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Bridging Skill Gaps for the Future: New Jobs Creation in the AI Age

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Prepared by Florence Jaumotte, Jaden Kim, David Koll, Elmer Z. Li, Longji Li, Giovanni Melina, Alina Song, and Marina M. Tavares*

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ABSTRACT: The demand and supply of new skills—especially in IT and AI—are reshaping labor markets, impacting wages and hiring. About 1 in 10 job vacancies in advanced economies demands at least one new skill, often appearing first in the United States. The incidence is about half of that in emerging market economies. These skills boost average wages and employment but deepen polarization, mostly benefitting high- and—through higher consumption of services—low-skilled workers, and potentially contributing to the shrinking of the middle class. Vacancies demanding AI skills post higher wages, but the diffusion of such skills is linked to lower employment in occupations with high exposure and low complementarity to AI, posing challenges for the youth. A Skill Imbalance Index reveals wide cross-country differences. Economies facing strong demand should prioritize education and reskilling, while those facing strong supply should foster firms' absorption through innovation and access to credit.

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Executive Summary

Labor markets are undergoing a fast transformation as new skills emerge and spread. Although barely present in the early 2010s, these new skills have grown substantially since. In data provided by Lightcast, roughly 1 in 10 job postings requires at least one new skill in advanced economies, and the incidence is about half of that for emerging market economies. New skills appear first in the labor demand of advanced economies—particularly the United States—and then spread to other countries. Demand is concentrated in professional, technical, and managerial occupations. Information technology (IT) skills account for more than half of new skills, with a growing share linked to artificial intelligence (AI), reflecting the general-purpose character of these technologies. Sector-specific skills, such as in health care, are also gaining ground. The analysis distinguishes between all new skills and AI-related new skills, which show important differences.

When considering all new skills, the increase in their demand benefits wages and employment. At the job-posting level, new skills are associated with 3–3.4 percent higher wage offers in the United States and the United Kingdom. In US local labor markets, an increase of 1 percentage point in the share of job postings with new skills is associated with an average wage gain of 2.3 percent and an employment gain of 1.3 percent. German local labor markets experience insignificant employment impacts, but still a sizeable wage gain of 0.9 percent. Both high- and—through higher consumption of services—low-skilled workers capture the largest benefits, with no significant benefits for middle-skilled workers, reinforcing job polarization and potentially contributing to the shrinking of the middle class. Cross-country evidence also shows that the incorporation of new tasks (another proxy for new skills) is associated with higher wages globally.

In contrast, focusing on new AI-related skills only, greater demand for these skills is linked to no gains in overall employment and to lower employment for some groups of workers. Although vacancies demanding new AI-related skills post higher wages, they have so far not boosted overall employment in US local labor markets. Further, the empirical analysis shows that—for occupations that are highly exposed to AI, but with limited scope for complementarity—employment levels are 3.6 percent lower in regions with greater demand for AI-related skills than in other regions five years after the appearance of these skills. This poses challenges for white-collar middle-skilled jobs, young workers, and some categories of IT specialists.

Countries' economic structure significantly dictates their demand for new skills. Economies with high shares of employment in professional, technical, and managerial occupations are likely to experience higher demand for new skills. In addition, young, innovative, and less financially constrained firms are found to be a driving source of demand for such new skills. Securing scarce expertise can spur talent-driven mergers and acquisitions ("acquire-hire"), potentially raising concerns about market concentration and skill diffusion.

Countries also differ widely in their ability to supply new skills. The supply of new skills draws heavily on workers with tertiary education, particularly in STEM (science, technology, engineering, and mathematics) and IT fields. Yet IT skills are found across all fields of study. A Skill Readiness Index is developed by combining the share of recent graduates able to supply new IT and non-IT skills, indicators of retraining frequency, and workforce literacy and numeracy scores.

Policy priorities differ across countries depending on their relative demand and supply of new skills as captured by a new Skill Imbalance Index. In economies where demand for new skills is high, but domestic supply remains relatively more constrained, the priority is to expand worker training opportunities, integrate IT training across all fields of study, favor labor mobility across regions, and strengthen STEM education. In contrast, countries in which domestic supply capacity is strong relative to demand should focus on stimulating innovation and improving access to finance so that firms absorb and deploy these skills. The IMF AI Preparedness Index can guide policymakers on which policy area to focus their efforts.

The diffusion of new skills requires facilitating workers' movement across occupations and regions. Active labor market policies and affordable housing can help accelerate this process. Collaboration between firms and unions to foster workers' adjustment to new technologies, and competition policies limiting non-compete agreements that may slow the spread of talent are equally important.

I. Introduction

Technological change, aging, and the energy transition continue to reshape global labor markets. Advances in automation, digitalization, and artificial intelligence (AI) are not only replacing humans in the execution of some tasks but also creating demand for new skills that were uncommon or nonexistent a decade ago such as using cloud computing platforms, visualizing data, or handling and analyzing large data sets. These emerging skills—ranging from advanced information technology (IT) to new business, social, administrative, and health care fields—are transforming occupations, the composition of employment, and the level and distribution of wages. Understanding where and how these skills are spreading, and whether workers and firms can adapt to these trends, is critical for sustaining growth as well as for ensuring that the benefits of technological progress are broadly shared and the preferences and needs of changing societies are met.

A key question is how new skills affect employment and wages. History shows that new technologies do not increase aggregate unemployment in the long term. Yet they change the structure of employment, and shifts in demand for certain skills can benefit the employment and wage prospects of some groups and harm others. The demand for new skills in an occupation or sector could lead to growing employment and wages in that occupation or sector. In addition, when sectors demanding new skills expand, they can generate income and spillover effects that lift employment and wages in complementary, often lower-skill services. However, the overall impact depends on two aspects. The first is productivity dynamics. If new skills enable strong productivity gains through automation and labor replacement, employment in high-productivity sectors may decrease even if output rises, pushing workers toward slower-growing sectors such as low-skill services. This pattern—known as the Baumol effect—was seen historically in agriculture and manufacturing. It could be at play this time again, as many occupations in the IT sector including software developers and web designers perform tasks that can be executed more productively by AI. The second aspect is how sensitive consumer demand is to price changes. To take another example, if AI boosts the productivity of judges and lawyers, employment in judicial services could still grow if lower fees encourage greater use of legal services.

