known occupation-based indices, such as the routine-task intensity (RTI) index (Autor et al., 2003) or the offshoreability index (Acemoglu and Autor, 2011). The latter includes a clear task-related occupational hierarchy concerning replacement risks vis-à-vis complementarity (i.e. occupations characterised by a relatively larger share of routine tasks are considered more at risk of technology-driven substitution), while no such hypotheses are made to build the AIOE.

Table 1
Top 10 most AI exposed occupations.

Ranking	ISCO 3-digit	ISCO 3-digit label
1	212	Mathematicians, Actuaries and Statisticians
2	241	Finance Professionals
3	261	Legal Professionals
4	242	Administration Professionals
5	431	Numerical Clerks
6	231	University and Higher Education Teachers
7	411	General Office Clerks
8	122	Sales, Marketing and Development Managers
9	251	Software and Applications Developers and Analysts
10	233	Secondary Education Teachers

Source: Authors' elaboration based on Felten et al. (2021).

Table 2
Bottom 10 least exposed occupations.

Ranking	ISCO 3-digit	ISCO 3-digit label
126	931	Mining and Construction Labourers
125	631	Subsistence Crop Farmers
124	912	Vehicle, Window, Laundry and Other Hand Cleaning Workers
123	911	Domestic, Hotel and Office Cleaners and Helpers
122	713	Painters, Building Structure Cleaners and Related Trades Workers
121	634	Subsistence Fishers, Hunters, Trappers and Gatherers
120	932	Manufacturing Labourers
119	921	Agricultural, Forestry and Fishery Labourers
118	633	Subsistence Mixed Crop and Livestock Farmers
117	712	Building Finishers and Related Trades Workers

Source: Authors' elaboration based on Felten et al. (2021).

At the other end of the spectrum (Table 2), we find mostly low-skilled occupations, in particular elementary ones. Common traits include the relatively lower technological intensity of their tasks, which are mostly manual and physical but not necessarily repetitive. Several of these occupations have little or no relevance anymore in most EU member states, which is particularly true for subsistence farmers or subsistence fishers and hunters.

Looking at the distribution of the AI exposure across European regions in Fig. 2, it is not surprising to find high AI exposure in many high-income regions, including regions where capital cities are located. Paradigmatic examples are: Ile de France (Paris region), Vienna, Berlin, Warsaw metropolitan area, Prague and many more. In other cases, larger areas of the country are identified as having high AI exposure, such as North Holland, South Holland and the Utrecht region in the Netherlands or Southern Sweden and Lower Bavaria in Germany. All these regions, however, are also high-income regions, both in an EU-wide comparison and a national comparison. In contrast, in the Southern periphery (Spain, Italy) and the Eastern periphery (Romania, Bulgaria) there are numerous regions with very low levels of AI exposure. These patterns coincide well with other measures for implicit technological capabilities across Europe, such as, for example, functional specialisation patterns (Kordalska et al., 2022).

5. Cluster analysis and employment patterns: results

This section presents the findings from our cluster analysis, which highlights significant regional differences in AI ‘readiness’, measured by combining AI exposure, sectoral composition, investments, productivity and skills.[14] We detail each cluster below, focusing on the key variables that differentiate them and their implications for employment dynamics.

Before conducting the cluster analysis, we examined correlations among the indicators (Fig. 3). Positive correlations between AI exposure, R&D investment, university education and the share of knowledge-intensive services (KIS) suggest that regions with higher innovation capacity and human capital are more likely to adopt AI technologies. Conversely, the negative correlation between AI exposure and manufacturing share (−0.28) does not imply that AI is absent from manufacturing. Instead, it reflects AI indicator’s emphasis on cognitive tasks, while overlooking interactions between AI and robotics in industrial settings. This is further supported by the weak correlation with robot density (0.17)—a widely-used measure for studying automation’s employment effects (Graetz and Michaels, 2018). Together, these findings suggest that AI exposure and robot adoption represent different facets of technological progress: AI exposure aligns closely with digitalisation and the ‘fourth industrial revolution’ (Industry 4.0), while robotics remains more connected to traditional automation associated with the ‘third industrial revolution’ (Industry 3.0).

