From Exposure to Resilience: How Skills Mediate the Employment Effects of Emerging Digital Technologies*

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Abstract

Advances in digital technologies are reshaping labour markets worldwide, raising important questions about how workers can adapt to digital transformation. This paper examines the employment effects of exposure to digital technologies and investigates whether subnational skill composition influences labour market adjustment to technological change. Combining harmonized subnational data for 69 countries with measures of digital technology exposure and skill endowments, we estimate the effects of digital exposure on employment outcomes using a shift-share instrumental variable approach. We then examine how baseline skill composition at the subnational level—measured by weighting occupation-specific skill requirements extracted from online vacancy data by each subnational occupational employment shares—modulates those impacts. Our findings show that local areas characterized by stronger cognitive skills endowments experience greater positive employment effects from digital exposure. Areas with higher levels of managerial and communication skills, such as project and process management or writing skills, also experience more favourable employment outcomes following digital exposure, whereas areas specialized in certain advanced technical skills—including machine learning and AI and software and technical skills—experience weaker employment outcomes. These results underscore the role of worker skill composition in shaping labour-market responses to digital shocks, offering valuable guidance for skill-development initiatives aimed at equipping workers with the skill sets most conducive to positive employment outcomes.

Keywords: Emerging Digital Technologies; Automation; Employment; Skills; Big Data.
JEL Codes: J24, O33, R23.

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1 Introduction

Technological change is transforming labour markets worldwide. The rapid diffusion of digital technologies—including artificial intelligence, big data analytics, and cloud-based systems—is altering production processes, reshaping industry structures, and changing the organization and task structure of work. While these developments have the potential to raise productivity and generate new employment opportunities, they also risk displacing workers, particularly those performing tasks more susceptible to automation (Acemoglu and Restrepo, 2018). As digital technologies diffuse across sectors and economies, understanding how workers adjust to technological change has therefore become increasingly important.

Skills play a central role in this context. On the one hand, the demand for skills is endogenous to technological adoption: as firms reorganize production and adopt new technologies, the task content of jobs evolves, increasing the value of certain capabilities. On the other hand, the local composition of skills conditions the capacity of workers and areas to adapt to digital shocks—shaping both the direction and magnitude of employment responses. Areas characterized by stronger demand for complementary skills may be better positioned to redeploy workers into new or transformed jobs, whereas areas with weaker demand for such skills may face greater risks of exclusion or polarization. Identifying the skills that facilitate adaptation, and whether they systematically mediate the employment effects of digital exposure, is therefore essential for understanding the employment consequences of digitalization.

Despite growing evidence on the labour market impacts of technological change, important gaps remain in our understanding of the mechanisms through which workers adapt to digital transformation. First, much of the existing evidence is concentrated in advanced economies, where digital technologies have generally diffused earlier and where detailed labour market data are more readily available. Consequently, relatively little is known about how digital transformation affects labour markets in low- and middle-income economies. Second, while recent advances in online labour market data have enabled researchers to observe the demand for specific skills directly (Escudero et al., 2024; Adamczyk et al., 2025), relatively little empirical work has examined whether differences in skill composition shape employment responses to emerging digital technologies. As a result, it remains unclear which skills facilitate labour market adjustment and whether the skills associated with successful adaptation play a similar role across countries at different levels of development.

Given these gaps in knowledge, this paper studies the employment effects of exposure to emerging digital technologies across a large set of countries and investigates whether these effects vary by skill composition of subnational areas. We address two related questions. First, what are the employment effects of exposure to emerging digital technologies? Second, to what extent does the composition of skills demanded by employers in subnational areas mediate the employment effects of digital exposure? By answering these questions, the paper contributes to a better understanding of how technological change affects labour markets and the role of skills in facilitating worker adjustment.

To shed light on these questions, we combine harmonized subnational employment data cov-

ering 69 countries with measures of subnational exposure to emerging digital technologies and indicators of the skill composition of subnational areas. Exposure to digital technologies is measured using the TechXposure index developed by Prytkova et al. (2024), which captures the extent to which employment is linked to industries operating at the technological frontier across 40 digital technologies—ranging from mobile payments and e-commerce platforms to industrial automation and machine learning—identified from patent data covering 2012–2021, before the emergence of generative AI. We quantify exposure at the first administrative subnational level and exploit variation across subnational areas (areas thereafter) to estimate the causal effects of digital exposure on employment outcomes. To address potential endogeneity, we employ a shift-share instrumental variable approach that combines industry-level technology exposure scores with baseline sectoral employment shares. We then analyse whether these effects differ depending on the prevalence of different skills compositions within countries. To do so, we construct subnational indicators of baseline skill composition by interacting occupation-level skill intensities with occupational employment shares, allowing us to capture the relative prevalence of various cognitive, socio-emotional, and manual skills across subnational areas.

Our results reveal substantial heterogeneity in the labour market effects of exposure to digital technologies. On average, greater digital exposure has a positive medium-term effect on employment-to-population ratios. Employment gains are strongest in low-income countries, moderate in high- and upper-middle-income economies, and weakest in lower-middle-income countries. The positive employment effects are larger for prime-age workers (25–54) than youth (15–24) and older workers (55+) from exposure. Importantly, the distribution of employment gains across education groups changes markedly with countries' income levels. While gains are concentrated among workers with low levels of education in lower-income countries, they increasingly extend to workers with high levels of education in upper-middle- and high-income economies; workers with intermediate levels of education, by contrast, tend to experience weaker or negative responses. Regional patterns also differ, with larger employment gains observed in North and sub-Saharan Africa and the Pacific, and weaker or negative effects in parts of East and Southeast Asia. Taken together, these results suggest that similar exposure to emerging technologies can translate into very different employment outcomes depending on the economic and workforce context in which it occurs.

We further examine how baseline skill-demand composition is associated with employment responses to digital transformation. Areas characterized by greater demand for a range of cognitive skills—including digital literacy, financial skills, and computer skills—exhibit stronger positive employment responses to digital exposure. Communication and managerial skills, including writing and project and process management, are also associated with stronger employment responses. Strikingly, however, the same is not true of the most technology-specific skills. Machine learning and AI skills—measured from vacancies posted prior to the emergence of generative AI—are associated with weaker employment responses, while software and technical skills do not exhibit a systematic positive relationship. Patterns suggest that adapting successfully to digital transformation may depend not only on having specialized technical expertise, but also on the broader cognitive and

managerial skills that complement technology as tasks and production processes change.

Moreover, these relationships vary substantially across countries' income levels and across workers with different levels of education. In lower-income economies, the favourable mediating role of cognitive skills is concentrated primarily among workers with low and intermediate levels of education, whereas in richer economies it increasingly extends to workers with high levels of education. Advanced digital skills display a different pattern, with particularly favourable responses among workers with intermediate levels of education across income groups and among those with high levels of education only in high-income economies. These results underscore that there is no single skill profile that universally facilitates adjustment to technological change and offer important insights for skill-development initiatives aimed at supporting worker adaptation in the context of digitalization.

Related literature. This paper relates to two broad strands of literature. First, it contributes to the literature examining the labour market effects of technological change and digitalization (Autor et al., 2003; Acemoglu and Autor, 2011; Goos et al., 2014; Acemoglu and Restrepo, 2020). Existing studies focusing on advanced economies show that exposure to automation and digital technologies generates substantial variation in employment outcomes depending on local economic conditions (e.g., Mann and Püttmann, 2023; Arntz et al., 2016; Aghion et al., 2020). There is marked within-country variation in the exposure to technological shocks because of differences in industrial composition, occupational specialization, and task content. As a result, areas concentrated in routine-intensive activities tend to experience larger employment losses and slower adjustment, whereas areas with occupational structures characterized by less automatable tasks often exhibit greater resilience and adaptability (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019).

While a growing body of research has extended this analysis to low- and middle-income economies, the evidence remains comparatively limited and mixed (Hjort and Tian, 2025). For instance, Almeida et al. (2020) find that the adoption of advanced digital technology in Chile shifted employment toward routine and manual tasks, while Hjort and Poulsen (2019) show that the arrival of fast internet increased employment in African countries, albeit unevenly across skill groups. These differences in the labour market effects of digitalization are due to factors such as production structures, labour market institutions, levels of informality, and the pace of technological adoption (Maloney and Molina, 2016; Lewandowski et al., 2023; Lo Bello et al., 2019). This paper contributes to this literature by providing new cross-country evidence on the employment effects of exposure to emerging digital technologies using harmonized subnational data covering countries at all income levels, substantially expanding the geographical scope of existing evidence.

Second, the paper contributes to the literature examining the role of skills in shaping labour market adjustment to technological change. Early contributions on skill-biased technological change emphasized how new technologies complement highly skilled workers while substituting for less-skilled labour, thereby contributing to rising wage inequality (Katz et al., 1999). More recent

task-based approaches have shown that workers' vulnerability to automation depends not only on educational attainment but also on the specific tasks performed within occupations (Autor et al., 2003; Spitz-Oener, 2006; Goos and Manning, 2007). In particular, occupations relying on problem-solving, interpersonal interaction, creativity, and adaptability appear more resilient than those dominated by routine tasks. However, much of this literature relies on broad indicators such as educational attainment, occupational structure, or task content to capture workers' capabilities.

Recent advances in online labour market data have enabled researchers to observe skill demand directly through job vacancies, providing new insights into the skills required by employers (Deming, 2017; Deming and Kahn, 2018; Escudero et al., 2024). While this emerging literature has documented substantial variation in the demand for cognitive, socio-emotional, and technical skills across occupations and industries, less attention has been devoted to understanding whether differences in subnational skill composition influence the capacity of areas to adapt to technological change. This paper contributes by linking measures of subnational skill composition derived from online vacancy data to employment outcomes following exposure to emerging digital technologies. Moving beyond conventional measures of task content provides new evidence on the specific skills that facilitate labour market adjustment and enable regions to benefit from digital transformation.

The remainder of the paper is structured as follows. Section 2 describes the data and presents descriptive statistics. Section 3 outlines the empirical strategy. Section 4 presents the results and discusses heterogeneity by country income group, demographic characteristics, and skills. Section 5 concludes.

2 Data

We combine multiple data sources to construct harmonized measures of employment outcomes, exposure to emerging digital technologies, and skill endowments at the subnational level.

2.1 Labour Force and Household Surveys

Our primary employment data come from the harmonized labour force and household survey microdata compiled by the International Labour Organization (ILO). These surveys provide consistent information on employment by sector and occupation, together with key socio-demographic characteristics, which we use to construct a panel of subnational areas over time.

A country is included in the analysis if it satisfies three criteria. First, it must have at least three survey waves between 2010 and 2021, with a baseline year as close as possible to 2010, a start year no earlier than 2014, and an end year no earlier than 2017. This requirement ensures a minimum time span of three years between the start and end of the analysis window. Second, the microdata must be available at the first administrative level, allowing for subnational analysis. Third, surveys must report employment disaggregated by 1-digit ISIC Rev. 3 or Rev. 4 sectors and 1-digit ISCO-88 or ISCO-08 occupations, as well as breakdowns by gender, age, and educational attainment. Together, these conditions ensure cross-country comparability and permit the integration of employment

outcomes with sector-specific technology exposure measures and subnational-level occupational skill composition indicators.

To maximize comparability across areas, we focus on employment changes over the period 2014–2019, which yields the largest balanced panel of countries while still spanning a sufficiently long horizon, ends before the COVID-19 pandemic, and lies within the period covered by the exposure measure. When survey waves do not align exactly with this window, we interpolate or extrapolate employment outcomes to the reference years using linear trends.[1] Areas whose extrapolated series imply an impossible value on any outcome—a non-positive working-age population, or an employment-to-population ratio outside the unit interval—are excluded, since a linear trend fitted to a short observation window far from the reference years need not remain in the admissible range. This removes 17 areas, of which six are the entirety of Togo. The baseline year is defined as the survey wave closest to 2010, from which we construct baseline employment shares and demographic controls. As baseline survey years vary only across countries, any systematic differences associated with baseline survey timing are absorbed by country fixed effects.

Applying these criteria yields a dataset covering 69 countries and 1,015 first-level administrative areas, spanning all World Bank income groups and ILO geographic subregions. Tables OA.1 and OA.2, in the appendix, provide detailed information on country coverage, survey years, and underlying data sources. This dataset forms the backbone of our empirical analysis, allowing us to track employment dynamics within subnational areas over time and relate them to variation in exposure to emerging digital technologies across subnational areas within countries.

Our primary outcome variable is the change in the employment-to-population ratio between 2014 and 2019, defined as the share of the working-age population that is employed. In our analysis, the working-age population comprises individuals aged 15 and above. We focus on this outcome because it captures changes in employment relative to demographic trends and is widely used to facilitate comparisons across countries and over time.

2.2 Exposure to Emerging Digital Technologies

To measure subnational exposure to emerging digital technologies, we combine the labour force and household survey data with sector-level indicators from the *TechXposure* database (Prytkova et al. 2024). *TechXposure* identifies 40 emerging digital technologies from patent data covering 2012–2021 and groups them into nine domains: 3D printing, embedded systems, smart mobility, food services, e-commerce, payment systems, digital services, computer vision, and health tech-

[1] For example, if survey data are available for 2012 and 2018, we linearly interpolate employment outcomes for 2014 and extrapolate to 2019.

nologies.[2] For each technology and year, it measures the exposure of industries and occupations, defined in standard classifications (NACE Rev. 2 and ISCO-08), as the semantic similarity between the technology's patents and the descriptions of those industries and occupations. These measures capture the extent to which different sectors are potentially affected by recent advances in digital technologies. The set spans technologies that transform production at the technological frontier, such as industrial automation and robot control or additive manufacturing, as well as application technologies that diffuse widely in lower-income economies, such as mobile and electronic payments, online shopping platforms, intelligent logistics, smart agriculture, e-learning, and e-healthcare. The latter are particularly relevant for developing economies, where the expansion of internet connectivity has been found to raise employment (Hjort and Poulsen, 2019; Hjort and Tian, 2025). The set also includes machine learning and a range of AI-based applications, such as natural language processing of medical information, recommender systems, and AI-driven digital advertising and workflow management.

We construct a subnational-level exposure index using a Bartik (shift-share) design. For each area a within a country c, exposure is defined as the weighted average of sector-level technology exposure scores, with weights given by baseline employment shares:

$$X_{ac} = \sum_j l_{jac} X_j, \tag{1}$$

where l_{acj} denotes the share of employment in sector j in area a of country c in the baseline year (the survey wave closest to 2010) and X_j measures the average exposure of sector j to emerging digital technologies over 2014–2019. Throughout the empirical analysis, X_{ac} enters the regressions standardized: it is z-scored over the pooled sample of subnational areas, using the (unweighted) global mean and standard deviation reported in Table 2, so that a unit increase in the regressor corresponds to a one-global-standard-deviation increase in exposure. The standardization is global rather than within-country or within-group, so coefficients remain comparable across the specifications reported below.

The timing of the exposure measure shapes the design of the analysis. We cumulate the technology-specific exposure scores over 2014–2019, the same period as the employment outcome, so that sectoral exposure reflects technological developments contemporaneous with the employment

[2] The 40 technologies are, by domain: *3D printing*: 3D printer hardware, 3D printing, and additive manufacturing; *embedded systems*: smart agriculture and water management, Internet of Things (IoT), predictive energy management and distribution, industrial automation and robot control, remote monitoring and control systems, and smart home and intelligent household control; *smart mobility*: intelligent logistics, autonomous vehicles and UAVs, parking and vehicle space management, vehicle telematics and electric vehicle management, and passenger transportation; *food services*: food ordering and vending systems; *e-commerce*: digital advertising, electronic trading and auctions, online shopping platforms, and e-coupons and promotion management; *payment systems*: electronic payments and financial transactions, mobile payments, and gaming and wagering systems; *digital services*: digital authentication, e-learning, location-based services and tracking, voice communication, electronic messaging, workflow management, cloud storage and data security, information processing, cloud computing, recommender systems, social networking and media platforms, and digital media content; *computer vision*: augmented and virtual reality (AR/VR), machine learning and neural networks, and medical imaging and image processing; *health technologies*: health monitoring, medical information, and e-healthcare. Online Appendix Table OA.3 describes each technology.

changes we study. We do not extend the window beyond 2019 for three reasons: the *TechXposure* data end in 2021, so later employment changes could not be matched with contemporaneous exposure; employment in 2020 and 2021 was dominated by the disruptions of the COVID-19 pandemic; and the 2014–2019 window yields the largest balanced panel of countries, as noted above. As a result, our measure captures the wave of digital technologies—including machine learning and earlier forms of AI—that diffused before the emergence of generative AI, whose rapid diffusion since late 2022 has prompted new assessments of its potential labour market effects (Gmyrek et al., 2023). Our estimates should therefore be read as evidence on the employment effects of the digital technologies that preceded generative AI, and as a benchmark against which the effects of generative AI can be assessed as data become available.

By construction, sector-level exposure measures do not capture cross-country or subnational differences in the capacity to adopt and deploy new technologies. For example, manufacturing is assigned the same sectoral exposure score across countries despite large differences in production technologies, digital infrastructure, and institutional environments. Our measure should therefore be interpreted as potential exposure associated with the baseline sectoral composition of each subnational area, rather than as a measure of actual technology adoption. In the empirical analysis, country fixed effects absorb time-invariant country-level differences in economic structure, while baseline controls account for observable within-country heterogeneity. Nonetheless, differences in technology adoption and utilization may persist across subnational areas and are not directly captured by the exposure measure.

A central hypothesis of this paper is that the employment response to a given level of digital exposure depends, in part, on the baseline skill composition of local labour demand. Skills may shape this response through two related channels. First, they may influence whether and how firms adopt and deploy emerging digital technologies, thereby affecting the extent to which potential exposure translates into actual technological change. Second, conditional on adoption, skills may shape how labour markets adjust, including the capacity to reorganize tasks, complement new technologies, and generate employment opportunities. Through either or both channels, areas with greater concentration of relevant skills may be better positioned to adopt and integrate emerging digital technologies and translate exposure into employment gains, whereas areas where these skills are less prominent may experience smaller or more adverse employment responses. For this reason, we explicitly incorporate measures of baseline subnational skill composition into the empirical framework to examine how skills mediate the employment effects of exposure to emerging digital technologies. Since actual technology adoption is not directly observed, our analysis captures the combined role of these potential channels without distinguishing between them.

2.3 Skill Composition at the Subnational Level

To assess whether the workforce's skills mediate the employment effects of exposure to emerging digital technologies, we construct measures of baseline skill composition for each subnational area. These measures are derived from large-scale online job vacancy data from Brazil, the Russian

Federation, South Africa, and Uruguay, which together provide broad coverage of labour market structures in low- and middle-income economies.[3]

We extract skill requirements from vacancy text using a natural language processing (NLP) pipeline that follows the methodology in Escudero et al. (2024). The procedure combines standard text preprocessing with a rule-based classification system that maps curated keyword lists and phrases to 15 skill categories: cognitive core, cognitive sophisticated, basic computer skills, software and technical skills, machine learning and artificial intelligence, financial skills, writing skills, project and process management, character skills, social skills, people management, customer service skills, finger dexterity, hand-foot-eye coordination, and physical skills. Appendix Table OA.4 provides detailed definitions for each category.