Past waves of automation highlight how difficult it is for workers, firms, and policymakers to anticipate and adapt to technological change. Automation and digitalization have repeatedly displaced routine jobs and contributed to job polarization, often in ways that were only fully recognized after the fact, as seen with the adoption of industrial robots and the information technology revolution. Workers in middle-skill occupations were particularly affected, with limited opportunities to transition into new high-paying jobs because of skill, sectoral, and geographic mismatches. These experiences underscore that technological change rarely unfolds smoothly: adjustment costs can be large, benefits unevenly distributed, and policy responses often lag behind. Distributional outcomes may also depend as much on market structures—such as firms' market power and the strength of labor institutions—as on the technologies themselves. Like previous waves of technological change, AI could bring disruptions and opportunities. Different from previous waves, it could have a much broader reach, affecting even occupations that were previously shielded from technological change, such as white-collar and high-skill jobs. Concerns are also that it could unfold more rapidly than previous waves of technological change. At the individual level, AI adoption has been extremely rapid: ChatGPT, for instance, reached around 100 million users in roughly two months, far outpacing the user-adoption speed of earlier digital innovations such as Facebook or the Internet. Yet, significant uncertainty remains about adoption at the firm level and its implications for productivity and jobs.[1] Speed is a concern because disruptions are more pronounced when change occurs over shorter horizons, while slower transformations that occur over the course of a working generation can more easily be absorbed through the turnover of the labor force.

[1] See Chatterji and others (2025).

Facing this challenge requires action on two fronts. Workers must be prepared to acquire and update the skills needed to succeed in rapidly changing labor markets. At the same time, firms must be able to access the talent required to deploy new technologies, foster innovation, and translate skill adoption into productivity gains. Policies that strengthen both sides of this market—supporting worker training and ensuring that firms can find and retain the skills they need—will determine whether the rise of new skills becomes a source of inclusive growth or a driver of widening gaps.

This Staff Discussion Note documents the rise in the demand for new skills and assesses its implications for labor markets. Technological change works through the labor demand side: as technology creates new tasks, existing occupations—characterized by a set of tasks—evolve or new occupations emerge. These new tasks or occupations in turn require certain skills from workers. The demand for new skills is the focus of the analysis in this note. Four questions guide the analysis. First, what type of new skills are employers demanding? Second, do new skills carry a wage premium, and how are they affecting wages and employment economywide? Which groups of workers—by education level, field of study, and occupation—are benefiting the most? Third, which firms are driving the demand for new skills? Finally, how well prepared are different countries to meet this rising demand, and what policies can help close the gap between demand and supply?

The analysis draws on a novel combination of cross-country data sources. At its core is the Lightcast vacancy data set. This data provider tracks millions of online job postings, providing a very large sample of the universe of vacancies. The countries analyzed represent a mix of advanced and emerging market economies: Brazil, Denmark, Germany, South Africa, the United Kingdom, and the United States. The demand for new skills from the Lightcast data is combined with data from the American Community Survey and from the German administrative labor market records (Sample of Integrated Labour Market Biographies) to estimate wage and employment effects of new skill demand at the local labor market level. The US vacancy data are also merged with US firm-level information available in the Compustat database. This approach enables the identification of key firm characteristics—such as size, age, market share, productivity, and innovation activity—associated with the demand for new skills. Next, the analysis relies on millions of worker profiles provided by Lightcast to analyze skill supply and to determine which types of workers possess new skills. Finally, the Lightcast data are complemented with employment and education statistics from the International Labour Organization (ILO) and the Organisation for Economic Co-operation and Development (OECD) to project potential new skills demand and supply for a wide range of countries, and to construct a Skill Readiness Index that captures the capacity of different economies to train workers to meet new skills demand.

Several limitations warrant caution in interpreting the results. Because Lightcast relies on online job postings, the data provide a detailed picture of skill demand in the formal economy but naturally overrepresent professional, technical, and higher-skill occupations. This bias is more significant in emerging markets, where large shares of employment remain informal or concentrated in agriculture and therefore are not fully captured in online vacancy postings. Coverage also varies across countries—for example, while for the United States postings start in 2010, for Brazil and South Africa they begin only in 2020—limiting the historical perspective. These caveats imply that the results speak most directly to the formal segments of labor markets, particularly in emerging market economies. In addition, in countries where firms rely heavily on internal labor markets—characterized by long tenure systems and internal training pipelines—vacancy data may understate new skill demand, potentially making it appear low even when technology adoption is high.

This note contributes to a growing literature on technological change and labor markets by shifting the focus from task automation and destruction to skill creation and diffusion. Earlier research has emphasized how automation displaces routine tasks and polarizes employment—with middle-skill routine occupations shrinking and workers reallocated toward non-routine services at lower pay (Autor, Levy, and Murnane 2003; Goos and Manning 2007; Autor and Dorn 2013; Acemoglu and Restrepo 2020). Recent research highlights how technological change generates both new tasks and entirely new occupations, which have played a key role in maintaining employment growth despite automation pressures (Acemoglu and Autor 2011; Autor 2015; Atalay and others 2018; Autor and others 2024). Yet little work has been conducted analyzing how new skills emerge and spread, what impact they have, and what policy implications follow, particularly in a global context with vacancy data. This note provides the first cross-country measurement of new skills using real-time vacancy data and links skill emergence to wages, employment, and firm dynamics. Unlike most existing studies, which focus on the United States, the analysis covers a set of advanced and emerging market economies.

In addition, the note contributes to the literature on AI and labor markets. A large body of this literature adopts a task-based approach to assess how occupations are exposed to AI or may benefit from productivity gains (Webb 2020; Felten and others 2021, 2023; Pizzinelli and others 2023; Cazzaniga and others 2024; Eloundou and others 2024; Korinek 2024; Korinek and Stiglitz 2025; Rockall and others 2025; Handa and others 2025), and a recent literature has started quantifying the impact of AI on labor markets in the United States (Pizzinelli and others 2023; Huang 2024; Brynjolfsson, Chandar, and Chen 2025; Hosseini and Lichtinger 2025; Liu and others 2025). Although most empirical evidence focuses on advanced economies, particularly the United States, recent cross-country studies highlight significant heterogeneity in AI's labor market effects across regions and demographic groups (OECD 2023; Briggs and Kodnani 2023; Gmyrek, Berg, and Bescond 2023; Albanesi and others 2024; Dorville and others, forthcoming), as well as in its macroeconomic effects (Korinek and Juelfs 2023; Brollo and others 2024; Berg and others 2025; Cerutti and others 2025). The contribution of this note is twofold: it examines both demand and supply for AI skills, and it provides early evidence on local labor-market adjustment, exploiting differences in the timing of AI-skill diffusion across commuting zones.

The remainder of the note proceeds as follows. Section II documents current labor market trends and the demand for new skills. Section III analyzes the wage and employment implications of new skill adoption. Section IV examines the new skills demand and supply and presents a new Skill Imbalance Index and Skill Readiness Index for a wide range of countries. Finally, Section V concludes.

