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The Employment Impact of Emerging Digital Technologies*

Ekaterina Prytkova[†] Fabien Petit[‡] Deyu Li[§]
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Abstract

This paper estimates industry and occupation exposure to a comprehensive set of emerging digital technologies and assesses their impact on European regional employment. Using a novel, scalable methodology based on advanced natural language processing techniques (sentence transformers), we measure technological exposure using semantic similarity between patents and standardized international classifications. Using an instrumental-variable shift-share approach, we find that higher regional exposure yields net employment gains. Explicitly accounting for complementarities between digital technologies, we estimate their individual effects and classify technologies as labor-saving or labor-augmenting, based on their impacts on aggregate employment. We identify distinct patterns of technological impacts across different skill groups, and we rationalize them within a task-based theoretical framework. Our findings highlight that focusing narrowly on specific technologies such as AI or robots, without accounting for complementarities across the broader digital technology landscape, can significantly understate the broader, positive effects of digital transformation on employment.

Keywords: Occupation Exposure; Industry Exposure; Text as Data; Natural Language Processing; Sentence Transformers; Emerging Digital Technologies; Automation; Employment
JEL Codes: C81, O31, O33, O34, J24, O52, R23

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1 Introduction

The past decade has seen rapid progress in digital technologies, such as artificial intelligence (AI), augmented and virtual reality, autonomous vehicles, drones, mobile robots, the Internet of Things (IoT), 3D printing, and blockchain. These technological advances have the potential to displace all types of workers, including even high-skilled ones. They are fundamentally reshaping economic production processes and have potentially profound implications for labor markets. While an extensive body of literature examines employment effects associated with established digital technologies—such as Information and Communications Technologies (ICTs) and industrial robots[1]—relatively little is known about the employment impacts of this broader set of emerging digital innovations.

This gap in the literature primarily stems from the inherent difficulty in systematically measuring the relevance of specific technologies for particular occupations or industries. Consequently, existing metrics capturing worker and industry exposure to emerging digital technologies provide either coarse or partial coverage of the complex digital transformation. In particular, existing measures either narrowly target specific technologies—often limited to particular applications of AI—or aggregate diverse technologies into broad automation indices.[2] A finer understanding of these heterogeneous impacts is also essential for innovation policy, enabling policymakers to steer support toward technologies that lift productivity while safeguarding employment opportunities. Furthermore, most existing evidence derives exclusively from the US, raising concerns about generalizability to other institutional and economic contexts.[3]

This measurement challenge also complicates the economic analysis of technological impacts on employment. In the absence of precise exposure metrics, it is difficult to isolate the individual contributions of specific digital technologies to observed labor market outcomes. Many emerging technologies exhibit complementarities, leading to their simultaneous adoption. Ignoring these complementarities risks significantly biasing estimates of each technology's distinct employment effects and thus misinforming economic policy discussions about technological change and labor market dynamics.

This paper addresses these gaps by providing a comprehensive analysis of how emerg-

[1] See, among others, Autor et al. (1998), Autor et al. (2003), Autor et al. (2006), Goos and Manning (2007), Goos et al. (2009, 2014), Michaels et al. (2014), and Akerman et al. (2015) for ICT-related technological change; and Graetz and Michaels (2018), Acemoglu and Restrepo (2020), Vries et al. (2020), Aksoy et al. (2021), Dauth et al. (2021), Aghion et al. (2023), Adachi et al. (2024), and Bonfiglioli et al. (2024) for industrial automation and robots.

[2] See Felten et al. (2018, 2021), Webb (2019), Alekseeva et al. (2021), and Acemoglu et al. (2022b) for AI-specific exposure metrics; also see Mann and Püttmann (2023), Autor et al. (2024), and Kogan et al. (2024) for broader automation measures.

[3] A notable exception is Albanesi et al. (2023), who examine labor market exposure to AI and software in 16 European countries, albeit using exposure metrics originally developed for the US (Felten et al. 2018, Webb 2019).

ing digital technologies affect employment. First, we estimate the exposure of industries and occupations to a wide range of digital technologies introduced over the past decade. Leveraging advanced Natural Language Processing (NLP) tools—specifically sentence transformer models—we introduce a novel, systematic, and scalable approach that quantifies technological relevance based on semantic similarity between patent descriptions and international industry and occupation classifications. Second, we use these measures in an instrumental-variable shift-share framework to estimate the employment effects of emerging digital technologies across European regions from 2012 to 2019, explicitly accounting for complementarities among technologies. Third, we classify these technologies into labor-saving, labor-neutral, and labor-augmenting categories, based on their impacts on aggregate employment. We identify distinct patterns of effects across different skill groups, and we rationalize these empirical findings within a task-based theoretical framework.

We begin by classifying patents into distinct technologies based on the semantic similarity of their descriptive titles. Specifically, we use the sample of core emerging digital technology patents from Chaturvedi et al. (2023), comprising innovations filed between 2012 and 2021 that are pivotal for the current and forthcoming development of digital technologies. To systematically quantify semantic content, we transform patent titles into numerical vector representations, or *embeddings*,[4] using the pre-trained sentence transformer model *all–mpnet–base–v2* (Reimers and Gurevych 2019; Song et al. 2020).[5] Applying k-means clustering to these embeddings yields 40 distinct emerging digital technologies, each comprising semantically related patents.

Next, we measure the exposure of industries and occupations to these technologies based on the semantic correspondence between patents and standardized descriptions from international classification systems. For each patent–industry and patent–occupation pair, we calculate cosine similarity scores, which quantify the semantic proximity between the texts. To enhance accuracy and relevance, we implement a filtering procedure that retains only highly relevant pairings. Subsequently, we aggregate these refined similarity scores from the patent level to the technology clusters, using a citation-weighted approach to reflect differential patent importance.

Our resulting exposure measure captures the *relevance* of a specific technology to a given industry or occupation. For industries, relevance corresponds to the potential incorporation

[4]Text embedding refers to the numerical representation of textual information (words, sentences, or documents) using NLP techniques. See Gentzkow et al. (2019) and Ash and Hansen (2023) for comprehensive surveys of NLP applications in economics.

[5]Sentence transformers constitute a deep neural network architecture designed to capture contextual meaning within text, thereby producing robust vector embeddings. The model *all-mpnet-base-v2* has been trained on extensive datasets, including academic texts, Wikipedia articles, and Stack Exchange posts—achieving state-of-the-art performance on sentence similarity benchmarks.

of technology into production processes or its capability to enhance output. For occupations, it reflects the technology's significance in performing tasks. Importantly, our metrics are intentionally neutral regarding whether technologies serve as substitutes or complements to labor. Instead, we explicitly investigate these relationships empirically in the second part of the paper.

We then estimate the causal effects of emerging digital technologies on employment across 320 NUTS-2 regions in 32 European countries for the period 2012–2019. Initially, we assess the aggregate impact of these technologies on regional employment-to-population ratios. Additionally, we disaggregate our analysis by demographic and skill characteristics, specifically examining differential effects by gender, age groups, and educational attainment levels, as well as by industries.

To address endogeneity concerns, we use an instrumental variable shift-share design, where industry-level exposure to digital technologies for the period 2012–2019 serves as the *shock*, interacted with baseline regional employment shares from 2010. Our identification strategy rests on the quasi-random assignment of global technological shocks, assuming that the development of emerging digital technologies occurs largely independently of local European labor market dynamics. To further reinforce identification, we recalculate industry-level exposure scores excluding patents originating from Europe, ensuring quasi-exogeneity of shocks relative to regional employment fluctuations. We also assume that regions with higher exposure to emerging digital technologies do not systematically experience different unobserved labor market shocks.[6]

Subsequently, we estimate the employment effects of individual digital technologies while explicitly controlling for exposure to other digital technologies. Based on their aggregate employment effects, we classify these technologies as either labor-saving or labor-augmenting. We then analyze their differential impacts across low-, middle-, and high-skilled employment groups. Finally, we interpret our empirical findings through the lens of a task-based theoretical framework, highlighting the underlying economic mechanisms driving these distinct labor market outcomes.

Our work reveals several new findings. First, we document substantial heterogeneity in exposure to emerging digital technologies across occupations and industries. Occupations involving routine tasks—such as clerical support workers, plant and machine operators, and assemblers—display the highest exposure, closely followed by high-skill occupations such as managers, professionals, technicians, and associate professionals. Exposure among these high-skilled occupations primarily occurs through recurrent rather than specialized tasks. More-

[6]Our econometric approach follows the equivalence condition established by Borusyak et al. (2021) and employs the AKM0 inference method developed by Adão et al. (2019).

over, we identify a clear divide between manual and cognitive occupations: manual occupations are rather exposed to tangible technologies, including 3D printing, embedded systems, and smart mobility, while cognitive occupations exhibit higher exposure to intangible technologies, such as computer vision, e-commerce, payment systems, health technologies, and digital services. We observe a similar tangible–intangible split across industries, with agriculture, manufacturing, and infrastructure-based services (e.g., transportation and storage) exhibiting greater exposure to tangible technologies, whereas intangible technologies predominate among other service industries.

Second, we find that the overall impact of emerging digital technologies on regional employment is positive; however, we observe a job polarization pattern. A one-standard-deviation increase in regional exposure raises the employment-to-population ratio by 0.963 percentage point (pp.) change, corresponding to 1.83%, between 2012 and 2019. Disaggregating these effects by skill level reveals a clear polarization pattern: employment gains are concentrated among low- and high-skilled workers— rising by 0.527 pp. (+4.46%) and 0.704 pp. (+4.71%) respectively—whereas middle-skilled employment declines by 0.297 pp. (−1.29%). Yet, the effect on low-skilled workers is only significant at the 10% level, suggesting substantial heterogeneity across European regions in the impact of digital technologies on these workers. Additionally, we find that employment gains are larger for female and young (aged 15–24) workers compared to male and mature (aged 25–64) workers. At the sectoral level, employment growth is driven by information and communication services, professional, scientific, technical, administrative, and support services, as well as other service sectors. These positive effects more than offset the employment losses observed in agriculture, manufacturing, financial and insurance activities, and public services.

Third, we find consistent patterns of employment impacts across several emerging digital technologies. We classify emerging digital technologies into three distinct categories based on their estimated aggregate employment effects: labor-saving technologies (which reduce employment), labor-augmenting technologies (which enhance employment), and labor-neutral technologies (with no measurable employment effect). Labor-saving technologies consistently follow a pattern of displacing low- and middle-skilled employment by automating simpler tasks, while simultaneously increasing demand for high-skilled workers through the creation of new and complex tasks. Prominent examples include industrial automation and robots, machine learning, electronic messaging, mobile payment systems, and social networking technologies.

In contrast, labor-augmenting technologies typically raise employment among low- and middle-skilled workers by augmenting their productivity and enabling them to perform increasingly complex tasks, outweighing any displacement of simpler tasks. However, these technologies tend to negatively affect high-skilled employment, suggesting that productivity gains and task expansion effects are insufficient to offset displacement within this group. Prominent examples include 3D printing, remote monitoring, and e-learning. For example, technologies like 3D printing can automate design and prototyping processes that previously required specialized engineering skills; remote monitoring systems can reduce the need for on-site experts; and e-learning platforms can substitute for high-skilled trainers and consultants.

This paper contributes to the literature on the labor market impacts of automation and digital technologies. Existing studies typically examine either specific technologies—such as industrial robots (Graetz and Michaels 2018; Acemoglu and Restrepo 2020; Vries et al. 2020; Dauth et al. 2021; Adachi et al. 2024) or AI (Webb 2019; Albanesi et al. 2023; Eloundou et al. 2024; Marguerit 2024; Hampole et al. 2025)—or use aggregate measures encompassing broad classes of automation technologies (Mann and Püttmann 2023; Autor et al. 2024; Kogan et al. 2024). These two strands of literature produce seemingly divergent results: analyses of individual technologies such as robots and AI tend to identify negative aggregate employment effects, whereas broader and more aggregated studies generally report neutral or positive impacts. We bridge these results by studying a comprehensive yet granular set of emerging digital technologies, explicitly accounting for the substantial heterogeneity and complementarities among them. Our findings reveal that although specific digital technologies may negatively impact employment when analyzed in isolation, their aggregate effect becomes positive when considered altogether. Thus, our analysis highlights the critical importance of accounting for technological complementarities when assessing the labor market effects of digital transformation.

Our work also contributes to the literature on the technology–skill complementarity (Goldin and Katz 1998; Autor et al. 2003, 2006; Goos et al. 2009; Autor and Dorn 2013; Goos et al. 2014; Kogan et al. 2024). Prior research has highlighted how evolving technologies reshape the allocation of tasks between workers and capital, potentially leading to either substitution or complementarity effects. We extend this literature by systematically identifying which individual emerging digital technologies act as substitutes or complements to different types of labor, highlighting clear and recurring empirical patterns.

Our paper also contributes methodologically by introducing a novel, scalable approach to measure technology exposure using advanced NLP techniques. Traditional exposure metrics typically rely on keyword-based matching between innovations and occupational or industry descriptions. For instance, Kelly et al. (2021) and Kogan et al. (2024) use token-based TF-IDF methods to link innovations to occupations, while Hémous et al. (2025) identify automation-related patents based on keyword frequencies, and Mann and Püttmann (2023) categorize patents by token presence. In contrast, our approach leverages state-of-the-art sentence transformer models, allowing us to quantify exposure based on semantic and contextual similarity rather than explicit keyword matches. Moreover, by clustering patents according to semantic similarity, our method enables a granular yet interpretable categorization of a diverse set of emerging digital technologies, extending well beyond robotics and artificial intelligence alone.

Lastly, our paper addresses a critical gap in existing exposure metrics, which have primarily relied on US-specific classifications or narrowly defined technological subsets. For example, Jurkat et al. (2022) provide international data focused exclusively on industrial robots, Frey and Osborne (2017) examine occupational exposure limited to computerization, and Webb (2019), Felten et al. (2021), and Felten et al. (2023) measure exposure solely for AI and recent advances in AI language modeling. In contrast, we introduce the first exposure metrics constructed at a granular level using international standard classifications—specifically NACE Rev. 2 (industries) and ISCO-08 (occupations)—covering a broad spectrum of digital technologies beyond robotics and AI. Additionally, our metrics use global patent data, thereby capturing technological advances worldwide rather than within specific geographic regions. To facilitate broad usage and future research, we make these measures publicly accessible through an open-access resource, the 'TechXposure' database, that we intend to continuously update with new technologies.

The paper is organized as follows. Section 2 introduces our NLP-based methodology for identifying emerging digital technologies and calculating exposure scores for industries and occupations. Section 3 provides descriptive evidence on the exposure of industries and occupations. Section 4 estimates the aggregate employment impacts of emerging digital technologies across European regions and explores heterogeneity by gender, age, skill, and industry. In Section 5, we examine the employment effects of individual digital technologies, explicitly accounting for technological complementarities. Section 6 further disaggregates these impacts by worker skill groups and identifies common patterns of employment effects across technologies. Section 7 concludes.

2 Semantic-based Exposure to Digital Technologies

This section outlines our NLP-based methodology for calculating industry- and occupation-level exposure to emerging digital technologies. We begin by describing the textual data sources that we leverage using a Sentence Transformer model. We provide a detailed rationale for selecting this model, focusing on the desirable properties of resulting textual representations (or embeddings)—particularly their ability to capture semantic similarity. Next, we define the set of emerging digital technologies as clusters of patent embeddings. Finally, we represent industries and occupations using embeddings of their textual descriptions and quantify their exposure to emerging digital technologies by aggregating the semantic similarity between industry or occupation embeddings and patent embeddings within each technology cluster.

2.1 Textual Data

Patents. We use a set $\mathcal{P}$ of 190,714 patent families from the Derwent Innovation Index (DII) database filed between 2012 and 2021.[7] These families, represented by standardized English titles and abstracts, are structured by experts into themed blocks (e.g., novelty, use, claims) to streamline searching.[8] For simplicity, we use the term 'patent' instead of 'patent family' to refer to a single invention across various patent offices. This patent set, constructed by Chaturvedi et al. (2023), captures prominent digital technologies and applications since 2011.[9]

The main advantage of the DII is that it provides expertly curated patent texts; both patent titles and abstracts are segmented into labeled topical blocks like novelty, use, claims, etc. In particular, patent titles are structured in two parts: the first part ($p_1 \in p$) provides a concise description of the technology, while the second part ($p_2 \in p$) explains *how the technology functions*. These two parts are separated by the first **comma–verb combination**.[10] This structure achieves a balanced representation of the invention, maintaining both generality and specificity; it enables us to control the actual content of the text, retaining only relevant information about the invention's essence and intended function, and excluding any other content that could reduce signal-to-noise ratio. The relevance of this structure stems from the fact that it is replicated in industrial and occupational descriptions. Specifically, anticipating the discussion ahead, we represent an industry or occupation with sentences that follow the same structure: essence (from the occupation/industry title) combined with function (a task for an occupation or an activity/process for an industry). Aligning the structure of patent titles with industrial and occupational texts enhances the matching between patents and these taxonomies. Finally, unlike abstracts, titles are consistently available for all patents.

We provide three examples of patent titles present in our sample:

[7] The DII covers over 120 million global patent publications from 59 worldwide patent-issuing authorities and assigns each invention to a unique patent family. Alongside CPC and IPC classifications, DII employs Derwent Manual Codes, a custom hierarchical indexing system reflecting technical and application content for improved patent retrieval.

[8] Each patent document details the invention and its distinctions from prior inventions. Information includes a title, abstract, and metadata, such as applicants, inventors, filing year, authority, citations, and technical classifications (e.g., International Patent Classification or IPC).

[9] We provide further details on the patent corpus construction in the Online Appendix.

[10] Using Part-of-Speech (POS) tagging, we identify this pattern in 87.3% of our sample, commonly appearing as ', has', ', includes', ', involves', and ', comprises'. For the remaining patents, titles are split at the nearest midpoint.

1. Method for targeting television advertisement based on profile linked to online device**, involves** *selecting television advertisement to be directed to set-top box based on profile information pertaining to user or online activity.* (Patent ID 2013B87254, 2013)
2. Vehicle intelligent logistics control device**, has** *GPS locating module for obtaining position information of transport vehicle through main control chip, RFID reader for reading RFID tag information, and 4G module connected with server.* (Patent ID 201713859U, 2017)
3. System for recognizing training speech**, has** *process or which is configured to increment counter associated with word sequences, and train language model of automatic transcription system using word sequences and counter.* (Patent ID 202048118D, 2020)

NACE Rev.2 Industries. We select the 3-digit NACE Rev.2 classification as the most disaggregated level at which we represent industries; see European Commission and Eurostat (2008) for more details on the classification. The primary reason is that 4-digit industries within the same 3-digit category produce a *variant* of a product or service category; for example, growing of different types of fruits—citrus, tropical, or pome—belongs to the growing of perennial crops industry. In the context of digital technologies, such product/service variants do not represent substantial differences. This enables us to include textual descriptions of the nested 4-digit level into the 3-digit descriptions, thereby expanding the textual representation of each industry.

Following the patent title structure we discussed in previous paragraphs, each industry i is represented with two components: its title and a set of individual sentences of the industrial description (merged text of 3-digit and nested 4-digit descriptions). This yields 271 industries at the 3-digit level, each represented by an average of 11 sentences.

ISCO-08 Occupations. We select the 4-digit ISCO-08 level as the most detailed for the textual description of occupations; see International Labor Organization (2012) for more details on the classification. Unlike industries, this level includes distinct occupations that provide valuable insights for our analysis. Each ISCO-08 occupation corresponds to a specific set of tasks, though some tasks may overlap across occupations.

Again mirroring the patent title structure and analogously to industries, each occupation o is represented with its title and a set of individual tasks listed for this occupation. This process yields 433 occupations at the 4-digit level, each represented by a title and an average of 7.5 tasks.

2.2 Embeddings with Sentence Transformer

We measure industrial and occupational exposure to the core digital technologies as *textual similarity* between the description of the innovation (from the patent) and industrial/occupational description. To leverage patent, industrial, and occupational descriptions for exposure estimation, we first need to represent these texts in a numerically meaningful form. To achieve this, we employ the state-of-the-art NLP techniques. We encode the raw text of each document into a numerical representation using a pre-trained language model; such n-dimensional dense vector representation of text is called *embedding*.

A variety of techniques can produce vector representations of text: from the simplest frequency-based methods, such as TF-IDF, to bag-of-words (BoW) models, such as Word2Vec or FastText, and seq2seq models, such as recurrent neural networks (RNNs), to various transformers. We choose the all-mpnet-base-v2 (Reimers and Gurevych 2019; Song et al. 2020) sentence transformer for two crucial reasons.

First, the all-mpnet-base-v2 transformer produces *contextual or dynamic embeddings*: encoding of a word's meaning that accounts for its surrounding context; the same word in different documents has a different vector that encodes its semantic meaning. Therefore, the content of the entire document is represented in greater detail than using BoW models that produce static embeddings, i.e., fixed vectors for a word in all documents. Encoded variety of semantic meanings per word and resulting contextual representation of the entire document in dynamic embeddings is a crucial advantage over static embeddings in tasks that involve cross-domain document matching, such as similarity between technology and industry/occupation. The frequency-based methods that represent documents as (weighted) word-count vectors, despite being used in recent works by Kogan et al. (2024) and Autor et al. (2024), are superseded by embeddings-based methods for a number of substantial reasons; for example, they cannot handle new words (fixed vocabulary), struggle with negation and polysemy, and require exact matching leading to sparse representation, etc. Therefore, matching documents represented by word-count vectors—especially between two *different* corpora—is substantially less robust than using contextual embeddings.

Second, even among models that produce contextual embeddings, the all-mpnet-base-v2 transformer has a significant advantage: it has been trained using *contrastive learning*.[11] During the training process, the all-mpnet-base-v2 transformer is given triplets of documents, each consisting of a focal document, one similar document (positive example), and one dissimilar document (negative example). The model's objective is to learn such document representations that similar documents have closely distanced embeddings and dissimilar doc-

[11]For technical discussion and overview, refer to Wang and Liu (2021) and Dell (2025).

uments have embeddings positioned far apart. Thus, contrastive learning explicitly ensures that *distances* between document-vectors represent their semantic (dis)similarity. Other models trained with alternative procedures, e.g., BERT with masked language modeling, produce nuanced document representations but *distances* between them are not accurate representations of semantic similarity between documents (Reimers and Gurevych 2019; Wang and Liu 2021).[12]

In sum, all-mpnet-base-v2 produces both nuanced document representations (contextual embeddings) and distances between them that accurately reflect semantic similarity.

2.3 Emerging Digital Technologies

We propose to represent technologies as *clusters of patent embeddings*. For each patent title $p \in \mathcal{P}$, we obtain its embedding E_p. We then cluster the embeddings using the k-means algorithm to obtain 40 clusters, which we designate as our set of digital technologies $\mathcal{K}$.[13] We find that 40 clusters are optimal for our analysis, as they align well with commonly discussed technologies in digital and automation literature (Acemoglu and Restrepo 2019; Martinelli et al. 2021; Zolas et al. 2021; Acemoglu et al. 2022a).