Using the vacancy-level skill indicators, we compute measures of skill composition by occupation within each country. Specifically, for each 1-digit ISCO occupation, we calculate the relative importance of a given skill by dividing the number of identified requirements for that skill by the total number of identified requirements across all skill categories in that occupation. The resulting measure captures the relative importance of each skill within the occupational skill bundle. To ensure that these measures reflect baseline conditions, we restrict attention to the earliest available years of vacancy data in each country (2010–2011 for Uruguay and Brazil; 2016–2017 for South Africa and the Russian Federation). We then average occupational skill shares across the four source countries to obtain a representative skill profile for each occupation.[4]

We aggregate these occupational skill profiles to the subnational level using a shift-share design analogous to that used to construct technology exposure. While the exposure measure combines sector-level technology shocks with baseline sectoral employment shares, the skill measures (one for each skill subcategory) combine occupational-specific skill shares with baseline occupational employment shares. Formally, the intensity of skill s in subnational area a in country c is given by

$$Skill^{s}_{ac} = \sum_{o} l_{oac} \times Skill^{s}_{o}, \tag{2}$$

where l_{oac} is the baseline share of employment in occupation o in subnational area a in country c in the baseline year, and $Skill^{s}_{o}$ is the share of all identified skill requirements in occupation o accounted for by skill s.

[3]For the Russian Federation and South Africa, vacancy data are sourced from Adzuna, an aggregator of postings from recruitment sites, job boards, and employers. The dataset spans April 2016 to December 2021 and is estimated to cover over 90 per cent of online vacancies in the Russian Federation and 85 per cent in South Africa. For Uruguay and Brazil, we use data from BuscoJobs covering January 2010 to December 2023, which represent close to 60 per cent of all online vacancies in Uruguay (Escudero et al., 2024). In all cases, duplicate postings are removed, and vacancy records include detailed job descriptions in addition to basic information on employers and occupations.

[4]Although the vacancy data are drawn from four countries, the mapping is performed at the occupational rather than the geographic level. Our objective is to characterize the relative skill composition of occupations, rather than country-specific labour demand. This approach assumes that the relative skill content of broad occupational groups is sufficiently comparable across countries, which is plausible given the relatively stable task and skill requirements of 1-digit ISCO occupations across institutional settings. Averaging skill shares across multiple labour markets further reduces the influence of country-specific differences in vacancy posting practices, yielding portable occupational skill profiles that can be applied consistently across subnational areas and countries in our sample.

These 15 measures capture the extent to which the baseline occupational structure of a subnational area embeds demand for each skill, independent of subsequent technological change. Areas with a higher concentration of jobs in occupations where a particular skill accounts for a larger share of the overall occupational skill bundle demanded will exhibit higher values of $Skill_r^s$ even prior to the diffusion of emerging digital technologies. The resulting indices provide a summary measure of baseline subnational skill endowments, which we use to examine how pre-existing workforce composition conditions the employment response to exposure to emerging digital technologies.

2.4 Descriptive Statistics

The data exhibit substantial heterogeneity in exposure to emerging digital technologies, as well as in underlying labour market characteristics, across areas, sectors, and stages of development. Skill demand also varies markedly across occupations: some skills are concentrated in a narrow set of jobs, while others are broadly distributed across the occupational structure. As a result, areas that differ in their occupational structures are endowed with markedly different mixes of cognitive, socio-emotional, technical, and manual skills. This section documents these patterns and motivates the empirical analysis that follows.

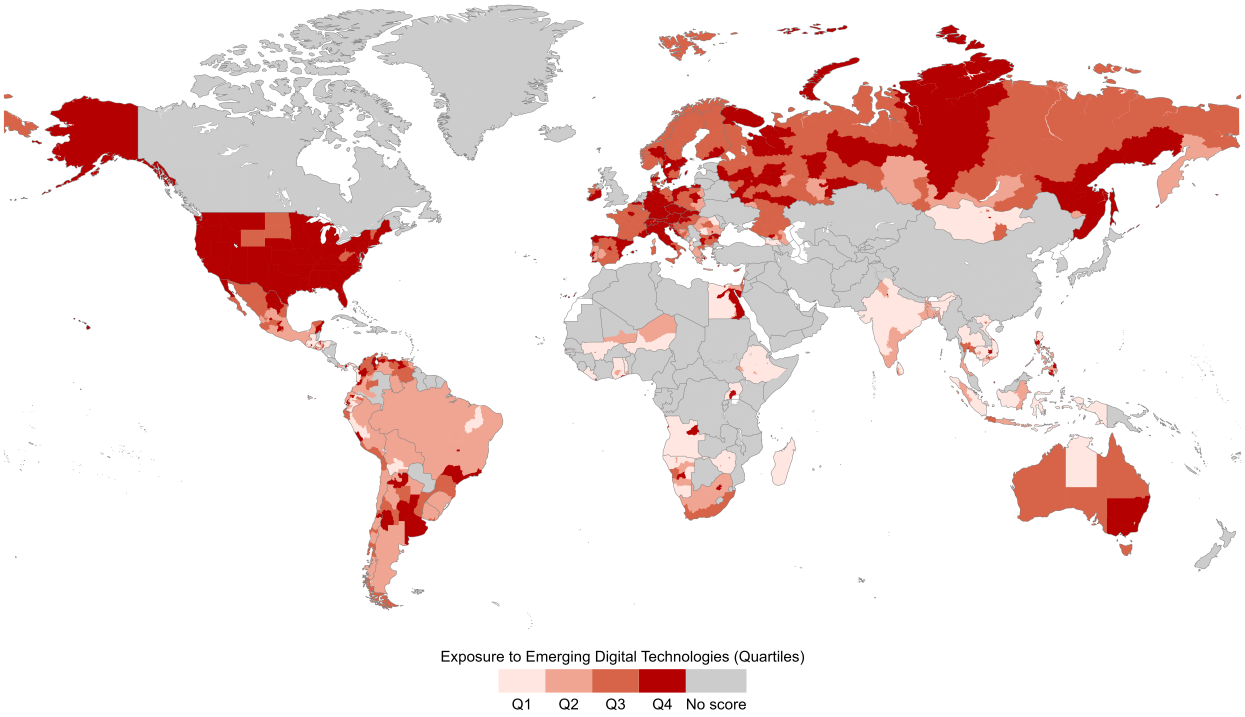
Geographic Variation. Figure 1 illustrates subnational exposure to emerging digital technologies over the period 2014–2019. Darker shades indicate subnational areas in the upper quartiles of the exposure distribution, reflecting a greater concentration of employment in sectors more intensively affected by recent digital technologies.

High-exposure areas are concentrated in North America (notably the United States and parts of Mexico), Northern and Western Europe, East Asia, Australia, and selected areas of South America and Southern Africa. These areas tend to specialize in sectors with relatively high digital intensity—such as advanced manufacturing, information and communication services, and technology-intensive transport and logistics. In contrast, low-exposure areas are predominantly located in sub-Saharan Africa, South and Southeast Asia, Central America, and parts of Eastern Europe and the Middle East, where employment remains more heavily concentrated in agriculture and other sectors less directly affected by the digital technologies considered.

Some areas appearing in the highest exposure quartile may initially seem unexpected. This pattern reflects baseline sectoral employment composition rather than contemporaneous technological sophistication or innovation capacity. For example, in parts of the Russian Federation, high exposure is driven by subnational employment concentrations in wholesale and retail trade and manufacturing—sectors that score highly on digital exposure in our framework—even though these areas are not typically viewed as frontier technology hubs.

Sectoral Structure. Table 1 reports average employment shares and sector-specific exposure to emerging digital technologies by ISIC sector. Employment is concentrated in a small number of broad sectors: agriculture, forestry, and fishing (A) accounts for 28.5 per cent of total employment

Figure 1: Subnational Exposure to Emerging Digital Technologies Across the World (2014–2019)



Notes: This map reports overall exposure scores to 40 emerging digital technologies at the first subnational administrative level. Exposure is measured using baseline employment structures (around 2010) and reflects the relevance of each technology to sectoral production processes—either through direct integration into production or by enhancing sectoral output. Subnational areas are grouped into quartiles of the exposure distribution, with darker shades (Q4) indicating higher exposure and lighter shades (Q1) indicating lower exposure.

on average, followed by wholesale and retail trade (G) (13.8 per cent) and manufacturing (C) (12.7 per cent). Together, these sectors represent over half of total employment across subnational areas.

In contrast, the largest technology exposure scores are observed in transportation, storage, information, and communication (H-J); other community, social, and personal services (R-S); and real estate, renting, and business activities (L-N). Several of these highly exposed sectors account for relatively modest shares of employment on average. As a result, aggregate exposure at the subnational level is shaped not only by the intensity of sector-specific technological change but also by the geographic concentration of employment in these sectors. Areas specializing in relatively small but highly exposed sectors may therefore experience substantial overall exposure to emerging digital technologies.

Summary Statistics. Table 2 reports summary statistics for the main variables used in the analysis. On average, the employment-to-population ratio was essentially unchanged between 2014 and 2019, holding at 0.60, though changes vary substantially across areas. Mean exposure to emerging digital technologies is 0.66, with considerable dispersion across the exposure distribution, reflecting heterogeneity in baseline sectoral composition.

Table 1: Employment Shares and Digital Technology Exposure by ISIC

		Emp. Share		
	ISIC Sector	Mean	SD	Shock
A	Agriculture, Forestry and Fishing	0.285	0.241	0.238
B	Mining and Quarrying	0.007	0.014	0.088
C	Manufacturing	0.127	0.056	0.850
D-E	Electricity, Gas and Water Supply	0.005	0.007	0.803
F	Construction	0.077	0.034	0.624
G	Wholesale and Retail Trade	0.138	0.046	0.921
H-J	Transportation, Storage, Information and Communication	0.062	0.028	1.622
I	Accommodation and Food Service Activities	0.034	0.023	1.105
K	Financial and Insurance Activities	0.017	0.016	0.911
L-N	Real Estate, Renting and Business Activities	0.049	0.046	1.110
O	Public Administration, Defense, and Compulsory Social Security	0.042	0.029	0.490
P	Education	0.052	0.029	0.351
Q	Human Health and Social Work Activities	0.046	0.050	0.390
R-S	Other Community, Social and Personal Services Activities	0.033	0.016	1.195
T	Activities of Households as Employers	0.018	0.024	0.149
U	Activities of Extraterritorial Organizations and Bodies	0.001	0.002	0.009

Notes: This table reports average employment shares and exposure to emerging digital technologies by ISIC sector. The 'Emp. Share' columns denote the baseline-working-age-population-weighted mean share of total employment in each sector and its population-weighted standard deviation (SD) across subnational areas. The 'Shock' column captures the average magnitude of sector-specific exposure to emerging digital technologies. Sectors are defined at the 1-letter ISIC level, with some categories combined (e.g., D-E for electricity, gas, and water supply; H-J for transportation, storage, information, and communication; etc.).

Table 2: Summary Statistics

	Mean	SD	Min	Q1	Median	Q3	Max
Emp-to-Pop. Ratio (2014)	0.60	0.12	0.24	0.53	0.59	0.66	0.96
Emp-to-Pop. Ratio (2019)	0.60	0.12	0.21	0.52	0.59	0.67	0.97
Emp-to-Pop. Ratio Change	−0.00	0.07	−0.46	−0.03	0.00	0.03	0.27
Exposure to Digital Technologies	0.66	0.15	0.21	0.54	0.70	0.78	0.93
Working-Age Population (in log)	6.60	1.56	1.88	5.65	6.73	7.61	11.58
Female Share	0.52	0.02	0.31	0.50	0.52	0.53	0.59
Age +55 Share	0.23	0.09	0.00	0.16	0.22	0.31	0.52
Pop. Share with Primary Education	0.55	0.28	0.03	0.30	0.60	0.77	1.00
Pop. Share with Secondary Education	0.30	0.18	0.00	0.16	0.28	0.42	0.73
Pop. Share with Tertiary Education	0.15	0.14	0.00	0.05	0.11	0.23	0.68
Industry Share	0.19	0.08	0.00	0.14	0.19	0.24	0.49

Notes: This table reports summary statistics for the main variables used in the analysis. The employment-to-population ratio is shown for 2014 and 2019, along with its change over the period. Exposure to Digital Technologies denotes the sectoral shock-weighted employment share, capturing potential workforce exposure to technological change. Working-age population is in log; Female Share is the proportion of women; and Age +55 Share is the share aged 55 and above. Educational attainment is measured as the share of the working-age population with primary, secondary, or tertiary education. Industry Share is the proportion of total employment in industry (ISIC B–F). For all variables, the table reports the mean, standard deviation, minimum, first quartile (Q1), median, third quartile (Q3), and maximum.

Demographic characteristics also differ across subnational areas. On average, women account for 52 per cent of the working-age population, while 23 per cent of individuals are aged 55 or older. Educational attainment varies considerably: 55 per cent of the working-age population has primary education or less, 30 per cent has secondary education, and 15 per cent has tertiary education. Finally, industry accounts for 19 per cent of total employment on average, although its employment share differs widely across subnational areas.

Heterogeneity by Income Group and ILO Subregion. Table 3 documents pronounced heterogeneity in exposure to emerging digital technologies, labour market outcomes, and workforce characteristics across World Bank income groups and ILO subregions. High-income countries exhibit the highest average exposure to emerging digital technologies (0.78) and, on average, modest increases in the employment-to-population ratio between 2014 and 2019. In contrast, low-income countries display substantially lower exposure (0.49) alongside the largest average declines in employment.

Educational attainment follows a steep income gradient. Only 3 per cent of the working-age population in low-income countries has a tertiary education, compared with 23 per cent in high-income economies. Differences in industrial structure are similarly stark: industry accounts for 22 per cent of employment in high-income countries but only 10 per cent in low-income countries, reflecting broad differences in sectoral specialization.

Regional patterns mirror these income-group contrasts. North America and Europe exhibit the highest average exposure to emerging digital technologies (0.82 and 0.76, respectively), while East Asia, South-East Asia, and sub-Saharan Africa display substantially lower exposure levels, clustered around 0.50. Industrial employment shares also vary markedly across ILO subregions, with Eastern Europe recording the highest average industry share (26 per cent) and sub-Saharan Africa and East Asia the lowest (11 per cent).

Table 3: Summary Statistics by Country Group

	Δ Emp-to-Pop.	Exposure	WAP	Female	Age 55+	Primary	Secondary	Tertiary	Industry	N
High-Income	0.02 (0.03)	0.78 (0.06)	6.97 (1.36)	0.51 (0.01)	0.34 (0.05)	0.30 (0.18)	0.47 (0.14)	0.23 (0.09)	0.22 (0.07)	290
Upper-Middle Income	-0.01 (0.06)	0.69 (0.11)	6.50 (1.46)	0.52 (0.02)	0.22 (0.06)	0.53 (0.26)	0.28 (0.14)	0.20 (0.16)	0.20 (0.07)	349
Lower-Middle Income	-0.01 (0.07)	0.54 (0.13)	6.47 (1.73)	0.51 (0.03)	0.17 (0.06)	0.75 (0.16)	0.20 (0.13)	0.05 (0.05)	0.16 (0.09)	327
Low-Income	-0.08 (0.13)	0.49 (0.19)	5.96 (1.69)	0.53 (0.02)	0.13 (0.03)	0.90 (0.08)	0.07 (0.07)	0.03 (0.04)	0.10 (0.07)	49
Arab States	-0.01 (0.03)	0.67 (0.05)	7.03 (0.39)	0.49 (0.00)	0.11 (0.01)	0.63 (0.05)	0.26 (0.04)	0.11 (0.01)	0.19 (0.16)	2
Central and Western Asia	0.01 (0.05)	0.66 (0.17)	5.27 (1.22)	0.53 (0.01)	0.31 (0.07)	0.43 (0.17)	0.42 (0.09)	0.15 (0.13)	0.14 (0.07)	26
East Asia[a]	0.03 (0.07)	0.50 (0.13)	4.03 (0.72)	0.51 (0.01)	0.12 (0.02)	0.45 (0.13)	0.44 (0.09)	0.11 (0.05)	0.11 (0.08)	22
Eastern Europe	-0.02 (0.07)	0.75 (0.07)	6.96 (0.84)	0.53 (0.01)	0.27 (0.07)	0.18 (0.09)	0.47 (0.11)	0.35 (0.17)	0.26 (0.07)	131
LatAm and the Caribbean	0.02 (0.07)	0.67 (0.11)	6.31 (1.47)	0.52 (0.02)	0.21 (0.05)	0.67 (0.13)	0.22 (0.12)	0.11 (0.07)	0.19 (0.06)	249
North Africa	-0.03 (0.04)	0.64 (0.13)	7.18 (1.18)	0.48 (0.04)	0.17 (0.03)	0.55 (0.10)	0.33 (0.07)	0.12 (0.04)	0.21 (0.07)	24
North America	0.02 (0.02)	0.82 (0.04)	7.95 (1.04)	0.51 (0.01)	0.32 (0.03)	0.06 (0.02)	0.59 (0.05)	0.35 (0.06)	0.18 (0.03)	51
Europe (excl. Eastern)	0.02 (0.03)	0.76 (0.09)	6.70 (1.37)	0.51 (0.01)	0.34 (0.05)	0.40 (0.16)	0.40 (0.13)	0.20 (0.08)	0.22 (0.06)	196
South-East Asia	-0.01 (0.08)	0.51 (0.13)	6.60 (1.51)	0.51 (0.02)	0.16 (0.05)	0.79 (0.11)	0.16 (0.08)	0.05 (0.03)	0.15 (0.09)	138
South Asia	-0.01 (0.04)	0.55 (0.11)	7.75 (2.06)	0.50 (0.03)	0.18 (0.05)	0.76 (0.09)	0.18 (0.10)	0.05 (0.05)	0.21 (0.08)	65
Sub-Saharan Africa	-0.06 (0.10)	0.51 (0.17)	6.04 (1.57)	0.53 (0.03)	0.14 (0.04)	0.90 (0.10)	0.07 (0.08)	0.03 (0.04)	0.11 (0.07)	99
The Pacific	-0.03 (0.07)	0.69 (0.14)	5.82 (2.13)	0.51 (0.03)	0.26 (0.06)	0.37 (0.12)	0.40 (0.06)	0.24 (0.15)	0.14 (0.06)	12

[a] China is not included in our sample due to the lack of available microdata.

Notes: This table reports summary statistics by World Bank income group and ILO subregional classification. The change in the employment-to-population ratio captures shifts between 2014 and 2019. Exposure denotes the sectoral shock-weighted employment share, measuring potential workforce exposure to emerging digital technologies. WAP is the working-age population (in log); Female is the share of women; and Age 55+ is the share of people aged 55 and above. Educational attainment is reported as the shares of the working-age population with primary, secondary, or tertiary education. Industry is the share of total employment in industry (ISIC B–F). Lastly, N refers to the number of first-level administrative areas. Reported values are means, with standard deviations in parentheses.

Occupation-Level Skill Composition Measures. A central requirement for our measures to characterize appropriately subnational skill endowments is first that the aggregated skill taxonomy meaningfully reflects occupational skill content. Appendix Figure OA.1 reports the average composition of skills across major occupational groups (ISCO 1–9). The patterns observed correspond closely to conventional expectations regarding occupational specialization. Occupations typically classified as high-skilled, including managers (ISCO 1), professionals (ISCO 2), and technicians and associate professionals (ISCO 3), exhibit substantially higher shares of cognitive and technical skills. These occupations exhibit relatively greater demand for core and sophisticated cognitive skills, computer skills, software and technical skills, and project and process management skills.