II. A Dynamic Labor Market

II.1 Increasing and Shrinking Occupations

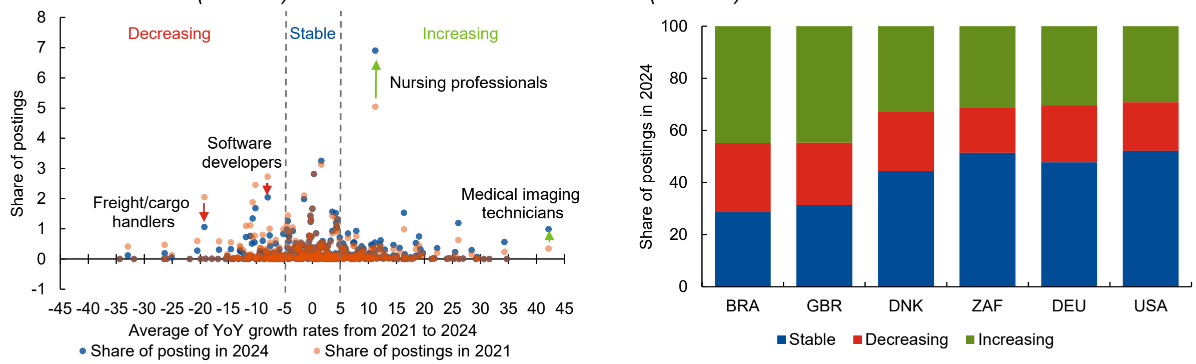
The labor market is dynamic, with some occupations rapidly expanding while others are in decline (Figure 1, panel 1). To shed light on these dynamics, this note leverages online vacancy data from Lightcast, which covers a broad set of countries. Vacancies from 2021 to 2024 are used to categorize occupations for each country as increasing, stable, or decreasing, based on whether the share of vacancies in a particular occupation rose or fell by more than 5 percent. A clear pattern emerges: increasing vacancies are concentrated in professional occupations—most notably in health care, reflecting societal preferences and population aging, and in areas such as engineering, legal services, and data analysis. By contrast, decreasing vacancies are concentrated in nonprofessional and routine-intensive occupations, such as freight handlers and drivers, which are highly vulnerable to the latest wave of automation. Still, some professional occupations are also in decline, most prominently software developers, whose tasks are increasingly automated by AI tools.

Cross-country comparisons reveal important differences in labor market dynamism (Figure 1, panel 2). Among the six countries analyzed, Brazil and the United Kingdom—with higher shares of decreasing and increasing occupations—display larger changes in the composition of labor demand, while Denmark and the United States exhibit greater stability. Germany and South Africa are somewhere in the middle. Despite these differences, the share of declining occupations remains relatively comparable at about 10 percent across countries. In contrast, the share of expanding occupations varies more widely, from about 10 to 20 percent, while stable occupations range between 30 and 60 percent.[2]

Figure 1. A Dynamic Labor Market

1. Dynamics of Vacancies by Occupation in the United States 2021–24 *(Percent)*

2. Share of Vacancies by Occupation Categories in 2024 *(Percent)*



Sources: Lightcast; and IMF staff calculations.
Note: Panel 1 shows the share of Lightcast's vacancies by 4-digit ISCO-08 occupation in the United States, along with the average year-over-year (YoY) growth rate of the posting share by occupation from 2021 to 2024. The two vertical lines (at –5% and +5%) define the three occupation groups estimated using 4-digit ISCO-08 occupations. Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2).

II.2 New Skills Demand

Jobs evolve not only because workers move across occupations but also because the skills required within the same occupation change over time. To capture changes in skills demanded across occupations and time, this section leverages information on skills demanded by firms and listed in job postings and focuses on the emergence of "new skills." In the Lightcast taxonomy, skills are defined as abilities, knowledge, and expertise needed to perform tasks effectively. New skills are defined as those that were barely present in vacancies at the start of the 2010s but have since become more common. Following the approach in Atalay and others (2020), a skill is classified as "new" if less than 1 percent of job postings that list this skill from 2010 to 2024 in the United States are posted in 2010–11, and its "year of emergence" is marked as the first year when it rises above the 1 percent threshold.[3] While the identification of new skills relies on the US data owing to its longer historical coverage, robustness checks using simpler country-specific definitions of new skills yield a similar distribution of these skills across occupations (see Annex Figure 1.2). Some skills may have originated in other countries before diffusing to the United States, as discussed in Section II.3.

The skill universe is large—with more than 30,000 distinct skills—reflecting the many-to-many mapping between tasks and skills: a single task may require multiple skills, and different skills (for example, alternative software tools) can be used to accomplish the same task. In recent data, broadly applicable skills such as communication, customer service, and management appear most frequently across job postings, while many skills remain specific to occupations. For example, a data analyst posting typically combines general skills (communication, problem-solving) with occupation-specific skills (SQL, Python) and, more recently, new skills such as Power BI (data visualization tool) and Tableau (data exploration tool) (Table 1).

[2] At first glance, the greater stability in the United States seems inconsistent with its dynamic labor market. However, Figure 1 captures only broad occupational shifts, not finer movements across jobs, regions, tasks, or skills.
[3] The analysis accounts for differences in the number of job postings over time by using the share of postings listing the respective skill within each year to construct the cumulative distribution of skill appearance over time and determine the year of emergence. New skills need to appear in at least 100 job postings in the United States to be included in the analysis.

Roughly 1 in 10 vacancies lists a new skill in advanced economies, demonstrating their macroeconomic importance (Figure 2, panel 1).[4] In emerging market economies, the share is closer to 1 in 20.[5] Much of this gap reflects differences in economic structure. New skills are closely tied to labor market dynamism, appearing more often in occupations that are expanding and rarely in those that are declining (Figure 2, panel 2). Across countries, a 1 percent increase in the number of new skills mentioned in postings within a given occupation is associated with about a 0.4 percentage point higher probability that the occupation is in the "increasing" group. Conversely, occupations with declining employment are much less likely to be associated with new skills. At the same time, the growth of new skills within occupations is also linked to greater demand for labor overall: a 1 percent increase in new skills demanded is associated with roughly a 0.1 percentage point increase in the average annual growth rate of vacancies. These findings underscore that demand for new skills is generally a marker of occupational growth.

Table 1: Examples of Occupations, Job Titles, and Skills Derived from Job Postings Data