To cluster regions, we first applied a hierarchical Ward’s linkage method to standardised data, determining the optimal number of clusters, and then used a non-hierarchical k-means analysis to fine-tune the grouping. The optimal number of clusters was found to be four,[15] based on the Calinski-Harabasz pseudo-F test. These clusters, mapped in Fig. 4, are labelled as follows: *high-tech service and capital centres, advanced manufacturing core, southern and eastern periphery*.[16] Table 3 provides key statistics for each cluster, offering a comparative overview of their distinct characteristics.

The first cluster*, high-tech service and capital centres,* is dominated by capital city regions and economically advanced areas such as Vienna, Brussels, Berlin, Madrid, Île-de-France, Helsinki, Lazio, Prague and Bratislava. Characterised by high AI exposure, a concentration of knowledge-intensive services (KIS), high levels of university graduates and substantial R&D investment, these regions are administrative, financial and innovation hubs. Given these favourable ‘conditions’, they are likely to experience positive employment outcomes if AI complements high-skilled labour in sectors such as ICT, finance and professional services. AI adoption in these regions is expected to enhance productivity while potentially creating new job opportunities, reinforcing their status as innovation-driven economic engines within their respective countries. Their strong absorptive capacity—rooted in robust technological capabilities and human capital—position them well to harness AI technologies (Boschma, 2017; Xiao and Boschma, 2023). In these regions, AI is likely to complement high-skilled labour, particularly in sectors like ICT, finance and professional services.

The second cluster, *advanced manufacturing core*, primarily consists of German regions but also includes other key industrial areas in Austria, Belgium, France, Italy and Spain (these results qualify the evidence provided by Stehrer and Stöllinger, 2015 analysing the German manufacturing core). These regions, such as Baden-Württemberg (Germany), Piedmont (Italy), Navarra (Spain), Alsace (France) and Styria (Austria), maintain strong industrial production bases, particularly in the automotive sector. This sectoral structure helps explain their moderate AI exposure but relatively high robot density, reflecting a focus on traditional forms of automation. The presence of large firms, robust R&D investment and highly skilled workforce endow these regions with the absorptive capacity needed to integrate AI into existing capital-intensive production systems. Although their AI exposure is not as high as in service-oriented regions, their high-tech specialisation and high robot density signal strong potential for AI integration and productivity gains within manufacturing.

The third cluster, *southern periphery*, includes regions from southern Europe, such as the Greek islands, southern Italy and Andalusia, along with some outliers. While some regions from Austria and Germany also appear in this cluster, the label reflects the structural challenges common in southern Europe: weaker innovation ecosystems, low productivity, limited investment and lower skill levels (Celi et al., 2018). These factors constrain these regions’ ability to reap benefits from the ongoing digital transition. Their lower AI exposure is unsurprising, as local economies still heavily rely on traditional sectors like tourism (e.g., the Greek islands) and agriculture (e.g., Andalusia, Northern Greece and southern Italy). These structural weaknesses, including low absorptive capacity, significantly limit their ability to adopt and take advantage of AI technologies.

The fourth cluster, *eastern periphery,* consists of regions from Eastern Europe, including Czechia, Poland, Hungary, Romania, Bulgaria and the Baltics. These regions share a strong industrial base but exhibit lower levels of AI exposure, robot adoption and R&D investment compared to the *advanced manufacturing core*. Despite their industrial strength, limited innovation capacity and relatively low levels of KIS and workforce skills restrict their ability to adopt advanced technologies. The lack of absorptive capacity—especially in terms of R&D and human capital—poses a challenge to fully exploit transformation potential of AI technologies.

Overall, each cluster presents distinct challenges and opportunities. In what follows, we discuss how these differences could shape the impact of AI technologies in the future.