Tables A.1 to A.3, in the appendix, present our set of prominent emerging digital technologies, grouped by technology families, and provide short descriptions of each technology. The grouping of these 40 technologies into 9 families is based on their semantic associations with the same set of occupations, as depicted in Figure A.1 in the appendix.

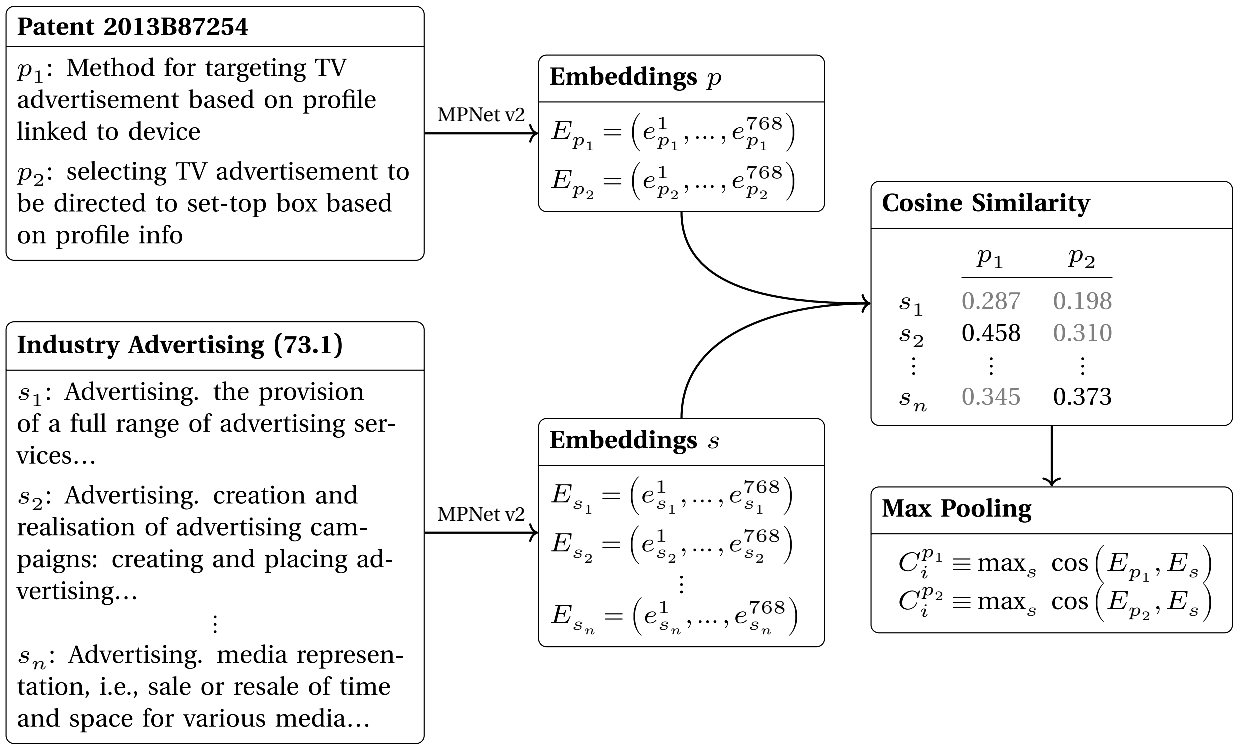
2.4 Semantic-based Exposure

We focus on providing the core intuition behind the proposed methodology to estimate the exposure scores of industries and occupations to emerging digital technologies, while the detailed technical commentary is relegated to the Online Appendix. We start by calculating the cosine similarity scores between industries/occupations and patents, filtering for relevant pairs. Then, we aggregate these similarity scores at the technology level to derive semantic-based exposure scores.

[12]In technical terms, the resulting embedding space is anisotropic, i.e. non-uniform in different directions, and frequent words concentrate densely while rare words are sparsely scattered; this problem propagates with pooling further to document level.

[13]Initially, we compute partitions ranging from 5 to 100 clusters and record each Davies-Bouldin Index (DBI) score (Davies and Bouldin 1979). The optimal range, based on the lowest DBI scores, lies between 30 and 45 clusters, indicating high within-cluster and low between-cluster similarity. We further examine these partitions by using the most representative phrases per cluster via c-TF-IDF, where 'c' stands for *class*, or in our case *cluster*. Human comprehension of clusters' content, summarized in representative phrases, helps determine the optimal number of clusters from a prospective data-driven range.

Figure 1: One-to-One Matching Pipeline: Patent–Industry Exposure Score with Sentence Transformer all-base-mpnet-v2



Before we dive into the estimation of exposure scores, it is worth noting that the resulting measure indicates the *relevance* of each technology to a given industry or occupation. For industries, relevance depends on whether a technology is integrated into the production process or constitutes an improved industry output. For occupations, relevance reflects the importance of technology in performing tasks and functions specific to that occupation.

Patent Level Similarity. We begin construction of exposure scores at the patent level. We describe the procedure for patent–industry cases while relegating analogous derivations for patent–occupation cases to the Online Appendix. Figure 1 illustrates our methodology using one of the patents introduced above and the industry Advertising (73.1) as an example.

The left part of the diagram represents the preprocessed input text. The top-left box contains both parts of the patent p_1 and p_2, while the bottom-left box contains a set of n individual industrial sentences $s \in \{s_1, \ldots, s_n\}$, each concatenated with the title of industry i.

The central part illustrates the transformation of the input text into corresponding embeddings. Applying the sentence transformer MPNet v2, we obtain two patent embeddings—one for each part p_1 and p_2—and n industry embeddings—one for each sentence s.

The rightmost part illustrates the calculation of the cosine similarity matrix of size $n \times 2$. A cell in this matrix corresponds to a measure of semantic similarity between a patent half and each sentence s of the industry description. Then, we select the most similar sentence for each half p_1 and p_2 independently, obtaining two values of cosine similarity: $C_i^{p_1}$ and $C_i^{p_2}$. By taking the maximum value per patent half, we ensure that industries with long descriptions (i.e., with many sentences) are not overrepresented. We repeat this procedure for each patent–industry combination.

For each patent–industry combination, we measure the relevance of the invention in patent p to industry i twice. We leverage this redundancy by using a majority vote to select relevant industries for each patent. We detail the filtering procedure in the Online Appendix. After filtering, each patent p is ultimately linked only to a subset of industries $i' \in \mathcal{I}$ with cosine similarity scores $C_i^p, \forall i \in i'$. On average, an invention described in a patent is relevant to around four industries.

Aggregation by Technology. We aggregate cosine similarity scores C_i^p and C_o^p from the patent level to the technology level. To do this, we sum up the cosine similarity scores of patents that belong to technology cluster k. C_d^k is a cumulative similarity measure between industry (if $d = i$) or occupation (if $d = o$) and technology k for the period 2012–2021.

We account for the variation in impact between patents, which may still reflect differences in the relevance and likelihood of use across industries and occupations, using citation-based weighting when aggregating (Hall et al. 2005; OECD 2009).[14]

Our final measure of exposure X_d^k for 3-digit NACE Rev.2 industries and 4-digit ISCO-08 occupations to emerging digital technologies is the inverse hyperbolic sine transformation of C_d^k to alleviate its right skewness.

Interpretation. While our exposure metric indicates the *relevance* of a specific technology to an industry or occupation, two clarifications are necessary. First, although exposure scores serve as a *proxy for technology adoption* across industries and occupations, they do not measure actual adoption but rather the potential adoption. Second, our exposure scores are neutral regarding the relationship between technology and labor, meaning they do not assume *ex-ante* whether they are complements or substitutes in production. This neutrality is deliberate, allowing us to estimate the nature of this relationship later in Section 6.

We provide these data as an open–access resource, the 'TechXposure' database. The database also includes exposure measures at higher levels of aggregation, such as the 1-digit and 2-digit

[14]To do this, we weight each patent-level cosine similarity score based on the number of citations the patent received relative to all other *relevant* patents filed during the same year. The Spearman rank correlation between weighted and unweighted cosine similarity scores is about 0.89 for both industries and occupations.

levels for industries, and the 1-digit to 3-digit levels for occupations, as well as exposure scores to individual technologies and over time.

Our exposure scores align with existing metrics in the literature but also capture additional dimensions of these technologies that previous studies have not addressed, either due to the nonexistence of these technological features or a narrower focus. For example, the AI exposure scores in Webb (2019) are limited to core aspects of AI, such as industrial automation, workflow management systems, cloud computing, and machine learning. In contrast, Felten et al. (2021) cover a broader scope but focus only on intangible AI applications, excluding AI embedded in tangible technologies like industrial and mobile robots, and IoT. The computerization metrics of Frey and Osborne (2017) correlate with a large segment of our emerging digital technologies, as both computerization and software are inherent to emerging digital technologies. We provide more details on the comparison in the Online Appendix.

3 The Exposure of Industries and Occupations to Emerging Digital Technologies

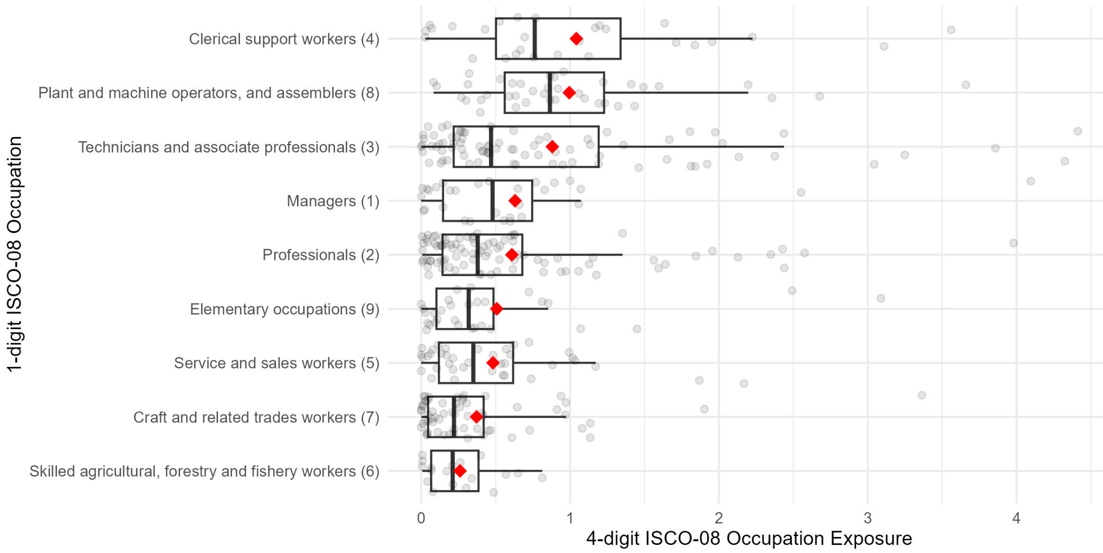
In this section, we describe the exposure of both occupations and industries to emerging digital technologies. We start with occupations and then look at industries.

3.1 Occupation Exposure

We first examine the overall exposure of occupations, defined as the average exposure across all technologies: $X_o = \frac{1}{40}\sum_k X_o^k$, where X_o^k is the exposure of occupation o to technology k. Figure 2 shows the distribution of exposure to emerging digital technologies across ISCO-08 occupations. In this figure, 4-digit occupations are grouped into their respective 1-digit categories, with their distribution presented as a boxplots. Occupation groups are ranked by their average exposure to emerging digital technologies, indicated by the diamond point.

We observe that Clerical Support Workers (ISCO-08 Group 4) and Plant and Machine Operators, and Assemblers (Group 8) are the most exposed to emerging digital technologies. Occupations in these groups typically involve a high proportion of routine tasks related to information handling and production equipment supervision, respectively. Although these middle-skilled jobs have already been significantly impacted by earlier ICT waves (Goos and Manning 2007, Goos et al. 2009, Goos et al. 2014), they remain strongly associated with newer ICT vintages, particularly emerging digital technologies that facilitate semi- or unsupervised information handling and equipment operation.

Figure 2: Overall Occupation Exposure by 1-digit ISCO-08 Occupation



Notes: This figure presents the distribution of exposure to emerging digital technologies across 4-digit ISCO-08 occupations, with each 1-digit occupation displayed separately in boxplots. Vertical bars indicate the median exposure for all 4-digit occupations within the same 1-digit occupation, and diamond points represent the average exposure for these 4-digit occupations.

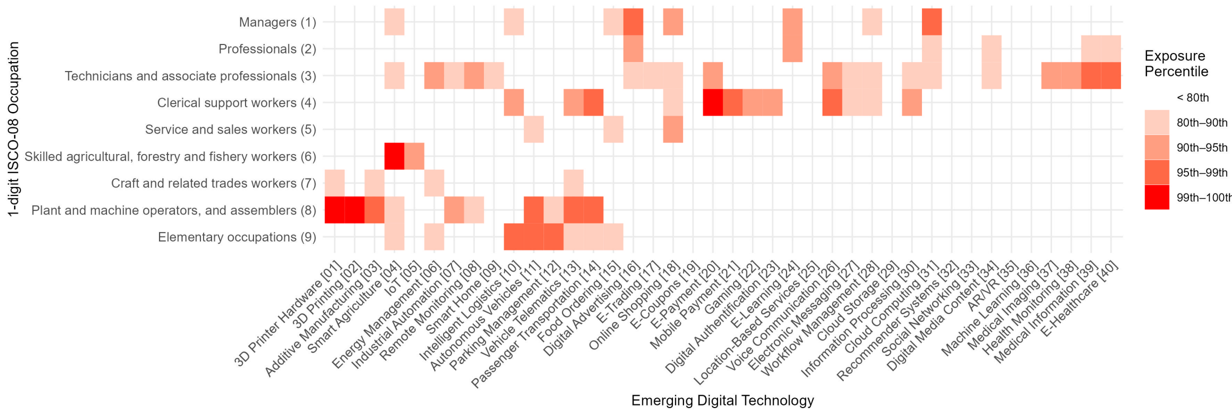
High-skilled occupations, such as Managers (Group 1), Professionals (Group 2), and Technicians and Associate Professionals (Group 3), are the next most exposed to emerging digital technologies. These roles predominantly involve non-routine cognitive tasks that frequently require a variety of digital technologies. As technologies evolve and new vintages emerge, these occupations may experience shifts in task structure due to the introduction of new tasks, representing the reinstatement mechanism at work.

Conversely, low-skilled occupations, such as Service and Sales Workers (Group 5), Skilled Agricultural, Forestry, and Fishery Workers (Group 6), Craft and Related Trades Workers (Group 7), and Elementary Occupations (Group 9), are less exposed to emerging digital technologies. These roles involve more interactive, non-routine tasks that are less dependent on these technologies.

Lastly, we observe greater heterogeneity in exposure to emerging digital technologies within high-skilled occupations (Groups 1, 2, and 3) compared to middling occupations (Groups 4 and 8). This suggests that only a subset of high-skilled roles is closely associated with these technologies, whereas middling occupations display more generalized exposure.

We analyze the overall exposure of 1-digit ISCO Groups by examining their exposure to each of the 40 emerging digital technologies. Figure 3 displays this exposure as a heatmap, with exposure percentiles shown at the intersections of 1-digit occupations (rows) and emerging digital technologies (columns). This visualization reveals two distinct patterns.

Figure 3: Occupation Exposure by Emerging Digital Technologies



Notes: Each cell shows the exposure of a 1-digit ISCO-08 occupation (row) to a given digital technology (column), expressed as a percentile. Exposure scores below the 80th percentile are transparent.

First, we observe a clear distinction between *tangible* and *intangible* technologies in their relevance to different occupations. *Tangible* technology families, such as 3D Printing, Embedded Systems, and Smart Mobility, are more relevant to manual occupations in ISCO Groups 6 to 9. In contrast, *intangible* technology families, including E-Commerce, Payment Systems, Digital Services, Computer Vision, and HealthTech, are more pertinent to cognitive occupations, particularly within ISCO Groups 1 to 4.

Second, we observe that Technicians and Associate Professionals (Group 3) and Clerical Support Workers (Group 4) are exposed to a broad range of emerging digital technologies. In contrast, Managers (Group 1) and Professionals (Group 2) are associated with a narrower scope of relevant technologies, primarily within the domain of intangible technologies. Similarly, exposure within ISCO Groups 6 to 9 is exclusively focused on tangible technologies.

Leveraging the semantic structure of tasks in the 4-digit ISCO-08 taxonomy, we identify the actions within tasks most exposed to our emerging digital technologies. By construction of the ISCO-08 taxonomy, task descriptions begin with *gerunds*, which define the primary action (e.g., planning, monitoring, developing, preparing, operating, cleaning). For each gerund, we calculate its *baseline frequency* or simply *task frequency*, representing its occurrence in a 1-digit group of the ISCO-08 taxonomy (i.e., the baseline corpus). The baseline frequency reflects how often the taxonomy uses a gerund to describe tasks within a 1-digit ISCO group, with more frequent gerunds being core to that group. Thus, we define the most frequent gerunds as *recurrent* tasks, and the less frequent ones as *specialized* tasks.

We then calculate the gerund's *target frequency* or *task exposure*, representing its occurrence among established task-technology pairs in a 1-digit group (i.e., the target corpus). The target frequency is high for tasks most exposed to emerging digital technologies, and low otherwise—

all frequencies are relative. While we report the most exposed tasks as a function of task frequency by 1-digit occupation groups in the Online Appendix, we summarize the main findings on the exposure of tasks to improve the understanding of occupation exposure.

We observe heterogeneity in task exposure both within and between 1-digit ISCO-08 groups. This suggests that the extent to which *recurrent* or *specialized* tasks are exposed to emerging digital technologies depends heavily on the 1-digit ISCO-08 group. However, all high-skilled occupation groups, including Managers (Group 1), Professionals (Group 2), and Technicians and Associate Professionals (Group 3), display a clear tendency for the majority of their *recurrent* tasks to be exposed.

Overall, the set of most exposed tasks is fairly unique to each 1-digit ISCO-08 group, with the exception of Technicians and Associate Professionals (Group 3) and Plant and Machine Operators (Group 8), who both prominently feature 'operating' and 'monitoring' tasks among their top exposures. This finding aligns with previous results, as these two groups are jointly identified as highly exposed to tangible emerging digital technologies, whereas Managers (Group 1) and Professionals (Group 2) are associated with a smaller, more specific subset of technologies (see Figure 3).

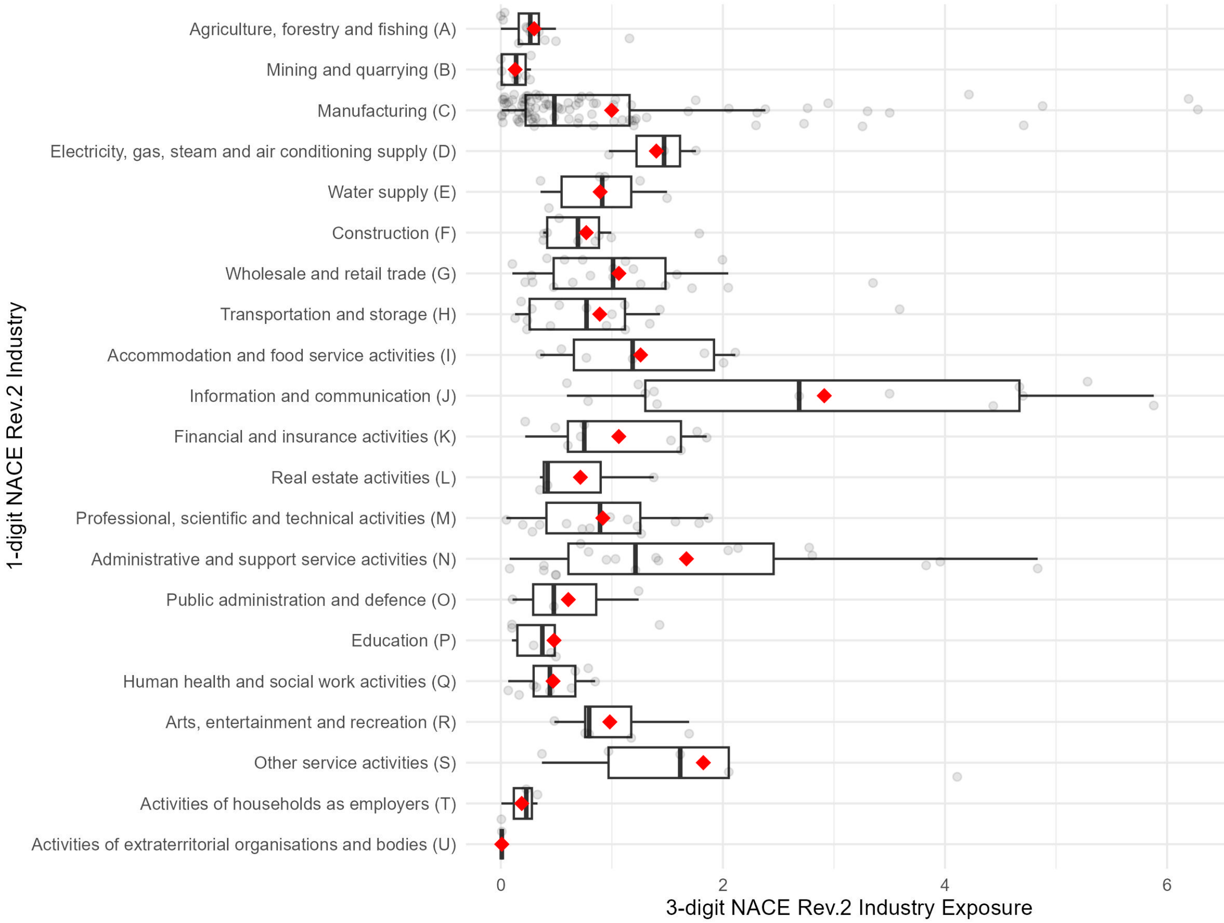
3.2 Industry Exposure

For industries, we examine overall exposure as the average exposure across all technologies: $X_i = \frac{1}{40}\sum_k X_i^k$, where X_i^k is the exposure of industry i to technology k. Figure 4 shows the distribution of overall exposure to emerging digital technologies across NACE Rev.2 industries. In this figure, 3-digit industries are grouped into their respective 1-digit sectors, with distributions presented as a boxplot.

We observe that the Information and Communication (J) and Manufacturing (C) sectors contain the most exposed 3-digit industries. This finding is notable given the substantial heterogeneity in exposure within these 1-digit sectors. Such differences in exposure may reflect whether industries act as producers or intensive users, rather than light users, of emerging digital technologies. Specifically, industries within the Information and Communication (J) sector are likely to produce intangible technologies, while certain industries within the Manufacturing (C) sector are likely to produce tangible technologies.