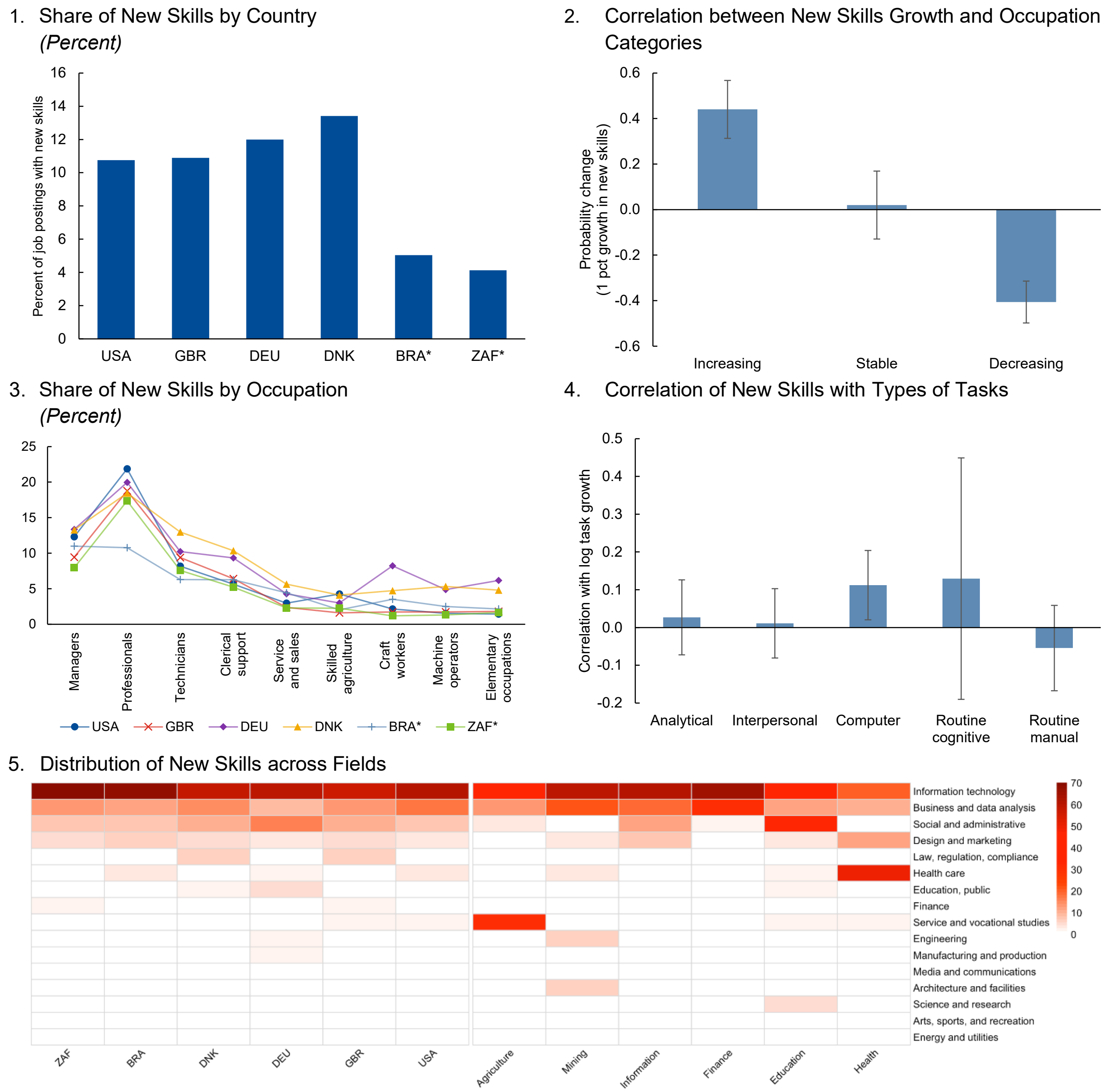
Occupation	2512 Software Developers		3251 Dental Assistants and Therapists	3314 Statistical, Mathematical, and Related Associate Professionals	5230 Cashiers and Ticket Clerks
Job Titles	Software Engineers	Data Engineers	Dental Hygienists	Data Analysts	Cashiers
Skills	Software Engineering	Data Engineering	Dental Hygiene	Data Analysis	Customer Service
	Software Development	SQL	Dentistry	SQL	Sales
	Computer Science	Python	Dental Health	Communication	Cash Register
	Agile Methodology	Extract Transform Load	Preventive Care	Python	Communication
	Python	**Data Pipelines***	Virtual Training	**Power BI***	Point of Sale
	Communication	Computer Science	CPR Certification	**Tableau***	Merchandising
	Java	Data Warehousing	Lifting Ability	Dashboard	Management
	Amazon Web Services*	**Amazon Web Services***	**Velscope***	Computer Science	General Mathematics
	JavaScript	Data Modeling	Periodontology	Problem Solving	Restaurant Operation
	SQL	Communication	Medical History Documentation	Data Visualization	Greeting Customers

Source: Lightcast; and IMF staff calculations.
Note: The table lists the top 10 skills in 2024 for four selected occupations (ISCO-08, 4-digit level) and job titles in the United States, ranked by their appearance in the number of job postings. New skills are highlighted as bolded red and have an asterisk (*). CPR = cardiopulmonary resuscitation; SQL = Structured Query Language.

New skills appear across a wide range of occupations but are particularly concentrated in managerial, technical, and professional ones (Figure 2, panel 3). Most are IT-related, partly reflecting the inherently rapid pace of technological innovation in this field, which leads to continuous updating of software, tools, and digital platforms and thus a greater "skill churn" than in other domains (Figure 2, panel 5). However other factors like the pandemic and hybrid work have also accelerated the demand of new IT skills (Jaumotte and others 2023). AI-related skills have been gaining prominence in recent years and now account for nearly one-third of all new IT skills. Among the most striking examples is generative AI, which recorded the largest absolute increase in demand in 2024 across all four advanced economies in the sample (see Annex Table 1.3 for the top growing new skills by country in 2024). Yet not all emerging skills are IT-related: postings also point to rising demand for business and data analysis, social and administrative skills such as social media marketing and management, and new health care skills related to remote-care.[6]

[4] Looking at historical data, Autor and others (2024) find that 60 percent of employment in 2018 is in occupations that did not exist in 1940, confirming the macroeconomic relevance of new skill and occupation creation.
[5] To mitigate the vacancy bias in Brazil and South Africa, the occupational shares of postings are reweighted to match proportionally each country's employment structure. Annex I provides details on data construction, harmonization, and the reweighting procedure.
[6] Skills groups are derived from the Lightcast Taxonomy. A detailed explanation can be found in Annex I.

Figure 2. New Skills



Sources: Lightcast; and IMF staff calculations.

Note: Panel 1 shows the share of new skills in job postings across countries (percent). Panel 2 plots the correlation between new skill growth and occupation categories. Estimates come from three separate regressions of new skill growth on the three occupation category identifiers. Panel 3 reports the share of new skills by occupation group (percent). Lines connect occupations across countries (USA, GBR, DEU, DNK, BRA, ZAF). Panel 4 uses keyword-based classification of job postings (Braxton and 2023; Deming and Kahn 2018) to tasks. Each job posting may contain multiple task categories, which are defined by keywords as follows: analytical (research, analyze, decision-making, math, statistics, thinking); interpersonal (communication, teamwork, negotiation, presentation); computer (all software skills); routine cognitive (bookkeeping, calculating, measuring); routine manual (operating, controlling equipment). Panel 5, on the left side, plots the distribution of new skills across broad fields using a heatmap, where each cell presents the proportion of posted new skills in that field compared to the total number of new skills posted across all fields. The fields are based on the Lightcast skill taxonomy. For details on the taxonomy, see Annex I.4. On the right, the panel plots the distribution of new skills across fields for selected sectors in the United States. Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2).

* The shares for Brazil (BRA) and South Africa (ZAF) in panel 1 and 3 are adjusted by summing over the share of new skills at the 2-digit ISCO occupation weighted with the respective occupation's employment share from the International Labour Organization (see Annex I.5).