By contrast, occupations characterized by manual and routine task content—such as craft and related trades workers (ISCO 7), plant and machine operators (ISCO 8), and workers in elementary occupations (ISCO 9)—show markedly higher shares of manual skills, including finger dexterity, hand-foot-eye coordination, and physical skills. Clerical support workers and service and sales workers (ISCO 4–5) instead display comparatively stronger demand for socio-emotional skills, particularly customer service skills, people management, character skills, and social skills. Figure OA.1 also demonstrates that, within occupational groups, skill requirements tend to be relatively stable across countries and institutional settings. This does not imply that countries have similar occupational structures, as the shares of workers across occupations can vary considerably. Rather, the skill composition of a given occupation exhibits relatively limited cross-country variation. Therefore, by aggregating information across multiple labour markets, we produce occupational skill profiles that can be consistently applied across countries in our analysis.

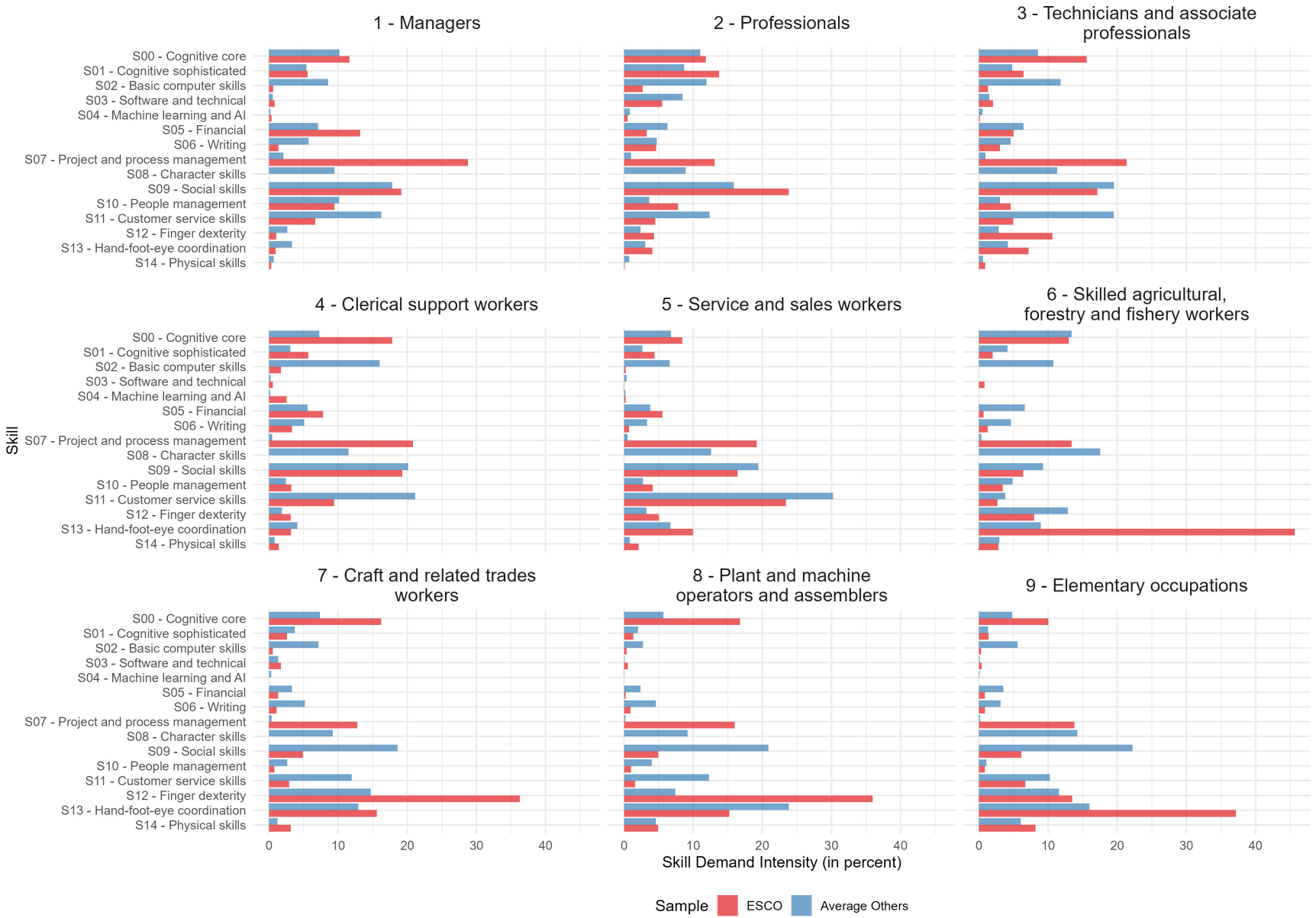
To further assess the validity of our skill measures, Figure 2 compares the occupation-level skill composition measures derived from our online vacancy data (averaged across the four countries) with corresponding measures constructed using the European Skills, Competences, Qualifications and Occupations (ESCO) skill mappings[5]. The two approaches yield broadly similar patterns in the relative skill composition of occupational groups. Occupations identified as more cognitively intensive in our vacancy-based measures also display higher cognitive content in the ESCO mapping, while occupations with greater manual task intensity similarly exhibit stronger manual skill requirements in both approaches. Service-oriented occupations likewise show relatively stronger social and customer-service skill content across the two measures.

At the same time, some differences remain in the relative importance assigned to particular skill categories across occupations, as expected given the distinct nature of the two data sources and the known limitations of online vacancy data in capturing some lower-skilled and manual occupations. Nevertheless, the relatively close correspondence between the vacancy-based indicators and the ESCO-based mapping provides evidence that the aggregated skill taxonomy captures meaningful differences in occupational skill requirements. These occupational skill profiles form the basis for constructing our subnational skill composition measures, $Skill_r^s$, defined in Eq. (2). Subnational

[5] A detailed explanation regarding the mapping between our skill taxonomy and the ESCO taxonomy can be found in the appendix.

areas with larger employment shares in managerial, professional, and technical occupations will therefore tend to display greater relative baseline intensity of cognitive and technical skills, whereas those with larger shares of manual occupations will exhibit higher relative intensity of manual skills. Similarly, areas with larger employment shares in service-oriented occupations will tend to display greater relative intensity of social skills.

Figure 2: Occupation-level Skill Composition: Vacancy-based Measures and ESCO Skills Mapping



Notes: The figure compares occupation-level skill composition derived from two sources: (i) ESCO occupation-skill matrices mapped to the skill taxonomy used in this paper (red bars); and (ii) online vacancy data averaged across Brazil, the Russian Federation, South Africa, and Uruguay (blue bars). Values represent the relative importance of each skill category within 1-digit ISCO occupational groups.

Taken together, these descriptive patterns underscore the heterogeneity in technology exposure, sectoral composition, and skill composition across contexts. This motivates our empirical focus on how baseline skill composition conditions the labour market impacts of digital technology exposure and why these effects may differ sharply across subnational areas.

3 Empirical Strategy

The objective of the paper is to estimate the effect of subnational exposure to emerging digital technologies on employment and to assess whether baseline skills composition mediates this relationship. The main outcome variable is the change in the employment-to-population ratio between 2014 and 2019, where the ratio is defined as the number of employed individuals divided by the working-age population aged 15 and above. This measure captures medium-run adjustments in local employment relative to the working-age population and facilitates comparisons across subnational areas with different population sizes and demographic structures.

3.1 Endogeneity and Identification

Estimating the effect of digital exposure on employment faces important endogeneity challenges. Industry composition is not randomly distributed across areas and may be correlated with unobserved local shocks—such as differential demand shifts, demographic trends, or policy interventions—that also affect employment outcomes. Moreover, technology adoption may itself respond to prevailing labour market conditions, generating concerns of reverse causality. These issues imply that a simple regression of employment changes on measured exposure would conflate the effect of digital technologies with pre-existing local trajectories and endogenous firm responses.

To address these concerns, we follow Prytkova et al. (2024) and construct a shift–share measure of subnational exposure to emerging digital technologies. The measure interacts baseline sectoral employment shares with sector-level exposure to digital technologies derived from the *TechXposure* database (see Section 2.2). Identification exploits cross-sector heterogeneity in the intensity with which emerging digital technologies affect production processes, combined with differences across subnational areas in historical sectoral specialisation. By construction, exposure varies across areas only through predetermined industry composition, isolating variation that is plausibly unrelated to contemporaneous local labour market shocks.

The validity of this design rests on the quasi-exogeneity of the sector-level shifters rather than on the exogeneity of baseline employment shares themselves. Following Borusyak et al. (2021), the key identifying assumption is that sector-level digital technology shocks are orthogonal to unobserved area-specific shocks to employment. This assumption is plausible in our setting because the *TechXposure* measures are constructed from global patenting activity in emerging digital technologies, reflecting frontier innovation processes that are determined at the global industry level and unlikely to respond to labour market conditions in subnational areas. These global technological advances, however, differentially affect areas depending on their initial sectoral structure.

A potential concern is that baseline sectoral composition is measured relatively close to the treatment window—around 2010 for exposure realized between 2014 and 2019. While this raises the possibility that sectoral shares may themselves reflect earlier local trends, our identification does not require baseline employment to be randomly assigned. Instead, it requires that global industry-level digitalization shocks are unrelated to unobserved subnational shocks affecting employment over the subsequent period. To further mitigate remaining concerns, all baseline specifications include country fixed effects and a rich set of local demographic controls, including population size, age structure, educational attainment, and the overall industry employment share. These controls strengthen the interpretation that estimated employment effects reflect exposure to exogenous global digitalization rather than correlated local dynamics.

3.2 Baseline Specification

We estimate the effect of exposure to emerging digital technologies on employment using the following specification:

$$\Delta Y_{ac} = \alpha + \beta X_{ac} + Z\delta + \phi_c + u_{ac}, \tag{3}$$

where ΔY_{ac} is the change in the employment-to-population ratio in subnational area a in country c between 2014 and 2019, X_{ac} is predicted subnational exposure to emerging digital technologies constructed using baseline employment shares and standardized over the pooled sample (see Section 2.2), so that β is the effect of a one-global-standard-deviation increase in exposure, Z is a vector of baseline subnational characteristics, ϕ_c are country fixed effects that absorb national-level shocks and differences in measurement, and u_{ac} is an error term. The coefficient of interest, β, captures the relationship between exposure to emerging digital technologies and employment changes across areas within the same country.

The vector of controls, Z, includes demographic and structural characteristics measured in the baseline period. Specifically, we control for the logarithm of the working-age population, the share of women, and the share of individuals aged 55 and above, which account for differences in labour force composition across areas. To capture heterogeneity in human capital endowments, we include the shares of the working-age population with secondary and tertiary education. Finally, we control for the share of employment in industry (ISIC B-F), as differences in industrial specialization may shape both exposure to digital technologies and subsequent employment dynamics.

In addition to aggregate employment outcomes, we estimate the specification separately for demographic groups. In these regressions, the dependent variable ΔY^d_{ac} is defined as the change in the ratio of employment of demographic group d normalized by the total working-age population in the subnational area. This allows us to assess whether exposure to emerging digital technologies differentially affects employment outcomes for women, older workers, and individuals with different levels of educational attainment.

Finally, we explore heterogeneity across countries by interacting exposure with an exhaustive set of country-group indicators, so that a single pooled regression yields one exposure coefficient

per World Bank income group and per ILO subregion while the controls and country fixed effects remain common to all areas. Estimating the groups jointly rather than one sample at a time keeps the estimates on a common scale and holds the number of observations fixed across groups. This disaggregation sheds light on how the employment effects of exposure to emerging digital technologies vary across stages of economic development and regional labour market structures, and provides an external benchmark for interpreting the magnitude and direction of the estimated subnational effects.

3.3 Skills as Mediating Factors

We next examine whether baseline occupational skill composition mediates the employment effects of exposure to emerging digital technologies. The central hypothesis is that subnational labour market adjustment to digitalization depends on pre-existing skill endowments, which may either complement or substitute for new technologies. To test this hypothesis, we extend the baseline specification to allow the effect of digital exposure to vary with subnational skill composition:

$$\Delta Y_{ac} = \alpha + \beta_1 X_{ac} + \beta_2 Skill^s_{ac} + \beta_3 X_{ac} \times Skill^s_{ac} + \delta Z + \phi_c + u_{ac}, \tag{4}$$

where $Skill^s_{ac}$ is the baseline employment-weighted share of demand for skill s embedded in the occupational structure of subnational area a in country c. The interaction coefficient β_3 is the parameter of interest and captures whether subnational areas with a higher baseline share of demand for a given skill experience systematically different employment responses to exposure to emerging digital technologies. The vector of controls Z includes the same baseline demographic and structural characteristics as in the baseline specification, including the logarithm of the working-age population, the shares of women and older workers, and overall industrial employment.

When assessing the mediating role of skills, it is important to recognize that labour demand and labour supply need not be perfectly aligned. A subnational area may exhibit high demand for a particular skill while lacking a correspondingly large pool of suitably skilled workers, or vice versa. To account for this, we additionally control for the baseline shares of low-, middle-, and highly-educated workers.[6] In our most saturated specification, we further interact these educational shares with X_{ac}, thereby flexibly controlling for heterogeneity in local labour supply responses to digital exposure. This helps ensure that the estimated coefficient β_3 captures the mediating role of the composition of skill demand, rather than simply reflecting differences in educational attainment across subnational areas.

The sign and magnitude of β_3 inform the mediating role of skills in shaping employment outcomes. A positive estimate indicates that areas where a given skill accounts for a larger share of baseline skill demand experience less adverse—or more positive—employment responses to digital exposure, consistent with complementarity between that skill and emerging digital technologies. Conversely, a negative estimate suggests less favourable employment responses in areas where such

[6] Since these shares sum to one, we omit one category to avoid multicollinearity with the constant.

skill accounts for a larger share of baseline skill demand, consistent with substitution between technology and tasks associated with that skill. Importantly, these patterns are interpreted as differential exposure effects conditional on baseline characteristics, rather than as direct causal effects of skill acquisition.

4 Results

This section presents our main findings on the effect of subnational exposure to emerging digital technologies on employment, followed by an analysis of how baseline skills composition mediates these effects. We first report average effects on the employment-to-population ratio and then examine heterogeneity by demographic group, country income level, and ILO subregion. We subsequently examine how demand for specific skills conditions these impacts.

4.1 Impact on Employment

Table 4 reports the estimated effect of subnational exposure to emerging digital technologies on changes in the employment-to-population ratio. Following recent literature on shift-share designs, we report AKM0 shift-share standard errors to account for arbitrary correlation in regression residuals across subnational areas (Adao et al. 2019).

The results suggest that greater exposure to emerging digital technologies has, on average, a positive impact on employment-to-population ratios at the subnational level. The estimated effect is consistent across specifications (columns 1 to 5 of Table 4).

Disaggregating by demographic group (Table 5), we find that exposure to emerging digital technologies positively affects employment for both women and men, with stronger effects for female workers. Prime-age workers (aged 25–54) experience the largest employment gains, while younger workers (aged 15–24) and older workers (aged 55 and above) benefit less. The strongest heterogeneity emerges by education. Exposure to emerging digital technologies raises the employment-to-population ratio of workers with low levels of education substantially, while the estimated effect is negligible (and statistically indistinguishable from zero) for workers with intermediate and high levels of education. Thus, the positive aggregate employment response appears to be concentrated among workers with lower levels of formal education.

Turning to income groups (Table 6), we find that the aggregate effects are primarily driven by low-income countries, which experience the largest employment gains, followed by high-income and upper-middle-income countries. By contrast, lower-middle-income countries exhibit more modest effects. Among low-income countries, the increase in the employment-to-population ratio was particularly pronounced among workers with low levels of education, women, and prime-age workers. Interestingly, the education gradient shifts with the level of development: in lower-income countries, employment gains from digital exposure are concentrated among workers with low levels of education, whereas in upper-middle- and high-income countries they increasingly extend to workers with high levels of education. By contrast, workers with intermediate levels of education tend to

experience weaker or negative responses. The variation in effects is even more pronounced at the ILO subregional level (see Table 7).

However, these results implicitly assume that different country groups can absorb similar absolute levels of digital technology exposure, which is unlikely given substantial cross-country differences in baseline exposure as well as in economic structure, institutions, and labour market characteristics that shape countries' ability to accommodate technological change. To facilitate comparisons of economically relevant magnitudes, Tables 8 and 9 rescale the estimated coefficients by the baseline-population-weighted within-group standard deviation of globally standardized exposure (country income groups and ILO subregions for Tables 8 and 9, respectively); the tables also report the corresponding population-weighted within-group standard deviation of raw exposure. The resulting estimates capture the employment effects of a one-standard-deviation increase in digital technology exposure relative to other subnational areas within the same income group or ILO subregion.

The results indicate that even relative to within-group standard deviations, low-income countries exhibit the largest employment gains, with a one-within-group standard deviation increase in digital exposure associated with a 3.03 percentage point rise in the employment-to-population ratio over the five-year period (Table 8). Employment responses are smaller in high-income and upper-middle-income countries, while lower-middle-income economies display the weakest relative effects. One possible explanation is that the nature and stage of technology diffusion differ across levels of development, with digital technologies in lower-income settings potentially operating more through labour-complementary applications—such as mobile-based services, e-commerce facilitation, digital payments, and logistics platforms—than through automation. The analysis does not directly identify this mechanism, however.

Heterogeneity is even more pronounced across ILO subregions (Table 9). North Africa exhibits the largest relative employment gain, at 2.69 percentage points for a one-within-subregion-standard-deviation increase in exposure over the period, followed by sub-Saharan Africa (2.30 pp), Central and Western Asia (1.98 pp), and the Arab States (1.76 pp). Positive but more moderate responses are observed across much of Europe, Latin America and the Caribbean, North America, and the Pacific. By contrast, East Asia[7] and South-East Asia exhibit employment declines of 4.16 and 0.68 percentage points, respectively. These regional differences may partly reflect the nature of digital transformation across economic contexts. In some African economies, digital technologies may be more likely to complement existing activities and facilitate the expansion of employment through improved market access and lower transaction costs, whereas in parts of East and South-East Asia, greater integration into manufacturing and global value chains may be associated with more labour-saving technological change.

Taken together, these findings highlight the strongly heterogeneous employment effects of digitalization across geographical context and stages of development. While the average employment

[7]The estimate for East Asia should be interpreted with caution, however, as China is not included in our sample due to the lack of available microdata. Given China's weight in the region, our estimates should therefore not be viewed as representative of East Asia as a whole.

Table 4: Effect of Emerging Digital Technologies on Subnational Employment

	Dep. var.: Δ Emp-to-Pop. Ratio (2014–2019) × 100				
	Weighted				Unweighted
	(1)	(2)	(3)	(4)	(5)
Exposure (Standardized)	0.532**	0.794***	1.144***	1.624***	1.042***
	(0.141)	(0.138)	(0.179)	(0.205)	(0.263)
Country FE	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓
Industry share			✓	✓	✓
Exclude Top 10% Exp.				✓	
R^2	0.596	0.598	0.600	0.613	0.561
Adj. R^2	0.566	0.566	0.567	0.578	0.526
Num. obs.	1015	1015	1015	913	1015

Notes: This table presents estimates of exposure to emerging digital technologies on subnational employment. It presents the coefficients measuring the effect of subnational exposure to emerging digital technologies, constructed as shift-shares and standardized, on the change in the employment-to-population ratio between 2014 and 2019, expressed in percentage points. Regressions are weighted by the working-age population in the baseline year. Column (1) includes country fixed effects; Column (2) adds demographics controls in the baseline year, including the logarithm of the working-age population, the proportion of females, the proportion of the population aged over 55, 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 areas; and Column (5) provides the unweighted estimates. 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 Adao et al. (2019).

response to digital exposure is positive, the incidence of these gains varies sharply across education groups and levels of development, and some subregions experience employment losses. This heterogeneity motivates the next part of the analysis, which examines whether differences in baseline skill composition help explain why similar levels of digital exposure translate into markedly different employment responses.