The Administrative and Support Service Activities (N) sector also exhibits a high average level of exposure to emerging digital technologies. Several 3-digit industries within this sector achieve overall exposure levels comparable to those in Sectors C and J. This observation is consistent with the findings presented for occupations, as Sector N is a significant employer of Clerical Support Workers (ISCO Group 4), identified as the most exposed 1-digit ISCO Group.

Figure 4: Overall Industry Exposure by 1-digit NACE Rev.2 Industry

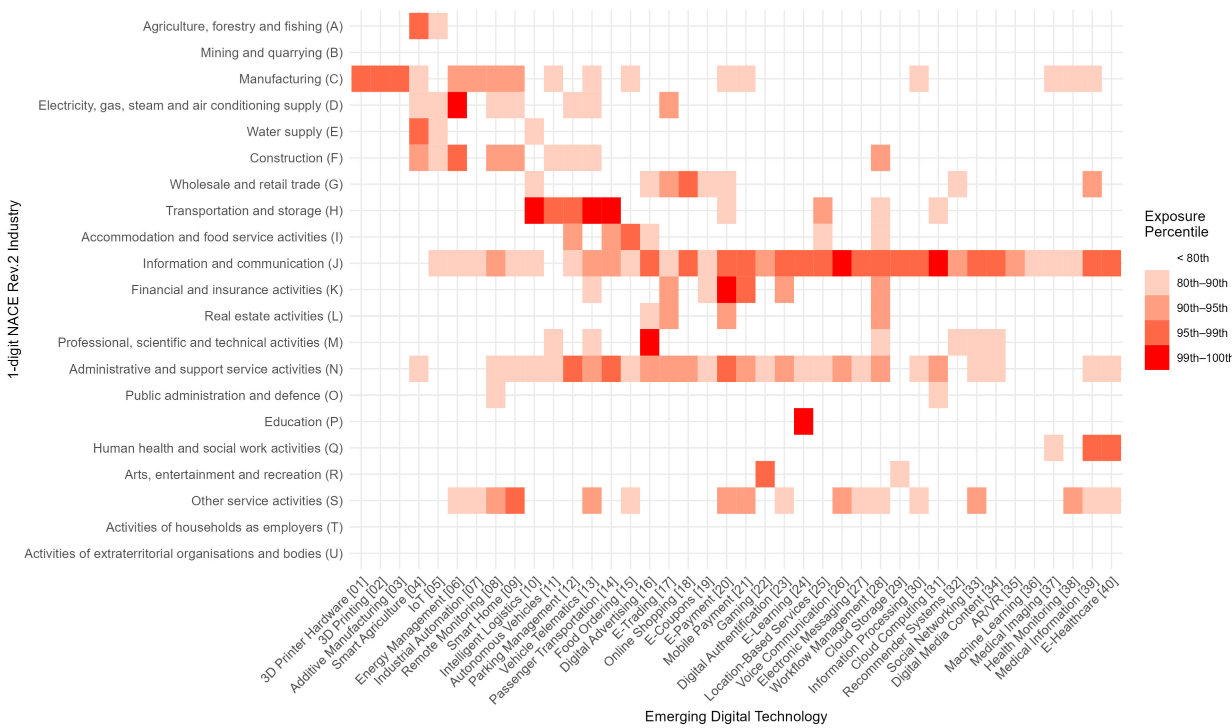


Notes: This figure presents the distribution of exposure to emerging digital technologies across 3-digit NACE Rev.2 industries, with each 1-digit industry displayed separately in boxplots. Vertical bars indicate the median exposure for all 3-digit industries within the same 1-digit industry, and diamond points represent the average exposure for these 4-digit industries.

We analyze the overall exposure of 1-digit NACE sectors by examining their exposure to each of the 40 digital technologies. Figure 5 shows the exposure percentile heatmap for 1-digit sectors.

As with occupations, we observe a divide between tangible and intangible digital technologies. In the figure, exposure cells follow a diagonal pattern from the top-left to the bottom-right, associating tangible technologies with sectors such as Agriculture (A), Mining and Quarrying (B), and Manufacturing (C), while aligning intangible technologies with service sectors from Financial and Insurance Activities (K) to Other Service Activities (S). Between these extremes, sectors like Electricity, Gas and Air Conditioning Supply (D) through Information and Communication (J) operate physical infrastructures and are thus more exposed to tangible but distributed technology families, such as Embedded Systems and Smart Mobility.

Figure 5: Industry Exposure by Emerging Digital Technologies



Notes: Each cell shows the exposure of a 1-digit NACE Rev.2 industry (row) to a given digital technology (column), expressed as a percentile. Exposure scores below the 80th percentile are transparent.

4 Overall Impact of Digital Technologies on Employment

In this section, we estimate the aggregate net impact of digital technologies on European regional employment. We start by presenting our empirical strategy and the data we use. Then, we report the estimation results before turning to the heterogeneity analysis by demographic and skill groups as well as by industry.

4.1 Empirical Strategy

We use employment data from the Regional European Labour Force Survey (EU-LFS), which provides information on the number of employees and population across several demographic and skill groups.[15] Our sample includes 320 NUTS-2 regions in 32 European countries.[16]

We define our main outcome variable as the change in the employment-to-population

[15]These demographic groups include male, female, young (aged 15 to 24 years), mature (aged 25 to 64 years), and low-, middle-, and high-skilled workers, defined by educational level (i.e., primary, secondary, and tertiary).

[16]The countries in the sample are (in alphabetical order): Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, and the United Kingdom.

ratio at the regional level between 2012 and 2019.[17] This ratio is defined as the number of employees within the group of interest (e.g., the total population or the youth population) divided by the total number of individuals aged 15 or older.

Estimating the causal impact of digital technologies on employment involves two main challenges: reverse causality and omitted variable bias. Reverse causality implies that technological advancements could be driven by labor shortages or rising labor costs. Furthermore, unobserved factors—such as shifts in industry organization or infrastructure investments—might simultaneously influence both technological change and employment levels.

To address these concerns, we adopt a shift-share strategy, leveraging recent advancements in this methodology (Adão et al. 2019; Goldsmith-Pinkham et al. 2020; Borusyak et al. 2021). Specifically, we use the Bartik instrument to measure the region's exposure X_r as follows:

$$X_r = \sum_j l_{rj} X_j, \tag{1}$$

where l_{rj} is the employment share of sector j in region r in the baseline year 2010.[18] The term X_j denotes the average exposure of sector j to emerging digital technologies from 2012 to 2019, calculated as

$$X_j \equiv \frac{1}{40} \times \sum_{k \in \mathcal{K}} X_j^k,$$

where X_j^k represents the average exposure of sector j to each technology k across all 1-digit NACE industries $i \in j$ during this period. Although our exposure metrics in Section 2 span 2012–2021, we recalculate them for the 2012–2019 period to ensure consistency with the timeframe in this analysis.

We argue that sectoral exposure to emerging digital technologies, X_j, which represents the *shock* in our shift-share design, is quasi-exogenous to changes in regional employment within Europe. Our metrics for industrial exposure, as derived in Section 2, rely on the semantic similarity between patents and industry descriptions. Notably, only 7.1% of the patents in our sample originate from Europe, indicating that the advancement of these technologies is largely a global phenomenon. Consequently, global technological trends are unlikely to be driven solely by regional labor markets in Europe. To reinforce this point, we recalculate our

[17] We begin in 2012, which is the starting year of our patent sample and therefore serves as the baseline for measuring exposure to emerging digital technologies. We conclude in 2019 to avoid potential confounding factors associated with employment and population changes due to the COVID-19 pandemic.

[18] Table A.4 in the appendix provides details on the average employment share by economic sector across European regions in 2010. The three largest sectors are Market Services (average employment share of 23.8%), the Public Sector (23.7%), and Industry (17.9%). The Information and Communication sector, which is highly exposed to emerging digital technologies, accounts for only 2.3% of employment on average.

exposure measure after excluding European patents to instrument the regional exposure.[19]

Since our shocks are assumed to be exogenous to local employment changes in European labor markets, we apply the equivalence proposed by Borusyak et al. (2021) and can thus consider our shift–share as a valid instrument.In addition to the quasi-random assignment of shocks, our second identifying assumption is that regions more exposed to emerging digital technologies are not disproportionately affected by other labor market shocks or trends, and that the number of observed shocks is sufficiently large.[20]

Figure 6 shows the geographic distribution of exposure across European regions. Emerging digital technologies are more prevalent in European capital cities, which typically have larger service sectors compared to more peripheral regions. Beyond capital cities, regions with the highest exposure levels are predominantly located in Western Europe, specifically in countries such as Germany, Italy, Spain, Switzerland, and the UK.

We estimate the impact of regional exposure to emerging digital technologies on the change in the regional employment-to-population ratio between 2012 and 2019, ΔY_r, using the following empirical specification:

$$\Delta Y_r = \alpha + \beta X_r + Z\delta + \phi_{c(r)} + u_r, \tag{2}$$

where Z is a set of covariates which capture regional characteristics,[21] $\phi_{c(r)}$ represents country fixed effects, and u_r is the error term.

4.2 Results

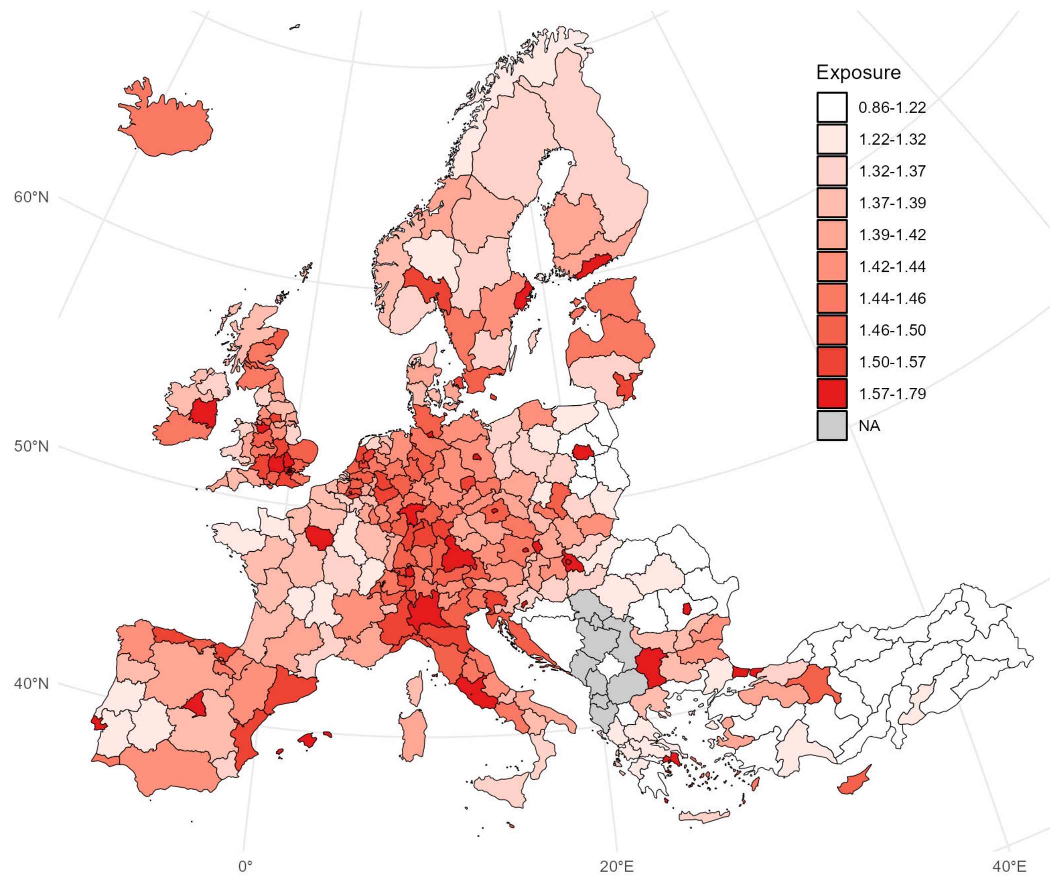
Table 1 presents the IV estimates of the effect of regional exposure to emerging digital technologies on the change in the employment-to-population ratio from 2012 to 2019. The estimated coefficient $\hat{\beta}$ in the table can be interpreted as the effect of a one-standard-deviation increase in regional exposure on the employment-to-population ratio, measured in percentage points (pp.). Following recent literature on shift-share designs, we control for the sum of exposure shares (Borusyak et al. 2021) and report AKM0 shift-share standard errors, which account for

[19] Comparing the 1-digit industry exposure scores with and without European patents (i.e., patents filed with the European Patent Office), the correlation remains approximately 0.99 across all 40 emerging digital technologies, underscoring the global nature of these technological advancements.

[20] The Herfindahl index (HHI) of average shock exposure is calculated as $\sum_j l_j^2 = 0.168$, where l_j represents the average employment share in sector j in 2010 across all regions, as shown in Table A.4. The index can be considered relatively small, as the minimum index under a uniform distribution would be $1/|J| = 0.1$, which supports that the number of observed shocks is sufficiently large. The effective sample size, corresponding to the inverse of the HHI, is 5.95.

[21] Our control variables, fixed at their 2010 values to avoid endogeneity, include the log of the population (in thousands), the proportion of females, the proportion of the population aged over 65, the proportion with secondary and tertiary education, and the proportion employed in the industry sector.

Figure 6: Regional Exposure to Emerging Digital Technologies in Europe (2012–2019)



Notes: This figure illustrates the geographic distribution of exposure to emerging digital technologies for NUTS-2 regions. Regional exposure is constructed as a shift-share variable by interacting the sectoral employment shares in the baseline year 2010 and sectoral exposure to these technologies from 2012 to 2019. Regions are categorized into deciles. Regions are shaded according to their exposure level, with the legend indicating the range of exposure. Areas not applicable (NA) are marked in grey.

arbitrary cross-regional correlation in the regression residuals (Adão et al. 2019).

We find a positive relationship between the change in the employment-to-population ratio from 2012 to 2019 and the regional exposure to emerging digital technologies. In our preferred specification, in column (2), a one-standard-deviation increase in regional exposure corresponds to a 0.913 pp. change, or 1.83%, in the employment-to-population ratio from 2012 to 2019. In column (3), we add the employment share of industry in the baseline year as a control to account for employment changes that would result from local exposure of the industry to other shocks, such as deindustrialization or the China shock. The results remain the same. In columns (4) and (5), we exclude the top 10% most exposed regions and unweighted observations and obtain similar coefficients.

Table 1: Effect of Digital Technologies on Regional Employment

	Dep. var: Δ Emp-to-pop. Ratio (2012-2019) $\times$ 100				
	Weighted				Unweighted
	(1)	(2)	(3)	(4)	(5)
Exposure (Standardized)	0.641^{**}	0.913^{***}	0.963^{***}	1.140^{***}	0.739^{***}
	(0.241)	(0.139)	(0.129)	(0.134)	(0.145)
Country FE	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industry share			✓	✓	✓
Exclude Top 10% Exposed Regions				✓	
First-stage coefficient	0.998	1.005	1.000	1.001	1.000
First-stage F-stat	2,351,984	1,659,087	5,476,403	4,986,600	6,586,903
R^2	0.668	0.697	0.697	0.707	0.721
Adj. R^2	0.629	0.654	0.653	0.660	0.681
Num. obs.	320	320	320	288	320

Notes: This table presents the IV estimates of exposure to emerging digital technologies on regional employment. It presents the coefficients measuring the effect of regional exposure to emerging technologies, constructed as shift-shares and standardized, on changes in the employment-to-population ratio between 2012 and 2019 in European regions, expressed in percentage points. Regressions are weighted by population in 2010. Column (1) includes country fixed effects; Column (2) adds demographics controls in 2010, including the logarithm of population, the proportion of females, the proportion of the population aged over 65, and the proportions of the population with secondary and tertiary education levels; Column (3) adds the share of employment in the industry sector, Column (4) excludes the top 10% most exposed regions; Column (5) reports the unweighted estimate. All columns control for the sum of exposure shares. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019).

4.3 Impact by Demographic and Skill Groups

Table 2 provides estimates of the same empirical specification, including country fixed effects and controlling for demographic characteristics of the region, for each demographic and skill group.

We find that emerging digital technologies have an overall positive impact on both female and male employment. A one-standard-deviation increase in regional exposure over the period leads to a 0.629 pp. change (equivalent to 2.83%) in the employment-to-population ratio for women and a 0.288 pp. change (1.03%) for men. Although the impact is twice as large for women, there is greater regional heterogeneity in this effect, as indicated by the larger standard errors compared to those for men.

Both young workers (aged 15 to 24) and mature workers (aged 25 to 64) experience a positive impact from emerging digital technologies. The former group experiences a 0.288 pp. change in the employment-to-population ratio, representing a 2.94% increase, while the latter group experiences a 0.779 pp. change, representing a 1.72% increase. This finding aligns with Adão et al. (2024), who show that labor market adjustments to technological innovations, or technological transitions, are often driven by the gradual entry of younger generations.

The overall positive effect of digital technologies on employment primarily reflects the displacement of middle-skilled workers and the increase in high-skilled employment, with

Table 2: Effect of Digital Technologies on Regional Employment by Demographic and Skill Groups

	Dep. var: Δ Emp-to-pop. Ratio (2012-2019) $\times$ 100							
	All	Gender		Age		Skill		
	Total	Female	Male	Y15-24	Y25-64	Low	Mid	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure (Standardized)	0.913^{***}	0.626^{***}	0.287^{***}	0.139^{***}	0.775^{***}	0.527^{*}	-0.297^{***}	0.704^{***}
	(0.139)	(0.118)	(0.031)	(0.027)	(0.119)	(0.240)	(0.066)	(0.129)
Emp-to-pop. Ratio in 2012	50.14	22.22	27.92	4.76	45.38	11.89	23.11	15.00
Change (in %)	1.83	2.83	1.03	2.94	1.72	4.46	−1.29	4.71
R^2	0.697	0.557	0.725	0.329	0.722	0.623	0.750	0.647
Adj. R^2	0.654	0.496	0.686	0.236	0.683	0.571	0.715	0.598
Num. obs.	320	320	320	320	320	320	320	320

Notes: This table presents the IV estimates of exposure to emerging digital technologies on regional employment by demographic and skill groups. It presents the coefficients measuring the effect of regional exposure to emerging technologies, constructed as shift-shares and standardized, on changes in the employment-to-population ratio between 2012 and 2019 in European regions, expressed in percentage points, for all workers, female and male workers, young (aged 15-24) and mature (aged 25-64) workers, and low-, middle-, and high-skilled workers. Regressions are weighted by population in 2010. All columns include a control for the sum of exposure shares; country fixed effects; demographics controls in 2010, including the logarithm of population, the proportion of females, the proportion of the population aged over 65, the proportions of the population with secondary and tertiary education levels. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019).

respective changes of −0.299 pp. in the employment-to-population ratio of the former and 0.707 pp. in the same ratio as the latter.

The effect on low-skill, although positive, is only significant at the 10% which may reflect important heterogeneity in the effects across regions and technologies.

As a robustness check, we conduct a placebo test by estimating the effect of regional exposure to emerging digital technologies from 2012 to 2019 on the change in the employment-to-population ratio during the pre-period, specifically from 2002 to 2009. These estimates, available in the Online Appendix, show null effects for all demographic groups in the pre-period, reinforcing the validity of our shift-share approach. The only notable exception is a positive and significant effect (at the 10% level only) on the employment of high-skilled workers. We interpret this result as consistent with our expectations, as regions more exposed to emerging digital technologies are likely those where the labor force was upskilling, and therefore better positioned to adopt and benefit from new digital technologies.

4.4 Impact by Industries

Table 3 presents estimates of the impact of digital technologies on the employment-to-population ratio across the 10 industries. These specifications include country fixed effects and control for regional demographic characteristics. Additionally, the employment share of the industry of interest in 2010 is included as a control variable. This control accounts for pre-existing trends that may disproportionately affect regions specialized in a given industry, thereby potentially confounding the estimated effect of digital technologies on that industry.

Aggregate positive employment impacts of digital technologies are observed only in certain service sectors, including Information and Communication (J); Real Estate Activities (L); Professional, Scientific, Technical, Administrative, and Support Services (M–N); and Other Services (R–U). These sectors typically employ a high proportion of high-skilled workers whose tasks are complementary to digital technologies.

Conversely, the negative effects of digital technologies on employment are primarily concentrated in industries such as Agriculture (A); Industry (B–E); Construction (F); Market Services (G–I); Financial and Insurance Activities (K); and Public Services (O–Q). The first three industries are characterized by manual and routine tasks, for which *tangible* emerging digital technologies are particularly effective at substituting repetitive physical labor. Similarly, the last two involve jobs with more cognitive and repetitive tasks, susceptible to substitution by *intangible* emerging digital technologies. This is consistent with the pattern observed in Figure 3, where manual occupations exhibit high exposure to tangible technologies, and cognitive occupations to intangible ones.

Interestingly, we find a relatively small negative effect for Market Services (G–I), which is statistically significant only at the 10% level. This sector typically comprises jobs that can be automated by both tangible technologies—such as those used in transportation—and intangible technologies—such as those used in retail and commerce. However, displacement effects may be partially offset by substantial productivity gains, resulting in a modest positive net impact. Moreover, the large standard errors suggest heterogeneity across regions in the impact of digital technologies within this sector.

Table 3: Effect of Digital Technologies on Regional Employment by Industry

	Dep. var: Δ Emp-to-pop. Ratio (2012-2019) $\times$ 100									
	Agriculture	Industry		Services						
	A	B-E	F	G-I	J	K	L	M-N	O-Q	R-U
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Exposure (Standardized)	-0.275^{**}	-0.448^{***}	-0.036^{***}	-0.169^{*}	0.051^{***}	-0.082^{**}	0.044^{***}	0.327^{***}	-0.129^{**}	0.189^{***}
	(0.102)	(0.026)	(0.019)	(0.084)	(0.016)	(0.021)	(0.010)	(0.042)	(0.032)	(0.023)
Emp-to-pop. Ratio in 2012	3.12	8.89	3.59	11.81	1.39	1.44	0.35	4.40	12.16	2.61
Change (in %)	−8.73	−5.04	−1.00	−1.44	3.66	−5.73	12.43	7.52	−1.06	7.28
R^2	0.507	0.565	0.589	0.527	0.412	0.230	0.292	0.465	0.555	0.478
Adj. R^2	0.436	0.503	0.530	0.459	0.328	0.119	0.191	0.388	0.491	0.403
Num. obs.	320	320	320	320	320	320	320	320	320	320

Notes: This table presents the IV estimates of exposure to emerging digital technologies on regional employment by industry. It presents the coefficients measuring the effect of regional exposure to emerging technologies, constructed as shift-shares and standardized, on changes in the employment-to-population ratio between 2012 and 2019 in European regions, expressed in percentage points, for Agriculture (A); Industry, excluding Construction (B-E); Construction (F); Market Services, excluding Information and Communication (G-I); Information and Communication (J); Financial and Insurance Activities (K); Real Estate Activities (L); Professional, Scientific, Technical, Administration and Support Services (M-N); Public Administration, Defence, Education, Human Health and Social Work (O-Q); Other Services (R-U). Regressions are weighted by population in 2010. All columns include a control for the sum of exposure shares; country fixed effects; demographics controls in 2010, including the logarithm of population, the proportion of females, the proportion of the population aged over 65, the proportions of the population with secondary and tertiary education levels; and the regional share of employment in the industry of interest in 2010. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019).