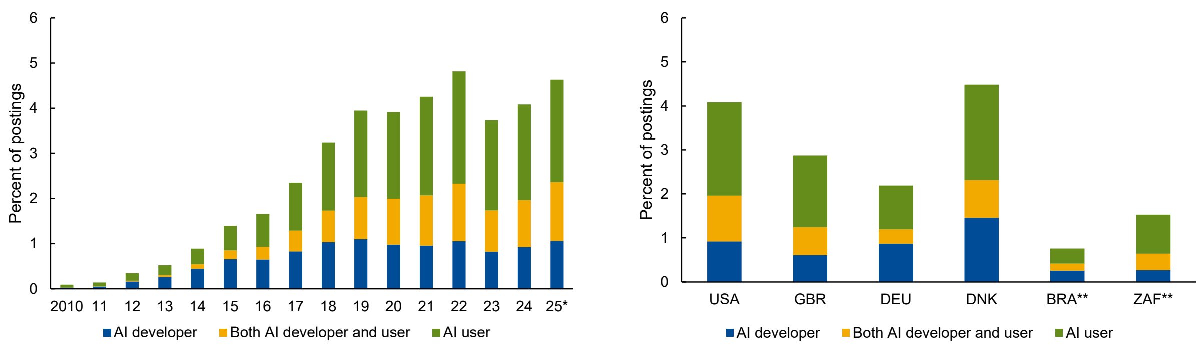
New skills are more closely associated with computer and routine cognitive-related tasks than with interpersonal, routine, or manual tasks (Figure 2, panel 4). This pattern—unveiled using a keyword-based classification of vacancies (Deming and Kahn 2018; Braxton and Taska 2023)—reflects the IT-intensive nature of most emerging skills. New skills are strongly linked to job postings that require software and computer tasks, underscoring their role in driving the technology frontier. By contrast, vacancies relying heavily on routine or manual tasks show less new skill demand, suggesting that innovation is less pronounced in these areas.

New skills are also widespread across all economic sectors (Figure 2, panel 5). Data from the United States—the only country with detailed sectoral information in the vacancy data sample—show that every sector demands new skills, particularly IT-related skills, reflecting the general-purpose character of the technology. At the same time, many emerging skills are sector specific. For example, telecare is becoming a highly demanded new skill in the health sector, while social media management and knowledge of apps such as TikTok and Instagram are becoming highly demanded skills in sales and marketing. Additionally, new skills related to the energy transition such as climate engineering, circular economy, and climate resilience, are also appearing, yet many of the key skills related to the energy transition were already present before 2010–11.

Figure 3. AI-Related New Skills

1. The Share of AI-related New Skills in the United States *(Percent of total job postings)*

2. The Share of AI-Related New Skills in 2024 *(Percent of total job postings)*



Sources: Lightcast; and IMF staff calculations.
Note: The figure presents the trend of the share for the United States (panel 1) and the 2024 share for six countries (panel 2) of job postings in the Lightcast database that require AI-related skills. AI-related skills are identified using an AI-based text classification method. Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2).
*The coverage for 2025 in panel 1 is limited to the period from January to June.
**The shares for Brazil (BRA) and South Africa (ZAF) in panel 2 are adjusted by summing over the share of AI-related new skills at the 2-digit ISCO occupation weighted with the occupation's employment share (see Annex I.5).

New AI-related skills have become a significant component of emerging skills in recent years. This trend is especially noteworthy considering that previous analysis has established that 40 percent of global employment is potentially exposed to AI, albeit with notable differences across countries (Cazzaniga and others 2024). Although in advanced economies this share rises to 60 percent, in emerging markets it remains at 40 percent, and in low-income countries it stands at 28 percent. In the United States—the country with the longest posting series—AI skills appeared in fewer than 1 percent of postings before 2015 but in almost 5 percent by 2025. The analysis further distinguishes between AI-user skills—use of generative-AI applications integrated into work processes (for example, ChatGPT, GitHub Copilot, and DALL-E image generator)—and AI-developer skills—competencies related to building and deploying models (for example, Python for machine learning, TensorFlow/PyTorch, model evaluation and ML-Ops).[7] This taxonomy allows to separate AI adoption and creation patterns. Within AI skills demand in the United States, AI-user skills experienced higher demand than AI-developer skills: in 2024, roughly half of postings mention only AI-user skills, one-fourth reference only AI-developer skills, and one-fourth both types of AI skills (Figure 3, panel 1). A similar pattern is observed across countries in 2024. Denmark and the United States display the highest prevalence of AI-related postings, with AI-user skills dominant in both countries, while Brazil and South Africa exhibit lower overall prevalence, below 2 percent (Figure 3, panel 2).

II.3 New Skills Diffusion

New skills tend to emerge in advanced economies before spreading to emerging markets (Figure 4, panel 1). A cross-country skill diffusion analysis—where arrows indicate flows from early adopters to later adopters—shows Germany, the United Kingdom, and the United States as the primary originators of new skills among the countries analyzed, with many arrows pointing toward Brazil and South Africa, which primarily act as recipients. Despite the dominant role of advanced economies in originating new skills, the network analysis also shows a meaningful amount of skill emergence from Brazil and South Africa, underscoring that diffusion is not a one-way process. In addition, there is frequent diffusion of skills within advanced economies themselves, reflecting their interconnectedness.

Advanced economies demand new skills more quickly than emerging markets. About half of the new skills identified in the authors' analysis diffused across countries between 2021 and 2024. Relative to the United States, the main originator, other advanced economies such as Denmark and the United Kingdom demand new skills within two to four months, while Germany shows a wider range (Figure 4, panel 2). By contrast, Brazil and South Africa experience average lags of about eight to nine months to demand new skills. Despite these differences, it is worth noting that for skills that diffuse, the speed is generally fast: it occurs within a year.

Demand for new skills does not only diffuse across countries, but also within them. A network analysis within the United States shows that the diffusion of firms' demand for new skills across US states is highly uneven and reflects the role of large, innovative hubs. California, along with other large states such as New York and Texas, serves as a major point of origin for new skills (Figure 4, panel 3). More generally, the dense web of connections in the map illustrates how new skills first originate in these hubs before diffusing outward to smaller states. Complementary analysis examining the speed of diffusion across time shows that new skills are diffusing more rapidly in recent years, consistent with the fast adoption of new AI technologies documented by Chatterji and others (2025) (see Annex II).