We begin by reporting the employment growth between 2011 and 2018 by cluster (Table 4). Interestingly, relatively higher employment growth is detected in regions where manufacturing plays an important role. The eastern periphery shows the highest employment growth, suggesting some convergence with more advanced regions, although AI is unlikely to be the driver of these changes. A slightly lower employment growth is detected in the ‘high-tech service regions & capital centres’ cluster while the southern periphery turns out to be the less dynamic. If anything, such patterns suggest that, so far, employment patterns are mostly driven by well-known structural drivers (i.e., share of manufacturing industries likely to capture most of the external demand and FDI flows) shaping growth and industrial restructuring in

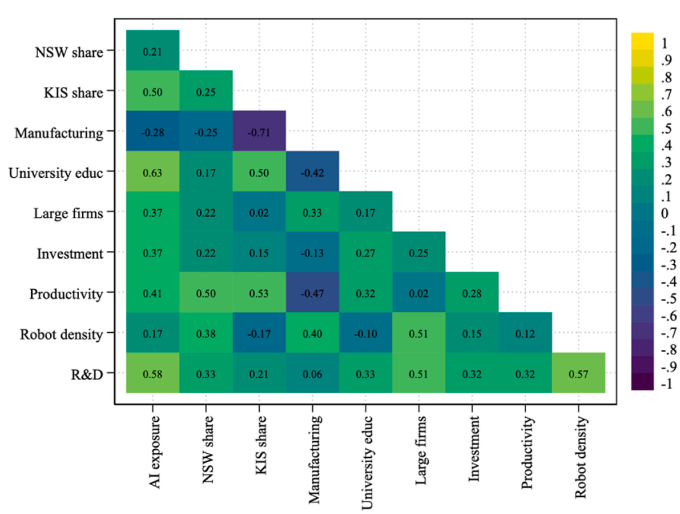

Fig. 3. Correlation matrix.
Source: Authors’ elaboration, *Note:* All variables refer to 2018; KIS refers to knowledge-intensive services.

[14] We thank the Editor for suggesting such analytical development. All the usual disclaimers apply.
[15] All four multivariate (MANOVA) tests reject the null hypothesis, indicating a significant difference between the 9-dimensional mean vectors across the four clusters.
[16] The full list of regions by cluster is provided in Table A3 in the Appendix.

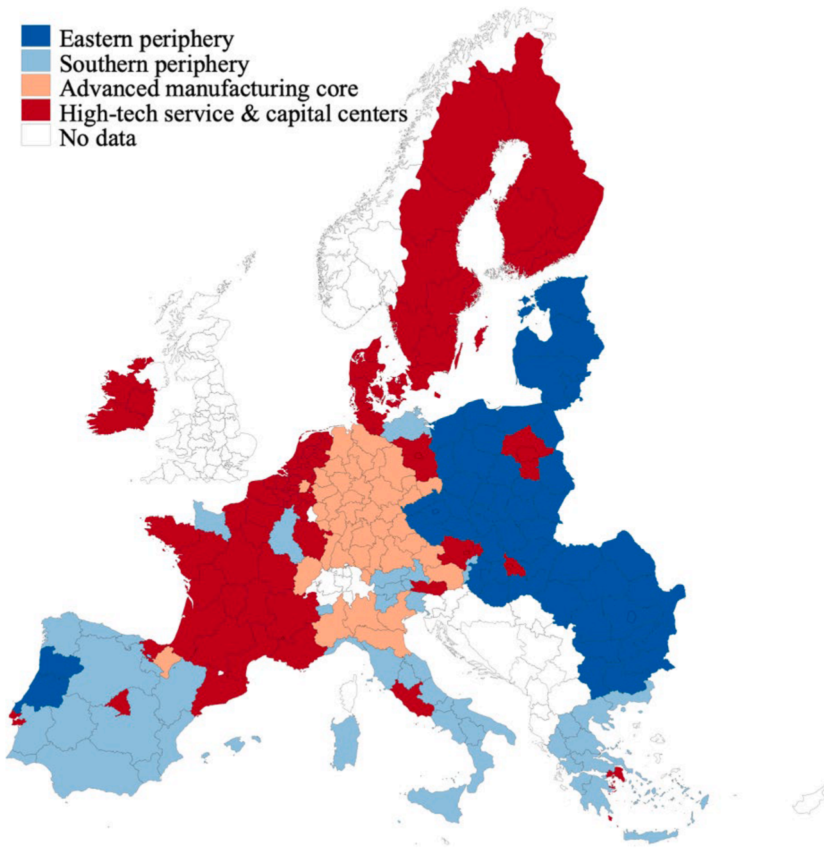

Fig. 4. Regional clusters.
Source: Authors' elaboration

Table 3
Descriptives by cluster.