5 Individual Impact of Digital Technologies and Complementarity

5.1 Empirical Strategy

Until now, we have examined the overall impact of digital technologies, treating them as a singular and unified factor affecting employment. However, the granularity of our TechXposure database allows us to assess the individual impacts of specific technologies. Different technologies may have positive effects on certain skill groups while negatively affecting others.

Estimating the impact of a specific technology on employment is subject to several identification challenges. One key issue is that many technologies are highly complementary and thus tend to be adopted simultaneously. For example, consider two technologies within digital services: cloud computing and cloud storage. The former enables the processing of large volumes of data, while the latter provides the infrastructure to store them. Their full potential is realized when used in combination. Another example from our set of digital technologies is industrial automation (which includes industrial robots), often adopted alongside other technologies within the same family of embedded systems, such as remote monitoring and control systems. Therefore, disentangling the individual impact of a given technology on employment requires accounting for its complementarity with other technologies *within* the same family.

In addition to complementarity within technology families, digital technologies can also interact with technologies across different families. For example, cloud technologies, which belong to digital services, can be integrated with e-commerce technologies, such as online shopping platforms and digital advertising. Similarly, industrial robots and control systems—technologies classified under embedded systems—can be combined with workflow management systems, which belong to digital services. Therefore, it is also essential to account for technology complementarity *between* digital technology families.

We estimate an empirical specification similar to that used for assessing the overall impact in the previous section, but with two key differences. First, our variable of interest is the shift-share exposure of a region to an *individual* digital technology, denoted as X_r^k. Second, we account for both within-family and between-family technology complementarities by including two control variables: the regional exposure to all other technologies within the same family (excluding the one of interest), $X_r^{K\setminus\{k\}}$, and the regional exposure to all remaining emerging digital technologies outside that family, X_r^{-K}. Both latter are computed as shift-share variables. Thus, our empirical specification is

$$\Delta Y_r = \alpha + \beta_k X_r^k + \underbrace{\gamma_{1k} X_r^{K\setminus\{k\}}}_{\substack{\text{Within-Family} \\ \text{Complementarity}}} + \underbrace{\gamma_{2k} X_r^{-K}}_{\substack{\text{Between-Family} \\ \text{Complementarity}}} + Z\delta + \phi_{c(r)} + u_r, \tag{3}$$

where ΔY_r is the change in the employment-to-population ratio between 2012 and 2019, Z includes the same set of covariates as in Equation (2) and $\phi_{c(r)}$ are country fixed effects.

For each of the 40 individual digital technologies, we estimate the regression model both with and without controls for within- and between-family technology complementarities. All estimates are reported in the Online Appendix. In the following, given the large number of estimates, we organize the results into visualizations to enhance their interpretability.

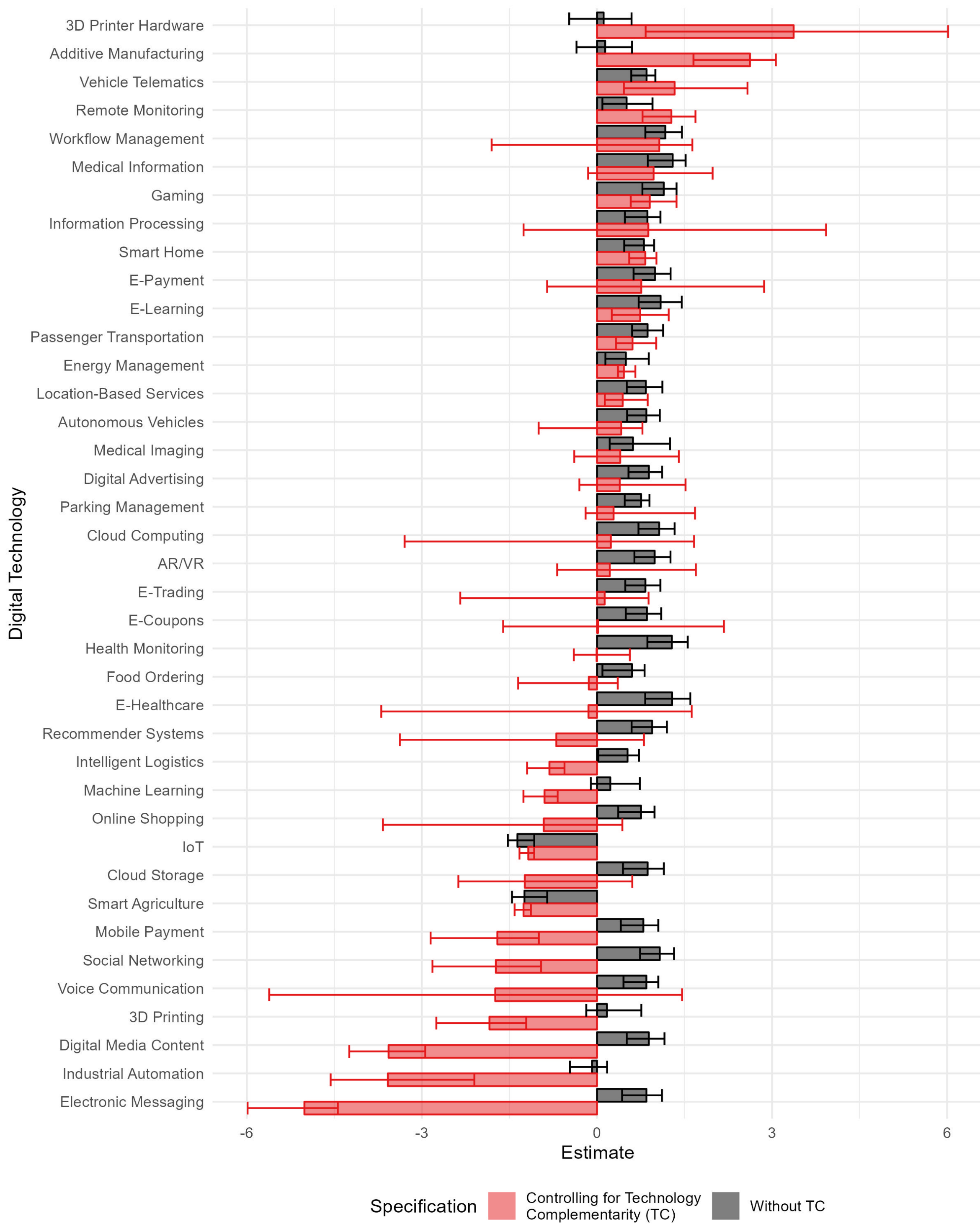
5.2 Results

Figure 7 presents the estimates of the net effect of each individual technology on the regional employment-to-population ratio. The grey bars correspond to the *naive* estimates, without controlling for technology complementarity, while the red bars account for both within and between technology complementarity. This figure delivers two key results.

First, accounting for complementarity between digital technologies is essential when assessing their impacts on employment. Starting with the naive estimates, we observe that the vast majority of digital technologies exhibit a positive effect on employment—except for IoT and Smart Agriculture, which show negative effects, and Industrial Automation, Machine Learning, and 3D Printing-related technologies, which display no significant impact. Accounting for technology complementarity, however, substantially alters these estimates. For instance, technologies that show no significant effect with naive estimation—such as Industrial Automation and 3D Printing—reveal significant positive or negative impacts once complementarities are considered. Conversely, technologies like AR/VR and Intelligent Logistics, which appear to have positive effects at first glance, actually exhibit non-significant or even negative impacts. These shifts reflect patterns of co-adoption: many of these technologies are deployed together, and failure to account for this joint adoption may bias estimates toward the average joint positive effect, as found in the previous section, obscuring the true individual contributions of each technology.

Second, the figure suggests that digital technologies can be grouped into three categories: *labor-augmenting* technologies, which have a positive impact on employment (e.g., E-Learning); *labor-saving* technologies, which reduce employment (e.g., Industrial Automation); and *neutral* technologies, which have no effect (e.g., Autonomous Vehicles). Several labor-saving digital technologies have received considerable attention in the literature, including industrial au-

Figure 7: Net Employment Effect by Emerging Digital Technology



Notes: This figure summarizes the IV estimates of the employment impact of digital technologies with and without controlling for technology complementarities. Estimated coefficients are reported in the Online Appendix. Confidence intervals are derived following the AKM0 inference procedure from Adão et al. (2019).

tomation and robot controls, machine learning and neural networks, and mobile payments.

Our findings highlight the importance of accounting for technology complementarity when estimating the impact of digital technologies on employment. Furthermore, the emphasis in the literature on technologies with negative employment impacts may lead to the neglect of other individual technologies, or combinations thereof, that could have a positive effect on employment.

6 Decomposing the Impacts by Skill

We further disaggregate the individual employment effects of each digital technology on each skill group by estimating Equation (3) for the employment-to-population ratio of each skill group (i.e., low, middle, and high skilled). As in the previous section, we organize the results into visualizations and provide the regression tables in the Online Appendix. Before diving into the empirical results, we develop a tractable task-based model to help interpret them—the details of the model are relegated to the Online Appendix.[22]

6.1 A Task-Based Model with Differentiated Input Factors

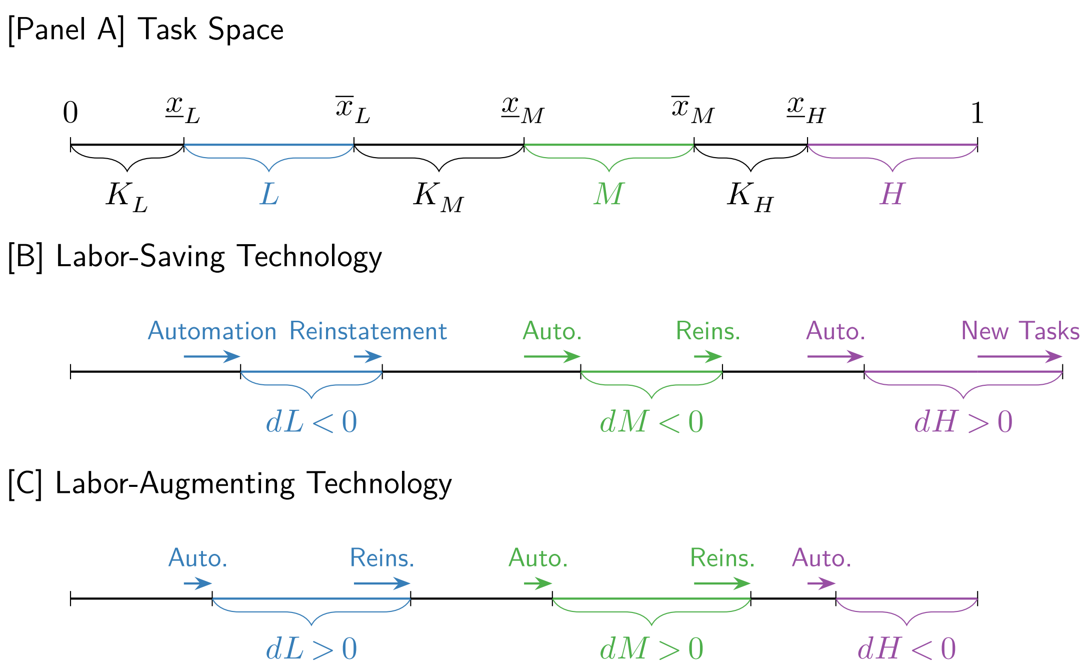
In our model, there are three types of labor, $l \in \{L, M, H\}$, and three corresponding types of capital associated with each labor $k \in \{K_L, K_M, K_H\}$, each designed to perform the simpler tasks typically handled by its associated labor type. Tasks are continuously distributed along a complexity spectrum and assigned to factors based on comparative advantage.

The economy produces a final good by aggregating a continuum of tasks through a CES aggregator, with the task space endogenously segmented by the relative unit costs of factors. Each factor's productivity in a given task reflects a fixed technological level and a task-specific comparative advantage profile. Labor and capital types are arranged hierarchically by skill, and each performs a contiguous segment of tasks. Panel A in Figure 8 shows the allocation of tasks along the task space. The boundaries of each labor type's task segment, denoted by $\underline{x}_l$ and $\overline{x}_l$, emerge endogenously from the equilibrium relative productivities across factors.

The introduction of an emerging digital technology affects task allocation through two distinct channels. First, it alters factor-specific productivity, which reshapes the allocation of existing tasks by changing relative unit costs. Second, it expands the task complexity frontier, creating new tasks that can only be performed by high-skilled labor. The resulting task allocation—driven by both reallocation and expansion—determines the demand for each la-

[22] For more details about the task-based framework, see the canonical model of Acemoglu and Autor (2011), and extensions focusing on technological change by Acemoglu and Restrepo (2018) and Acemoglu et al. (2024).

Figure 8: Task Space and the Reassignment of Tasks with Labor-Saving and Labor-Augmenting Technology



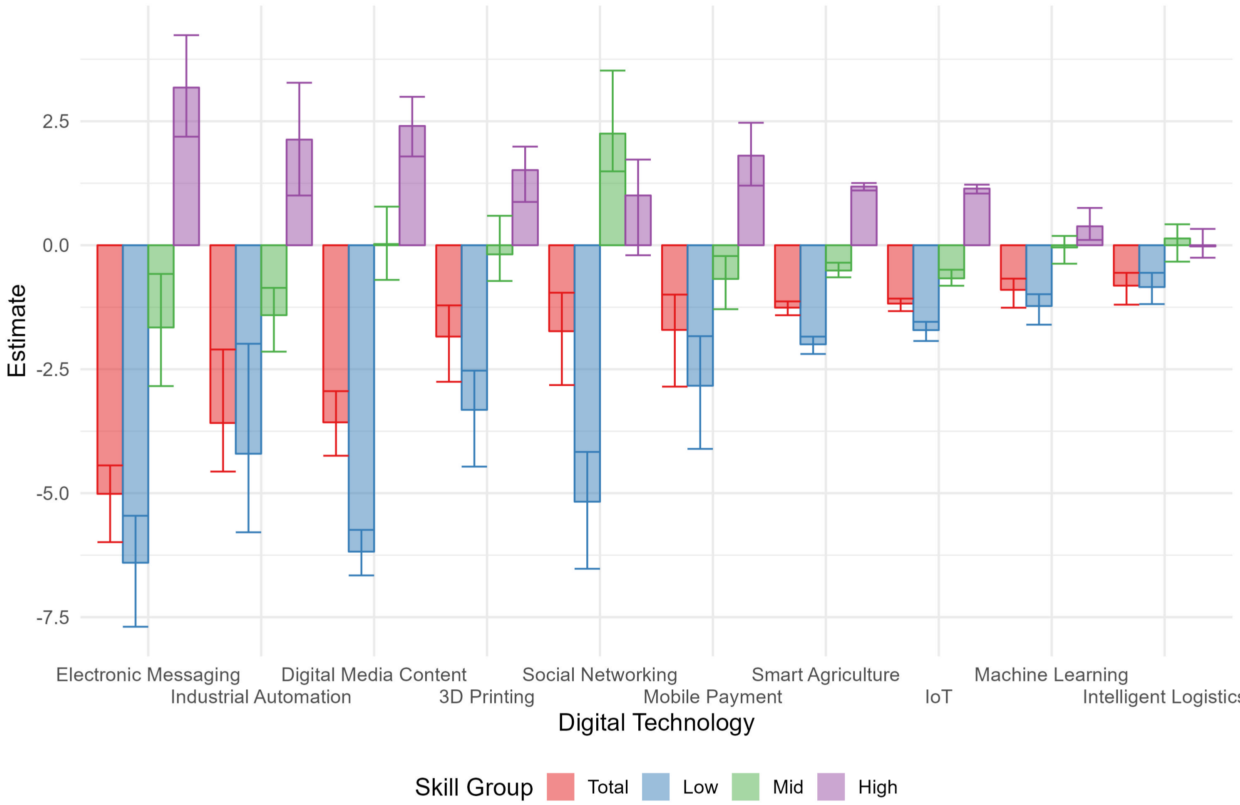
Notes: This figure displays the assignment of tasks to production factors along the task space in Panel A, and the reallocation of tasks following the introduction of a labor-saving technology (Panel B) and of a labor-augmenting technology (Panel C).

bor type based on the quantity and complexity of tasks assigned and the corresponding productivity gains.

We use this framework to interpret how digital technologies impact employment across skill groups, identifying four distinct channels through which technology reshapes labor demand. First, aggregate productivity gains raise labor demand uniformly across all factors. Second, task price effects reduce demand for more productive labor types as tasks become cheaper to perform. Third, relative productivity shifts between labor and capital lead to task reallocation: this can result in displacement, as simpler tasks are automated, or in upskilling, as more complex tasks are reinstated to labor. The direction of reallocation depends on how technology alters the unit cost structure. Fourth, when technologies expand the task frontier, they generate a reinstatement effect by introducing entirely new tasks for high-skilled workers. By examining changes in employment patterns across skill groups, we infer the dominant mechanisms at play for each digital technology.

Panels B and C in Figure 8 illustrate how labor-saving and labor-augmenting technologies reshape task allocation and, consequently, labor demand. These examples are discussed below in the light of the empirical results.

Figure 9: Employment Effects of Labor-Saving Digital Technologies by Skill Groups



Notes: This figure summarizes the IV estimates of the employment impact of labor-saving digital technologies by skill groups. Estimated coefficients are reported in the Online Appendix. Confidence intervals are derived following the AKM0 inference procedure from Adão et al. (2019).

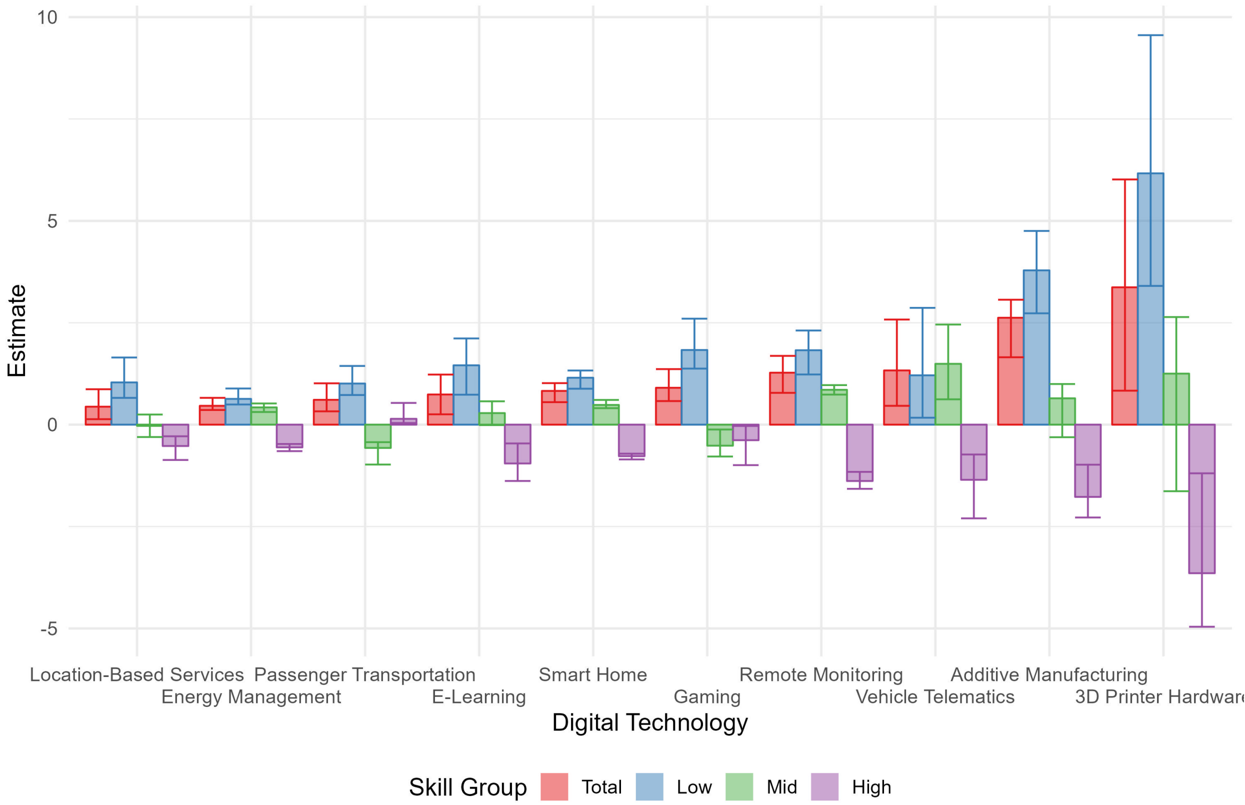
6.2 Results

Figures 9 and 10 report the estimated employment effects by skill groups for emerging digital technologies identified as labor-saving and labor-augmenting, respectively.[23]

Labor-Saving Technologies. In line with our model's characterization of labor-saving technologies (i.e., those with an individual negative effect on aggregate employment), these latter tend to reduce employment among low- and middle-skilled workers while increasing it for high-skilled workers. Technologies such as Electronic Messaging, Industrial Automation, Mobile Payment, Smart Agriculture, and the Internet of Things (IoT) reduce lower-skill employment due to the dominance of simple task automation over complex task reinstatement. In these cases, capital productivity gains outweigh those of labor, and aggregate output effects fail to offset employment losses. At the same time, the increase in high-skilled employment

[23]Figure A.2, in the appendix, presents the estimates for labor-neutral technologies.

Figure 10: Employment Effects of Labor-Augmenting Digital Technologies by Skill Groups



Notes: This figure summarizes the IV estimates of the employment impact of labor-augmenting digital technologies by skill groups. Estimated coefficients are reported in the Online Appendix. Confidence intervals are derived following the AKM0 inference procedure from Adão et al. (2019).

suggests that these technologies expand the task frontier by generating new high-complexity tasks.

Some technologies yield more nuanced effects. Machine Learning, for instance, significantly reduces low-skilled employment but leaves middle-skilled employment unchanged—indicating limited task reallocation, possibly due to a balance between automation and reinstatement. Social media technologies also exhibit skill-specific heterogeneity: Social Networking reduces low-skilled employment while increasing demand for middle-skilled labor, whereas Digital Media Content negatively affects only low-skilled workers. Intelligent Logistics stands out as a purely labor-displacing technology, reducing employment among low-skilled workers without generating compensatory gains for any skill group.

Labor-Augmenting Technologies. Figure 10 shows the estimated employment effects across skill groups for digital technologies classified as labor-augmenting—those with an individual positive impact on aggregate employment.