Table 5: Effect of Emerging Digital Technologies on Subnational Employment by Demographic and Educational Groups

	Dep. var.: Δ Employment-to-Population Ratio (2014–2019) × 100								
	All	Gender		Age			Education		
	Total	Female	Male	Y15-24	Y25-54	Y55+	Low	Mid	High
Exposure (Standardized)	0.794***	0.527***	0.267**	0.163**	0.577***	0.037	0.878***	−0.137	0.000
	(0.138)	(0.078)	(0.088)	(0.051)	(0.088)	(0.054)	(0.133)	(0.117)	(0.116)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓	✓
Emp-to-Pop. Ratio in 2014	0.56	0.22	0.35	0.08	0.40	0.09	0.30	0.15	0.11
Change (in %)	1.41	2.42	0.77	2.02	1.46	0.41	2.94	−0.89	0.00
R^2	0.598	0.447	0.644	0.572	0.518	0.522	0.875	0.791	0.768
Adj. R^2	0.566	0.403	0.616	0.537	0.479	0.484	0.865	0.774	0.749
Num. obs.	1015	1015	1015	1015	1015	1015	1015	1015	1015

Notes: This table presents estimates of exposure to emerging digital technologies on subnational employment. It presents the coefficients measuring the effect of subnational exposure to emerging digital technologies, constructed as shift-shares and standardized, on the change in the employment-to-population ratio between 2014 and 2019, expressed in percentage points. Regressions are weighted by the working-age population in the baseline year. Column (1) reports the results for the full sample, while Columns (2) and (3) focus on females and males, respectively. Columns (4) to (6) report the results by age group, and Columns (7) to (9) by educational level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adao et al. (2019).

Table 6: Effect of Emerging Digital Technologies on Subnational Employment by Demographic Groups and Income Level

	Dep. var.: Δ Emp-to-Pop. Ratio (2014–2019) × 100								
	All	Gender		Age			Education		
	Total	Female	Male	Y15-24	Y25-54	Y55+	Low	Mid	High
Exposure × Low-Income	2.746***	2.063***	0.682***	1.031***	1.649***	0.031	3.367***	−0.642***	0.008
	(0.226)	(0.128)	(0.118)	(0.075)	(0.162)	(0.063)	(0.199)	(0.185)	(0.119)
× Lower-Middle	0.284*	0.244**	0.040	0.053	0.322**	−0.075*	0.451***	0.070	−0.244**
	(0.128)	(0.074)	(0.072)	(0.057)	(0.094)	(0.047)	(0.128)	(0.104)	(0.097)
× Upper-Middle	1.397***	0.577***	0.820***	−0.056	0.905***	0.571***	0.813***	−0.450***	0.928***
	(0.159)	(0.064)	(0.112)	(0.045)	(0.114)	(0.055)	(0.125)	(0.150)	(0.101)
× High-Income	1.601***	0.451***	1.150***	0.294**	0.178	0.110	0.672**	−1.546***	1.429***
	(0.280)	(0.151)	(0.181)	(0.126)	(0.190)	(0.125)	(0.276)	(0.313)	(0.223)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.607	0.458	0.650	0.579	0.523	0.530	0.878	0.793	0.774
Adj. R^2	0.574	0.413	0.621	0.544	0.483	0.490	0.868	0.776	0.755
Num. obs.	1015	1015	1015	1015	1015	1015	1015	1015	1015

Notes: This table presents estimates of exposure to emerging digital technologies on subnational employment. It presents the coefficients measuring the effect of subnational exposure to emerging digital technologies, constructed as shift-shares and standardized, on the change in the employment-to-population ratio between 2014 and 2019, expressed in percentage points. Regressions are weighted by the working-age population in the baseline year. Column (1) reports the results for the full sample, while Columns (2) and (3) focus on females and males, respectively. Columns (4) to (6) report the results by age group, and Columns (7) to (9) by educational level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adao et al. (2019).

Table 7: Effect of Emerging Digital Technologies on Subnational Employment by Demographic Groups and ILO Subregions

	Dep. var.: Δ Emp-to-Pop. Ratio (2014–2019) × 100								
	All	Gender		Age			Education		
	Total	Female	Male	Y15-24	Y25-54	Y55+	Low	Mid	High
Exposure × North Africa	3.105***	2.360***	0.745***	0.125	2.412***	0.712***	3.213***	2.371***	−1.798***
	(0.138)	(0.087)	(0.072)	(0.085)	(0.123)	(0.055)	(0.166)	(0.207)	(0.120)
× Sub-Saharan Africa	1.841***	1.491***	0.350***	0.753***	0.915***	0.177***	2.574***	−0.496***	−0.208
	(0.205)	(0.102)	(0.130)	(0.085)	(0.127)	(0.060)	(0.228)	(0.134)	(0.154)
× Arab States	8.607***	1.049	7.558***	1.109**	6.265***	1.479*	0.310	2.077	6.526***
	(2.067)	(0.720)	(1.612)	(0.519)	(1.470)	(0.853)	(1.510)	(1.314)	(1.442)
× Central and Western Asia	2.037***	0.584***	1.453***	1.202***	2.431***	−1.719***	−0.075	3.153***	−1.174***
	(0.175)	(0.127)	(0.090)	(0.073)	(0.203)	(0.068)	(0.176)	(0.370)	(0.179)
× East Asia[a]	−3.201***	−1.559***	−1.643***	0.697***	−2.080***	−1.652***	1.629***	−4.210***	−0.087
	(0.249)	(0.117)	(0.174)	(0.103)	(0.183)	(0.088)	(0.242)	(0.265)	(0.190)
× South Asia	1.008***	0.514***	0.494***	0.045	0.604***	0.387***	1.265***	−0.094	−0.131
	(0.093)	(0.059)	(0.046)	(0.061)	(0.095)	(0.040)	(0.108)	(0.080)	(0.097)
× South-East Asia	−0.815***	−0.339***	−0.476***	−0.080	0.024	−0.734***	−0.882***	−0.230**	0.099
	(0.155)	(0.085)	(0.091)	(0.061)	(0.114)	(0.042)	(0.090)	(0.117)	(0.109)
× The Pacific	4.140***	0.169	3.971***	−1.058***	5.681***	−0.726***	1.660***	2.491**	0.691
	(0.492)	(0.385)	(0.218)	(0.214)	(0.651)	(0.235)	(0.607)	(1.172)	(0.528)
× Eastern Europe	1.617***	0.340**	1.276***	0.128	−0.374**	0.590***	1.382***	−1.983***	0.935***
	(0.233)	(0.140)	(0.124)	(0.098)	(0.150)	(0.061)	(0.299)	(0.167)	(0.167)
× Northern, Southern and Western Europe	1.120***	0.801***	0.319***	0.647***	0.670***	0.160	0.638**	−0.828**	1.603***
	(0.215)	(0.146)	(0.103)	(0.126)	(0.206)	(0.096)	(0.306)	(0.342)	(0.222)
× Latin America and the Caribbean	1.233***	0.204***	1.029***	0.379***	0.254**	0.634***	0.055	−0.220	1.323***
	(0.153)	(0.061)	(0.112)	(0.037)	(0.128)	(0.058)	(0.109)	(0.172)	(0.106)
× North America	1.281***	1.188***	0.093	0.325*	1.494***	0.085	0.024	−0.531	2.434***
	(0.420)	(0.303)	(0.251)	(0.171)	(0.407)	(0.154)	(0.445)	(0.727)	(0.438)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.617	0.471	0.659	0.580	0.530	0.557	0.883	0.800	0.779
Adj. R^2	0.582	0.422	0.627	0.541	0.487	0.516	0.872	0.782	0.759
Num. obs.	1015	1015	1015	1015	1015	1015	1015	1015	1015

[a] China is not included in our sample due to the lack of available microdata.

Notes: This table presents estimates of exposure to emerging digital technologies on subnational employment. It presents the coefficients measuring the effect of subnational exposure to emerging digital technologies, constructed as shift shares and standardized, on the change in the employment-to-population ratio between 2014 and 2019, expressed in percentage points. Regressions are weighted by the working-age population in the baseline year. Column (1) reports the results for the full sample, while Columns (2) and (3) focus on females and males, respectively. Columns (4) to (6) report the results by age group, and Columns (7) to (9) by educational level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses are derived following the AKM0 inference procedure from Adao et al. (2019).

Table 8: Effect of a Within-Group SD Increase in Exposure to Emerging Digital Technologies on Subnational Employment (in pp.), by World Bank Income Groups

		All	Gender		Age			Education		
	Weighted SD	Total	Female	Male	Y15-24	Y25-54	Y55+	Low	Mid	High
Low-Income	0.17	3.03	2.28	0.75	1.14	1.82	0.03	3.71	-0.71	0.01
Lower-Middle	0.10	0.19	0.16	0.03	0.04	0.21	-0.05	0.30	0.05	-0.16
Upper-Middle	0.10	0.90	0.37	0.53	-0.04	0.58	0.37	0.52	-0.29	0.60
High-Income	0.04	0.47	0.13	0.33	0.09	0.05	0.03	0.20	-0.45	0.42

Notes: The table reports the estimated change in the subnational employment-to-population ratio (in pp) associated with a one-within-group standard deviation increase in exposure to emerging digital technologies. The first column reports the population-weighted standard deviation (SD) of raw exposure among subnational areas within each World Bank income group, using baseline working-age population weights. Because the regressions use globally standardized exposure, the remaining columns multiply each group-specific coefficient by the population-weighted within-group SD of that standardized exposure. The resulting values are equivalent to the effect of a one-within-group-SD increase in raw exposure.

Table 9: Effect of a Within-Group SD Increase in Exposure to Emerging Digital Technologies on Subnational Employment (in pp.), by ILO Subregion

		All	Gender		Age			Education		
	Weighted SD	Total	Female	Male	Y15-24	Y25-54	Y55+	Low	Mid	High
North Africa	0.13	2.69	2.05	0.65	0.11	2.09	0.62	2.79	2.06	-1.56
Sub-Saharan Africa	0.19	2.30	1.87	0.44	0.94	1.14	0.22	3.22	-0.62	-0.26
Arab States	0.03	1.76	0.21	1.55	0.23	1.28	0.30	0.06	0.42	1.33
Central and Western Asia	0.15	1.98	0.57	1.41	1.17	2.36	-1.67	-0.07	3.06	-1.14
East Asia[a]	0.20	-4.16	-2.03	-2.14	0.91	-2.71	-2.15	2.12	-5.48	-0.11
South Asia	0.08	0.51	0.26	0.25	0.02	0.31	0.20	0.64	-0.05	-0.07
South-East Asia	0.13	-0.68	-0.28	-0.40	-0.07	0.02	-0.61	-0.74	-0.19	0.08
The Pacific	0.04	0.95	0.04	0.91	-0.24	1.30	-0.17	0.38	0.57	0.16
Eastern Europe	0.08	0.81	0.17	0.64	0.06	-0.19	0.30	0.69	-0.99	0.47
Northern, Southern and Western Europe	0.05	0.38	0.27	0.11	0.22	0.23	0.05	0.22	-0.28	0.54
Latin America and the Caribbean	0.09	0.75	0.12	0.63	0.23	0.15	0.39	0.03	-0.13	0.81
North America	0.03	0.21	0.20	0.02	0.05	0.25	0.01	0.00	-0.09	0.41

[a] China is not included in our sample due to the lack of available microdata.

Notes: The table reports the estimated change in the subnational employment-to-population ratio (in pp) associated with a one-within-group standard deviation increase in exposure to emerging digital technologies. The first column reports the population-weighted standard deviation (SD) of raw exposure among subnational areas within each ILO subregion, using baseline working-age population weights. Because the regressions use globally standardized exposure, the remaining columns multiply each subregion-specific coefficient by the population-weighted within-subregion SD of that standardized exposure. The resulting values are equivalent to the effect of a one-within-subregion-SD increase in raw exposure.

4.2 The Mediating Role of Skills

Next, we examine whether baseline subnational skill composition shapes the employment effects of digital exposure. Table 10 reports interaction effects between subnational exposure to emerging digital technologies (X_{ac}) and the baseline skill composition ($Skills^{s}_{ac}$) at the first subnational administrative level.

Our parameter of interest, β_3, captures the heterogeneity in the employment response to digital exposure as a function of baseline skill-demand composition, indicating whether a greater relative importance of particular skills in local labour demand amplifies or dampens employment responses to digital exposure across subnational areas. Importantly, since actual technology adoption is not observed, this interaction may capture differences both in the extent to which potential expo-

sure translates into technology adoption and in subsequent employment adjustment conditional on adoption. Our estimates cannot disentangle the contributions of these two channels.

Table 10 reports estimates of this interaction term for the full sample under alternative specifications with increasingly rich sets of controls. Our preferred specification, reported in Column (3), includes a comprehensive set of controls, most notably, the baseline educational composition of the subnational area and its interaction with X_{ac}. Controlling for education is particularly important given that the skills measures are derived from the demand side (vacancy data), as this adjustment helps account for differences in labour supply readiness of the workforce and ensures that the estimated interaction effects reflect the mediating role of skills rather than subnational variation in educational attainment.

To further investigate heterogeneity in the mediating role of skills, Table 11 reports results separately for high-income, upper-middle-income, and lower-income countries (the latter combining lower-middle and low-income economies), and by workers' educational attainment (low, middle, and high).

Several key findings emerge. First, a set of cognitive skills plays a central role in mediating the positive employment effects of digital exposure. Subnational areas with a higher concentration of jobs requiring financial, computer, writing, sophisticated cognitive, and core cognitive skills exhibit statistically significant positive interaction effects. These results suggest that areas with stronger demand for analytical reasoning, digital literacy, and planning and problem-solving are better positioned to capture the employment benefits of digital exposure, consistent with skill-technology complementarity (see Acemoglu and Restrepo, 2022). Importantly, these effects persist after controlling for the overall educational composition of the workforce, suggesting that specific skill composition matters beyond differences in formal educational attainment.

Although positive mediating effects of cognitive skills are observed across all country-income groups, their magnitudes are generally larger in high-income countries, particularly for core cognitive, financial, and writing skills. This pattern is consistent with the possibility that cognitive skills become particularly complementary to emerging technologies in more technologically advanced labour markets, where firms may be better positioned to reorganize production and tasks around new technologies. At the same time, the presence of positive effects across income groups suggests that the relevance of these skills is not confined to advanced economies.

Table 10: Mediating Role of Skills – Interacted Coefficient β_3

	(1)	(2)	(3)
Exposure × S00 - Cognitive core	0.55***	0.51***	0.43***
	(0.05)	(0.03)	(0.02)
× S01 - Cognitive sophisticated	1.10***	1.07***	1.47***
	(0.08)	(0.07)	(0.07)
× S02 - Basic computer skills	0.99***	1.00***	1.05***
	(0.05)	(0.05)	(0.04)
× S03 - Software and technical	−0.04	−0.06	0.17*
	(0.11)	(0.10)	(0.10)
× S04 - Machine learning and AI	−2.58**	−2.09**	−2.56**
	(1.01)	(0.81)	(0.99)
× S05 - Financial	1.78***	1.84***	1.69***
	(0.09)	(0.08)	(0.07)
× S06 - Writing	2.63***	2.70***	3.61***
	(0.22)	(0.17)	(0.15)
× S07 - Project and process management	2.23***	2.44***	5.08***
	(0.47)	(0.35)	(0.35)
× S08 - Character skills	0.04	0.03	0.05
	(0.03)	(0.02)	(0.03)
× S09 - Social skills	−0.21***	−0.19***	−0.19***
	(0.03)	(0.02)	(0.02)
× S10 - People management	1.34***	1.35***	1.26***
	(0.08)	(0.09)	(0.09)
× S11 - Customer service skills	−0.16***	−0.15***	−0.26***
	(0.01)	(0.01)	(0.01)
× S12 - Finger dexterity	0.05	0.04	0.03
	(0.04)	(0.03)	(0.03)
× S13 - Hand-foot-eye coordination	−0.35***	−0.37***	−0.44***
	(0.04)	(0.04)	(0.04)
× S14 - Physical skills	−0.35***	−0.35***	−0.60***
	(0.09)	(0.07)	(0.09)
Country FE	✓	✓	✓
Demographics (excluding education shares)	✓	✓	✓
Education shares		✓	✓
Exposure × Education shares			✓

Notes: This table presents the interaction effects between subnational exposure to emerging digital technologies (X_{ac}) and the baseline skills composition ($Skills^s_{ac}$), to assess whether and how skills mediate the employment effects of exposure to emerging digital technologies for all workers. Each coefficient is a separate regression since the baseline skills composition is provided for each skill subcategory separately. Column (1) includes country fixed effects as well as demographic controls in the baseline year, including the logarithm of the working-age population, the proportion of females and the proportion of the population aged over 55; Column (2) includes additional controls for the baseline educational composition of the workforce, measured by the shares of workers with low, intermediate and high levels of education. Column (3) additionally interacts the baseline educational shares with exposure to emerging digital technologies. Standard errors between parentheses are derived following the AKM0 inference procedure from Adao et al. (2019). $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 11: Mediating Role of Skills by Country Income Group and Educational Attainment — Interacted Coefficient β_3