	High-tech service regions & capital centers	Advanced manufacturing core	Southern periphery	Eastern periphery
AIOE	0,944	0,196	−0,619	−0,660
Robot density	5534	15,271	4202	3345
NSW	0,304	0,369	0,322	0,157
KIS	0,544	0,419	0,466	0,371
Manufacturing	0,130	0,242	0,136	0,270
University graduates	0,414	0,286	0,294	0,268
Large firms	0,452	0,519	0,298	0,413
Investments	20,956,683	16,547,184	6321,443	3823,107
GVA/EMP	83,739	73,509	79,683	23,665
R&D	2188	2680	0,936	0,886

Source: Authors' elaboration; Notes: NSW stands for non-standard work.

Table 4
Employment growth by cluster.

	High-tech service regions & capital centers	Advanced manufacturing core	Southern periphery	Eastern periphery
Employment growth 2011–2018	6031	9363	4830	14,193

Source: Authors' elaboration.

Europe over the last decades (for a thorough discussion, see Guarascio et al., 2024; Celi et al., 2018). Moreover, the positive relationship between AI exposure and employment dynamics documented, among the others, by Albanesi et al. (2023) and Guarascio and Reljic (2024) becomes more nuanced as far as regional and structural heterogeneities are explicitly considered.

To push the analysis further, the scatterplots in Fig. 5 illustrate the relationship between AI exposure and employment growth across the four clusters. By inspecting such heterogeneous patterns, it is possible to speculate around possible future scenarios for AI's impact on employment in different regions.

In *high-tech services and capital centres*, the positive association between AI exposure and employment growth reflects a broader process, whereby strong innovation systems create an environment conducive to adopting new technologies. High AI in these regions, coupled with a virtuous circle linking R&D, skills and economic activity, forms a reinforcing mechanism that is likely to drive productivity and employment growth (Pianta and Reljic, 2022). Rather than being disruptive, AI in these regions is expected to complement high-skilled labour, enhancing existing competencies and expanding job opportunities within knowledge-intensive industries such as ICT, finance and professional services.

In the *advanced manufacturing core*, the positive association between AI exposure and employment growth should be interpreted with caution. Here, AI plays a secondary role to more traditional forms of automation, particularly industrial robots, which remain the backbone of production systems. AI's contribution, by making robots more flexible, autonomous and intelligent, is likely to drive process innovation without fundamentally altering their underlying structures. As a result, AI in this context is less about disruption—displacing labour en masse—and more about enhancing the efficiency of established processes.