Consistent with our characterization of labor-augmenting technologies, these latter tend to increase employment for low- and middle-skilled workers while reducing demand for high-skilled labor. This pattern reflects a form of upskilling in which digital tools enhance the productivity of lower-skilled workers, enabling them to take on more complex tasks that would otherwise fall to higher-skilled counterparts.[24] However, the combined effects of aggregate productivity gains and task expansion are insufficient to fully compensate for the displacement of high-skilled labor, resulting in a net decline in their employment.

Among the labor-augmenting technologies, 3D Printing stands out for its pronounced effect, significantly increasing employment for low-skilled workers without materially affecting middle-skilled employment. Other technologies—including Vehicle Telematics, Remote Monitoring, Smart Home systems, and Energy Management platforms—boost employment across both low- and middle-skill groups. These patterns support the interpretation that such technologies promote task reassignment and skill broadening rather than simple substitution across occupations exposed to them.

6.3 Discussion

This section presents a comprehensive overview of the empirical results obtained at the different levels of analysis and connects them to the theoretical underpinnings of the model.

First, we demonstrate that the overall impact of emerging digital technologies on employment is positive (see Table 1). However, once we split this aggregate positive effect into individual technologies in Figure 7, they form three distinct groups: 1) those that reduce employment (*labor-saving*), 2) those that have a positive impact on employment (*labor-augmenting*), and 3) technologies that exert no impact on employment (*labor-neutral*).

Then, we delve deeper into the impact of labor-saving and labor-augmenting technologies among low-, middle-, and high-skilled employment. Figure 10 reveals that labor-augmenting technologies increase low- and middle-skilled employment while reducing the high-skilled one. In contrast, labor-saving technologies lead to a decline in low- and middle-skilled employment and a rise in high-skilled employment, as depicted in Figure 9.

To interpret these results, we return to our theoretical framework to show how its underlying mechanisms can generate the observed outcomes. Both labor-saving and labor-augmenting emerging digital technologies lead to task reallocation between capital and labor, affecting factor-specific productivities and creating new tasks.

Specifically, labor-saving digital technologies, shown in Panel B of Figure 8, are characterized by larger productivity gains for capital relative to labor. This leads to the automation of

[24]See Agrawal et al. (2023) for a discussion of the upskilling effect of AI.

simpler tasks across all skill groups. Because the relative productivity losses are not accompanied by sufficient reinstatement of more complex tasks, low- and middle-skilled workers experience a net loss in task assignments. However, these technologies often expand the task frontier, introducing new tasks that benefit high-skilled workers. As a result, demand declines for low- and middle-skilled labor but increases for high-skilled labor.

By contrast, labor-augmenting technologies, shown in Panel C of Figure 8, enhance labor productivity more than capital productivity. While automation of simple tasks still occurs, these losses are offset by the reinstatement of more complex tasks to labor, particularly benefiting low- and middle-skilled workers. However, because these technologies contribute minimally to the expansion of the task frontier, they offer limited gains for high-skilled labor at the upper end of the task space.

Finally, the overall effect of emerging digital technologies across three skill groups estimated in Table 2 suggests ongoing polarization: low- and high-skilled labor experiences overall positive impact, while the middle-skilled workers are being substituted. This means that, for low-skilled workers, upskilling toward more complex tasks enabled by labor-augmenting technologies outweighs the automation of simple tasks by labor-saving technologies, while the opposite is the case for middle-skilled jobs. Lastly, for high-skilled labor creation of new high-complexity tasks by labor-saving technologies offsets the loss of simple tasks to automation by labor-augmenting technologies.

7 Conclusion

Recent advancements in digital technologies have heightened public and academic interest in understanding their future implications for employment. Determining whether these technologies will create more jobs than they displace remains a critical question for policymakers and workers alike. However, existing research has largely focused either narrowly—examining specific technologies such as industrial robots or artificial intelligence (AI)—or broadly, using aggregate measures encompassing a wide variety of automation technologies.

This paper addresses these limitations by systematically identifying and analyzing the employment impacts of a broad and granular set of emerging digital technologies. We find that, overall, these technologies have a net positive effect on regional employment-to-population ratios. A key insight from our analysis is the crucial role of technological complementarities: while individually some technologies negatively impact employment, collectively their complementary interactions lead to net positive aggregate outcomes. Our results thus indicate that focusing solely on prominent technologies like AI and robotics risks overlooking the broader, positive employment effects arising from interactions among diverse digital innovations.

When accounting explicitly for technology complementarities, we categorize digital technologies based on their aggregate employment effects. We identify two distinct types: labor-saving technologies—including industrial automation, machine learning, electronic messaging, mobile payments, and social networking—that tend to displace low- and middle-skilled workers through task automation, while simultaneously creating new employment opportunities for high-skilled workers; and labor-augmenting technologies—such as 3D printing, remote monitoring, and e-learning—that enhance employment among low- and middle-skilled workers by upgrading their task capabilities, though at the cost of reduced employment among high-skilled groups.

Central to this study is our development of novel exposure measures for industries and occupations to 40 emerging digital technologies introduced over the past decade. Leveraging advanced NLP methods—specifically, sentence transformers—–we construct granular, internationally applicable exposure scores. Our open-access dataset, the 'TechXposure' database, provides an extensive resource for future research.

The 'TechXposure' database offers several distinct advantages. First, because it uses textual descriptions from international standard classifications (NACE and ISCO), our exposure measures are universally applicable beyond any single national context. Second, our methodology does not rely on keyword-based matching but instead leverages semantic and contextual similarity, making the approach readily adaptable to future contexts and other technology domains, such as green innovations or forthcoming classification revisions.

Nonetheless, our exposure metrics reflect only the technological relevance to industries and occupations, not the direction (augmenting or automating) of their employment effects. While this limitation constrains interpretability in certain contexts, it also reduces assumptions in data construction and acknowledges the context-specific nature of technological impacts on employment.

We view our work as providing foundational infrastructure for ongoing research into technological change and labor markets. By making this detailed and comprehensive dataset publicly available, we anticipate enabling future analyses to investigate a wide range of emerging technologies, extending beyond commonly studied areas such as AI and robots to include less-examined domains such as cloud computing, social networks, and health technologies. Furthermore, our reliance on international classifications ensures broad applicability, which would facilitate studies that explore technology impacts across diverse institutional and economic settings, particularly within Europe, where institutional variation significantly influences technology adoption and labor market outcomes. Our database aims to be both accessible and user-friendly for researchers and policymakers alike.

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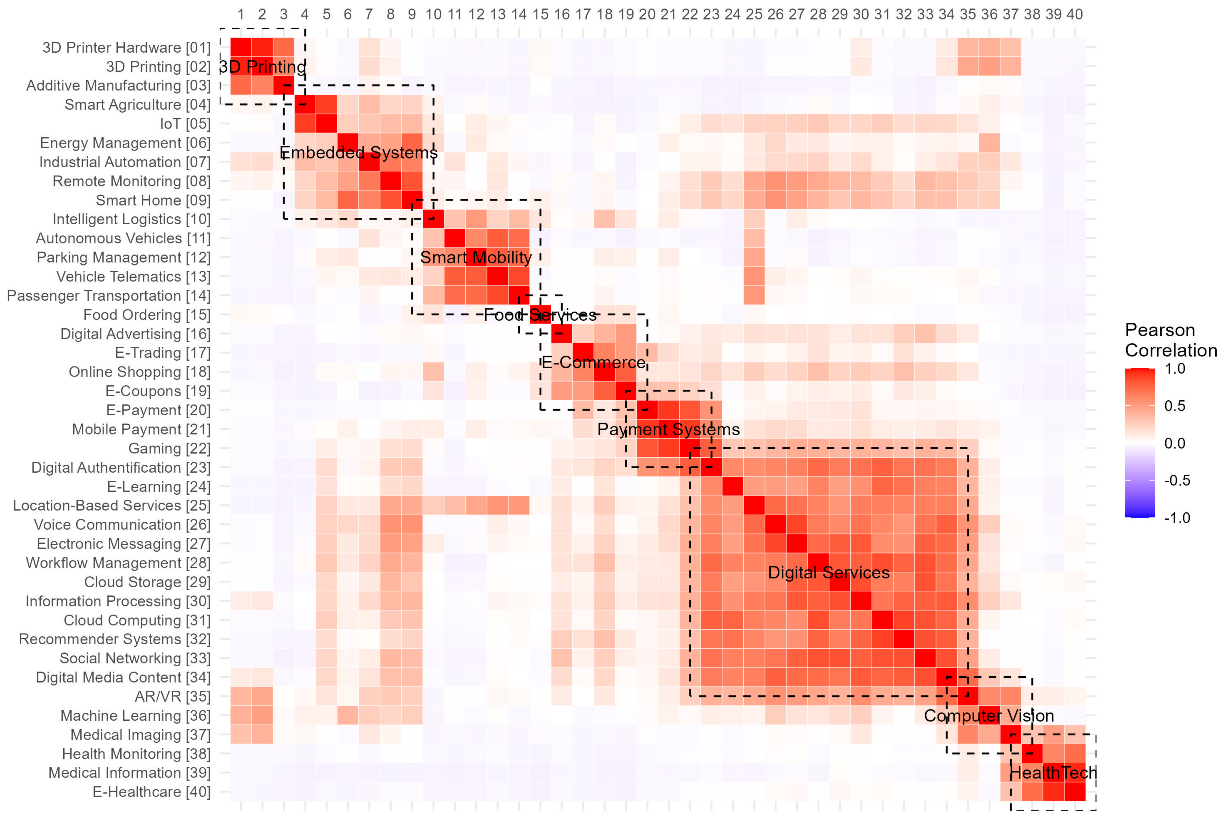
Appendix

Figure A.1: Semantic Co-Occurrence of Technologies Across 3-digit ISCO-08 Occupations



Notes: This figure shows all pairwise semantic-based co-occurrences of emerging digital technologies across 3-digit occupations as a correlation matrix, which is symmetric with diagonal values of 1. The matrix categorizes technologies into blocks, grouping them according to their semantic associations with the same set of occupations.

Table A.1: Emerging Digital Technologies (1/3)

	Technology	Description
		[F1] 3D Printing
1	3D Printer Hardware	Three-dimensional printers and their components, such as printing heads, pens, nozzles, platforms, and devices for printing, extruding, cleaning, recycling, heating, and cooling.
2	3D Printing	Printing systems for creating three-dimensional objects using a variety of materials and techniques, like photocuring and powder spreading.
3	Additive Manufacturing	Technologies and processes for additive manufacturing, with applications such as prostheses and building materials.
		[F2] Embedded Systems
4	Smart Agriculture & Water Management	Various Internet of Things (IoT) technologies for intelligent and remote management in agriculture, and water and sewage systems.
5	Internet of Things (IoT)	Systems and devices interconnected via IoT for data collection, remote control, and real-time monitoring in diverse applications, including agriculture, home automation, and environmental monitoring.
6	Predictive Energy Management and Distribution	A combination of network, data management, and AI technologies for monitoring, distribution, and efficient use of electrical power and energy, including renewable energy sources, and for consumption prediction in intelligent power management.
7	Industrial Automation & Robot Control	Industrial process automation, including robots, programmable logic controllers, and related control apparatuses such as remote control and fault diagnosis.
8	Remote Monitoring & Control Systems	Real-time remote monitoring and management technologies for factories, building management, warehouses, intelligent homes, disaster management, and network security.
9	Smart Home & Intelligent Household Control	Various IoT technologies for the intelligent control of homes and buildings, including household appliances, home environments, and smart home integrations, often utilizing wireless communication and monitoring.
		[F3] Smart Mobility
10	Intelligent Logistics	A combination of monitoring, remote control technologies, data acquisition, and mobile robot technologies for logistics and delivery applications, including supply chain management, warehouse operations, package tracking, and courier services.
11	Autonomous Vehicles & UAVs	Developments in unmanned aerial vehicles (UAVs), drones, and autonomous driving technologies, with an emphasis on vehicle control, navigation, and sensor integration.
12	Parking & Vehicle Space Management	Networking technologies for parking management, including systems for monitoring available spaces and intelligent parking solutions.
13	Vehicle Telematics & Electric Vehicle Management	Technologies for intra-vehicle information management, especially in electric vehicles, including aspects of real-time monitoring, traffic information, and vehicle diagnostics.
14	Passenger Transportation	Technologies for ride-sharing, taxi hailing, and public transportation reservations using real-time information, electronic ticketing, and route optimization.

Table A.2: Emerging Digital Technologies (2/3)

	[F4] Food Ordering	
15	Food Ordering & Vending Systems	Wireless infrastructures, encryption, monitoring, and remote control technologies for food order management, such as automatic vending, self-service ordering, meal preparation, and delivery.
	[F5] E-Commerce	
16	Digital Advertising	Automated tracing and tagging, and AI technologies for digital advertisements, including targeted delivery on mobile devices.
17	Electronic Trading and Auctions	Online trading platforms, financial instrument exchanges, and auction mechanisms, focusing on real-time bidding, trading, and market data.
18	Online Shopping Platforms	Wireless technologies (e.g., RFID and mobile terminals), encryption (e.g., blockchain), and AI technologies for e-commerce transactions, and digital tools related to the purchase, sale, and display of product information, including recommendation systems.
19	E-Coupons & Promotion Management	Data management platforms for electronic coupon distribution, management, redemption, and associated loyalty programs.
	[F6] Payment Systems	
20	Electronic Payments & Financial Transactions	A combination of wireless (e.g., mobile) and encryption (e.g., blockchain) technologies for processing electronic payments (e.g., credit card transactions) and interfacing with financial institutions.
21	Mobile Payments	A combination of mobile technologies for processing electronic payments.
22	Gaming & Wagering Systems	A combination of user interface and data management technologies for gaming, both online and physical, including gambling and gaming machines.
	[F7] Digital Services	
23	Digital Authentication	Encryption and robotic processing technologies for verifying user identities, securing transactions, and safeguarding data through various authentication mechanisms, such as biometrics and cryptographic methods.
24	E-Learning	A combination of AI and data management technologies for digital platforms and systems in education, including teaching, learning, and classroom management.
25	Location-Based Services & Tracking	Technologies that provide location-based content and services, often relying on global positioning and navigation systems and related communication technology.
26	Voice Communication	Technologies focusing on voice communication, including communication protocols and user interfaces.
27	Electronic Messaging	Digital communication methods, infrastructure, and user interfaces for services such as email and conferences.
28	Workflow Management	A combination of AI and network technologies for management applications, including workflow automation, recruitment, event scheduling, and building and property management.

Table A.3: Emerging Digital Technologies (3/3)

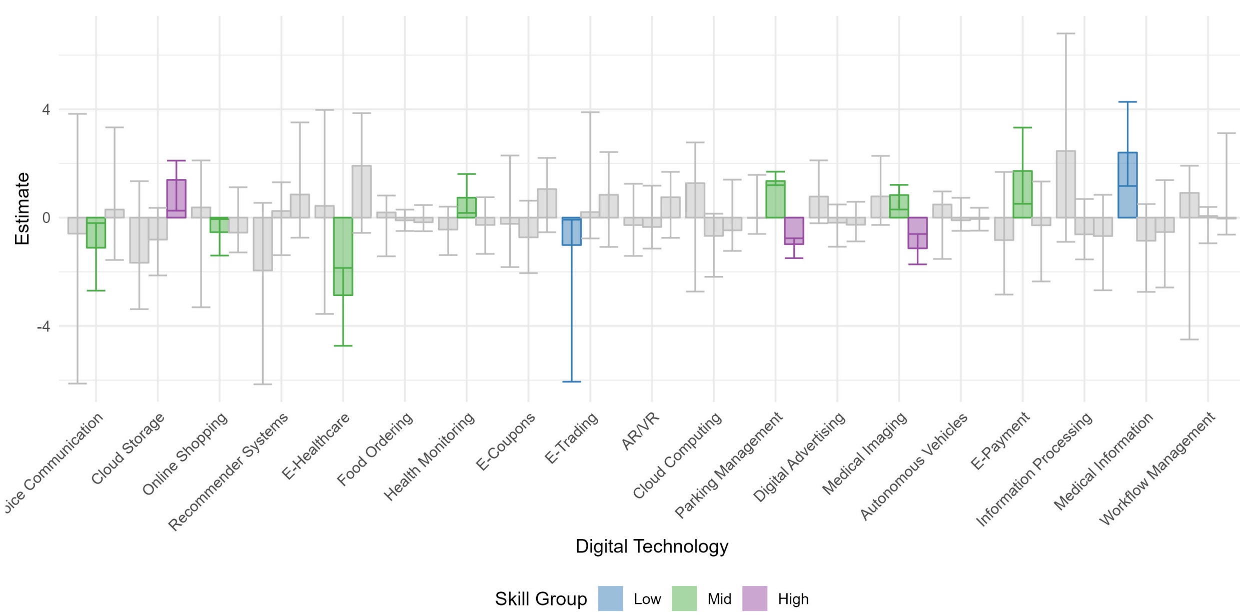
	[F7] Digital Services (continued)	
29	Cloud Storage & Data Security	Cloud-based data storage, distributed data management, encryption, and backup, often integrated with blockchain technology.
30	Information Processing	Systems for managing, processing, and delivering data and information across various domains, potentially including content generation, transmission, and verification.
31	Cloud Computing	Cloud computing and virtual machines, focusing on cloud platforms and resource allocation in cloud environments.
32	Recommender Systems	Algorithms and systems for providing recommendations and personalized content delivery based on user behavior, search queries, and similarity metrics.
33	Social Networking & Media Platforms	User interfaces for online social networking services, content sharing, and recommendation systems.
34	Digital Media Content	Tools and platforms for digital media content creation, management, distribution, and access.
	[F8] Computer Vision	
35	Augmented and Virtual Reality (AR/VR)	Augmented reality (AR) and virtual reality (VR) models, devices, interfaces, and experiences, including head-mounted displays and interactions in virtual environments.
36	Machine Learning & Neural Networks	Machine learning training techniques, model architectures, and data processing for computer vision applications.
37	Medical Imaging & Image Processing	Diverse applications for acquiring and analyzing medical images from various modalities, such as computed tomography (CT), ultrasound, magnetic resonance imaging (MRI), and virtual reality (VR), for purposes including diagnosis, surgical planning, and the design of prostheses.
	[F9] HealthTech	
38	Health Monitoring	Wearable and implantable devices and systems for real-time health monitoring that track vital signs such as blood pressure, heart rate, and temperature, coupled with comprehensive medical data management.
39	Medical Information	A combination of data sharing, encryption, and Natural Language Processing (NLP) technologies for the storage, retrieval, and management of medical and patient information, encompassing electronic medical records, prescription management, and remote healthcare services.
40	E-Healthcare	An integration of data sharing, wireless communication, monitoring, and user interface technologies for healthcare and health management systems, including those used in hospitals and cloud-based platforms.

Table A.4: Average Employment Share by Sector of Activities in 2010

	NACE Sector	Emp. Share Mean	Emp. Share SD	Shock
A	Agriculture	0.068	0.010	0.42
B-E	Industry, excluding Construction	0.179	0.006	1.38
F	Construction	0.076	0.000	1.19
G-I	Market Services, excluding Information and Communication	0.238	0.001	1.94
J	Information and Communication	0.026	0.000	4.30
K	Financial and Insurance Activities	0.028	0.000	1.56
L	Real Estate Activities	0.007	0.000	0.95
M-N	Professional, Scientific, Technical, Administration and Support Services	0.083	0.001	2.59
O-Q	Public Administration, Defence, Education, Human Health and Social Work	0.237	0.004	0.70
R-U	Other Services	0.053	0.000	1.04

Notes: This table presents the employment share and sectoral shock by sector of activities averaged across all the European regions in 2010. Regions are weighted by population in 2010. The first column indicates the 1-digit NACE codes, the second column is the name of the NACE sector, the third column is the average employment share in 2010, the fourth column gives the standard errors, and the fifth column is the shock, as measured by the sectoral exposure to digital technologies.

Figure A.2: Employment Effects of Neutral Digital Technologies by Skill Groups



Notes: This figure summarizes the IV estimates of the employment impact of labor-neutral digital technologies by skill groups. Confidence intervals are derived following the AKM0 inference procedure from Adão et al. (2019).

Online Appendix

The Employment Impact of Emerging Digital Technologies

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OA.1 Patent Corpus Construction

Query and Patent Corpus. The patent corpus in Chaturvedi et al. (2023) is constructed by querying the Derwent Innovation Index (DII) database. The query has two components, using patent codes (Derwent Manual Codes and International Patent Classification codes) and keywords from previous studies on digital automation technologies and Industry 4.0 (Cockburn et al. 2019; Webb 2019; Martinelli et al. 2021). The first component retrieves digital automation inventions related to *i)* process and machine control in physical production sectors like manufacturing, agriculture, mining, and construction, and *ii)* process and workflow control in services. The second component narrows the sample to large technology families, such as AI, computing, networking, data management, and user interfaces, based on prior research on emerging digital technologies (Savona et al. 2022). The final sample includes 1,143,033 patent families from 2000 to 2021. Figure OA.1 illustrates the SQL-style structure of the query, with the full details available in the Online Appendix.

Patent Embeddings. To analyze emerging digital technologies, Chaturvedi et al. (2023) concatenate patent titles and abstracts to create embeddings. Using the pre-trained sentence transformer model *all-mpnet-base-v2* (Song et al. 2020), each patent text is mapped into a 768-dimensional space, converting text into semantic vectors. This transformation enables large-scale analysis and comparison of document meanings using other ML and NLP methods.

Core Digital Patents. To identify the backbone of the corpus of digital automation inventions, the Local Outlier Factor (LOF) algorithm is employed. Proposed by Breunig et al. (2000), LOF is an anomaly detection algorithm applied by Chaturvedi et al. (2023) to search for semantic core among patents. Thus, it measures the local density of a focal document compared to the local density of its k-nearest neighbors in the semantic space. The locality (i.e., the size of the neighborhood) is set by the parameter k. A document with a notably dense neighborhood is considered part of the backbone. For identification of the backbone among digital innovations, larger values of k are more suitable as they allow for larger neighborhoods and

Figure OA.1: SQL-Stylized Structure of the Patent Query

```
SELECT Process and machine control in production AS A,
Process and workflow control in services AS B
   FROM Derwent Innovation Index
   WHERE technology IN (Networking,
                        Data acquisition,
                        Data management,
                        AI and Intelligent Systems,
                        User Interfaces,
                        Computing)
   AND year BETWEEN 2000 AND 2021
UNION
SELECT Additive manufacturing AS C
   FROM Derwent Innovation Index
   WHERE year BETWEEN 2000 AND 2021
```

Notes: This figure presents the structure of the patent query used to construct the total sample in Chaturvedi et al. (2023). The list of CPC codes in A, B, and C is available in Chaturvedi et al. (2023).

hence, a wider reference group of patents to compute LOF measure. Chaturvedi et al. (2023) use $k = 1000$ and the LOF measure is computed for each patent in year t using the cumulative set of patents up to year $(t-1)$.