	Low & Lower-Middle Income				Upper-Middle Income				High Income			
	All	Low	Mid	High	All	Low	Mid	High	All	Low	Mid	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exposure × S00 - Cognitive core	0.56***	0.61***	0.14***	−0.03	0.18***	0.04	−0.22***	0.20**	2.04***	−1.68***	−3.40***	2.51***
	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)	(0.08)	(0.02)	(0.09)	(0.12)	(0.24)	(0.08)	(0.28)
× S01 - Cognitive sophisticated	1.71***	1.28***	1.04***	−0.25***	0.64***	−0.82***	0.25***	1.00***	0.86***	−1.25***	3.54***	1.44***
	(0.06)	(0.06)	(0.02)	(0.03)	(0.12)	(0.17)	(0.09)	(0.08)	(0.05)	(0.08)	(0.05)	(0.07)
× S02 - Basic computer skills	1.32***	1.62***	0.50***	−0.59***	0.89***	−0.02	−0.54***	1.32***	1.24***	−1.06***	2.91***	2.45***
	(0.05)	(0.06)	(0.02)	(0.03)	(0.04)	(0.12)	(0.04)	(0.11)	(0.06)	(0.12)	(0.05)	(0.11)
× S03 - Software and technical	0.13	−0.70***	1.60***	−0.52***	−2.32***	−1.99***	2.27***	−2.77***	−1.24***	−2.45***	3.05***	1.12***
	(0.09)	(0.11)	(0.02)	(0.04)	(0.19)	(0.21)	(0.04)	(0.07)	(0.14)	(0.15)	(0.04)	(0.05)
× S04 - Machine learning and AI	−3.30***	−11.33***	9.79***	−1.15***	−12.81***	−15.37***	14.35***	−12.25***	−10.10***	−27.54***	17.09***	26.14***
	(0.76)	(1.04)	(0.15)	(0.28)	(1.57)	(2.06)	(0.42)	(0.57)	(1.72)	(2.31)	(0.31)	(0.55)
× S05 - Financial	2.31***	2.79***	0.52***	−0.55***	0.80***	−0.30	−0.60***	1.44***	2.32***	−2.82***	3.91***	3.23***
	(0.09)	(0.11)	(0.05)	(0.05)	(0.09)	(0.21)	(0.07)	(0.20)	(0.17)	(0.34)	(0.14)	(0.32)
× S06 - Writing	4.13***	4.10***	1.40***	−0.89***	2.30***	−0.45	−0.67***	2.95***	6.93***	−1.29***	−12.67***	14.24***
	(0.17)	(0.24)	(0.07)	(0.09)	(0.28)	(0.49)	(0.20)	(0.43)	(0.37)	(0.42)	(0.27)	(0.24)
× S07 - Project and process management	6.15***	6.28***	2.53***	−1.27***	1.30***	−1.98**	1.33***	2.71***	1.32***	−9.26***	12.79***	19.30***
	(0.35)	(0.41)	(0.03)	(0.09)	(0.45)	(0.88)	(0.18)	(0.43)	(0.22)	(0.38)	(0.10)	(0.21)
× S08 - Character skills	0.06*	0.34***	−0.30***	0.02	0.13***	0.61***	0.20***	−0.71***	1.81***	2.86***	−0.49***	−5.21***
	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.07)	(0.02)	(0.04)	(0.10)	(0.20)	(0.04)	(0.13)
× S09 - Social skills	−0.32***	−0.29***	−0.04***	−0.06***	0.06***	−0.23***	0.10***	0.20***	−1.18***	0.79***	3.22***	−0.95***
	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.04)	(0.06)	(0.14)	(0.04)	(0.19)
× S10 - People management	1.67***	2.03***	0.20***	−0.33***	−0.05	−0.44***	−0.48***	0.69***	2.21***	−1.72***	−2.44***	3.72***
	(0.09)	(0.11)	(0.04)	(0.05)	(0.07)	(0.13)	(0.03)	(0.15)	(0.22)	(0.28)	(0.10)	(0.20)
× S11 - Customer service skills	−0.35***	−0.30***	−0.04***	−0.06**	−0.17***	−0.17***	0.13***	−0.11***	−0.84***	−0.31***	1.61***	0.25***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.05)	(0.10)	(0.04)	(0.09)
× S12 - Finger dexterity	0.16***	0.11***	−0.14***	0.16***	0.25***	0.37***	−0.25***	0.08***	0.35***	1.16***	−0.79***	−1.82***
	(0.02)	(0.04)	(0.02)	(0.02)	(0.04)	(0.06)	(0.02)	(0.02)	(0.07)	(0.07)	(0.02)	(0.03)
× S13 - Hand-foot-eye coordination	−0.64***	−0.80***	−0.18***	0.28***	−0.02	0.26***	0.08**	−0.31***	−0.07***	0.69***	−1.63***	−0.90***
	(0.05)	(0.05)	(0.03)	(0.03)	(0.04)	(0.06)	(0.04)	(0.06)	(0.01)	(0.03)	(0.02)	(0.03)
× S14 - Physical skills	−0.63***	−0.58***	−0.33***	0.28***	−0.01	0.72***	−0.30***	−0.47***	0.17	3.03***	−2.79***	−5.16***
	(0.08)	(0.10)	(0.04)	(0.06)	(0.10)	(0.12)	(0.06)	(0.09)	(0.14)	(0.17)	(0.05)	(0.08)

Notes: This table presents the interaction effects between subnational exposure to emerging digital technologies (X_{ac}) and the baseline skills composition ($Skills^s_{ac}$), separately by country income group and workers' educational attainment. Each coefficient is a separate regression since the baseline skills composition is provided for each skill subcategory separately. Standard errors between parentheses are derived following the AKM0 inference procedure from Adao et al. (2019). $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The extent to which skills mediate employment responses also varies systematically by the level of educational attainment of workers within income groups. In upper-middle and high-income countries, the positive mediating effects of cognitive skills are concentrated among workers with high levels of education, although in high-income countries the pattern varies across cognitive skill categories for workers with intermediate levels of education. This finding is consistent with digital technologies complementing workers with sufficient capacity to adapt to task upgrading and to leverage complementary technologies (Goldin and Katz, 2008). By contrast, in lower-income countries, highly exposed areas with strong demand for cognitive skills experience employment gains primarily among workers with low and intermediate levels of education, while workers with high levels of education experience less favourable employment responses. This pattern is consistent with an early stage of digital adoption, in which employment gains associated with cognitive skill demand do not yet extend to high-end roles.

Turning to technical digital skills, we find more nuanced—and in some cases surprising—patterns. Skills related to Machine learning & AI are associated with negative mediating effects on employment following digital exposure across income groups, while software and technical skills show negative aggregate effects in upper-middle- and high-income countries but no significant effect in lower-income countries. However, the distribution of these effects across educational groups differs markedly. In high-income countries, these skills are associated with positive employment effects for workers with intermediate and high levels of education, consistent with their complementary role in digitally mature production environments. In contrast, in lower-income and upper-middle-income countries, workers with intermediate levels of education benefit the most, while workers with low and high levels of education generally experience less favourable employment responses—a pattern potentially consistent with an intermediate-skill upgrading (i.e., inverted polarization) mechanism with limited absorption at the upper end of the skill distribution (Acemoglu and Restrepo, 2022). These patterns may reflect a misalignment between growing demand for advanced digital skills and workforce preparedness, although the analysis does not directly test for skill mismatch. They may also be influenced by the fact that the data predate the rapid diffusion of generative AI, which has increasingly reshaped tasks within jobs rather than directly displacing employment.

The mediating effects of socio-emotional skills are generally smaller and more heterogeneous across income groups. People management skills display a positive mediating role in both low- and high-income countries, suggesting that competencies related to team coordination and supervisory responsibilities may support employment resilience during digital transformation. By contrast, social and customer service skills tend to attenuate the employment effects of digital exposure in low- and high-income countries. When further disaggregating by educational attainment, a more nuanced pattern emerges: in high-income countries, social and customer-service skills are associated with positive mediating effects among workers with intermediate levels of education, likely reflecting complementarities between interpersonal skills and technology in service-oriented roles that are augmented rather than substituted by digital tools. At the tails of the education distribution the effects are smaller and mixed in sign—negative for social skills among workers with

high levels of education, and for customer-service skills among those with low levels of education—suggesting that these skills function primarily as complementary inputs rather than as stand-alone buffers against technological disruption.

Finally, manual skills exhibit substantial heterogeneity in their mediating role. In high-income countries, stronger demand for manual skills is associated with employment gains among workers with low levels of education, but with negative effects among those with intermediate and high levels of education. This pattern may reflect differences in the types of tasks performed across educational groups in increasingly technology-intensive environments. While demand persists for non-automatable tasks typically performed by workers with low levels of education, workers with manual skill profiles who have intermediate and high levels of education may be more exposed to displacement. Upper-middle-income countries display a less systematic pattern across manual skill categories and educational groups. By contrast, in low- and lower-middle-income countries, manual skills are associated with generally negative employment effects for workers with low and intermediate levels of education, while workers with high levels of education tend to benefit. One possible explanation lies in differences in the composition of local labour demand and the ways in which digital technologies interact with existing economic activities: areas with greater demand for manual skills may be more exposed to the displacement of routine, physically intensive tasks, whereas in other contexts, manual skills may complement more technologically advanced activities, such as advanced manufacturing, medical technologies, or the maintenance of complex equipment.

Taken together, the analysis underscores that employment responses to digital technology exposure are highly heterogeneous and strongly mediated by the skill composition of local labour demand. Not all skills provide equal protection against technological change, and education alone is insufficient to explain variation across subnational areas in outcomes. These findings highlight the importance of moving beyond education-based frameworks toward a more granular, skill-based understanding of how digital transformation shapes employment, and they point to the critical role of complementarities across skill types in determining whether subnational areas can turn technological exposure into inclusive job growth.

5 Conclusion

This paper examines how subnational exposure to emerging digital technologies affects employment and how baseline skill composition mediates these effects, using a novel dataset that combines the *TechXposure* measure with harmonized subnational labour force data for 69 countries across all income groups. Employing a shift-share identification strategy, we find that greater exposure to emerging digital technologies is, on average, associated with increases in the employment-to-population ratio. However, these average gains mask substantial heterogeneity across demographic groups, country income groups, and ILO subregions. Employment gains are concentrated among prime-age workers and workers with low levels of education in the full sample, although the education gradient changes with country income-level, with gains increasingly extending to workers

with high levels of education in upper-middle- and high-income countries. Low-income countries register the largest gains, whereas lower-middle-income countries see little change, and East and South-East Asia experience modest declines.

Our analysis of the mediating role of skills shows that not all skill types shape employment responses to technological change in the same way. Cognitive skills—particularly financial, sophisticated cognitive, computer, and writing skills—enhance the positive employment effects of digital exposure, as do project and process management skills. By contrast, some advanced technical skills, such as machine learning and AI, and software and technical skills, are associated with weaker employment outcomes in areas with greater digital exposure. Because both our exposure and skill measures predate the emergence of generative AI, this result concerns machine learning and AI expertise as it was demanded before that shift. Socio-emotional and manual skills exhibit more heterogeneous patterns, with their mediating role varying substantially across income and education groups. People management is more often associated with employment gains, while customer service and social skills are often linked to weaker employment effects. More broadly, the results show that the skills associated with more favourable adjustment to digital exposure differ across country income levels and across segments of the workforce.

These findings have several policy implications. First, they underscore the importance of skills development strategies that go beyond educational attainment to focus on specific competencies that complement digital technologies. While advanced digital skills remain important in many contexts, our results suggest that cognitive, managerial, and communication skills are critical for enabling workers and areas to harness the benefits of technological change. Second, the heterogeneity in effects across income groups points to the need for context-specific policy design. In lower-income countries, the expansion of basic digital infrastructure and technical skills can still generate job creation, while in upper-middle- and high-income economies, a key challenge is preventing job polarization and ensuring that the workforce can transition into complementary roles.

Finally, our results highlight the value of integrated policy approaches that link technological change with workforce development and active labour market policies. The substantial heterogeneity we document suggests that technological exposure alone does not determine employment outcomes: the skills demanded within local labour markets are an important part of the conditions shaping adjustment. Without targeted investment in complementary skills, the diffusion of emerging digital technologies may exacerbate inequalities between subnational areas and population groups. With the right skill foundations, however, digital transformation is more likely to generate broad-based and inclusive employment growth.

Our analysis covers the period before the emergence of generative AI, and its lessons for the current wave of technological change should be drawn with care. Unlike most of the technologies studied here, generative AI can directly perform a range of cognitive tasks. Global evidence suggests that its potential effects are concentrated in clerical occupations, are larger in higher-income countries, and are more likely to augment than to automate jobs (Gmyrek et al., 2023). Whether the cognitive, managerial, and communication skills that we find to complement earlier digital

technologies continue to do so when generative AI can perform part of these tasks remains an open question. The framework developed in this paper—which combines technology exposure with the baseline skill composition of local labour markets—provides a basis for investigating this question as post-2022 employment data become available. An important avenue for future research would be to complement this approach with direct measures of technology adoption, allowing us to examine not only whether skills shape employment adjustment to generative AI, but also whether they influence its adoption and deployment in the first place. Distinguishing between these channels would help explain why similar levels of technological exposure may translate into different employment outcomes across labour markets.

References

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, volume 4, pages 1043–1171. Elsevier.

Acemoglu, D. and Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American economic review*, 108(6):1488–1542.

Acemoglu, D. and Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of economic perspectives*, 33(2):3–30.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, 128(6):2188–2244.

Acemoglu, D. and Restrepo, P. (2022). Tasks, automation, and the rise in u.s. wage inequality. *Econometrica*, 90(5):1973–2016.

Adamczyk, W., Boehmer, S., Delaporte, I., Escudero, V., and Liepmann, H. (2025). Developing a new method to uncover skills trends in emerging economies using online data and nlp techniques. Research brief, International Labour Organization. Accessed 2025-01-06.

Adao, R., Kolesár, M., and Morales, E. (2019). Shift-share designs: Theory and inference. *The Quarterly Journal of Economics*, 134(4):1949–2010.

Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. (2020). What are the labor and product market effects of automation? new evidence from france.

Almeida, R. K., Fernandes, A. M., and Viollaz, M. (2020). Software adoption, employment composition, and the skill content of occupations in chilean firms. *The Journal of Development Studies*, 56(1):169–185.

Arntz, M., Gregory, T., and Zierahn, U. (2016). The risk of automation for jobs in oecd countries: A comparative analysis. *OECD social, employment and migration working papers*, 2016.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4):1279–1333.

Borusyak, K., Hull, P., and Jaravel, X. (2021). Quasi-Experimental Shift-Share Research Designs. *The Review of Economic Studies*, 89(1):181–213.

Deming, D. and Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of labor economics*, 36(S1):S337–S369.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The quarterly journal of economics*, 132(4):1593–1640.

Escudero, V., Liepmann, H., and Podjanin, A. (2024). Using online vacancy and job applicants' data to study skills dynamics. In *Big Data Applications in Labor Economics, Part B*, pages 35–99. Emerald Publishing Limited.

Gmyrek, P., Berg, J., and Bescond, D. (2023). Generative ai and jobs: A global analysis of potential effects on job quantity and quality. *ILO Working Paper*, 96.

Goldin, C. and Katz, L. F. (2008). Harvard University Press, Cambridge, MA.

Goos, M. and Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in britain. *The review of economics and statistics*, 89(1):118–133.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American economic review*, 104(8):2509–2526.

Hjort, J. and Poulsen, J. (2019). The arrival of fast internet and employment in africa. *American Economic Review*, 109(3):1032–1079.

Hjort, J. and Tian, L. (2025). The economic impact of internet connectivity in developing countries. *Annual Review of Economics*, 17.

Katz, L. F. et al. (1999). Changes in the wage structure and earnings inequality. In *Handbook of labor economics*, volume 3, pages 1463–1555. Elsevier.

Lewandowski, P., Park, A., and Schotte, S. (2023). Global divergence in the de-routinization of jobs. *Tasks, skills, and institutions: The changing nature of work and inequality*, pages 33–51.

Lo Bello, S., Sanchez Puerta, M. L., and Winkler, H. (2019). From ghana to america: The skill content of jobs and economic development. Technical report, IZA Discussion Papers.

Maloney, W. F. and Molina, C. (2016). Are automation and trade polarizing developing country labor markets, too? *World Bank Policy Research Working Paper*, (7922).

Mann, K. and Püttmann, L. (2023). Benign effects of automation: New evidence from patent texts. *Review of Economics and Statistics*, 105(3):562–579.

McCrae, R. R., Costa, P. T., et al. (2008). Empirical and theoretical status of the five-factor model of personality traits. *The SAGE handbook of personality theory and assessment*, 1:273–294.

Prytkova, E., Petit, F., Li, D., Chaturvedi, S., and Ciarli, T. (2024). The Employment Impact of Emerging Digital Technologies. *SSRN Electronic Journal*.

Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of labor economics*, 24(2):235–270.

Online Appendix

From Exposure to Resilience: How Skills Mediate the Employment Effects of Emerging Digital Technologies

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Table OA.1: Shift–Share Eligibility and Data Availability of Countries (1/2)

			Emp-to-pop. Ratio										
			Baseline		Start		End		Gap				
	Country	N	Year	Cdt	Year	Cdt	Year	Cdt	Year	Cdt	Dem.	ISIC-ISCO	Sample
AGO	Angola	18	2009		2011		2019		8		✓	✓	✓
ALB	Albania	12	2009		2010	X	2019		9		✓	✓	✓
ARG	Argentina	24	2010		2014		2019		5		✓	✓	✓
AUS	Australia	8	2010		2014		2019		5		✓	✓	✓
AUT	Austria	9	2010		2014		2019		5		✓	✓	✓
BEL	Belgium	3	2010		2014		2019		5		✓	✓	✓
BGD	Bangladesh	6	2010		2013		2017		4		✓	✓	✓
BGR	Bulgaria	6	2010		2014		2019		5		✓	✓	✓
BIH	Bosnia and Herzegovina	3	2009		2014		2019		5		✓	✓	✓
BOL	Plurinational State of Bolivia	9	2007		2014		2019		5		✓	✓	✓
BRA	Brazil	27	2009		2014		2019		5		✓	✓	✓
CHE	Switzerland	26	2010		2014		2019		5		✓	✓	✓
CHL	Chile	16	2010		2014		2019		5		✓	✓	✓
COL	Colombia	24	2010		2014		2019		5		✓	✓	✓
CYP	Cyprus	9	2010		2014		2019		5		✓	✓	✓
CZE	Czechia	8	2010		2014		2019		5		✓	✓	✓
DEU	Germany	16	2010		2014		2019		5		✓	✓	✓
DNK	Denmark	5	2010		2014		2019		5		✓	✓	✓
ECU	Ecuador	24	2010		2014		2017		3		✓	✓	✓
EGY	Egypt	27	2012		2013		2019		6		✓	✓	✓
ESP	Spain	19	2010		2014		2019		5		✓	✓	✓
ETH	Ethiopia	11	2005		2013		2021		8		✓	✓	✓
FIN	Finland	5	2010		2014		2019		7		✓	✓	✓
FRA	France	22	2010		2014		2019		5		✓	✓	✓
GBR	United Kingdom	12	2010		2014		2019		5		✓	✓	✓
GEO	Georgia	10	2010		2014		2017		3		✓	✓	✓
GHA	Ghana	10	2006		2013		2017		4		✓	✓	✓
GMB	Gambia	8	2012		2018	X	2023	X	5		✓	✓	✓
GRC	Greece	13	2010		2014		2019		5		✓	✓	✓
GTM	Guatemala	3	2010		2014		2021		7		✓	✓	✓
HND	Honduras	14	2010		2014		2019		5		✓	✓	✓
HRV	Croatia	2	2010		2014		2019		5		✓	✓	✓
HUN	Hungary	7	2010		2014		2019		5		✓	✓	✓
IDN	Indonesia	33	2007		2014		2019		5		✓	✓	✓
IND	India	34	2010		2012		2019		7		✓	✓	✓
IRL	Ireland	3	2012		2014		2019		5		✓	✓	✓
ISR	Israel	7	2012		2014		2019		5		✓	✓	✓
ITA	Italy	21	2010		2014		2019		5		✓	✓	✓

Table OA.1: Shift–Share Eligibility and Data Availability of Countries (2/2)