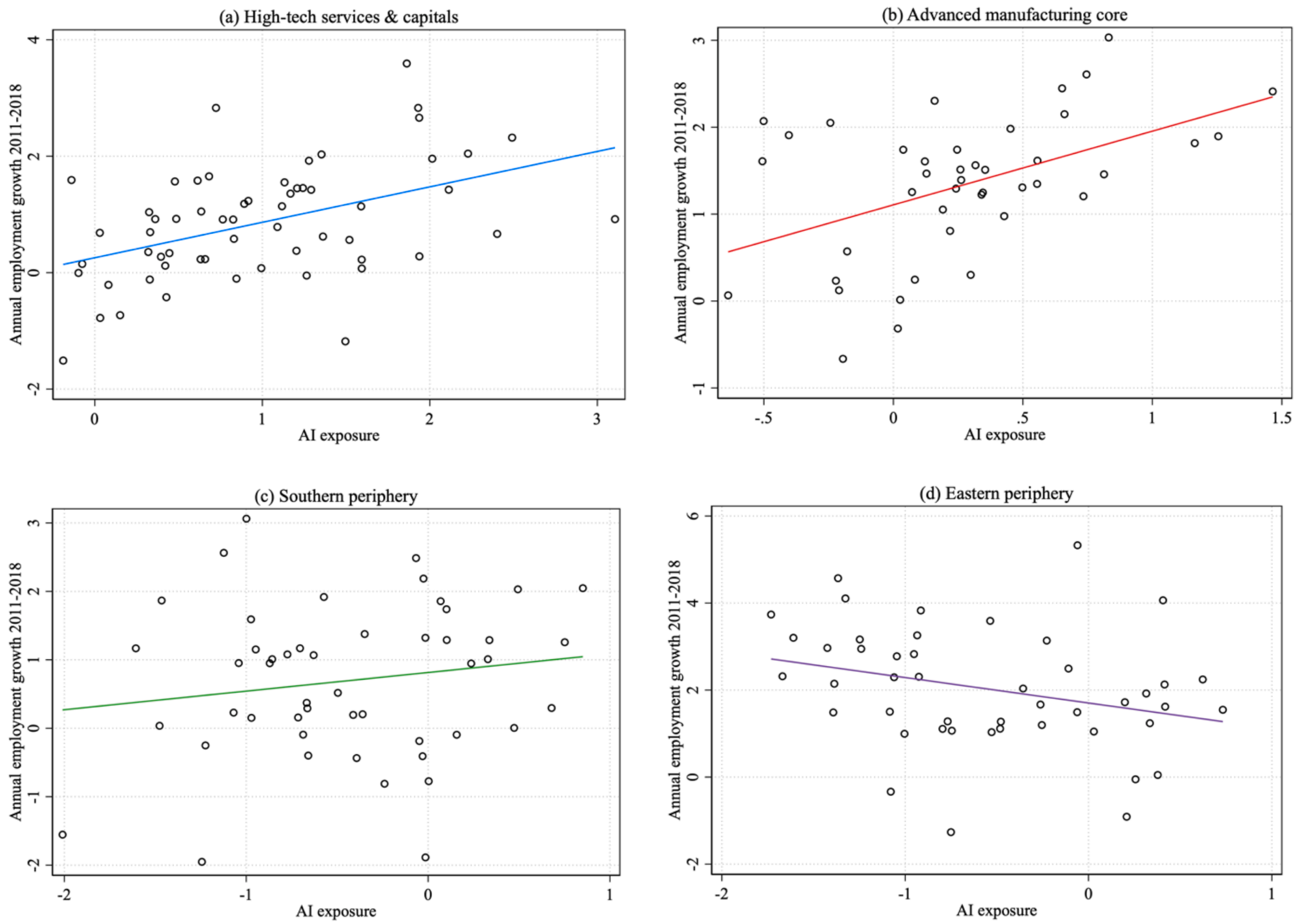

Fig. 5. Employment growth and AI exposure.
Source: Authors' elaboration

Moreover, in this area employment growth has been mostly driven by the remarkable export performance of (to a significant extent German-based) exporting industries. Yet, as the global landscape is rapidly changing with a potential downsizing of export-led growth opportunities, the employment dynamics of this cluster could also change (Guarascio et al., 2024). What could be the role of AI in such a changing scenario is still hard to say.

In the *southern periphery*, the relatively flat line suggests that AI has had—and is likely to continue having—a limited impact on labour market dynamics. These regions are characterised by low levels of AI exposure and a smaller share of high-tech services and manufacturing industries, factors that are likely to impede the adoption of AI technologies. Moreover, the absence of large firms and low absorptive capacity further constraint their potential for structural upgrading. This places the southern periphery on a 'low-road' trajectory, leaving little room for AI to spur significant changes in terms of productivity and employment.