Since Chaturvedi et al. (2023) are interested in emerging digital automation technologies whose impact on labor markets is unfolding, they identify established/core digital patents in the most recent decade of the patent sample, i.e., 2012–2021. They begin with a base sample of 258,344 patents from 2001-–2011 and calculate the LOF measure for each year from 2012 to 2021, updating the base sample iteratively. For example, to compute the LOF measure for patents filed in 2014, the base sample includes patents from 2001–2013.

Lastly, *core patents* are defined as those in the bottom 10% of the LOF measure for each year over the 2012–2021 period. These patents form the backbone of the patent corpus, being the most representative of digital automation technologies. A low LOF measure indicates a dense semantic neighborhood, meaning these patents are highly central within their local semantic spaces.

Offshoots. To track the development of these core technological innovations throughout the 2012–2021 period, Chaturvedi et al. (2023) identify their offshoots (i.e., subsequent inventions that build on and are semantically similar to the core ones). For each core patent, the authors compute cosine similarity to all patents in each subsequent year and define as offshoots patents in the top 10% of cosine similarity within each year.

The final patent corpus $\mathcal{P}$ comprises 190,714 core digital automation patents and their offshoots.

OA.2 Filtering Pairs Using Redundancy

To filter out irrelevant pairs, we incorporate *redundancy* in calculating cosine similarity for industry–patent pairs (i,p). For each patent, we rank the sub-pairs (i,p_1) and (i,p_2) separately by their cosine similarity scores, $C_i^{p_1}$ and $C_i^{p_2}$. We then classify a pair (i,p) as relevant (denoted as $(i,p)^\star$) if *both* sub-pairs rank within the top 10 in their respective lists. This approach excludes pairs that do not achieve a top-10 rank for both components. Thus, we retain only those inventions where both the description and function are relevant to the industry. The redundancy is robust to thresholds other than the top 10.

Additionally, we manually exclude three very specific connections to improve our exposure scores. We make the following manual adjustments:

- We exclude the exposure scores that relate to 'Printing and service activities related to printing' (18.1) due to the persistent conflation of its intended meaning (i.e. printing products with text, symbols (e.g. musical notation), and imagery (e.g. maps, engraving, etc.)) with emerging digital technologies.
- We exclude the sentence "*manufacture of computer printout paper ready for use*" (Sentence ID 17.2_11) from the industry description text of 'Manufacture of articles of paper and paperboard' (17.2) when combining tasks with patents belonging to the technologies within the 3D Printing family.
- We exclude the sentence "*units giving this type of instructions might be named "schools", "studios", "classes" etc.*" (Sentence ID 85.5_17) from the industry description text of 'Other education' (85.5) when combining tasks with patents belonging to the technology Machine Learning.

For each identified relevant pair $(i,p)^\star$, we calculate the harmonic mean of the cosine similarity scores for both the invention's description and its function. This yields the composite cosine similarity score for industry–patent pairs:

$$C_i^p = 2\left(\frac{1}{C_i^{p_1}} + \frac{1}{C_i^{p_2}}\right)^{-1}.$$

This establishes a connection between an invention, identified in a single patent $p \in \mathcal{P}$, and a set of relevant industries, where the innovation can enhance process, output, or organizational aspects.

Table OA.1 illustrates the redundancy principle using our patent example, which details a targeted TV advertising method based on user profile information. For this patent, redundancy filters out industries irrelevant to the innovation, such as 'Activities of employment placement agencies((78.1) and 'Beverage serving activities' (56.3).

Table OA.1: Example of Redundancy Filtering of Industries for Targeted TV Advertising

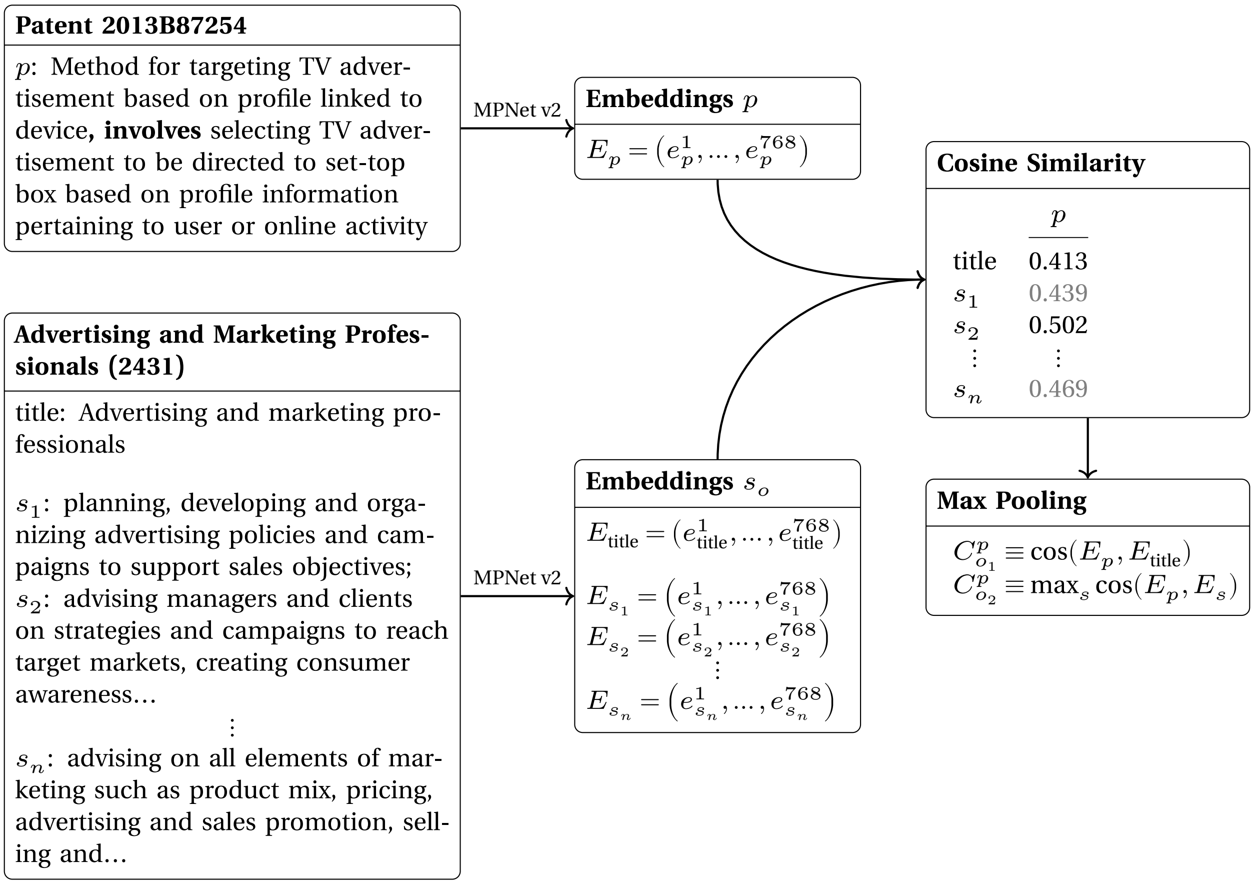
		Cosine Similarity		
Code	NACE Industry	$C_i^{p_1}$	$C_i^{p_2}$	C_i^p
60.2	Television programming and broadcasting activities	0.391	0.445	0.416
73.1	Advertising	0.458	0.373	0.411
73.2	Market research and public opinion polling	0.295	0.272	0.283
59.1	Motion picture, video and television programme activities	0.271	0.263	0.267
61.2	Wireless telecommunications activities	0.290	0.229	0.256
26.3	Manufacture of communication equipment	0.257	0.240	0.249
78.1	Activities of employment placement agencies	0.265		
47.9	Retail trade not in stores, stalls or markets	0.263		
56.3	Beverage serving activities	0.261		
80.1	Private security activities	0.253		
61.3	Satellite telecommunications activities		0.294	
61.1	Wired telecommunications activities		0.237	
97.0	Activities of households as employers of domestic personnel		0.231	
58.1	Publishing of books, periodicals and other publishing activities		0.223	

Notes: This table presents the redundancy filtering of industries for the Patent ID 2013B87254. It displays the cosine similarity of distinct 3-digit NACE Rev.2 industry descriptions with the patent description "Method for targeting television advertisement based on profile linked to online device" (Column 3) and the function principle "selecting television advertisement to be directed to set-top box based on profile information pertaining to the user or online activity" (Column 4). Industries are ranked according to Column 3 in decreasing order. Cosine similarity scores in Columns 3 and 4 are displayed only for sub-pairs belonging to their respective top 10. Column 5 shows the composite patent-industry cosine similarity score, which corresponds to the harmonic mean of Columns 3 and 4. Cosine similarity scores in Column 5 are displayed only for pairs that rank simultaneously in both the top 10.

OA.3 Methodology for Occupation Exposure Scores

Patent Level Similarity. The methodology to derive occupation exposure scores is analogous to that of industry ones. Figure OA.2 illustrates our methodology to obtain patent–occupation cosine similarity scores using our patent example on Targeted TV Advertising and the occupation Advertising and marketing professionals (2431).

Figure OA.2: One-to-One Matching Pipeline: Patent–Occupation Exposure Score with Sentence Transformer all-base-mpnet-v2



The left part of the diagram represents the preprocessed input text. The top-left box contains the patent text p, while the bottom-left box contains the description of the occupation: its title and the task description that we split into n individual tasks $s \in \{1, \dots, s_n\}$.

The next part illustrates the transformation of the input text into corresponding embeddings. Applying the sentence transformers MPNet v2, we obtain one patent embedding and $n+1$ occupation embeddings—one for each task s and one for the title.

The rightmost part illustrates the calculation of the cosine similarity scores. Each element of the vector corresponds to a measure of semantic similarity between the patent and the title, as well as each task s of the occupation description. Then, we select the most similar task, obtaining two values of cosine similarity: $C_{o_1}^p$ and $C_{o_2}^p$. No aggregation is needed for o_1 as each occupation has only one title. These scalars summarize the quality of the semantic match between an occupation and a patent, either through the occupation's title or its associated tasks. We repeat this procedure for each patent–occupation combination.

Redundancy. We then apply the same redundancy methodology as for industries, designating occupation–patent pairs (o,p) as relevant (denoted $(o,p)^\star$) if *both* sub-pairs (o_1,p) and (o_2,p) rank within the top 10 of their respective lists. This way, we retain only inventions relevant to the occupation.

As with industries, we manually exclude three specific connections to improve our exposure scores. We make the following manual adjustments:

- Analogously with industry 18.1, we exclude the exposure scores that relate to 'Printing trades workers' (732) and its nested occupations (7321, 7322, 7323) due to the persistent conflation of its intended meaning with emerging digital technologies.
- We exclude the task "*creating the blueprint or pattern pieces for a particular apparel design with the aid of a computer;*" (Task ID 7532_2) from the occupation description text of 'Printers' (7532) when combining tasks with patents belonging to the technology Machine Learning.
- We exclude the task "*preparing and developing instructional training material and aids such as handbooks, visual aids, online tutorials, demonstration models and supporting training reference documentation;*" (Task ID 2424_3) from the occupation description text of 'Training and staff development professionals' (2424) when combining tasks with patents belonging to the technology Machine Learning.

For each relevant pair, we calculate the harmonic mean of both cosine similarity scores, yielding the composite cosine similarity score for occupation–patent pairs $(o,p)^\star$ as:

$$C_o^p = 2\left(\frac{1}{C_{o_1}^p} + \frac{1}{C_{o_2}^p}\right)^{-1}.$$

This establishes a connection between an invention, identified in a single patent, and a set of relevant occupations, where the innovation can be used. Tables OA.2 illustrate the redundancy principle for our example.

OA.4 Comparing Exposure Scores with Other Metrics

We compare our occupational exposure scores with metrics from Frey and Osborne (2017), Webb (2019), and Felten et al. (2021), which provide exposure scores for specific digital technologies that are subsets of our list. Challenges in comparison are the different occupational classifications and variations in the definitions of technologies among the studies. To address classification differences, we use crosswalks between classifications, aggregating exposure scores within a 4-digit ISCO-08 occupation by averaging exposures across all matched occupations. We compute the correlation between our exposure scores for each technology and

Table OA.2: Example of Redundancy Filtering of Occupations for Targeted TV Advertising

		Cosine Similarity		
Code	ISCO Occupation	$C^p_{o_1}$	$C^p_{o_2}$	C^p_o
2431	Advertising and marketing professionals	0.413	0.502	0.453
1222	Advertising and public relations managers	0.308	0.420	0.356
3521	Broadcasting and audio-visual technicians	0.274	0.380	0.318
3322	Commercial sales representatives	0.250	0.394	0.306
2434	ICT sales professionals	0.297		
7422	ICT installers and servicers	0.282		
4227	Survey and market research interviewers	0.279		
2656	Announcers on radio, television and other media	0.278		
1330	ICT service managers	0.262		
3512	ICT user support technicians	0.252		
5242	Sales demonstrators		0.396	
1420	Retail and wholesale trade managers		0.393	
3432	Interior designers and decorators		0.388	
2153	Telecommunications engineers		0.374	
3323	Buyers		0.358	
9520	Street vendors (excluding food)		0.357	

Notes: This table presents the redundancy filtering of occupations for the Patent ID 2013B87254 (i.e., "Method for targeting television advertisement based on profile linked to online device, involves selecting television advertisement to be directed to set-top box based on profile information pertaining to user or online activity"). It displays the cosine similarity of the patent title with the 4-digit ISCO-08 title (Column 3) and the task with the highest cosine similarity (Column 4). Occupations are ranked according to Column 3 in decreasing order. Cosine similarity scores in Columns 3 and 4 are displayed only for sub-pairs belonging to their respective top 10. Column 5 shows the composite patent-occupation cosine similarity score, which corresponds to the harmonic mean of Columns 3 and 4. Cosine similarity scores in Column 5 are displayed only for pairs that rank simultaneously in both the top 10.

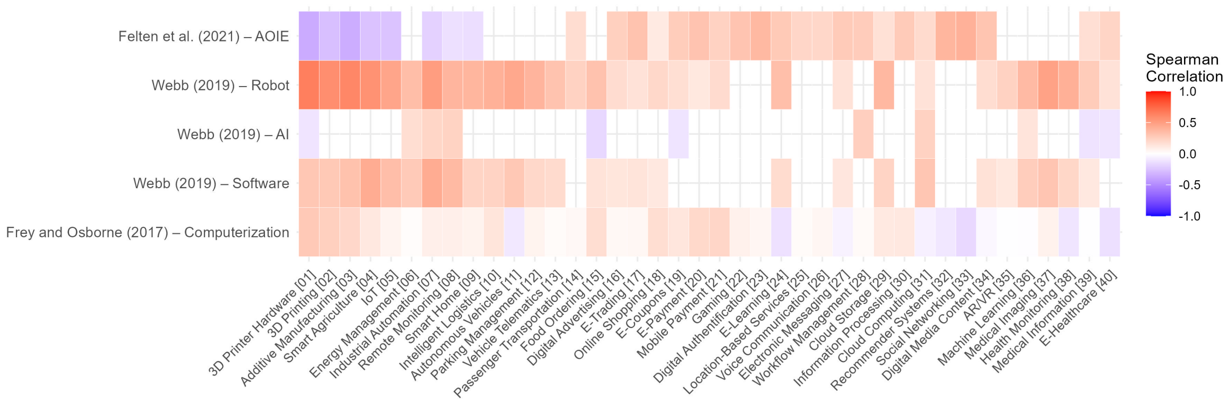
those obtained with these metrics at the 4-digit ISCO-08 level and report the correlations as a heatmap in Figure OA.3.

The figure reveals several insights. First, our exposure metrics correlate overall with those in the literature. The robot and software exposure scores in Webb (2019) align with our metrics across a range of emerging digital technologies. Specifically, Webb's robot exposure scores are highly correlated with our *tangible* emerging digital technologies and capture occupation exposure to industrial robots.

Conversely, we find that AI exposure scores in Webb (2019) are confined to core AI applications, such as some embedded technologies (i.e., energy management, industrial automation, and remote monitoring) and data-intensive technologies (i.e., machine learning, workflow management systems, and cloud computing), thus missing broader AI applications like medical imaging or information processing.

Exposure scores in Felten et al. (2021) correlate with a broader set of our technologies,

Figure OA.3: Correlation of Occupation Exposure with Other Metrics in the Literature



Notes: This figure presents the correlation between occupational exposure scores to digital technologies (column) and other occupational exposure metrics available in the literature (rows), both measured at the 4-digit ISCO-08 level. Each cell shows the Spearman correlation ranging from -1 to 1. Correlations with a p-value above 0.05 are transparent. Exposure scores in the literature are from Felten et al. (2021), Webb (2019), and Frey and Osborne (2017) and are converted into 4-digit ISCO-08 exposure scores using several crosswalks.

indicating they cover a wider spectrum of AI applications as compared to Webb (2019). However, they are negatively correlated with embedded systems as none of the 10 AI applications considered in their metric includes any embedded AI, reflecting that their exposure scores are more oriented toward high-skilled jobs.

Lastly, software exposure in Webb (2019) and computerization exposure in Frey and Osborne (2017) correlate with a large segment of our emerging digital technologies. However, the magnitudes of these correlations are smaller, as both computerization and software are inherent to emerging digital technologies.

OA.5 Task Exposure

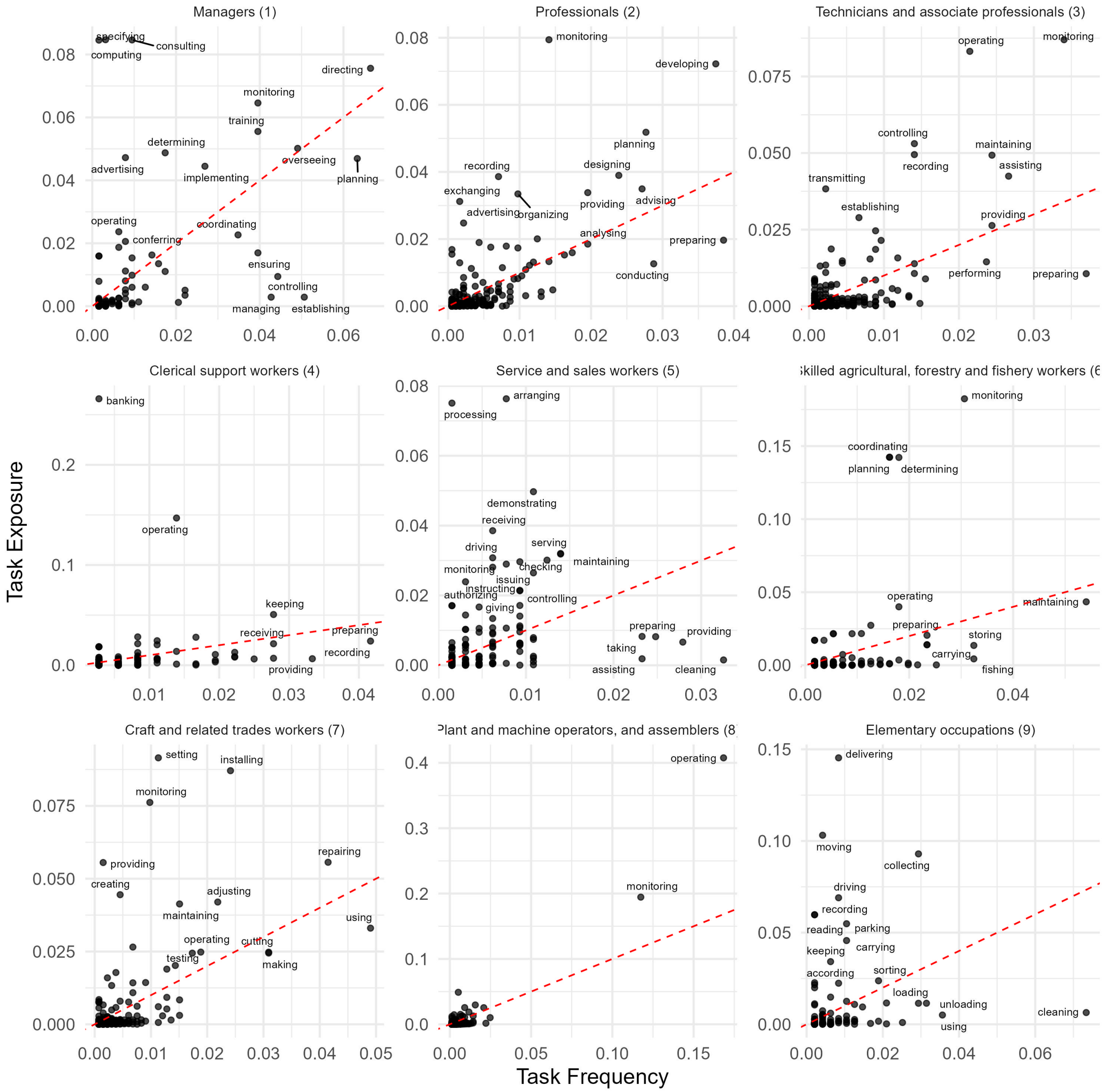
Figure OA.4 displays the most exposed tasks, expressed as gerunds, for 1-digit ISCO-08 groups. It highlights actions to which emerging digital technologies are the most relevant.

OA.6 Placebo Estimates

To further validate the shift-share approach, we conduct a placebo analysis by estimating the effect of regional exposure to emerging digital technologies on the change in the employment-to-population ratio during the pre-period (2002–-2009). The results are presented in Table OA.3. We find no evidence of regional exposure effects in the pre-period across any demographic and skill groups.

The placebo analysis is based on the pre-period (2002–-2009), but employment data for

Figure OA.4: Task Exposure to Emerging Digital Technologies and Task Frequency by 1-digit ISCO-08 Occupation Groups



Notes: This figure displays the exposure of tasks, which are summarized with their gerunds, to emerging digital technologies and their frequency among 1-digit ISCO-08 occupations. The task frequency (on the x-axis) is the gerund's baseline (relative) frequency, which indicates how often the gerund appears in the ISCO-08 classification of that 1-digit group. The task exposure (on the y-axis) is the gerund's (relative) frequency in the target corpus weighted by the cosine similarity, which indicates how often the gerund appears in the exposed occupations. The dashed line is the 45-degree line.