					Emp-to-pop. Ratio								
			Baseline		Start		End		Gap				
	Country	N	Year	Cdt	Year	Cdt	Year	Cdt	Year	Cdt	Dem.	ISIC-ISCO	Sample
KHM	Cambodia	24	2010		2014		2020		6		✓	✓	✓
LBR	Liberia	15	2010		2014		2016	X	2	X	✓	✓	✓
LKA	Sri Lanka	25	2011		2014		2019		5		✓	✓	✓
LUX	Luxembourg	1	2010		2014		2019		5		✓	✓	✓
LVA	Latvia	1	2010		2014		2019		5		✓	✓	✓
MDG	Madagascar	22	2012		2015	X	2022	X	7			✓	
MEX	Mexico	32	2013		2014		2019		5		✓	✓	✓
MLI	Mali	8	2014	X	2018	X	2020		2	X	✓	✓	✓
MNG	Mongolia	22	2010		2014		2019		5		✓	✓	✓
NAM	Namibia	13	2012		2013		2018		5		✓	✓	✓
NER	Niger	8	2011		2012		2017		5			✓	
NOR	Norway	6	2010		2014		2020		8		✓	✓	✓
PAN	Panama	12	2011		2014		2019		5		✓	✓	✓
PER	Peru	8	2010		2014		2019		5		✓	✓	✓
PHL	Philippines	17	2012		2013		2019		6			✓	
POL	Poland	16	2010		2014		2019		5		✓	✓	✓
PRT	Portugal	7	2010		2014		2019		5		✓	✓	✓
PSE	Palestine	2	2010		2014		2019		5		✓	✓	✓
ROU	Romania	8	2010		2014		2019		5		✓	✓	✓
RUS	Russia	82	2010		2014		2019		5		✓	✓	✓
SLV	El Salvador	14	2010		2014		2019		5		✓	✓	✓
SVK	Slovakia	4	2010		2014		2019		5		✓	✓	✓
SVN	Slovenia	2	2010		2014		2019		5		✓	✓	✓
SWE	Sweden	8	2010		2014		2019		5		✓	✓	✓
TGO	Togo	6	2011		2015	X	2017		2	X	✓	✓	
THA	Thailand	5	2010		2014		2019		5		✓	✓	✓
TLS	Timor-Leste	13	2010		2013		2021		8		✓	✓	✓
UGA	Uganda	4	2010		2014		2019		5		✓	✓	✓
URY	Uruguay	19	2010		2014		2019		5		✓	✓	✓
USA	United States	51	2010		2014		2019		7		✓	✓	✓
VEN	Bolivarian Rep. of Venezuela	24	2010		2012		2017		5		✓	✓	✓
VNM	Viet Nam	63	2010		2014		2019		5		✓	✓	✓
WSM	Samoa	4	2012		2017	X	2022	X	5		✓	✓	✓
ZAF	South Africa	9	2010		2014		2019		5		✓	✓	✓
ZWE	Zimbabwe	10	2011		2014		2019		5		✓	✓	✓

Notes: The table reports the eligibility criteria and data availability for constructing the employment-to-population ratio panel. *N* denotes the number of first-level administrative areas available in each country. The *Baseline* column reports the survey year used to construct baseline controls and employment shares, while the *Start* and *End* columns indicate the years used to measure employment changes. *Cdt* indicates whether the country satisfies the corresponding sample-selection criterion; an "X" denotes that the criterion is not met. The *Gap* column reports the number of years between the start and end observations. Countries satisfying all eligibility criteria are included directly in the estimation sample. Countries failing one or more criteria are retained when employment outcomes can be interpolated or extrapolated to the reference years using adjacent survey waves. The *Dem.* column (which stands for demographics) indicates the availability of employment breakdowns by gender, age group, and educational attainment. *ISIC–ISCO* indicates the availability of employment data disaggregated by 1-digit ISIC sectors and 1-digit ISCO occupations, which are required to construct technology exposure measures and skill composition indicators. The *Sample* column indicates whether a country is included in the final analysis. As a result, a total of 73 countries are presented in this table and for which an exposure score to emerging digital technologies was calculated. However, the analysis includes 69 countries and 1,015 first-level administrative areas. Madagascar, Niger, and the Philippines are excluded because we do not have breakdowns for all demographics, and Togo is excluded because extrapolating its 2015–2017 observation window to the 2014–2019 reference years implies employment-to-population ratios outside the unit interval.

Table OA.2: Micro Employment Data — Sources by Country

Country	Country Code	Survey Year and Name
Angola	AGO	QUIBB 2009; QUIBB 2011; IEA 2019
Albania	ALB	LFS 2009; LFS 2010; LFS 2019
Argentina	ARG	EPH 2010; EPH 2014; EPH 2019
Australia	AUS	HILDA 2010; HILDA 2014; HILDA 2019
Austria	AUT	LFS 2010; LFS 2014; LFS 2019
Belgium	BEL	EULFS 2010; EULFS 2014; EULFS 2019
Bangladesh	BGD	LFS 2010; LFS 2013; LFS 2017
Bulgaria	BGR	EULFS 2010; EULFS 2014; EULFS 2019
Bosnia and Herzegovina	BIH	LFS 2009; LFS 2014; LFS 2019
Plurinational State of Bolivia	BOL	EH 2007; EH 2014; EH 2019
Brazil	BRA	PNAD 2009; PNADC 2014; PNADC 2019
Switzerland	CHE	ESPA 2010; ESPA 2014; ESPA 2019
Chile	CHL	ENE 2010; ENE 2014; ENE 2019
Colombia	COL	GEIH 2010; GEIH 2014; GEIH 2019
Cyprus	CYP	LFS 2010; LFS 2014; LFS 2019
Czechia	CZE	EULFS 2010; EULFS 2014; EULFS 2019
Germany	DEU	EULFS 2010; EULFS 2014; EULFS 2019
Denmark	DNK	EULFS 2010; EULFS 2014; EULFS 2019
Ecuador	ECU	ENEMDU 2010; ENEMDU 2014; ENEMDU 2017
Egypt	EGY	LFS 2012; LFS 2013; LFS 2019
Spain	ESP	EULFS 2010; EULFS 2014; EULFS 2019
Ethiopia	ETH	NLFS 2005; NLFS 2013; NLFS 2021
Finland	FIN	EULFS 2010; EULFS 2014; EULFS 2019
France	FRA	EULFS 2010; EULFS 2014; EULFS 2019
United Kingdom	GBR	EULFS 2010; EULFS 2014; EULFS 2019
Georgia	GEO	IHS 2010; IHS 2014; IHS 2017
Ghana	GHA	LSS 2006; LSS 2013; LSS 2017
Gambia	GMB	LFS 2012; LFS 2018; LFS 2023
Greece	GRC	EULFS 2010; EULFS 2014; EULFS 2019
Guatemala	GTM	ENEI 2010; ENEI 2014; ENEI 2021
Honduras	HND	EPHPM 2010; EPHPM 2014; EPHPM 2019
Croatia	HRV	EULFS 2010; EULFS 2014; EULFS 2019
Hungary	HUN	LFS 2010; LFS 2014; LFS 2019
Indonesia	IDN	LFS 2007; LFS 2014; LFS 2019
India	IND	NSS 2010; NSS 2012; PLFS 2019
Ireland	IRL	EULFS 2012; EULFS 2014; EULFS 2019
Israel	ISR	LFS 2012; LFS 2014; LFS 2019
Italy	ITA	EULFS 2010; EULFS 2014; EULFS 2019
Cambodia	KHM	HSES 2010; HSES 2014; HSES 2020
Liberia	LBR	LFS 2010; HIES 2014; HIES 2016
Sri Lanka	LKA	LFS 2011; LFS 2014; LFS 2019

Table OA.2: Micro Employment Data - Sources by Country

Country	Country Code	Survey Year and Name
Luxembourg	LUX	EULFS 2010; EULFS 2014; EULFS 2019
Latvia	LVA	EULFS 2010; EULFS 2014; EULFS 2019
Madagascar	MDG	ENESI 2012; ENESI 2015; EPM 2022
Mexico	MEX	ENOE 2013; ENOE 2014; ENOE 2019
Mali	MLI	EMOP 2014; EMOP 2018; EMOP 2020
Mongolia	MNG	LFS 2010; LFS 2014; LFS 2019
Namibia	NAM	LFS 2012; LFS 2013; LFS 2018
Niger	NER	ECVM 2011; ENESI 2012; ENESI 2017
Norway	NOR	EULFS 2010; EULFS 2014; EULFS 2020
Panama	PAN	EML 2011; EML 2014; EML 2019
Peru	PER	ENAHO 2010; ENAHO 2014; ENAHO 2019
Philippines	PHL	LFS 2012; LFS 2013; LFS 2019
Poland	POL	EULFS 2010; EULFS 2014; EULFS 2019
Portugal	PRT	EULFS 2010; EULFS 2014; EULFS 2019
Palestine	PSE	LFS 2010; LFS 2014; LFS 2019
Romania	ROU	LFS 2010; LFS 2014; LFS 2019
Russian Federation	RUS	LFS 2010; LFS 2014; LFS 2019
El Salvador	SLV	EHPM 2010; EHPM 2014; EHPM 2019
Slovakia	SVK	EULFS 2010; EULFS 2014; EULFS 2019
Slovenia	SVN	LFS 2010; LFS 2014; LFS 2019
Sweden	SWE	EULFS 2010; EULFS 2014; EULFS 2019
Togo	TGO	QUIBB 2011; QUIBB 2015; ERIESI 2017
Thailand	THA	LFS 2010; LFS 2014; LFS 2019
Tajikistan	TJK	LSS 2007; LSS 2009; LFS 2016
Timor-Leste	TLS	LFS 2010; LFS 2013; LFS 2021
Uganda	UGA	NPS 2010; NPS 2014; NPS 2019
Uruguay	URY	ECH 2010; ECH 2014; ECH 2019
United States	USA	CPS 2010; CPS 2014; CPS 2019
Bolivarian Republic of Venezuela	VEN	EHM 2010; EHM 2012; EHM 2017
Viet Nam	VNM	LFS 2010; LFS 2014; LFS 2019
Samoa	WSM	LFS 2012; LFS 2017; LFS 2022
South Africa	ZAF	QLFS 2010; QLFS 2014; QLFS 2019
Zimbabwe	ZWE	LFS 2011; LFS 2014; LFS 2019

Notes: Countries not appearing in the table were excluded because the required employment data were unavailable or did not satisfy the sample-selection criteria described in the text. QUIBB - Questionnaire sur les Indicateurs de Base du Bien-être; IEA - Inquérito ao Emprego; LFS - Labor Force Survey; EPH - Encuesta Permanente de Hogares; HILDA - Household, Income and Labour Dynamics; EULFS - EU Labour Force Survey; EH - Encuesta de Hogares; PNAD - Pesquisa Nacional por Amostra de Domicílios; PNADC - Pesquisa Nacional por Amostra de Domicílios Contínua; ESPA = Swiss Labour Force Survey; ENE - Encuesta Nacional de Empleo; GEIH - Gran Encuesta Integrada de Hogares; ENEMDU - Encuesta Nacional de Empleo, Desempleo y Subempleo; NLFS - National Labour Force Survey; IHS - Integrated Household Survey; LSS - Living Standards Survey; GHS - General Household Survey; EPHPM - Encuesta Permanente de Hogares de Propósitos Múltiples; NSS - National Sample Survey; PLFS = Periodic Labour Force Survey; HSES - Household Socio-Economic Survey; HIES - Household Income and Expenditure Survey; ENESI - Enquête Permanente auprès des Ménages; ENOE - Encuesta Nacional de Ocupación y Empleo; EMOP - Enquête Modulaire et Permanente auprès des Ménages; EML - Encuesta de Mercado Laboral; ENAHO - Encuesta Nacional de Hogares; EHPM - Encuesta de Hogares de Propósitos Múltiples; NPS = National Panel Survey; ECH - Encuesta Continua de Hogares; CPS - Current Population Survey; EHM - Encuesta de Hogares por Muestreo; QLFS = Quarterly Labour Force Survey; ERIESI - Enquête Régionale Intégrée sur lEmploi et le Secteur Informel.

Table OA.3: Emerging Digital Technologies in TechXposure

Technology	Description
3D Printing	
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.
3D Printing	Printing systems for creating three-dimensional objects using a variety of materials and techniques, like photocuring and powder spreading.
Additive Manufacturing	Technologies and processes for additive manufacturing, with applications such as prostheses and building materials.
Embedded Systems	
Smart Agriculture & Water Management	Various Internet of Things (IoT) technologies for intelligent and remote management in agriculture, and water and sewage systems.
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.
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.
Industrial Automation & Robot Control	Industrial process automation, including robots, programmable logic controllers, and related control apparatuses such as remote control and fault diagnosis.
Remote Monitoring & Control Systems	Real-time remote monitoring and management technologies for factories, building management, warehouses, intelligent homes, disaster management, and network security.
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.
Smart Mobility	
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.
Autonomous Vehicles & UAVs	Developments in unmanned aerial vehicles (UAVs), drones, and autonomous driving technologies, with an emphasis on vehicle control, navigation, and sensor integration.
Parking & Vehicle Space Management	Networking technologies for parking management, including systems for monitoring available spaces and intelligent parking solutions.
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.
Passenger Transportation	Technologies for ride-sharing, taxi hailing, and public transportation reservations using real-time information, electronic ticketing, and route optimization.
Food Services	

Table OA.3: Emerging Digital Technologies in TechXposure *(continued)*

Technology	**Description**
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.
E-Commerce	
Digital Advertising	Automated tracing and tagging, and AI technologies for digital advertisements, including targeted delivery on mobile devices.
Electronic Trading and Auctions	Online trading platforms, financial instrument exchanges, and auction mechanisms, focusing on real-time bidding, trading, and market data.
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.
E-Coupons & Promotion Management	Data management platforms for electronic coupon distribution, management, redemption, and associated loyalty programmes.
Payment Systems	
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.
Mobile Payments	A combination of mobile technologies for processing electronic payments.
Gaming & Wagering Systems	A combination of user interface and data management technologies for gaming, both online and physical, including gambling and gaming machines.
Digital Services	
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.
E-Learning	A combination of AI and data management technologies for digital platforms and systems in education, including teaching, learning, and classroom management.
Location-Based Services & Tracking	Technologies that provide location-based content and services, often relying on global positioning and navigation systems and related communication technology.
Voice Communication	Technologies focusing on voice communication, including communication protocols and user interfaces.
Electronic Messaging	Digital communication methods, infrastructure, and user interfaces for services such as email and conferences.
Workflow Management	A combination of AI and network technologies for management applications, including workflow automation, recruitment, event scheduling, and building and property management.
Cloud Storage & Data Security	Cloud-based data storage, distributed data management, encryption, and backup, often integrated with blockchain technology.
Information Processing	Systems for managing, processing, and delivering data and information across various domains, potentially including content generation, transmission, and verification.

Table OA.3: Emerging Digital Technologies in TechXposure *(continued)*

Technology	**Description**
Cloud Computing	Cloud computing and virtual machines, focusing on cloud platforms and resource allocation in cloud environments.
Recommender Systems	Algorithms and systems for providing recommendations and personalized content delivery based on user behavior, search queries, and similarity metrics.
Social Networking & Media Platforms	User interfaces for online social networking services, content sharing, and recommendation systems.
Digital Media Content	Tools and platforms for digital media content creation, management, distribution, and access.
Computer Vision	
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.
Machine Learning & Neural Networks	Machine learning training techniques, model architectures, and data processing for computer vision applications.
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.
HealthTech	
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.
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.
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.

Notes: The table lists the 40 emerging digital technologies covered by the *TechXposure* database (Prytkova et al., 2024), grouped into nine domains, with a short description of each. The technologies are identified from patent data covering 2012–2021. Exposure scores measure the semantic similarity between the patents associated with each technology and the descriptions of industries and occupations in standard classifications.

Table OA.4: Skill Categories and Definitions

Skill group	Definition
Cognitive skills	
Cognitive skills (core)	Skills needed to perform tasks that require analysis and calculation, problem-solving, intuition, and flexibility.
Cognitive skills (sophisticated)	Skills needed to perform more sophisticated tasks that require analysis, modelling, and creativity.
General computer skills, Software skills and technical support, Machine learning and AI, Financial skills, Writing skills, Project and process management	These six subcategories relate closely to the cognitive skills described above. They correspond to skills that are needed in specific areas of work. They are listed as separate subcategories because they are often specifically mentioned in job adverts and in applicants' work experiences. They are mostly geared towards white-collar jobs, in line with the aim of the work by Deming and Kahn (2018).
Socio-emotional skills	
Character skills	Character skills include three of the five categories of the five-factor personality model commonly used in the psychological literature (McCrae et al., 2008): conscientiousness, openness to experience, and emotional stability. In addition, this subcategory includes dimensions such as being relaxed, independent, self-confident, and vulnerable to stress.
Social skills	Social skills include those character traits from the five-factor personality model that are less related to one's personal attributes and more related to how one interacts with other people, specifically agreeableness and extraversion. Other keywords that relate to the general ability to have personal interactions, such as working in teams or holding presentations, are included as well.
People management skills, Customer service skills	These two subcategories refer to specific abilities within the broader realm of social interactions, and are often listed as particular requirements in job adverts.
Manual skills	
Finger-dexterity skills	This category focuses on manual skills that are usually classified as "routine" by Autor et al. (2003) and which are common in machine operation and the production or handling of goods. Examples include picking and sorting in agriculture or working in an assembly line.
Hand-foot-eye coordination skills	These manual skills are usually understood as "non-routine" by Autor et al. (2003). They are more commonly used in services-related occupations and include working in changing environments that necessitate adaptation. This category encompasses, for example, driving cars or repairing and cleaning items.
Physical skills	This subcategory focuses on more innate bodily characteristics, such as physical strength, endurance, the ability to lift heavy objects, or working while standing or walking.

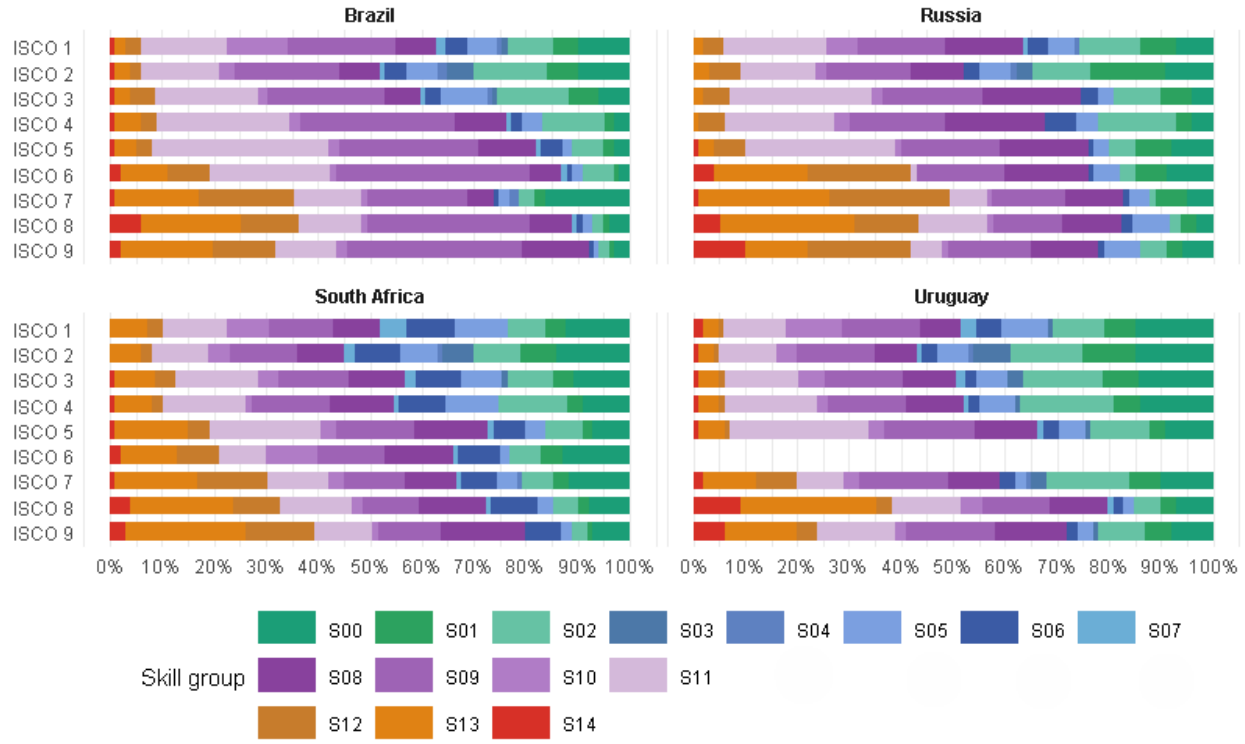
Notes: The table reports the skill categories used in the analysis along their definition. Skills are grouped into three broad categories—cognitive, socio-emotional, and manual skills—and further divided into 15 subcategories. The methodology is developed by Escudero et al. (2024) and further refined by Adamczyk et al. (2025).