In the *eastern periphery*, although these regions experienced the highest employment growth between 2011 and 2018, low AI exposure suggests that this growth was driven by factors other than AI (see the discussion above). Minimal AI adoption, low R&D investment and limited skills indicate that these employment gains are largely the result of labour-intensive manufacturing rather than technological transformation. Looking forward, AI adoption could lead to labour displacement rather than job creation, given these regions' specialisation in labour-intensive stages of production, such as fabrication (Kordalska et al., 2022). To benefit from AI, these regions would require structural upgrading toward more advanced manufacturing activities and, potentially, increasing the share of high-tech services Without this shift, the potential for AI to contribute to productivity and employment growth remains limited.

This analysis reveals not only the uneven exposure to AI technologies across regional clusters but also the asymmetric distribution of capabilities required to fully harness AI's transformative potential. The scenarios illustrated here reflect how technological, institutional and economic factors interact to determine which regions will be the early adopters-and beneficiaries- and which are likely to lag behind.

The heterogeneity across clusters underscores the path-dependent and context-specific nature of AI's impact on employment. In high-tech services and capital regions, accumulated technological capabilities are likely to enable AI to complement existing economic activities, potentially leading to positive employment outcomes. By contrast, the southern and eastern peripheries face significant structural barriers—including sectoral specialisation, low R&D investment, limited skills—which hinder both their ability to adopt AI technologies and ultimately benefit from them.

6. Conclusion and policy implications

This paper adds to the nascent literature on the exposure to AI technologies and their expected employment implications. We focus on Europe, which is a relevant case in point for at least three reasons. First, promoting the adoption of digital technologies is now at the centre of the EU industrial policy strategy, given the widely acknowledged technological gap vis-à-vis the US and China (Guarascio et al., 2024). Second, the available empirical evidence on AI is to a significant extent US centric while less is known about exposure, adoption and impact in

Europe. This lag is primarily due to better data availability for the US economy, where researchers can draw on publicly available data on occupational profiles as well as employment and wage data at a very granular level. Third, Europe is characterised by significant structural and territorial heterogeneities which may affect in a fundamental way the economic and employment impact of AI.

In this context, country and region-specific empirical analyses are indispensable, as structural heterogeneities may lead to completely different outcomes when it comes to the diffusion of potentially disruptive technologies such as AI. Our analysis reveals significant regional differences in AI 'readiness' across Europe, driven by key factors such as accumulated technological capabilities, R&D investment, sectoral composition (e.g., a large share of knowledge-intensive services) and the availability of a highly skilled workforce. This confirms the importance of considering the differences between national and local innovation systems when assessing the impact of specific technologies. Regions where high-tech service centres and advanced manufacturing hubs are located, seem to have the most favourable conditions for adopting AI and, potentially, seizing the associated economic and employment opportunities. In contrast, regions in the southern and eastern peripheries —characterised by lower R&D investment, weaker innovation ecosystems and a reliance on labour-intensive industries—lack these key enablers, limiting the opportunities for AI adoption.

This is related to a more general aspect of technological change, Kranzberg's Law, which holds that, *"Technology is neither good nor bad; nor is it neutral"* (Kranzberg, 1986, p. 545). The point the technological historian put forward in his writings is that the consequences of technology depend not only on its technical features but on the societal and temporal context. Hence, chances are that there is no single answer to the question of what AI means for jobs that researchers are so eager to answer. Rather, answers can only be partial, specific to the locations and time periods analysed.