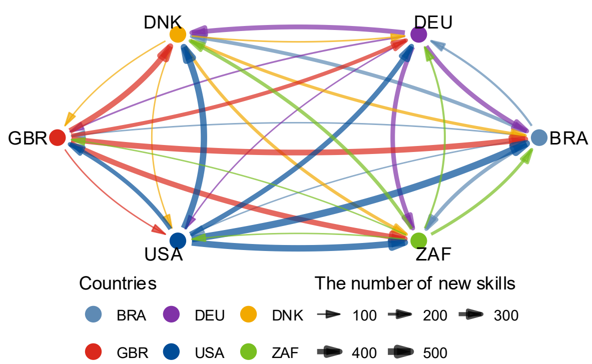
Higher education levels and more flexible labor markets are associated with greater adoption. Using California's new skill adoption to predict adoption in other commuting zones (Figure 4, panel 4), shows that areas with higher education levels—measured by literacy, numeracy, and college attainment—are significantly more likely to demand new skills that first appeared in California. In contrast, commuting zones with higher union coverage and membership display lower demand for new skills, suggesting that there is a potential for unions in the United States to enhance their role in the adoption of new skills thereby inducing higher labor market dynamism. This is in line with Schoefer (2025), who emphasizes that European labor market institutions might have slowed down labor market dynamism—specifically showing that labor market rigidities hindered information and communication technology (ICT) adoption. In contrast, other studies have shown that unions

[7] AI skills are defined by prompting ChatGPT 4.1-nano to classify the identified new skills into three categories: (1) AI developer, that is, core skills required to build or develop AI systems/models, excluding general software development skills; (2) AI user, that is, skills needed to effectively use AI tools or applications, excluding general software skills with only a weak link to AI; (3) unrelated/non-AI, that is, skills that do not fit into either of the above categories.

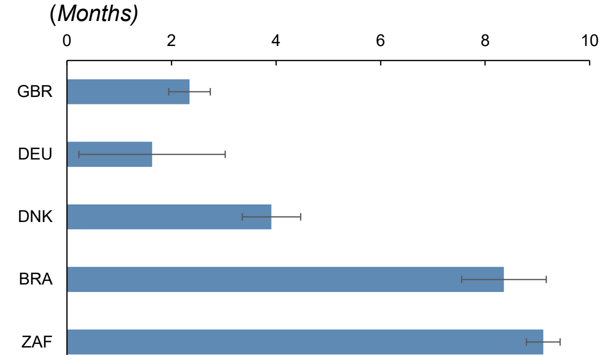
and, more generally, worker representation have played a supportive role in worker transitions in some European countries. For instance, recent evidence from Germany shows that worker representation reduced the displacement risk of automation for incumbent workers and led to adopting higher-quality robots. This, combined with worker retraining, resulted in higher productivity growth (Findeisen, Dauth, and Schlenker 2025).[8] Similarly, the analysis in IMF (2022) finds that unionized workers were more likely to move away from pollution-intensive to neutral and green jobs in response to the implementation of environmental policies.

Figure 4. Skill Diffusion across Countries and within the United States

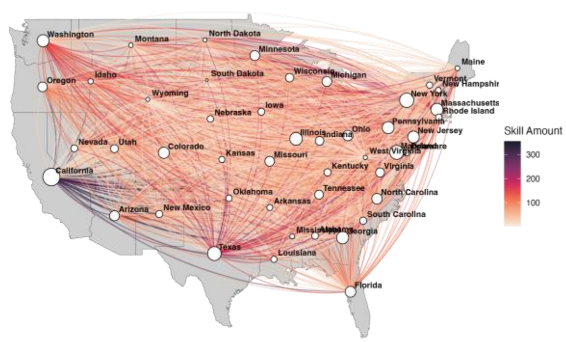
1. Network of Skill Diffusion across Countries



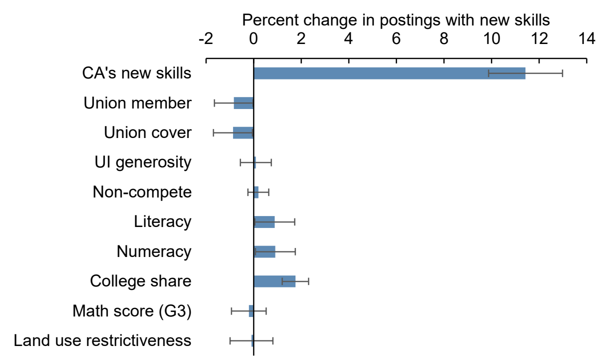
2. Skill Appearance Time Lag Relative to the United States (*Months*)



3. Network of New Skill Diffusion across US States



4. California's New Skills: Predictive Power and Interactions



Sources: Lightcast, American Community Survey (ACS), Current Population Survey (CPS, via UnionStats); Opportunity Lab; Programme for the International Assessment of Adult Competencies (PIACC); Reinmuth and Rockall 2023; Wharton Residential Land Use Regulatory Index; and IMF staff calculations.
Note: Panel 1 plots the global skill diffusion network across advanced and emerging market economies. Panel 2 shows the distribution of time lags in skill demand. Time lags are measured in months relative to the United States. Panel 3 presents the US state-level diffusion network. Panel 4 reports the regression results using California's new skill adoption to predict adoption in other commuting zones, with 95 percent confidence intervals. All measures are based on Lightcast job posting data, with skill appearance defined by the first recorded posting in each location. All local policies are measured prior to the diffusion of new skills: Union membership and coverage from www.unionstats.com; state non-compete index from Reinmuth and Rockall (2023); college share from ACS in 2010, land-use restrictiveness from the 2008 Wharton Index, literacy and numeracy scores in 2012 are from PIACC, and third grade (G3) math scores from Opportunity Lab (Chetty and others 2014). Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2).