Table OA.5: ISIC 3 and ISIC 4 Correspondence

	ISIC Rev. 3		**ISIC Rev. 4**
A	Agriculture, Hunting and Forestry	A	Agriculture, Forestry and Fishing
B	Fishing		
C	Mining and Quarrying	B	Mining and Quarrying
D	Manufacturing	C	Manufacturing
E	Electricity, Gas and Water Supply	D	Electricity, Gas, Steam and Air Conditioning Supply
		E	Water Supply, Sewerage, Waste Management and Remediation Activities
F	Construction	F	Construction
G	Wholesale and Retail Trade: Repair of Motor Vehicles, Motorcycles and Personal and Household Goods	G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles
H	Hotels and Restaurants	I	Accommodation and Food Service Activities
I	Transport, Storage and Communications	H	Transportation and Storage
		J	Information and Communication
J	Financial Intermediation	K	Financial and Insurance Activities
K	Real Estate, Renting and Business Activities	L	Real Estate Activities
		M	Professional, Scientific and Technical Activities
		N	Administrative and Support Service Activities
L	Public Administration and Defense; Compulsory Social Security	O	Public Administration and Defense; Compulsory Social Security
M	Education	P	Education
N	Health and Social Work	Q	Human Health and Social Work Activities
O	Other Community, Social and Personal Services Activities	S	Other Service Activities
		R	Arts, Entertainment and Recreation
P	Activities of Private Households as Employers and Undifferentiated Production Activities of Private Households	T	Activities of Households as Employers; Undifferentiated Goods- and Services-Producing Activities of Households for Own Use
Q	Extraterritorial Organizations and Bodies	U	Activities of Extraterritorial Organizations and Bodies

Notes: The table shows the correspondence between 1-letter ISIC Revision 3 and ISIC Revision 4 sector classifications. This mapping is used to harmonize employment data across countries and survey waves reporting different ISIC revisions and to construct comparable sectoral employment shares for the shift-share exposure measure.

Figure OA.1: Skills Composition by 1-digit ISCO and Country



Source: BuscoJobs vacancy data for Uruguay (2010–2023) and Brazil (2010–2023) and Adzuna vacancy data for South Africa (2016–2021) and the Russian Federation (2016–2021).
Notes: The figure shows the composition of skills required in online job vacancies by major occupational group (ISCO 1–9) for Brazil (2010–2023), the Russian Federation (2016–2021), South Africa (2016–2021), and Uruguay (2010-2023). Skills are grouped into 15 categories (S00 Cognitive core, S01 Cognitive sophisticated, S02 Basic computer, S03 Software and technical, S04 Machine learning & AI, S05 Financial, S06 Writing, S07 Project and process management, S08 Character, S09 Social, S10 People management, S11 Customer service, S12 Finger dexterity, S13 Hand-foot-eye coordination, and S14 Physical skills) and 3 broader categories: cognitive (S00 to S07), socio-emotional (S08 to S11) and manual (S12 to S14) skills categories. Each horizontal bar represents the share of all identified skill requirements within that occupation accounted for by each skill, with shares normalized to sum to 100 per cent within each occupation. The ordering runs from ISCO 1 (Managers) at the top to ISCO 9 (Elementary occupations) at the bottom.

Mapping our taxonomy to the ESCO taxonomy The most disaggregated ESCO matrix links 2,942 occupations to 13,485 skills and knowledge concepts. These detailed classifications can be aggregated to broader occupational and skill groups. For validation purposes, we map our taxonomy to ESCO's level-2 skill and knowledge classifications. This level provides a sufficiently rich representation of skill heterogeneity while remaining manageable for constructing a crosswalk.

The ESCO level-2 skill classification comprises 74 skill categories nested within eight broad skill groups: communication, collaboration and creativity; information skills; assisting and caring; management skills; working with computers; handling and moving; constructing; and working with machinery and specialized equipment. The corresponding knowledge classification comprises 11 broad knowledge domains, ranging from education and social sciences to Information and Communications Technology (ICT), engineering, health and services.

We manually mapped each ESCO skill and knowledge category to the corresponding skill subcategory. When a level-2 category was ambiguous, we consulted the more detailed level-3 classification to determine the most appropriate match. Once the crosswalk was established, we combined it with the ESCO occupation-skill and occupation-knowledge matrices, which link ISCO-08 occupations to ESCO skill and knowledge categories and provide scores reflecting the skill composition of occupations.

Table OA.6: Mapping Between ESCO and our Skills Categories (Part 1/11)

ESCO 2		**ESCO 3**		
code	**label**	**code**	**label**	**ILO skill subcategory**
(1)	(2)	(3)	(4)	(5)
S01.00	communication, collaboration and creativity	S01.00.00	communication, collaboration and creativity	S09 social skills
S01.01	negotiating	S01.01.00	negotiating	S09 social skills
S01.01	negotiating	S01.01.01	negotiating and managing contracts and agreements	S09 social skills
S01.01	negotiating	S01.01.02	mediating and resolving disputes	S09 social skills
S01.01	negotiating	S01.01.03	responding to complaints	S09 social skills
S01.02	liaising and networking	S01.02.00	liaising and networking	S09 social skills
S01.02	liaising and networking	S01.02.01	communicating with colleagues and clients	S09 social skills
S01.02	liaising and networking	S01.02.03	developing professional relationships or networks	S09 social skills
S01.02	liaising and networking	S01.02.04	advocating for individual or community needs	S09 social skills
S01.02	liaising and networking	S01.02.05	collaborating and liaising	S09 social skills
S01.03	teaching and training	S01.03.00	teaching and training	S09 social skills
S01.03	teaching and training	S01.03.01	teaching academic or vocational subjects	S09 social skills
S01.03	teaching and training	S01.03.02	teaching safety procedures	S09 social skills
S01.03	teaching and training	S01.03.03	training on operational procedures	S09 social skills
S01.03	teaching and training	S01.03.04	training on health or medical topics	S09 social skills
S01.03	teaching and training	S01.03.05	coaching and mentoring	S10 people management skills
S01.04	presenting information	S01.04.00	presenting information	S09 social skills
S01.04	presenting information	S01.04.01	presenting general information	S09 social skills
S01.04	presenting information	S01.04.02	presenting research or technical information	S09 social skills
S01.04	presenting information	S01.04.03	presenting information in legal proceedings	S09 social skills
S01.05	advising and consulting	S01.05.00	advising and consulting	S09 social skills
S01.05	advising and consulting	S01.05.01	advising on legal, regulatory or procedural matters	S09 social skills
S01.05	advising and consulting	S01.05.02	providing financial advice	S05 financial skills
S01.05	advising and consulting	S01.05.03	advising on products and services	S11 customer service skills
S01.05	advising and consulting	S01.05.04	providing medical advice	S09 social skills
S01.05	advising and consulting	S01.05.05	advising on environmental issues	S09 social skills
S01.05	advising and consulting	S01.05.06	advising on design or use of technologies	S03 software and technical support
S01.05	advising and consulting	S01.05.07	advising on business or operational matters	S07 project and process manag.
S01.05	advising and consulting	S01.05.08	advising on educational or vocational matters	S09 social skills
S01.05	advising and consulting	S01.05.09	advising on workplace health and safety issues	S09 social skills
S01.06	promoting, selling and purchasing	S01.06.00	promoting, selling and purchasing	S11 customer service skills

Table OA.6: Mapping Between ESCO and our Skills Categories (Part 2/11)

ESCO 2		**ESCO 3**		
code	**label**	**code**	**label**	**ILO skill subcategory**
(1)	(2)	(3)	(4)	(5)
S01.06	promoting, selling and purchasing	S01.06.01	selling products or services	S11 customer service skills
S01.06	promoting, selling and purchasing	S01.06.02	promoting products, services, or programmes	S11 customer service skills
S01.06	promoting, selling and purchasing	S01.06.03	purchasing goods or services	S11 customer service skills
S01.07	obtaining information verbally	S01.07.00	obtaining information verbally	S09 social skills
S01.07	obtaining information verbally	S01.07.01	interviewing	S09 social skills
S01.07	obtaining information verbally	S01.07.02	engaging with others to identify needs	S09 social skills
S01.07	obtaining information verbally	S01.07.03	listening and asking questions	S09 social skills
S01.08	working with others	S01.08.00	working with others	S09 social skills
S01.08	working with others	S01.08.01	working in teams	S09 social skills
S01.08	working with others	S01.08.02	giving instructions	S10 people management skills
S01.08	working with others	S01.08.03	giving feedback	S10 people management skills
S01.08	working with others	S01.08.04	accepting feedback	S09 social skills
S01.08	working with others	S01.08.05	following instructions and procedures	S09 social skills
S01.08	working with others	S01.08.06	assisting and supporting co-workers	S09 social skills
S01.09	solving problems	S01.09.00	solving problems	S00 core cognitive skills
S01.09	solving problems	S01.09.01	developing solutions	S00 core cognitive skills
S01.09	solving problems	S01.09.02	implementing new procedures or processes	S07 project and process manag.
S01.11	designing systems and products	S01.11.00	designing systems and products	S03 software and technical support
S01.11	designing systems and products	S01.11.01	designing ict systems or applications	S03 software and technical support
S01.11	designing systems and products	S01.11.02	designing electrical, electronic systems or equipment	S03 software and technical support
S01.11	designing systems and products	S01.11.03	developing recipes or menus	S01 sophisticated cognitive skills
S01.11	designing systems and products	S01.11.04	designing structures or facilities	S03 software and technical support
S01.11	designing systems and products	S01.11.05	designing industrial materials, systems or products	S03 software and technical support
S01.12	creating artistic, visual or instructive mat.	S01.12.00	creating artistic, visual or instructive materials	S01 sophisticated cognitive skills
S01.12	creating artistic, visual or instructive mat.	S01.12.01	creating visual displays and decorations	S12 finger-dexterity skills
S01.12	creating artistic, visual or instructive mat.	S01.12.02	developing instructive or promotional materials	S01 sophisticated cognitive skills

Table OA.6: Mapping Between ESCO and our Skills Categories (Part 3/11)

ESCO 2		**ESCO 3**		
code	**label**	**code**	**label**	**ILO skill subcategory**
(1)	(2)	(3)	(4)	(5)
S01.12	creating artistic, visual or instructive mat.	S01.12.03	creating artistic designs or performances	S13 hand-foot-eye coordination
S01.13	writing and composing	S01.13.00	writing and composing	S06 writing skills
S01.13	writing and composing	S01.13.01	composing music	S06 writing skills
S01.13	writing and composing	S01.13.02	artistic and creative writing	S06 writing skills
S01.13	writing and composing	S01.13.03	technical or academic writing	S06 writing skills
S01.14	performing and entertaining	S01.14.00	performing and entertaining	S13 hand-foot-eye coordination
S01.14	performing and entertaining	S01.14.01	practising sports	S13 hand-foot-eye coordination
S01.14	performing and entertaining	S01.14.02	performing artistic or cultural activities	S13 hand-foot-eye coordination
S01.14	performing and entertaining	S01.14.03	conducting gaming activities	S13 hand-foot-eye coordination
S01.15	using more than one language	S01.15.00	using more than one language	S09 social skills
S01.15	using more than one language	S01.15.01	using foreign languages	S09 social skills
S01.15	using more than one language	S01.15.02	translating and interpreting	S09 social skills
S02.00	information skills	S02.00.00	information skills	S00 core cognitive skills
S02.01	conducting studies, investigations	S02.01.00	conducting studies, investigations and examinations	S01 sophisticated cognitive skills
S02.01	conducting studies, investigations	S02.01.01	conducting academic or market research	S01 sophisticated cognitive skills
S02.01	conducting studies, investigations	S02.01.02	diagnosing health conditions	S01 sophisticated cognitive skills
S02.01	conducting studies, investigations	S02.01.03	interpreting technical documentation and diagrams	S00 core cognitive skills
S02.01	conducting studies, investigations	S02.01.04	carrying out forensic and police investigations	S01 sophisticated cognitive skills
S02.02	documenting and recording information	S02.02.00	documenting and recording information	S06 writing skills
S02.02	documenting and recording information	S02.02.01	preparing financial documents, records, reports	S05 financial skills
S02.02	documenting and recording information	S02.02.02	recording legal information	S06 writing skills
S02.02	documenting and recording information	S02.02.03	preparing documentation for contracts, applications	S06 writing skills
S02.02	documenting and recording information	S02.02.04	maintaining or preparing medical documentation	S06 writing skills
S02.02	documenting and recording information	S02.02.05	maintaining operational records	S00 core cognitive skills
S02.02	documenting and recording information	S02.02.06	documenting technical designs, procedures, problems	S00 core cognitive skills
S02.02	documenting and recording information	S02.02.07	reporting incidents and defects	S06 writing skills

Table OA.6: Mapping Between ESCO and our Skills Categories (Part 4/11)

ESCO 2		**ESCO 3**		
code	**label**	**code**	**label**	**ILO skill subcategory**
(1)	(2)	(3)	(4)	(5)
S02.03	managing information	S02.03.00	managing information	S00 core cognitive skills
S02.04	processing information	S02.04.00	processing information	S00 core cognitive skills
S02.04	processing information	S02.04.01	gathering information from physical or electronic	S00 core cognitive skills
S02.04	processing information	S02.04.02	entering and transforming information	S00 core cognitive skills
S02.05	measuring physical properties	S02.05.00	measuring physical properties	S00 core cognitive skills
S02.05	measuring physical properties	S02.05.01	measuring dimensions and related properties	S00 core cognitive skills
S02.05	measuring physical properties	S02.05.02	weighing	S00 core cognitive skills
S02.06	calculating and estimating	S02.06.00	calculating and estimating	S00 core cognitive skills
S02.06	calculating and estimating	S02.06.01	performing calculations	S00 core cognitive skills
S02.06	calculating and estimating	S02.06.02	determining values of goods or services	S05 financial skills
S02.06	calculating and estimating	S02.06.03	estimating resource needs	S05 financial skills
S02.07	analysing and evaluating information	S02.07.00	analysing and evaluating information and data	S01 sophisticated cognitive skills
S02.07	analysing and evaluating information	S02.07.01	assessing land or real estate	S01 sophisticated cognitive skills
S02.07	analysing and evaluating information	S02.07.02	analysing scientific and medical data	S01 sophisticated cognitive skills
S02.07	analysing and evaluating information	S02.07.03	analysing financial and economic data	S05 financial skills
S02.07	analysing and evaluating information	02.07.04	analysing business operations	S07 project and process manag.
S02.07	analysing and evaluating information	S02.07.05	performing risk analysis and management	S07 project and process manag.
S02.07	analysing and evaluating information	S02.07.06	evaluating systems, programmes, equipment	S01 sophisticated cognitive skills
S02.08	monitoring, inspecting and testing	S02.08.00	monitoring, inspecting and testing	S00 core cognitive skills
S02.08	monitoring, inspecting and testing	S02.08.01	testing electrical and mechanical systems	S12 finger-dexterity skills
S02.08	monitoring, inspecting and testing	S02.08.02	monitoring operational activities	S07 project and process manag.
S02.08	monitoring, inspecting and testing	S02.08.03	monitoring financial and economic resources	S05 financial skills
S02.08	monitoring, inspecting and testing	S02.08.04	monitoring safety or security	S00 core cognitive skills
S02.08	monitoring, inspecting and testing	S02.08.05	monitoring environmental conditions	S00 core cognitive skills
S02.08	monitoring, inspecting and testing	S02.08.06	monitoring health conditions of humans and animals	S00 core cognitive skills
S02.08	monitoring, inspecting and testing	S02.08.08	testing and analysing substances	S00 core cognitive skills

Table OA.6: Mapping Between ESCO and our Skills Categories (Part 5/11)

ESCO 2		**ESCO 3**		
code	**label**	**code**	**label**	**ILO skill subcategory**
(1)	(2)	(3)	(4)	(5)
S02.08	monitoring, inspecting and testing	S02.08.09	inspecting food safety and quality	S00 core cognitive skills
S02.08	monitoring, inspecting and testing	S02.08.10	monitoring quality of products	S00 core cognitive skills
S02.08	monitoring, inspecting and testing	S02.08.11	testing vehicles	S13 hand-foot-eye coordination
S02.09	monitoring developments in area of expertise	S02.09.00	monitoring developments in area of expertise	S01 sophisticated cognitive skills
S03.00	assisting and caring	S03.00.00	assisting and caring	S09 social skills
S03.01	counselling	S03.01.00	counselling	S09 social skills
S03.01	counselling	S03.01.01	counselling on personal, family or social issues	S09 social skills
S03.01	counselling	S03.01.02	providing support to resolve problems	S09 social skills
S03.01	counselling	S03.01.03	assisting people to access services	S09 social skills
S03.02	providing healthcare or medical treatments	S03.02.00	providing healthcare or medical treatments	S11 customer service skills
S03.02	providing healthcare or medical treatments	S03.02.01	providing medical, dental and nursing care	S11 customer service skills
S03.02	providing healthcare or medical treatments	S03.02.02	performing surgical procedures	S11 customer service skills
S03.02	providing healthcare or medical treatments	S03.02.03	providing physical therapies	S11 customer service skills
S03.02	providing healthcare or medical treatments	S03.02.04	providing psychological and occupational therapies	S11 customer service skills
S03.02	providing healthcare or medical treatments	S03.02.05	prescribing and ordering medical tests, treatments	S11 customer service skills
S03.02	providing healthcare or medical treatments	S03.02.06	fitting assistive devices	S11 customer service skills
S03.03	protecting and enforcing	S03.03.00	protecting and enforcing	S07 project and process manag.
S03.03	protecting and enforcing	S03.03.01	complying with health and safety procedures	S07 project and process manag.
S03.03	protecting and enforcing	S03.03.02	complying with environmental protection laws	S07 project and process manag.
S03.03	protecting and enforcing	S03.03.03	complying with operational procedures	S07 project and process manag.
S03.03	protecting and enforcing	S03.03.04	verifying identities and documentation	S07 project and process manag.
S03.03	protecting and enforcing	S03.03.05	maintaining and enforcing physical security	S07 project and process manag.
S03.03	protecting and enforcing	S03.03.06	protecting privacy and personal data	S07 project and process manag.
S03.03	protecting and enforcing	S03.03.07	ensuring compliance with legislation	S07 project and process manag.
S03.04	providing information and support to public	S03.04.00	providing information and support to the public	S11 customer service skills
S03.04	providing information and support to public	S03.04.01	providing information to the public and clients	S11 customer service skills
S03.04	providing information and support to public	S03.04.02	accompanying and welcoming people	S11 customer service skills

Table OA.6: Mapping Between ESCO and our Skills Categories (Part 6/11)

ESCO 2		**ESCO 3**		
code	**label**	**code**	**label**	**ILO skill subcategory**
(1)	(2)	(3)	(4)	(5)
S03.04	providing information and support to public	S03.04.04	providing general assistance to people	S11 customer service skills
S03.05	preparing and serving food and drinks	S03.05.00	preparing and serving food and drinks	S11 customer service skills
S03.05	preparing and serving food and drinks	S03.05.01	preparing food and drinks	S11 customer service skills
S03.05	preparing and serving food and drinks	S03.05.02	serving food and drinks	S11 customer service skills
S03.06	providing general personal care	S03.06.00	providing personal care	S11 customer service skills
S03.06	providing general personal care	S03.06.01	assisting people with mobility	S11 customer service skills
S03.06	providing general personal care	S03.06.02	assisting with personal needs	S11 customer service skills
S03.06	providing general personal care	S03.06.03	caring for children	S11 customer service skills
S03.06	providing general personal care	S03.06.04	styling hair and providing beauty treatments	S11 customer service skills
S04.00	management skills	S04.00.00	management skills	S10 people management skills
S04.01	developing objectives and strategies	S04.01.00	developing objectives and strategies	S00 core cognitive skills
S04.01	developing objectives and strategies	S04.01.01	identifying opportunities	S00 core cognitive skills
S04.01	developing objectives and strategies	S04.01.02	developing financial, business or marketing plans	S05 financial skills
S04.01	developing objectives and strategies	S04.01.03	developing operational policies and procedures	S00 core cognitive skills
S04.01	developing objectives and strategies	S04.01.04	developing policies and legislation	S00 core cognitive skills
S04.01	developing objectives and strategies	S04.01.05	developing health programmes	S00 core cognitive skills
S04.01	developing objectives and strategies	S04.01.06	developing educational programmes	S00 core cognitive skills
S04.01	developing objectives and strategies	S04.01.07	developing contingency and emergency response	S07 project and process manag.
S04.02	organizing, planning and scheduling work	S04.02.00	organising, planning and scheduling work	S07 project and process manag.
S04.02	organizing, planning and scheduling work	S04.02.01	directing operational activities	S07 project and process manag.
S04.02	organizing, planning and scheduling work	S04.02.02	planning events and programmes	S07 project and process manag.
S04.02	organizing, planning and scheduling work	S04.02.03	directing, supervising and coordinating projects	S07 project and process manag.
S04.02	organizing, planning and scheduling work	S04.02.04	managing transport and logistics activities	S07 project and process manag.
S04.02	organizing, planning and scheduling work	S04.02.06	planning production processes	S07 project and process manag.