2002 are unavailable in 62 regions, requiring us to restrict the sample to 258 regions. Estimating the baseline empirical specification for the period 2012–2019 for this restricted sam-

Table OA.3: Placebo Estimates of the Effect of Emerging Digital Technologies on Regional Employment by Demographic Groups

	Dep. var: Δ Emp-to-pop. Ratio (2002-2009) $\times$ 100							
	All	Gender		Age		Skill		
	Total	Female	Male	Y15-24	Y25-64	Low	Mid	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure (Standardized)	-0.176	-0.067	-0.109	-0.010	-0.175	-0.042	-0.089	0.318^{*}
	(0.263)	(0.145)	(0.162)	(0.102)	(0.244)	(0.193)	(0.196)	(0.186)
Emp-to-pop. Ratio in 2012	50.93	22.25	28.69	5.70	45.23	14.22	24.52	11.39
Change (in %)	-0.35	-0.30	-0.38	-0.17	-0.39	-0.29	-0.36	2.79
R^2	0.713	0.709	0.766	0.676	0.692	0.747	0.767	0.625
Adj. R^2	0.667	0.663	0.729	0.625	0.643	0.708	0.731	0.565
Num. obs.	258	258	258	258	258	258	258	258

Notes: This table presents the placebo estimates of exposure to emerging digital technologies on regional employment by demographic groups. It presents the coefficients measuring the effect of regional exposure to emerging technologies, constructed as shift-shares and standardized, on changes in the employment-to-population ratio between 2002 and 2009 in European regions, expressed in percentage points, for all workers, female and male workers, young (aged 15-24) and mature (aged 25-64) workers, and low-, middle-, and high-skilled workers. Regressions are weighted by population in 2010. All columns include country fixed effects; demographics controls in 2010, including the logarithm of population, the proportion of females, the proportion of the population aged over 65, the proportions of the population with secondary and tertiary education levels; and the share of employment in the industry sector. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019).

ple yields similar estimates to those of the baseline estimates. This suggests that the placebo analysis results are not influenced by the exclusion of specific regions. These estimates are available upon request.

OA.7 Individual Technology Impact Regression Tables

Table OA.4: Employment Effect of 3D Printing, Embedded Systems, Smart Mobility, and Food Ordering

	Effect of a 1-STD ↑ in Exp. on the Emp-to-pop. Ratio			
	(1)	(2)	(3)	(4)
3D Printer Hardware	0.11	-3.42^{***}	-0.15^{*}	3.37^{**}
	(0.27)	(0.78)	(0.09)	(1.32)
3D Printing	0.17	1.28^{***}	-0.21^{**}	-1.84^{***}
	(0.24)	(0.18)	(0.12)	(0.39)
Additive Manufacturing	0.14	-0.11	-0.11	2.62^{***}
	(0.24)	(1.09)	(0.08)	(0.36)
Smart Agriculture	-1.24^{***}	-1.32^{***}	-0.89^{***}	-1.26^{***}
	(0.15)	(0.09)	(0.08)	(0.07)
IoT	-1.36^{***}	-1.40^{***}	-1.06^{***}	-1.18^{***}
	(0.11)	(0.09)	(0.08)	(0.06)
Energy Management	0.50^{**}	0.70^{***}	0.04	0.46^{***}
	(0.19)	(0.08)	(0.15)	(0.08)
Industrial Automation	-0.09	1.05	-0.66^{***}	-3.58^{***}
	(0.16)	(1.18)	(0.11)	(0.63)
Remote Monitoring	0.51^{**}	1.48^{***}	-0.11	1.27^{***}
	(0.22)	(0.04)	(0.24)	(0.23)
Smart Home	0.80^{***}	0.96^{***}	0.47^{*}	0.83^{***}
	(0.13)	(0.03)	(0.21)	(0.12)
Intelligent Logistics	0.52^{**}	-0.79^{***}	-0.25	-0.82^{***}
	(0.18)	(0.27)	(0.28)	(0.16)
Autonomous Vehicles	0.85^{***}	0.39	0.50^{*}	0.42
	(0.14)	(0.54)	(0.26)	(0.45)
Parking Management	0.76^{***}	0.29	0.62^{***}	0.28
	(0.11)	(0.56)	(0.16)	(0.48)
Vehicle Telematics	0.85^{***}	0.93^{**}	1.22^{***}	1.33^{***}
	(0.11)	(0.68)	(0.30)	(0.54)
Passenger Transportation	0.87^{***}	0.62^{**}	0.68^{***}	0.61^{**}
	(0.14)	(0.15)	(0.21)	(0.18)
Food Ordering	0.60^{**}	0.60^{**}	-0.14	-0.14
	(0.18)	(0.18)	(0.44)	(0.44)
	Controlling for Technology Complementarity			
Within Family		✓		✓
Between Family			✓	✓

Notes: This table presents the estimates of the employment effect of individual digital technologies with and without controlling for technology complementarity. Each entry is a separate regression. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019).

Table OA.5: Employment Effect of E-Commerce, Payment Systems, Computer Vision, and HealthTech

	Effect of a 1-STD ↑ in Exp. on the Emp-to-pop. Ratio			
	(1)	(2)	(3)	(4)
Digital Advertising	0.89^{***}	0.13	0.20	0.39
	(0.15)	(0.24)	(0.40)	(0.46)
E-Trading	0.83^{***}	0.61^{***}	0.17	0.13
	(0.15)	(0.33)	(0.96)	(0.82)
Online Shopping	0.75^{***}	-0.47	-0.12	-0.91
	(0.16)	(0.80)	(0.73)	(1.05)
E-Coupons	0.86^{***}	-0.82^{*}	0.13	0.02
	(0.15)	(0.55)	(0.37)	(0.97)
E-Payment	0.99^{***}	0.98^{*}	0.74	0.76
	(0.16)	(0.71)	(0.88)	(0.95)
Mobile Payment	0.79^{***}	-0.99^{***}	-0.23	-1.71^{***}
	(0.16)	(0.13)	(1.13)	(0.47)
Gaming	1.14^{***}	0.86^{***}	0.75^{***}	0.90^{***}
	(0.15)	(0.20)	(0.14)	(0.20)
AR/VR	0.99^{***}	1.11^{***}	0.15	0.22
	(0.16)	(0.20)	(0.69)	(0.61)
Machine Learning	0.23	-1.05^{***}	-0.29^{**}	-0.90^{***}
	(0.21)	(0.16)	(0.10)	(0.15)
Medical Imaging	0.62^{***}	-0.28	-0.12	0.40
	(0.26)	(0.48)	(0.28)	(0.46)
Health Monitoring	1.28^{***}	0.48	0.67^{***}	-0.01
	(0.18)	(0.50)	(0.20)	(0.24)
Medical Information	1.30^{***}	1.54^{*}	0.87^{***}	0.97^{*}
	(0.17)	(0.88)	(0.10)	(0.54)
E-Healthcare	1.29^{***}	-1.51^{***}	0.79^{***}	-0.15
	(0.20)	(0.81)	(0.09)	(1.36)
	Controlling for Technology Complementarity			
Within Family		✓		✓
Between Family			✓	✓

Notes: This table presents the estimates of the employment effect of individual digital technologies with and without controlling for technology complementarity. Each entry is a separate regression. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019).

Table OA.6: Employment Effect of Digital Services

	Effect of a 1-STD ↑ in Exp. on the Emp-to-pop. Ratio			
	(1)	(2)	(3)	(4)
Digital Authentification	1.16^{***}	0.67	0.70^{***}	
	(0.15)	(1.78)	(0.15)	
E-Learning	1.09^{***}	0.32^{*}	0.58^{***}	0.74^{***}
	(0.19)	(0.18)	(0.13)	(0.25)
Location-Based Services	0.84^{**}	0.47^{**}	0.49^{**}	0.44^{**}
	(0.16)	(0.23)	(0.15)	(0.19)
Voice Communication	0.85^{***}	0.10	-0.46	-1.74
	(0.15)	(0.45)	(1.34)	(1.81)
Electronic Messaging	0.85^{***}	-1.18^{**}	-1.85^{**}	-5.01^{***}
	(0.17)	(1.42)	(0.58)	(0.39)
Workflow Management	1.17^{***}	0.93	0.83^{*}	1.07
	(0.16)	(0.91)	(0.42)	(0.88)
Cloud Storage	0.87^{***}	-0.14	-0.87	-1.24
	(0.18)	(1.17)	(0.82)	(0.76)
Information Processing	0.86^{***}	0.42^{*}	0.27	0.88
	(0.16)	(0.37)	(1.37)	(1.32)
Cloud Computing	1.07^{***}	-0.08	0.45	0.24
	(0.16)	(0.99)	(0.31)	(1.26)
Recommender Systems	0.94^{***}	-0.49^{*}	0.32^{*}	-0.70
	(0.15)	(0.51)	(0.15)	(1.07)
Social Networking	1.08^{***}	-0.95^{**}	0.33^{**}	-1.73^{***}
	(0.15)	(0.32)	(0.14)	(0.48)
Digital Media Content	0.89^{***}	-1.81^{***}	-0.94^{***}	-3.57^{***}
	(0.16)	(0.68)	(0.36)	(0.33)
	Controlling for Technology Complementarity			
Within Family		✓		✓
Between Family			✓	✓

Notes: This table presents the estimates of the employment effect of individual digital technologies with and without controlling for technology complementarity. Each entry is a separate regression. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019).

Table OA.7: Employment Effect of 3D Printing, Embedded Systems, Smart Mobility, and Food Ordering, by Demographic and Skill Groups

	Effect of a 1-STD ↑ in Exp. on the Emp-to-pop. Ratio							
	Total	Female	Male	Y15-24	Y25-64	Low	Mid	High
3D Printer Hardware	3.37^{**}	2.89^{**}	0.49	−0.28	3.64^{**}	6.17^{***}	1.25	-3.64^{**}
	(1.32)	(1.12)	(0.43)	(0.21)	(1.17)	(1.57)	(1.09)	(0.96)
3D Printing	-1.84^{***}	-1.74^{***}	−0.10	−0.00	-1.84^{***}	-3.32^{***}	−0.18	1.52^{***}
	(0.39)	(0.29)	(0.15)	(0.08)	(0.34)	(0.49)	(0.34)	(0.28)
Additive Manufacturing	2.62^{***}	2.67^{***}	−0.05	0.09	2.52^{***}	3.79^{***}	0.65	-1.77^{***}
	(0.36)	(0.28)	(0.15)	(0.10)	(0.30)	(0.52)	(0.33)	(0.33)
Smart Agriculture	-1.26^{***}	-1.12^{***}	-0.14^{***}	-0.13^{***}	-1.13^{***}	-2.00^{***}	-0.51^{***}	1.18^{***}
	(0.07)	(0.06)	(0.02)	(0.02)	(0.06)	(0.09)	(0.08)	(0.04)
IoT	-1.18^{***}	-1.01^{***}	-0.16^{***}	-0.10^{***}	-1.08^{***}	-1.71^{***}	-0.67^{***}	1.14^{***}
	(0.06)	(0.06)	(0.03)	(0.03)	(0.05)	(0.10)	(0.08)	(0.05)
Energy Management	0.46^{***}	0.48^{***}	−0.02	−0.01	0.47^{***}	0.63^{***}	0.42^{***}	-0.56^{***}
	(0.08)	(0.07)	(0.02)	(0.02)	(0.06)	(0.10)	(0.05)	(0.04)
Industrial Automation	-3.58^{***}	-2.98^{***}	-0.61^{***}	-0.59^{***}	-3.00^{***}	-4.20^{***}	-1.41^{***}	2.13^{***}
	(0.63)	(0.67)	(0.12)	(0.05)	(0.62)	(0.97)	(0.33)	(0.58)
Remote Monitoring	1.27^{***}	1.28^{***}	−0.00	0.22^{***}	1.06^{***}	1.83^{***}	0.86^{***}	-1.38^{***}
	(0.23)	(0.20)	(0.07)	(0.03)	(0.22)	(0.28)	(0.06)	(0.11)
Smart Home	0.83^{***}	0.81^{***}	0.02	0.04^{*}	0.78^{***}	1.15^{***}	0.48^{***}	-0.77^{***}
	(0.12)	(0.09)	(0.03)	(0.02)	(0.10)	(0.11)	(0.05)	(0.04)
Intelligent Logistics	-0.82^{***}	-0.50^{***}	-0.32^{***}	-0.22^{***}	-0.59^{***}	-0.84^{***}	0.14	−0.02
	(0.16)	(0.19)	(0.06)	(0.02)	(0.16)	(0.16)	(0.19)	(0.15)
Autonomous Vehicles	0.42	0.34	0.07	0.13	0.28	0.48	−0.10	−0.05
	(0.45)	(0.35)	(0.23)	(0.08)	(0.40)	(0.64)	(0.31)	(0.22)
Parking Management	0.28	0.62^{***}	-0.34^{*}	-0.24^{**}	0.52^{***}	−0.01	1.35^{***}	-0.98^{***}
	(0.48)	(0.35)	(0.14)	(0.08)	(0.41)	(0.56)	(0.13)	(0.19)
Vehicle Telematics	1.33^{***}	1.33^{***}	0.00	−0.07	1.40^{***}	1.21^{**}	1.49^{***}	-1.35^{***}
	(0.54)	(0.36)	(0.27)	(0.12)	(0.43)	(0.69)	(0.47)	(0.40)
Passenger Transportation	0.61^{**}	0.26^{*}	0.35^{**}	0.17^{**}	0.44^{**}	1.01^{**}	-0.57^{**}	0.14^{**}
	(0.18)	(0.14)	(0.10)	(0.04)	(0.17)	(0.18)	(0.14)	(0.13)
Food Ordering	−0.14	−0.06	−0.08	-0.10^{**}	−0.05	0.19	−0.10	−0.17
	(0.44)	(0.37)	(0.12)	(0.08)	(0.37)	(0.57)	(0.20)	(0.25)

Notes: This table presents the estimates of the employment effect of individual digital technologies by demographic and skill groups. Each entry is a separate regression. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019).

Table OA.8: Employment Effect of E-Commerce, Payment Systems, Computer Vision, and HealthTech, by Demographic and Skill Groups

	Effect of a 1-STD ↑ in Exp. on the Emp-to-pop. Ratio							
	Total	Female	Male	Y15-24	Y25-64	Low	Mid	High
Digital Advertising	0.39	0.19	0.20^{*}	0.31^{**}	0.09	0.78	−0.19	−0.26
	(0.46)	(0.34)	(0.17)	(0.18)	(0.35)	(0.59)	(0.40)	(0.37)
E-Trading	0.13	−0.26	0.39^{*}	-0.27^{**}	0.40	-1.01^{**}	0.21	0.84
	(0.82)	(0.68)	(0.21)	(0.47)	(0.66)	(1.53)	(1.19)	(0.89)
Online Shopping	−0.91	−0.20	-0.71^{***}	-0.26^{***}	−0.66	0.38	-0.54^{**}	−0.55
	(1.05)	(0.90)	(0.20)	(0.14)	(0.93)	(1.38)	(0.34)	(0.61)
E-Coupons	0.02	−0.70	0.73	0.35^{***}	−0.34	−0.23	−0.73	1.05
	(0.97)	(0.58)	(0.61)	(0.17)	(0.97)	(1.05)	(0.68)	(0.70)
E-Payment	0.76	0.10	0.65^{***}	−0.13	0.91	−0.83	1.72^{***}	−0.28
	(0.95)	(0.74)	(0.31)	(0.14)	(0.95)	(1.15)	(0.72)	(0.94)
Mobile Payment	-1.71^{***}	-1.49^{***}	-0.22^{***}	-0.56^{***}	-1.16^{***}	-2.83^{***}	-0.68^{***}	1.81^{***}
	(0.47)	(0.44)	(0.07)	(0.10)	(0.41)	(0.58)	(0.27)	(0.32)
Gaming	0.90^{***}	0.57^{***}	0.34^{***}	0.36^{***}	0.55^{***}	1.83^{***}	-0.52^{**}	-0.38^{**}
	(0.20)	(0.17)	(0.05)	(0.04)	(0.19)	(0.31)	(0.17)	(0.25)
AR/VR	0.22	−0.14	0.36^{**}	0.16^{*}	0.06	−0.28	−0.35	0.75
	(0.61)	(0.54)	(0.22)	(0.09)	(0.59)	(0.68)	(0.59)	(0.62)
Machine Learning	-0.90^{***}	-0.47^{***}	-0.43^{***}	-0.21^{***}	-0.69^{***}	-1.23^{***}	−0.04	0.38^{***}
	(0.15)	(0.09)	(0.10)	(0.04)	(0.13)	(0.16)	(0.14)	(0.16)
Medical Imaging	0.40	0.44	−0.04	0.02	0.39	0.78	0.83^{***}	-1.13^{***}
	(0.46)	(0.41)	(0.11)	(0.11)	(0.38)	(0.65)	(0.23)	(0.29)
Health Monitoring	−0.01	−0.03	0.02	0.03	−0.03	−0.44	0.73^{**}	−0.27
	(0.24)	(0.29)	(0.24)	(0.08)	(0.29)	(0.46)	(0.37)	(0.53)
Medical Information	0.97^{*}	0.77	0.20	0.14	0.83	2.40^{**}	−0.85	−0.53
	(0.54)	(0.60)	(0.37)	(0.13)	(0.58)	(0.79)	(0.83)	(1.01)
E-Healthcare	−0.15	−0.26	0.10	0.50^{**}	−0.64	0.43	-2.87^{***}	1.91^{*}
	(1.36)	(1.30)	(0.91)	(0.27)	(1.38)	(1.92)	(0.73)	(1.13)

Notes: This table presents the estimates of the employment effect of individual digital technologies by demographic and skill groups. Each entry is a separate regression. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019).

Table OA.9: Employment Effect of Digital Services by Demographic and Skill Groups

	Effect of a 1-STD ↑ in Exp. on the Emp-to-pop. Ratio							
	Total	Female	Male	Y15-24	Y25-64	Low	Mid	High
Digital Authentification								
E-Learning	0.74^{***}	0.73^{***}	0.01	0.32^{***}	0.43^{*}	1.46^{***}	0.28^{*}	-0.95^{***}
	(0.25)	(0.18)	(0.09)	(0.03)	(0.24)	(0.35)	(0.15)	(0.23)
Location-Based Services	0.44^{**}	0.43^{***}	0.01	0.01	0.42^{**}	1.04^{***}	-0.03	-0.52^{***}
	(0.19)	(0.14)	(0.09)	(0.05)	(0.18)	(0.25)	(0.14)	(0.15)
Voice Communication	-1.74	-1.44	-0.30	-0.48^{***}	-1.28	-0.59	-1.11^{**}	0.30
	(1.81)	(1.71)	(0.23)	(0.18)	(1.65)	(2.54)	(0.64)	(1.25)
Electronic Messaging	-5.01^{***}	-4.28^{***}	-0.73^{**}	-0.49^{***}	-4.53^{***}	-6.40^{***}	-1.66^{**}	3.18^{***}
	(0.39)	(0.31)	(0.36)	(0.17)	(0.42)	(0.57)	(0.58)	(0.52)
Workflow Management	1.07	0.88	0.19^{*}	0.10	0.97	0.91	0.06	-0.04
	(0.88)	(0.89)	(0.15)	(0.16)	(0.74)	(1.64)	(0.34)	(0.96)
Cloud Storage	-1.24	-1.46^{*}	0.22	-0.06	-1.17	-1.67	-0.81	1.39^{**}
	(0.76)	(0.62)	(0.32)	(0.19)	(0.73)	(1.21)	(0.64)	(0.47)
Information Processing	0.88	0.48	0.41^{*}	0.37^{**}	0.52	2.46	-0.62	-0.68
	(1.32)	(1.21)	(0.26)	(0.20)	(1.16)	(1.96)	(0.57)	(0.90)
Cloud Computing	0.24	1.05	-0.82^{***}	0.32^{**}	-0.09	1.27	-0.67	-0.47
	(1.26)	(0.92)	(0.37)	(0.12)	(1.22)	(1.40)	(0.59)	(0.67)
Recommender Systems	-0.70	-0.96	0.26	-0.60^{***}	-0.11	-1.95	0.24	0.85
	(1.07)	(0.88)	(0.33)	(0.14)	(0.98)	(1.71)	(0.69)	(1.09)
Social Networking	-1.73^{***}	-2.29^{***}	0.56^{*}	-0.43^{**}	-1.31^{***}	-5.17^{***}	2.25^{***}	1.00^{*}
	(0.48)	(0.31)	(0.27)	(0.19)	(0.51)	(0.60)	(0.52)	(0.49)
Digital Media Content	-3.57^{***}	-3.30^{***}	-0.28^{**}	-0.48^{***}	-3.10^{***}	-6.18^{***}	0.02	2.41^{***}
	(0.33)	(0.27)	(0.11)	(0.07)	(0.30)	(0.23)	(0.38)	(0.31)

Notes: This table presents the estimates of the employment effect of individual digital technologies by demographic and skill groups. Each entry is a separate regression. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adão et al. (2019).

OA.8 Task-Based Model

OA.8.1 Environment

Consider a continuum of production tasks indexed by their complexity level, denoted by $x \in [0, 1+\eta]$. The benchmark economy includes a unit measure of tasks, while $\eta \geq 0$ represents the creation of new, higher-complexity tasks enabled by advances in digital technologies.

The final good aggregates tasks using a constant elasticity of substitution (CES) technology with elasticity $\lambda \in (0,1)$, according to:

$$Y = \left(\int_0^{1+\eta} y(x)^{\frac{\lambda-1}{\lambda}} dx \right)^{\frac{\lambda}{\lambda-1}}. \tag{4}$$

The final good serves as the numeraire, with its price normalized to one.

The parameter η can be interpreted as a measure of technological frontier expansion: a higher η reflects the creation of new, more complex tasks enabled by ongoing digital innovation. In the model, we treat η as exogenous and constant, but it can be endogenized in extensions where task innovation responds to R&D investments or shifts in factor costs.

Each task x can be performed by various factors of production, including different types of labor $l \in \mathcal{L}$ and capital $k \in \mathcal{K}$. The quantity of task x produced is given by:

$$y(x) = \sum_k A_k \cdot \psi_k(x) \cdot k(x) + \sum_l A_l \cdot \psi_l(x) \cdot l(x),$$

where A_k and A_l represent factor-augmenting technologies, and $\psi_k(x)$ and $\psi_l(x)$ capture the task-specific comparative advantage of each type of capital and labor, respectively.

The sets $\mathcal{L}$ and $\mathcal{K}$ can accommodate multiple types of labor and capital. For example, with three types of labor—low-skilled, middle-skilled, and high-skilled—$\mathcal{L} = \{L, M, H\}$, and corresponding types of capital $\mathcal{K} = \{K_L, K_M, K_H\}$. In the simplest case, there is only one type of labor and one type of capital. Throughout the analysis, we focus on an economy with three types of workers.

Each factor of production is supplied inelastically and in fixed quantity. Specifically, the economy is endowed with unit measures of each labor type and each capital type. We abstract from household behavior and savings decisions; the model focuses exclusively on the production side.

The productivity of each factor $j \in \mathcal{K} \cup \mathcal{L}$ in task x is given by $A_j \cdot \psi_j(x) \geq 0$. Here, $\psi_j(x)$ captures the relative suitability of factor j for task x (i.e., its comparative advantage schedule), while A_j captures technological improvements that uniformly enhance the productivity of factor j across all tasks.