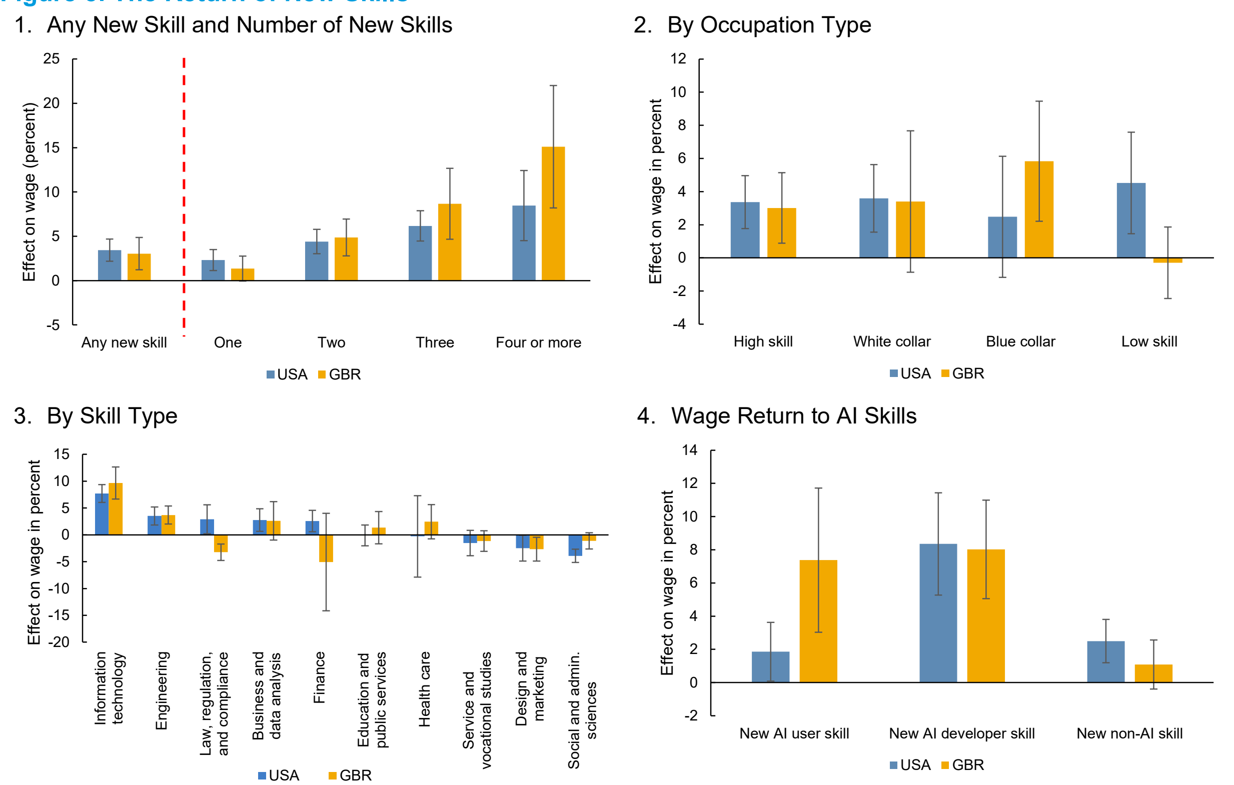
II.4 Individual Return to New Skills

New skills are associated with wage gains in both the United Kingdom and the United States—the two countries for which the data allow such an analysis. To assess the return to new skills compared to already

[8] Dauth and others (2021) show that workers exposed to automation are less likely to be displaced if they work in a region with high union coverage and move to better-paid roles within the same establishment, suggesting firm-level investment into retraining.

existing skills, this section uses wage offer information reported in vacancies collected by Lightcast.[9] The analysis employs an ordinary least squares regression framework incorporating comprehensive fixed effects controlling for various dimensions. First, fixed effects account for the number of skills specified in each vacancy to ensure that the coefficient of interest captures the marginal gain of a new skill over an existing skill. Second, a fixed effect is included for every unique combination of year, 6-digit industry classification, county, and detailed 4-digit International Standard Classification of Occupations (ISCO) occupation to rely only on the variation between very similar vacancies. Finally, fixed effects are applied for the posted pay period categories interacted with year (see Koll and others, forthcoming, for details).

Figure 5. The Return of New Skills



Sources: Lightcast; and IMF staff calculations.
Note: The plots show the results of separate regressions for the United Kingdom and the United States using job postings between 2020 and 2024 with information on posted wages, skills, 6-digit North American Industry Classification System (NAICS) industry, 4-digit International Standard Classification of Occupations (ISCO) occupation, pay period, county, and year of posting. Panel 1 relies on detailed fixed-effect regressions of the log hourly wage on the presence of a new skill in the job posting or indicators for the number of new skills and plots the resulting coefficients. Panel 2 allows the coefficient on the presence of new skills to differ between low-skill, blue-collar, white-collar, and high-skill occupations following the definition by Acemoglu and Autor (2011). Panel 3 plots the heterogeneity of the presence of new skills by skill type. Panel 4 shows coefficients of fixed-effect regressions of the posted log hourly wage on the presence of either a new AI user skill, a new AI developer skill, or a new non-AI skill in a job posting for the United Kingdom and the United States using Lightcast postings data between 2020 and 2024, with information on posted wages, skills, 6-digit NAICS industry, 4-digit ISCO occupation, pay period, county, and year of posting. Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2).

The presence of a new skill in a vacancy is associated with about 3 to 3.4 percent higher wages (Figure 5, panel 1). The wage premium is higher when employers demand multiple new skills—reaching 15.1 percent in the United Kingdom for vacancies listing four or more new skills and 8.5 percent in the United States. Importantly, the benefits of new skills extend across different occupations: in the United Kingdom and the

[9] Although Lightcast wage information was initially missing or not representative in the early part of the sample (Batra, Michaud, and Mongey 2023), coverage has improved recently with the introduction of pay transparency laws (Koll and others, forthcoming).

United States, wage gains are found for new skills across all types of occupations, except new skills in low-skill occupations in the United Kingdom (Figure 5, panel 2). Among skill categories, the highest wage premiums are linked to IT, business and data analysis, and engineering (Figure 5, panel 3).[10]

AI-related skills are also associated with a wage return, but with notable cross-country differences (Figure 5, panel 4). In the United Kingdom, both AI-developer and user skills are associated with posted wage premiums of about 7.5–8 percent within occupations. In contrast, in the United States, high wage premiums of above 8 percent are concentrated among AI-developer skills, whereas AI-user skill postings display a smaller premium close to 2 percent. By comparison, other non-AI new skills in the United States carry a premium of about 2.5 percent.

III. Economywide Return to New Skills

III.1 United States

Beyond individual gains for workers with new skills, a key question is how new skills affect more broadly wages and employment in the economy. This question can be examined by estimating how new skills impact wages and employment at the local labor market level. Focusing on local labor markets provides a richer perspective, as it captures how skill shifts play out across regions with different economic structures, rather than being diluted by national averages. The analysis tracks how wages and employment evolved across commuting zones between 2013 and 2023 depending on their exposure to new skills, measured using a shift-share variable that captures local demand for new skills. Commuting zones are considered more exposed if they had a larger share of workers in occupations where the nationwide demand for new skills expanded rapidly, weighted by the importance of those occupations in each local economy as of 2000—before such skills became widespread. In this way, the measure reflects pre-existing local employment composition rather than outcomes shaped by recent changes. The regressions control for differences in industry structure, demographics, and education following the design of recent studies on the effect of robots on regional labor markets (Acemoglu and Restrepo 2020; Dauth and others 2021).

To establish a causal relationship, the analysis leverages that new skills diffuse domestically and globally from early-adopting regions. New skill adoption in commuting zones is instrumented using the 2013 share of job postings requiring new skills in California and the United Kingdom, that is, before the main outcome period.[11] The external new skill adoption is further weighted by local occupational employment shares in the base period.[12]

New skills are significantly associated with higher wages and employment at the local labor market level in the United States (Figure 6, panels 1 and 2). A 1 percentage point increase in job postings requiring new skills raises average hourly wages by 2.3 percent, which translates into a predicted gain of about 7.6 percent given the observed increase in new skill postings of 3.3 percentage points over the period considered. Employment effects are also positive, with the same increase in new skills linked to 1.3 percent higher