This means that there is no universal answer to the question if – and in the affirmative –how AI will affect labour markets in general. We do not know whether the 'future of work' will resemble the rosy world envisaged by Keynes (2010[1931]) in his essay on the *Economic Possibilities for Our Grandchildren*, in which new technologies – in our context AI – lead to such massive increases in productivity, essentially freeing society from scarcities and allowing people to indulge in science, arts and philosophy. We would see this as the positive or 'Star Trek' scenario. Things could play out very differently, though. As outlined by Leontief (1983), humans may face the same destiny as horses in their function as 'workforce', meaning they will just not be needed anymore, apart for some curious nostalgic purposes such as tourist entertainment showing the ways of the past, sports, or the circus. This 'Death of the Workhorse' scenario in which men lose the race against machines has become popular among economists with many facets of it. This prevalence of the pessimistic view is the result of two characteristics and their interaction: one related to AI, the other to the current economic paradigm. Leontief's point is that the horse as a production input became obsolete because the steam engine outcompeted the workhorse in its core competencies – physical strength and stamina. Likewise, AI in many work contexts now outcompetes humans in cognitive tasks and also seriously challenges them in (simple) social interaction. This feeds the 'this time is different' narrative which often comes with a Luddite undertone but in principle could be counteracted by the fact that, unlike the horse, humans themselves can decide whether, to what extent and for which purposes they want to introduce the new technologies now available. However, this safety valve for meaningful human labour risks being undermined by the current economic paradigm, which induces firms to use AI not primarily to find valuable solutions to societal challenges but to maximise shareholder value. The latter typically involves the replacement of labour with AI algorithms (see Acemoglu and Johnson, 2023)[17] – typically in combination with robots and other machines.

Our findings suggest that regions with a high robot density and AI exposure—particularly in capital-intensive production systems—may end up losing jobs in some cases. However, we argue that, in the European advanced manufacturing core, AI is more likely to enhance process innovation rather than displace labour *en masse*. In contrast, in the eastern periphery, given its specialisation in labour-intensive manufacturing industries, AI-enhanced automation could potentially lead to labour displacement. This underlines the fact that labour market effects emanating from AI may be very heterogenous across EU regions.

Our results must be interpreted with great care for a number of reasons. First, a more robust mapping of AI diffusion would have required data on actual adoption and information on specific AI technologies/applications, as these may lead to rather heterogeneous outcomes. Yet, so far, the variables capturing the potential diffusion of AI technologies are, de facto, the best tool to sketch scenarios about their economic and employment implications. In this regard, firm-level data on AI adoption would be invaluable for updating and enriching existing evidence. Second, an important caveat of this study is that by focusing on employment, only one aspect of labour markets is captured, while other relevant dimensions of work are neglected, in particular working conditions. It could very well be that while new jobs are created, these jobs are of a poor quality, meaning they are low in terms of skill requirements but above all they lack a sense of meaning. The working conditions related to many of these newly created jobs could be described as underpaid, isolated, where workers are stuck at home in front of their computers with work and leisure time getting increasingly blurred. While the results of this first regional analysis have little to say in this regard, the fact that AI exposure is skewed towards high-skilled jobs and that other studies (Albanesi, et al., 2023; Felten et al., 2019) found that AI leads to employment growth primarily for high-skilled labour may question this prediction. At the same time, it cannot be ruled out that even jobs of high-skilled workers are getting increasingly monotonous and meaningless.

In addition to the omission of job quality, there are a number of important methodological limitations which have to be kept mind. Firstly, quantitative work of the kind undertaken here is bound to make inferences from the past onto the future. While this is legitimate, the predictions emerging from such an undertaking may be less accurate and reliable when they deal with a potentially disruptive technology, i.e., AI. Secondly, the diffusion of AI in the economy may still be too limited so that its macroeconomic consequences (such as employment growth) are hard to identify in the data. Furthermore, there are institutional factors, notably the existence of labour unions, which are likely to influence labour market outcomes. More specifically, labour unions may to some extent be able to soften AI-related labour-saving. As such this constitutes an interesting avenue for further research, as does a more differentiated analyses of employment effects by skill groups.

CRediT authorship contribution statement

Dario Guarascio: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jelena Reljic:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Roman Stöllinger:** Writing – review & editing, Writing – original draft, Visualization, Validation,

[17] The situation is aggravated by the fact that in the US, a major innovator in this domain, AI technologies are under the control of a few powerful firms.

Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

APPENDIX

Table A1
AI indicators: findings and limitations.