We impose a *single-crossing structure* on the productivity schedules:

$$\frac{\psi_L(x)}{\psi_{K_L}(x)},\ \frac{\psi_{K_M}(x)}{\psi_L(x)},\ \frac{\psi_M(x)}{\psi_{K_M}(x)},\ \frac{\psi_{K_H}(x)}{\psi_M(x)},\ \frac{\psi_H(x)}{\psi_{K_H}(x)} \text{ are increasing in } x.$$

This structure entails two key properties. First, higher-skilled labor has a comparative advantage in more complex tasks relative to lower-skilled labor. Second, each type of labor has a comparative advantage over its corresponding capital in more complex tasks, but not necessarily over the capital associated with higher-skilled labor.

Under these conditions, each task price x equals the minimum unit cost among all available production technologies:

$$p(x) = \min\left\{c_j\right\}_{j\in\mathcal{K}\cup\mathcal{L}},$$

where unit costs are defined as

$$c_j \equiv \frac{p_j}{A_j\cdot\psi_j(x)}, \qquad \text{with} \quad p_j = \begin{cases} r & \forall j\in\mathcal{K} \\ w_l & \forall j\in\mathcal{L} \end{cases},$$

where r denotes the rental rate of capital and w_l the wage rate of labor type l.

Since ψ-schedules satisfy strict increasing single-crossing, the cost curves for different factors intersect exactly once, generating an ordered set of task cutoffs:

$$\underline{x}_L \le \overline{x}_L \le \underline{x}_M \le \overline{x}_M \le \underline{x}_H,$$

such that tasks are assigned as follows:

$$\begin{aligned}
&x \in [0, \underline{x}_L) && \text{are performed by } K_L,\\
&x \in [\underline{x}_L, \overline{x}_L) && \text{are performed by } L,\\
&x \in [\overline{x}_L, \underline{x}_M) && \text{are performed by } K_M,\\
&x \in [\underline{x}_M, \overline{x}_M) && \text{are performed by } M,\\
&x \in [\overline{x}_M, \underline{x}_H) && \text{are performed by } K_H,\\
&x \in [\underline{x}_H, 1+\eta) && \text{are performed by } H.
\end{aligned}$$

The structure of comparative advantages across labor and capital types implies that tasks are naturally segmented along the complexity spectrum. Simpler tasks (lower x) are performed by lower-skill capital, followed by low-skill labor, then medium-skill capital, and so forth, with the most complex tasks ultimately assigned to high-skill labor. This sequential assignment is characterized by a set of task boundaries, determined by points of indifference between adjacent factors' costs.

At each boundary between adjacent production factors, the cost of performing the marginal task is equalized. For any two adjacent factors j and j', the cutoff $\hat{x}$ satisfies:

$$\frac{p_j}{A_j \psi_j(\hat{x})} = \frac{p_{j'}}{A_{j'} \psi_{j'}(\hat{x})}.$$

Specifically, the first two cutoffs are characterized by:

$$\frac{r}{A_{K_L} \cdot \psi_{K_L}(\underline{x}_L)} = \frac{w_L}{A_L \cdot \psi_L(\underline{x}_L)}, \tag{5}$$

$$\frac{w_L}{A_L \cdot \psi_L(\overline{x}_L)} = \frac{r}{A_{K_M} \cdot \psi_{K_M}(\overline{x}_L)}, \tag{6}$$

Given the equilibrium assignment of tasks, we can now aggregate labor demand across the range of tasks performed by each type of worker. Labor demand for each type reflects both their relative productivity and the breadth of their assigned task domain. The labor demand for workers of type $l \in \mathcal{L}$ is given by:

$$l = Y \cdot w_l^{-\lambda} \cdot A_l^{\lambda-1} \cdot \Gamma_l(\underline{x}_l, \overline{x}_l), \tag{7}$$

where Γ_l is the share of tasks assigned to workers of type l. Task shares are defined as

$$\Gamma_l \equiv \int_{\underline{x}_l}^{\overline{x}_l} \psi_l(x)^{\lambda-1} dx,$$

with the convention that $\overline{x}_H \equiv 1 + \eta$.

Shifts in productivity directly affect task allocation. The share of tasks allocated to each labor type is determined by the location of the boundary tasks, which reflect differences in productivity between labor and adjacent capital types along the task space. Any increase in the productivity of an adjacent capital type shifts these boundaries, reducing the range of tasks assigned to labor and lowering labor demand—*leading to labor displacement*. Conversely, an improvement in labor productivity pushes the boundaries outward, expanding labor's task domain and *increasing labor demand*.

OA.8.2 Equilibrium

Equilibrium in this economy consists of a mapping from tasks to the most cost-effective production factor, a set of consistent task prices, and factor prices that support optimal task assignment. Factor demands respond endogenously to the wage-rental structure and the task allocation implied by comparative advantage.

An equilibrium in this static partial equilibrium setting is defined by an assignment of tasks to production factors $\{j(x) \in \mathcal{L} \cup \mathcal{K}\}_{x \in [0,1+\eta]}$, task prices $\{p(x)\}_{x \in [0,1+\eta]}$, factor demands $\{l, k\}_{l \in \mathcal{L}, k \in \mathcal{K}}$, a positive vector of factor prices $\{w_l, r\}_{l \in \mathcal{L}}$ such that:

1. **Task Assignment:** Each task x is performed by the factor that minimizes unit cost:

$$p(x) = \min_{j \in \mathcal{L} \cup \mathcal{K}} \left\{ \frac{p_j}{A_j \psi_j(x)} \right\}, \quad \forall x \in [0, 1+\eta].$$

2. **Cutoff Conditions:** At each endogenous boundary between adjacent factors, unit costs are equalized. For example,

$$\frac{r}{A_{K_L} \psi_{K_L}(\underline{x}_L)} = \frac{w_L}{A_L \psi_L(\underline{x}_L)},$$

and similarly for other cutoffs.

3. **Factor Demand:** Labor demand is proportional to task-weighted productivity across the domain of tasks assigned to each labor type:

$$l = Y \cdot w_l^{-\lambda} \cdot A_l^{\lambda-1} \cdot \Gamma_l(\underline{x}_l, \overline{x}_l), \quad \forall l \in \mathcal{L}.$$

4. **Output Aggregation:** Aggregate output is a CES function of task-level production:

$$Y = \left(\int_0^{1+\eta} y(x)^{\frac{\lambda-1}{\lambda}} dx \right)^{\frac{\lambda}{\lambda-1}}.$$

Factor endowments are fixed and normalized to one for each type. Equilibrium wages and the rental rate adjust to ensure market clearing for all production factors.

This equilibrium structure provides a transparent mapping from technology and factor prices to task assignment and output. We next examine how shifts in productivity or technological frontier expansion reshape this allocation.

OA.8.3 Comparative Statics: Task Reallocation Following a Technology Shock

We model the introduction of digital technologies as inducing changes in the productivity schedules of production factors (dA_j), and potentially extending the task complexity frontier ($d\eta$). To isolate these effects, we abstract from endogenous factor price responses, holding wages and the rental rate constant ($dw_l = 0$ and $dr = 0$). Aggregate output Y responds endogenously via task reallocation and productivity changes.

We characterize task reallocation by differentiating the equal-cost boundary conditions (e.g., Equation (5)) with respect to the underlying productivities. The change in task boundaries for labor type l is given by:

$$d\underline{x}_l = \underline{\Psi}_l \cdot (g_k - g_l), \tag{8}$$

$$d\overline{x}_l = \overline{\Psi}_l \cdot (g_l - g_{k+1}), \tag{9}$$

where $g_j \equiv dA_j/A_j$ is the growth rate in productivity of factor $j \in \mathcal{K} \cup \mathcal{L}$, and

$$\underline{\Psi}_l \equiv \left(\frac{\partial \ln(\psi_l/\psi_k)}{\partial \underline{x}_l}\right)^{-1} > 0, \quad \overline{\Psi}_l \equiv \left(\frac{\partial \ln(\psi_l/\psi_{k+1})}{\partial \overline{x}_l}\right)^{-1} > 0,$$

and $k+1$ denotes the next higher skill capital type.[25] The upper boundary shift for the highest skill type is simply $d\overline{x}_H = d\eta$.

We now formalize the main comparative statics implications of technological change for task assignment. First, consider the case where capital productivity improves:

Proposition 1 (Capital-Augmenting Technological Change) *Suppose a technology shock raises the productivity of a skill-specific capital, $g_k > 0$. Then, the task boundary $\underline{x}_l$ ($\overline{x}_{l-1}$) shifts to the right (left), reducing the range of tasks performed by the adjacent labor types and reallocating more tasks toward capital.*

Proof. Follows directly from differentiating the unit cost equalization condition, which implies $d\underline{x}_l = \underline{\Psi}_l \cdot g_k > 0$ and $d\overline{x}_{l-1} = \overline{\Psi}_{l-1} \cdot g_k < 0$. ■

Next, consider the reverse case in which labor productivity increases:

Proposition 2 (Labor-Augmenting Technological Change) *Suppose a technology shock raises the productivity of a labor type, $g_l > 0$. Then, the task boundary $\underline{x}_l$ ($\overline{x}_l$) shifts to the left (right), expanding the range of tasks performed by labor and reallocating intermediate tasks from capital to labor.*

[25] The terms $\underline{\Psi}_l$ and $\overline{\Psi}_l$ capture the sensitivity of task boundaries to productivity differences between labor and its adjacent capital competitors, as determined by the slope of their relative comparative advantage schedules.

Proof. Follows directly from differentiating the unit cost equalization condition, which implies $d\underline{x}_l = \underline{\Psi}_l \cdot g_l < 0$ and $d\overline{x}_l = \overline{\Psi}_l \cdot g_l > 0$. ■

Finally, consider how the creation of entirely new tasks reshapes production:

Proposition 3 (Task Frontier Expansion) *Suppose a technology shock expands the complexity frontier, $d\eta > 0$. Then, the range of tasks performed by high-skilled labor (H) expands by $d\eta$.*

Proof. Follows immediately from model construction, since $d\overline{x}_H = d\eta$. ■

Thus, digital innovation reallocates existing tasks among production factors through relative productivity shifts, while expanding the task domain assigned to high-skilled labor through frontier extension. These two forces jointly determine the restructuring of production following technological change: capital-augmenting shocks tend to displace labor, labor-augmenting shocks reinstate labor, with frontier expansion benefiting the most skilled workers.

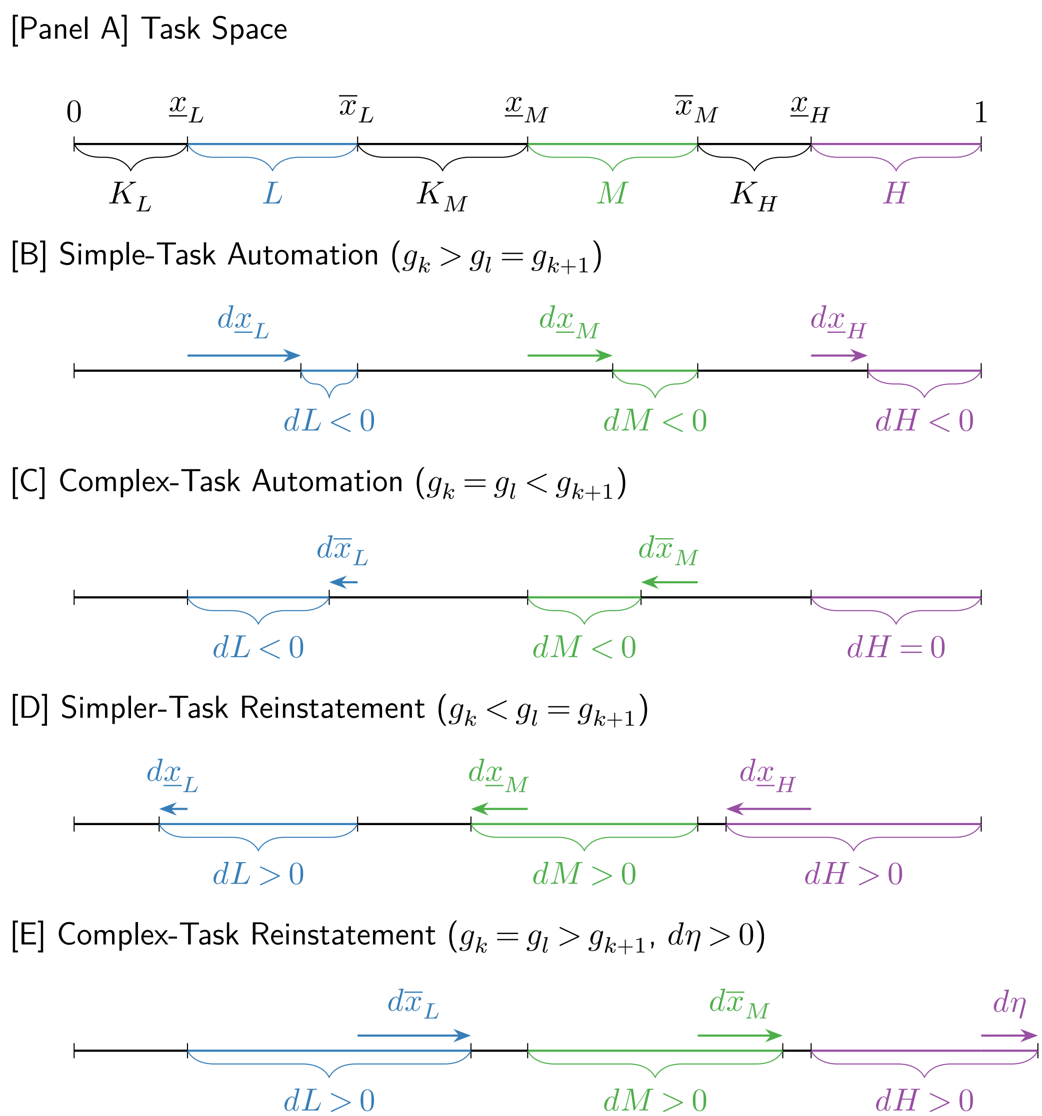
Figure OA.5 shows the assignment of tasks to production factors along the task space and illustrates several types of technologies that reallocate tasks between factors. Panel A depicts the baseline assignment of tasks based on comparative advantage, with each skill group performing a contiguous segment of tasks defined by boundaries $\underline{x}_L$, $\overline{x}_L$, $\underline{x}_M$, $\overline{x}_M$, and $\underline{x}_H$.

Simple-Task Automation. Panel B illustrates the impact of a technology that automates simple tasks performed by labor. This technology raises the productivity of labor less than that of the corresponding capital associated with it (i.e., $g_k > g_l$), but of the same magnitude as the higher-skilled capital (i.e., $g_l = g_{k+1}$). As capital becomes relatively more productive in simple tasks, it takes over these tasks previously performed by labor. All lower task boundaries $\underline{x}_L$, $\underline{x}_M$, and $\underline{x}_H$ shift rightward, shrinking the task spans assigned to all types of workers.

Complex-Task Automation. Panel C shows an automation technology that, instead, automates complex tasks performed by labor. This technology raises the productivity of labor as much as that of the corresponding capital (i.e., $g_l = g_k$), but less than the productivity of the higher-skilled capital (i.e., $g_l < g_{k+1}$). As capital becomes relatively more productive in complex tasks, it takes over these tasks previously performed by labor. The upper task boundaries $\overline{x}_L$ and $\overline{x}_M$ shift leftward, shrinking the task spans assigned to low- and middle-skilled workers. Note that the set of tasks allocated to high-skilled workers does not change since we assume there is no higher-skilled capital.

Simple-Task Reinstatement. Panel D shows a technology that reinstates simple tasks to labor. This technology raises the productivity of labor more than that of the corresponding cap-

Figure OA.5: Task Space and the Reassignment of Tasks with Automation and Reinstatement



Notes: This figure displays the assignment of tasks to production factors along the task space in Panel A, the effect of the introduction of a technology that automates simple tasks in Panel B, automates complex tasks in Panel C, that reinstates simple tasks in Panel D, and that reinstates complex tasks in Panel E.

ital associated with it (i.e., $g_k < g_l$), but of the same magnitude as the higher-skilled capital (i.e., $g_l = g_{k+1}$). As labor becomes relatively more productive in simpler tasks, it takes over these tasks previously performed by capital. All lower task boundaries $\underline{x}_L$, $\underline{x}_M$, and $\underline{x}_H$ shift leftward, expanding the task spans assigned to all types of workers.

Complex-Task Reinstatement. Panel E shows a technology that reinstates complex tasks to labor. This technology raises the productivity of labor as much as that of the corresponding capital (i.e., $g_l = g_k$), but more than the productivity of the higher-skilled capital (i.e., $g_l > g_{k+1}$). In addition, it creates new tasks for high-skilled labor (i.e., $d\eta > 0$). As labor becomes relatively more productive in more complex tasks, it takes over these tasks previously performed by capital. All upper task boundaries $\overline{x}_L$, $\overline{x}_M$, and $\overline{x}_H$ shift rightward, expanding the task spans assigned to all types of workers.

To summarize, the introduction of a new digital technology can either automate tasks or reinstate tasks; the tasks that are affected can either be simple or complex ones. Eventually, technologies can have a combination of several effects, such as simple-task automation with complex-task reinstatement. These changes in task allocation are reflected in the demand for labor types.

OA.8.4 Labor Demand Changes Following a Technology Shock

We now analyze how technological shocks affect labor demand by differentiating the labor demand for each worker type. This decomposition separates the overall change in employment into distinct economic channels: output expansion, task-specific price adjustments, task reallocation, and task creation.

Differentiating the labor demand from Equation (7), we obtain

$$\begin{aligned}
\frac{dL}{L} &= \frac{dY}{Y} - (1-\lambda)\cdot g_L - \frac{\psi_L(\underline{x}_L)^{\lambda-1}}{\Gamma_L}\cdot d\underline{x}_L + \frac{\psi_L(\overline{x}_L)^{\lambda-1}}{\Gamma_L}\cdot d\overline{x}_L,\\
\frac{dM}{M} &= \frac{dY}{Y} - (1-\lambda)\cdot g_M - \frac{\psi_M(\underline{x}_M)^{\lambda-1}}{\Gamma_M}\cdot d\underline{x}_M + \frac{\psi_M(\overline{x}_M)^{\lambda-1}}{\Gamma_M}\cdot d\overline{x}_M,\\
\frac{dH}{H} &= \frac{dY}{Y} - (1-\lambda)\cdot g_H - \frac{\psi_H(\underline{x}_H)^{\lambda-1}}{\Gamma_H}\cdot d\underline{x}_H + \frac{\psi_H(1+\eta)^{\lambda-1}}{\Gamma_H}\cdot d\eta,
\end{aligned}$$

where the aggregate output Y responds endogenously to technology shocks through the reallocation and expansion of tasks, as captured in the term dY/Y.

Substituting for $d\underline{x}_l$ and $d\overline{x}_l$ using Equations (8) and (9) and rearranging, the change in labor demand for low-skilled workers becomes:

$$\frac{dL}{L} = \underbrace{\frac{dY}{Y}}_{\substack{\text{Aggregate}\\ \text{productivity}\\ \text{effect}}} \underbrace{-(1-\lambda)\cdot g_L}_{\substack{\text{Task price}\\ \text{effect}}} + \underbrace{\underline{\phi}_L\cdot\left(g_L - g_{K_L}\right)}_{\substack{\text{Simple Task}\\ \text{Reinstatement/Automation}\\ \text{effect}}} + \underbrace{\overline{\phi}_L\cdot\left(g_L - g_{K_M}\right)}_{\substack{\text{Complex Task}\\ \text{Reinstatement/Automation}\\ \text{effect}}}, \tag{10}$$

where $\underline{\phi}_L \equiv \underline{\Psi}_L\cdot\psi_L(\underline{x}_L)^{\lambda-1}/\Gamma_L$ and $\overline{\phi}_L \equiv \overline{\Psi}_L\cdot\psi_L(\overline{x}_L)^{\lambda-1}/\Gamma_L > 0$.

Similarly, for middle-skilled workers:

$$\frac{dM}{M} = \underbrace{\frac{dY}{Y}}_{\substack{\text{Aggregate}\\ \text{productivity}\\ \text{effect}}} \underbrace{-(1-\lambda)\cdot g_M}_{\substack{\text{Task price}\\ \text{effect}}} + \underbrace{\underline{\phi}_M \cdot \left(g_M - g_{K_M}\right)}_{\substack{\text{Simple Task}\\ \text{Reinstatement/Automation}\\ \text{effect}}} + \underbrace{\overline{\phi}_M \cdot \left(g_M - g_{K_H}\right)}_{\substack{\text{Complex Task}\\ \text{Reinstatement/Automation}\\ \text{effect}}}, \tag{11}$$

where $\underline{\phi}_M \equiv \underline{\Psi}_M \cdot \psi_M(\underline{x}_M)^{\lambda-1}/\Gamma_M$ and $\overline{\phi}_M \equiv \overline{\Psi}_M \cdot \psi_M(\overline{x}_M)^{\lambda-1}/\Gamma_M > 0$.

Finally, for high-skilled workers:

$$\frac{dH}{H} = \underbrace{\frac{dY}{Y}}_{\substack{\text{Aggregate}\\ \text{productivity}\\ \text{effect}}} \underbrace{-(1-\lambda)\cdot g_H}_{\substack{\text{Task price}\\ \text{effect}}} + \underbrace{\underline{\phi}_H \cdot \left(g_H - g_{K_H}\right)}_{\substack{\text{Simple Task}\\ \text{Reinstatement/Automation}\\ \text{effect}}} + \underbrace{\phi_\eta \cdot d\eta}_{\substack{\text{Complex Task}\\ \text{Reinstatement}\\ \text{effect}}}, \tag{12}$$

where $\underline{\phi}_H \equiv \underline{\Psi}_H \cdot \psi_H(\underline{x}_H)^{\lambda-1}/\Gamma_H > 0$, and $\phi_\eta \equiv \psi_H(1+\eta)^{\lambda-1}/\Gamma_H > 0$.

Emerging digital technologies affect labor demand through four main channels:

- **Aggregate Productivity Effect ($+$)**: An increase in overall output that raises the demand for all inputs proportionally.
- **Task Price Effect ($-$)**: A decline in the unit cost of performing tasks, proportional to the productivity growth of labor types, modulated by the elasticity of substitution between tasks.
- **Reinstatement/Automation Effect ($+/-$)**: A reallocation of tasks between capital and labor based on relative productivity changes, leading to either an expansion or contraction of the task domain assigned to each labor group.
- **Frontier Expansion Effect ($+$)**: The creation of new tasks that benefit workers capable of performing the highest complexity tasks, namely, high-skilled workers.

The introduction of a digital technology can be considered as the combination of productivity shocks on production factors, dA_j, which grow factor productivity by a rate of g_j, and the creation of new tasks for high-skilled workers, $d\eta$. These latter may also raise output dY. Depending on the technology, this theoretical framework helps in understanding the impact of digital technologies on employment.