Table OA.6: Mapping Between ESCO and our Skills Categories (Part 7/11)

ESCO 2		**ESCO 3**		
code	**label**	**code**	**label**	**ILO skill subcategory**
(1)	(2)	(3)	(4)	(5)
S04.03	allocating and controlling resources	S04.03.00	allocating and controlling resources	S07 project and process manag.
S04.03	allocating and controlling resources	S04.03.01	managing budgets or finances	S05 financial skills
S04.03	allocating and controlling resources	S04.03.02	managing and administering human resources	S07 project and process manag.
S04.03	allocating and controlling resources	S04.03.04	allocating and controlling physical resources	S07 project and process manag.
S04.04	performing administrative activities	S04.04.00	performing administrative activities	S00 core cognitive skills
S04.04	performing administrative activities	S04.04.02	executing financial transactions	S05 financial skills
S04.04	performing administrative activities	S04.04.03	performing general clerical and administrative tasks	S00 core cognitive skills
S04.05	leading and motivating	S04.05.00	leading and motivating	S10 people management skills
S04.06	building and developing teams	S04.06.00	building and developing teams	S10 people management skills
S04.07	recruiting and hiring	S04.07.00	recruiting and hiring	S10 people management skills
S04.08	supervising people	S04.08.00	supervising people	S10 people management skills
S04.08	supervising people	S04.08.01	supervising a team or group	S10 people management skills
S04.08	supervising people	S04.08.02	assigning work to others	S10 people management skills
S04.08	supervising people	S04.08.03	monitoring and evaluating the performance	S10 people management skills
S04.09	making decisions	S04.09.00	making decisions	S00 core cognitive skills
S05.00	working with computers	S05.00.00	working with computers	S02 computer (general) skills
S05.01	programming computer systems	S05.01.00	programming computer systems	S03 software and technical support
S05.02	setting up and protecting computer systems	S05.02.01	setting up computer systems	S03 software and technical support
S05.02	setting up and protecting computer systems	S05.02.02	protecting ict devices	S03 software and technical support
S05.02	setting up and protecting computer systems	S05.02.03	resolving computer problems	S03 software and technical support
S05.05	accessing and analysing digital data	S05.05.00	accessing and analysing digital data	S01 sophisticated cognitive skills
S05.05	accessing and analysing digital data	S05.05.01	browsing, searching and filtering digital data	S01 sophisticated cognitive skills
S05.05	accessing and analysing digital data	S05.05.02	managing, gathering and storing digital data	S01 sophisticated cognitive skills
S05.06	using digital tools for collaboration, content	S05.06.00	using digital tools for collaboration, content creation	S02 computer (general) skills

Table OA.6: Mapping Between ESCO and our Skills Categories (Part 8/11)

ESCO 2		**ESCO 3**		
code	**label**	**code**	**label**	**ILO skill subcategory**
(1)	(2)	(3)	(4)	(5)
S05.06	using digital tools for collaboration, content	S05.06.01	using digital tools for collaboration and productivity	S02 computer (general) skills
S05.06	using digital tools for collaboration, content	S05.06.02	using word processing, publishing and presentation	S02 computer (general) skills
S05.06	using digital tools for collaboration, content	S05.06.03	using computer aided design and drawing tools	S02 computer (general) skills
S05.06	using digital tools for collaboration, content	S05.06.04	using digital tools for processing sound and images	S02 computer (general) skills
S05.07	using digital tools to control machinery	S05.07.00	using digital tools to control machinery	S12 finger-dexterity skills
S06.00	handling and moving	S06.00.00	handling and moving	S14 physical skills
S06.01	sorting and packaging goods and materials	S06.01.00	sorting and packaging goods and materials	S12 finger-dexterity skills
S06.01	sorting and packaging goods and materials	S06.01.01	sorting materials or products	S12 finger-dexterity skills
S06.01	sorting and packaging goods and materials	S06.01.02	marking materials or objects for identification	S12 finger-dexterity skills
S06.01	sorting and packaging goods and materials	S06.01.03	packaging objects	S12 finger-dexterity skills
S06.02	moving and lifting	S06.02.00	moving and lifting	S14 physical skills
S06.02	moving and lifting	S06.02.01	loading and unloading goods and, materials	S14 physical skills
S06.02	moving and lifting	S06.02.02	moving or lifting materials, equipment, or supplies	S14 physical skills
S06.02	moving and lifting	S06.02.03	storing goods and materials	S14 physical skills
S06.02	moving and lifting	S06.02.04	positioning materials, tools or equipment	S14 physical skills
S06.03	transforming and blending materials	S06.03.00	transforming and blending materials	S12 finger-dexterity skills
S06.03	transforming and blending materials	S06.03.01	preparing mixtures or solutions	S12 finger-dexterity skills
S06.03	transforming and blending materials	S06.03.03	preparing industrial materials for processing or use	S12 finger-dexterity skills
S06.03	transforming and blending materials	S06.03.06	collecting and preparing specimens or materials	S12 finger-dexterity skills
S06.04	tending plants and crops	S06.04.00	tending plants and crops	S13 hand-foot-eye coordination
S06.04	tending plants and crops	S06.04.01	cultivating land and crops	S13 hand-foot-eye coordination
S06.04	tending plants and crops	S06.04.02	planting, pruning and harvesting trees, crops	S13 hand-foot-eye coordination
S06.05	assembling and fabricating products	S06.05.00	assembling and fabricating products	S12 finger-dexterity skills
S06.05	assembling and fabricating products	S06.05.01	fabricating precision instruments or jewellery	S12 finger-dexterity skills
S06.05	assembling and fabricating products	S06.05.02	fabricating medical and prosthetic devices	S12 finger-dexterity skills
S06.05	assembling and fabricating products	S06.05.03	assembling electrical and electronic products	S12 finger-dexterity skills

Table OA.6: Mapping Between ESCO and our Skills Categories (Part 9/11)

ESCO 2		**ESCO 3**		
code	**label**	**code**	**label**	**ILO skill subcategory**
(1)	(2)	(3)	(4)	(5)
S06.05	assembling and fabricating products	S06.05.04	assembling mechanical products	S12 finger-dexterity skills
S06.05	assembling and fabricating products	S06.05.05	assembling furniture	S12 finger-dexterity skills
S06.05	assembling and fabricating products	S06.05.06	fabricating garments and textile products	S12 finger-dexterity skills
S06.05	assembling and fabricating products	S06.05.07	fabricating food and related products	S12 finger-dexterity skills
S06.05	assembling and fabricating products	S06.05.08	fabricating tobacco products	S12 finger-dexterity skills
S06.06	making moulds, casts, models and patterns	S06.06.01	making production moulds and casts	S12 finger-dexterity skills
S06.06	making moulds, casts, models and patterns	S06.06.02	making patterns and templates	S12 finger-dexterity skills
S06.06	making moulds, casts, models and patterns	S06.06.03	making models	S12 finger-dexterity skills
S06.07	using hand tools	S06.07.00	using hand tools	S12 finger-dexterity skills
S06.07	using hand tools	S06.07.01	cutting materials and drilling holes	S12 finger-dexterity skills
S06.07	using hand tools	S06.07.02	shaping materials to create products	S12 finger-dexterity skills
S06.07	using hand tools	S06.07.03	smoothing surfaces of objects or equipment	S12 finger-dexterity skills
S06.07	using hand tools	S06.07.04	using precision hand tools	S12 finger-dexterity skills
S06.07	using hand tools	S06.07.05	hammering, nailing and riveting	S12 finger-dexterity skills
S06.09	handling animals	S06.09.00	handling animals	S13 hand-foot-eye coordination
S06.09	handling animals	S06.09.01	tending and breeding animals	S13 hand-foot-eye coordination
S06.09	handling animals	S06.09.02	tending and breeding aquatic animals	S13 hand-foot-eye coordination
S06.09	handling animals	S06.09.03	moving and herding animals	S13 hand-foot-eye coordination
S06.09	handling animals	S06.09.04	hunting, trapping and slaughtering animals	S13 hand-foot-eye coordination
S06.09	handling animals	S06.09.05	feeding and grooming animals	S13 hand-foot-eye coordination
S06.09	handling animals	S06.09.06	training animals	S13 hand-foot-eye coordination
S06.09	handling animals	S06.09.07	providing therapy or veterinary treatment	S13 hand-foot-eye coordination
S06.11	cleaning	S06.11.00	cleaning	S13 hand-foot-eye coordination
S06.11	cleaning	S06.11.01	cleaning tools, equipment, workpieces and vehicles	S13 hand-foot-eye coordination
S06.11	cleaning	S06.11.02	cleaning interior and exterior of buildings	S13 hand-foot-eye coordination
S06.11	cleaning	S06.11.03	cleaning outdoor spaces	S13 hand-foot-eye coordination
S06.12	washing and maintaining textiles and clothing	S06.12.00	washing and maintaining textiles and clothing	S13 hand-foot-eye coordination
S06.13	handling and disposing of waste	S06.13.00	handling and disposing of hazardous materials	S13 hand-foot-eye coordination

Table OA.6: Mapping Between ESCO and our Skills Categories (Part 10/11)

ESCO 2		**ESCO 3**		
code	**label**	**code**	**label**	**ILO skill subcategory**
(1)	(2)	(3)	(4)	(5)
S06.13	handling and disposing of waste	S06.13.01	handling and disposing of waste and hazardous	S13 hand-foot-eye coordination
S06.13	handling and disposing of waste	S06.13.02	disposing of non-hazardous waste or debris	S13 hand-foot-eye coordination
S07.00	constructing	S07.00.00	constructing	S14 physical skills
S07.01	building and repairing structures	S07.01.00	building and repairing structures	S13 hand-foot-eye coordination
S07.01	building and repairing structures	S07.01.01	installing structural masonry materials	S13 hand-foot-eye coordination
S07.01	building and repairing structures	S07.01.02	installing wooden and metal components	S13 hand-foot-eye coordination
S07.01	building and repairing structures	S07.01.04	installing concrete components	S13 hand-foot-eye coordination
S07.01	building and repairing structures	S07.01.05	installing roofing	S13 hand-foot-eye coordination
S07.01	building and repairing structures	S07.01.06	joining parts using soldering, welding or brazing	S12 finger-dexterity skills
S07.01	building and repairing structures	S07.01.07	installing and assembling building fixtures	S13 hand-foot-eye coordination
S07.01	building and repairing structures	S07.01.08	installing and assembling rigging equipment	S13 hand-foot-eye coordination
S07.02	installing interior or exterior infrastructure	S07.02.00	installing interior or exterior infrastructure	S13 hand-foot-eye coordination
S07.02	installing interior or exterior infrastructure	S07.02.01	installing heating, ventilation and air conditioning	S13 hand-foot-eye coordination
S07.02	installing interior or exterior infrastructure	S07.02.02	installing plumbing or piping equipment or systems	S13 hand-foot-eye coordination
S07.02	installing interior or exterior infrastructure	S07.02.03	installing insulation materials	S13 hand-foot-eye coordination
S07.03	finishing interior or exterior of structures	S07.03.00	finishing interior or exterior of structures	S13 hand-foot-eye coordination
S07.03	finishing interior or exterior of structures	S07.03.01	applying material to fill gaps in surfaces	S13 hand-foot-eye coordination
S07.03	finishing interior or exterior of structures	S07.03.02	appyling textured or masonry coatings	S13 hand-foot-eye coordination
S07.03	finishing interior or exterior of structures	S07.03.03	applying protective or decorative solutions	S13 hand-foot-eye coordination
S07.03	finishing interior or exterior of structures	S07.03.04	installing floor and wall coverings	S13 hand-foot-eye coordination
S08.00	working with machinery and specialized equip.	S08.00.00	working with machinery and specialized equipment	S12 finger-dexterity skills
S08.01	operating mobile plant	S08.01.00	operating mobile plant	S13 hand-foot-eye coordination
S08.01	operating mobile plant	S08.01.01	operating earthmoving equipment	S13 hand-foot-eye coordination
S08.01	operating mobile plant	S08.01.02	operating agricultural or forestry equipment	S13 hand-foot-eye coordination
S08.01	operating mobile plant	S08.01.03	operating lifting or moving equipment	S13 hand-foot-eye coordination
S08.02	driving vehicles	S08.02.00	driving vehicles	S13 hand-foot-eye coordination
S08.02	driving vehicles	S08.02.01	driving heavy vehicles	S13 hand-foot-eye coordination
S08.02	driving vehicles	S08.02.02	driving light vehicles	S13 hand-foot-eye coordination
S08.02	driving vehicles	S08.02.03	operating rail vehicles	S13 hand-foot-eye coordination

Table OA.6: Mapping Between ESCO and our Skills Categories (Part 11/11)

ESCO 2		**ESCO 3**		
code	**label**	**code**	**label**	**ILO skill subcategory**
(1)	(2)	(3)	(4)	(5)
S08.03	operating watercraft	S08.03.00	operating watercraft	S13 hand-foot-eye coordination
S08.04	operating machinery for the extraction	S08.04.00	operating machinery for the extraction	S12 finger-dexterity skills
S08.04	operating machinery for the extraction	S08.04.01	operating mining, drilling and mineral processing	S12 finger-dexterity skills
S08.04	operating machinery for the extraction	S08.04.02	operating metal processing and finishing machinery	S12 finger-dexterity skills
S08.04	operating machinery for the extraction	S08.04.03	operating pumping systems or equipment	S12 finger-dexterity skills
S08.04	operating machinery for the extraction	S08.04.04	operating energy production or distribution equip.	S12 finger-dexterity skills
S08.04	operating machinery for the extraction	S08.04.05	operating petroleum, chemical or water processing	S12 finger-dexterity skills
S08.04	operating machinery for the extraction	S08.04.06	operating wood processing and papermaking	S12 finger-dexterity skills
S08.04	operating machinery for the extraction	S08.04.07	operating kilns, furnaces and drying equipment	S12 finger-dexterity skills
S08.05	operating machinery for the manufacture	S08.05.00	operating machinery for the manufacture	S12 finger-dexterity skills
S08.05	operating machinery for the manufacture	S08.05.01	operating painting or coating machinery	S12 finger-dexterity skills
S08.05	operating machinery for the manufacture	S08.05.02	operating packaging machinery	S12 finger-dexterity skills
S08.05	operating machinery for the manufacture	S08.05.03	operating machinery for the manufacture	S12 finger-dexterity skills
S08.05	operating machinery for the manufacture	S08.05.04	operating food processing machinery	S12 finger-dexterity skills
S08.05	operating machinery for the manufacture	S08.05.05	operating mixing and separating machinery	S12 finger-dexterity skills
S08.05	operating machinery for the manufacture	S08.05.06	operating print and photographic production equip.	S12 finger-dexterity skills
S08.05	operating machinery for the manufacture	S08.05.07	operating metal, plastic or rubber forming equip.	S12 finger-dexterity skills
S08.05	operating machinery for the manufacture	S08.05.08	operating cutting, grinding and smoothing	S12 finger-dexterity skills
S08.06	using precision instrumentation and equip.	S08.06.00	using precision instrumentation and equipment	S12 finger-dexterity skills
S08.06	using precision instrumentation and equip.	S08.06.01	operating medical equipment	S12 finger-dexterity skills
S08.06	using precision instrumentation and equip.	S08.06.02	operating audiovisual equipment	S12 finger-dexterity skills
S08.06	using precision instrumentation and equip.	S08.06.03	operating scientific and laboratory equipment	S12 finger-dexterity skills
S08.06	using precision instrumentation and equip.	S08.06.04	operating communications equipment	S12 finger-dexterity skills
S08.06	using precision instrumentation and equip.	S08.06.05	operating precision industrial equipment	S12 finger-dexterity skills
S08.06	using precision instrumentation and equip.	S08.06.06	using precision measuring equipment	S12 finger-dexterity skills
S08.07	installing, maintaining and repairing mechan.	S08.07.00	installing, maintaining and repairing mechanical	S12 finger-dexterity skills
S08.07	installing, maintaining and repairing mechan.	S08.07.01	repairing and installing mechanical equipment	S12 finger-dexterity skills
S08.07	installing, maintaining and repairing mechan.	S08.07.02	maintaining mechanical equipment and tools	S12 finger-dexterity skills
S08.07	installing, maintaining and repairing mechan.	S08.07.03	maintaining mechanical machinery	S12 finger-dexterity skills
S08.08	installing, maintaining and repairing electr.	S08.08.00	installing, maintaining and repairing electrical	S12 finger-dexterity skills
S08.08	installing, maintaining and repairing electr.	S08.08.01	installing and repairing electrical, electronic	S12 finger-dexterity skills
S08.08	installing, maintaining and repairing electr.	S08.08.02	maintaining electrical, electronic and precision	S12 finger-dexterity skills
S08.09	operating aircraft	S08.09.00	operating aircraft	S13 hand-foot-eye coordination