Data Source	Findings	Limitations
AI-related Online Job Vacancies (e.g., Burning Glass)	Acemoglu et al. (2022) found no significant effects of AI at the occupation and industry level in the US	Online job vacancies are not representative of overall labour demand; occupation- industry- and country-biased
Patents	Damioli et al. (2023) studied 3500 leading companies with AI-related patents and found a moderate positive employment impact of AI	Not an indicator of adoption, but innovation (partial, as not all innovations are patented); sample includes only patenting companies, silent on net effects (i.e., business stealing)
AI Patents and O*NET Tasks	Webb (2020) used verb-noun pairs in AI patent titles and O*NET tasks to measure automation. AI more likely to affect skilled and older workers compared to previous innovation waves (ICT and robots)	Focuses on exposure rather than adoption; patent titles may not fully describe the underlying technology; selection of keywords is arbitrary
Occupation-based Indicators	Felten et al. (2018, 2021) found positive effects on wages but no impact on employment in the US; Gmyrek et al. (2023), focusing on GPTs, reveal that 24 % of clerical tasks are highly exposed	Focuses on exposure rather than adoption; silent on industry and firm-level technological differences

Source: Authors' elaboration.

Table A2
List of variables.

Variable	Definition	Source
AI exposure	Standardised with 0 mean and a unit standard deviation	Felten et al. (2021)
Robot density	Robot stock in manufacturing industries per 1000 employees	IFR
Total employment	Annual employment growth	EU LFS
University degree	Share of employees with tertiary education	EU LFS
KIS	Share of employees in knowledge-intensive services	EU LFS
Non-standard work	Share of employees without permanent full-time contract	EU LFS
Manufacturing	Share of manufacturing employment	EU LFS
Large firms	Share of firms with 50+ employees	EU LFS
R&D investments	R&D as percentage of GDP	Eurostat
Investment	Gross fixed capital formation	ARDECO
Labour productivity	Gross value added per employee	ARDECO

Source: Authors' elaboration.

Table A3
List of regions by cluster.

Cluster	Regions
High-tech service regions & capital centers	AT12, AT13, AT21, BE10, BE21, BE23, BE24, BE25, BE31, BE32, BE33, BE34, BE35, CZ01, DE30, DE40–42, DE60, DEF0, DK01–05, ES21, ES30, ES51, FI18–1C, FI19, FI1A-1D, FR10, FRB0, FRC1, FRD2, FRE1, FRE2, FRF3, FRG0, FRH0, FRI1, FRI2, FRI3, FRJ1, FRJ2, FRK1, FRK2, FRL0, GR30, HU10–12, IE01–06, ITI4, NL00, PL12–92, PT17, RO32, SE11, SE12, SE21, SE22, SE23, SE31, SE32, SE33, SK01
Advanced manufacturing core	AT22, AT31, AT34, BE22, DE11, DE12, DE13, DE14, DE21, DE22, DE23, DE24, DE25, DE26, DE27, DE50, DE71, DE72, DE73, DE91, DE92, DE93, DE94, DEA1, DEA2, DEA3, DEA4, DEA5, DEB0-B3, DEC0, DED2, DED4, DED5, DEE0-E3, DEG0, ES22, FRC2, FRF1, ITC1, ITC4, ITH3, ITH5
Southern periphery	AT11, AT32, AT33, DE80, ES11, ES12, ES13, ES23, ES24, ES41, ES42, ES43, ES52, ES53, ES61, ES62, ES63, ES70, FRD1, FRF2, GR42, GR43, GR51, GR52, GR53, GR54, GR61, GR63, GR64, GR65, ITC2, ITC3, ITF1, ITF2, ITF3, ITF4, ITF5, ITF6, ITG1, ITG2, ITH1, ITH2, ITH4, ITI1, ITI2, ITI3, PT15, PT18, PT20, PT30
Eastern manufacturing periphery	BG31–33, BG41, BG42–34, CZ02, CZ03, CZ04, CZ05, CZ06, CZ07, CZ08, EE00, HU21, HU22, HU23, HU31, HU32, HU33, LT00–02, LV00, PL21, PL22, PL41, PL42, PL43, PL51, PL52, PL61, PL62, PL63, PL71, PL72, PL81, PL82, PL84, PT11, PT16, RO11, RO12, RO21, RO22, RO31, RO41, RO42, SK02, SK03, SK04

Source: Authors' elaboration.

Data availability

Data will be made available on request.

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