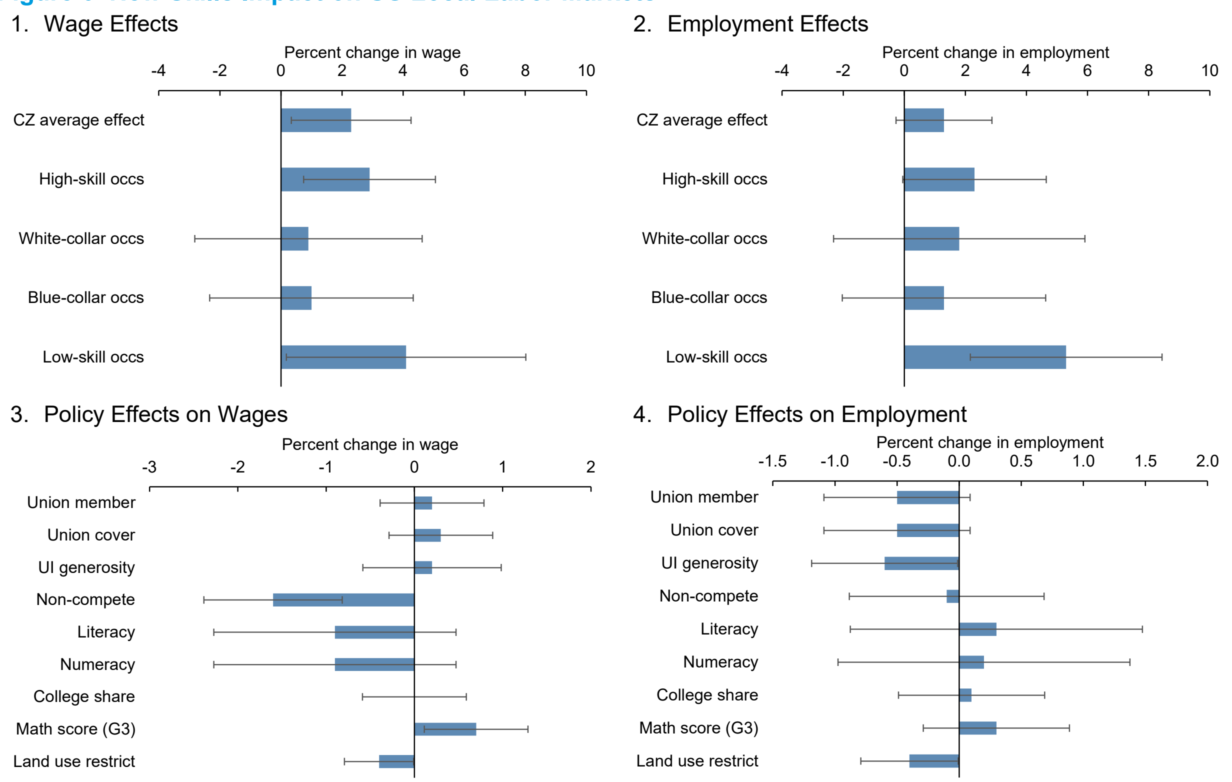
[10] In the United States, job postings with new, emerging job titles are twice as likely to list a new skill as opposed to postings with existing titles (16.8 percent versus 8.8 percent). Yet job postings with emerging titles are not associated with higher wages.

[11] Job postings with remote work opportunities might induce some measurement error if the hired workers live in different commuting zones than the hiring firm. This is mitigated by the use of an instrumental variable approach and the inclusion of a large set of controls of covariates in the regressions, including demographic controls and where feasible commuting zones fixed effects which help account for the propensity to work remotely.

[12] First-stage results confirm that the instruments are strong, with high *F*-statistics, and valid, with Hansen J-tests indicating exogeneity.

employment, amounting to a predicted rise of about 4.3 percent, while the estimated effect on population is at 5.3 percent. High-skill occupations, such as managers and engineers, benefit the most, while low-skill occupations also experience gains likely due to aggregate income effects increasing demand for services—evidence of the positive effects new skills can have on the broader economy. By contrast, effects on white-collar and blue-collar occupations are smaller and statistically insignificant. These results are consistent with the literature on labor market polarization (Goos and Manning 2007; Acemoglu and Autor 2011; Autor and Dorn 2013), which shows that technological change can simultaneously boost high-skill occupations and create demand for certain types of low-skill work, while eroding opportunities in routine middle-skill occupations. However, the patterns observed here capture a new wave of technological change, distinct from the earlier automation episodes documented in the polarization literature. This new transformation is driven by the rise of new skills—including digital and AI-related—that cut across a much broader range of occupations.[13] Subsection III.4 focuses on the impact of new AI skills.

Figure 6. New Skills Impact on US Local Labor Markets



Sources: Lightcast, American Community Survey (ACS), Current Population Survey (CPS, via UnionStats); Opportunity Lab, Wharton Residential Land Use Regulatory Index, Programme for the International Assessment of Adult Competencies (PIACC); Reinmuth and Rockall 2023; and IMF staff calculations.

Note: This figure shows the estimation of wage and employment effects of new skill adoption across commuting zones. Panels 1 and 2 report the average effects of a 1 percentage point rise in new skill postings on wages and employment using a long-difference design (2013–23) with a shift-share measure of exposure, using an instrumental variable design based on early adoption in California and the United Kingdom. Panels 3 and 4 report heterogeneity results, where the effects of new skill adoption are interacted with local characteristics. All local policies are measured prior to the diffusion of new skills: Union membership and coverage from www.unionstats.com; state non-compete index from Reinmuth and Rockall (2023); college share from ACS in 2010, land-use restrictiveness from the 2008 Wharton Index, literacy, and numeracy scores in 2012 are from PIACC, and third grade (G3) math scores from Opportunity Lab (Chetty and others 2014). Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2). Occupational groups in all panels are defined following Acemoglu and Autor (2011). See Annex II.1 for details. CZ = commuting zone; occs = occupations; UI = unemployment insurance.

[13] There could be some mobility within the white-collar and blue-collar occupations that the analysis does not examine.

New skills produce larger wage and employment effects in commuting zones with better neighborhood quality, less restrictive land-use policies, and more flexible labor markets (Figure 6, panels 3 and 4). These effects correspond to the coefficients on the interaction between new skill adoption and each policy measure, where all policies are measured prior to skill adoption—in 2013 or earlier. The analysis does not estimate the causal effects of policies but estimates heterogeneous causal effects of new skill demand for regions with different initial characteristics or policies. Wage gains are significantly higher where third-grade math scores—a proxy for neighborhood quality—are stronger, while commuting zones with more restrictive land-use experience smaller gains. Moreover, stricter non-compete agreements dampen the pass-through of new-skill adoption into wages. A similar pattern holds for employment, although the neighborhood quality effect is less precise for employment outcomes (Figure 6, panel 4). Commuting zones with stronger union presence prior to the adoption of new skills also exhibit slightly smaller employment gains, although the interaction effects are not statistically significant. This finding suggests that closer collaboration between unions and the private sector could help strengthen both the adoption of new skills and the expansion of employment opportunities. Finally, higher unemployment insurance generosity is associated with smaller employment gains, highlighting the importance of linking these benefits with effective retraining and upskilling programs. All in all, these results underscore that local institutions and policies can play a critical role in shaping the extent to which new skills translate into wage and employment gains.

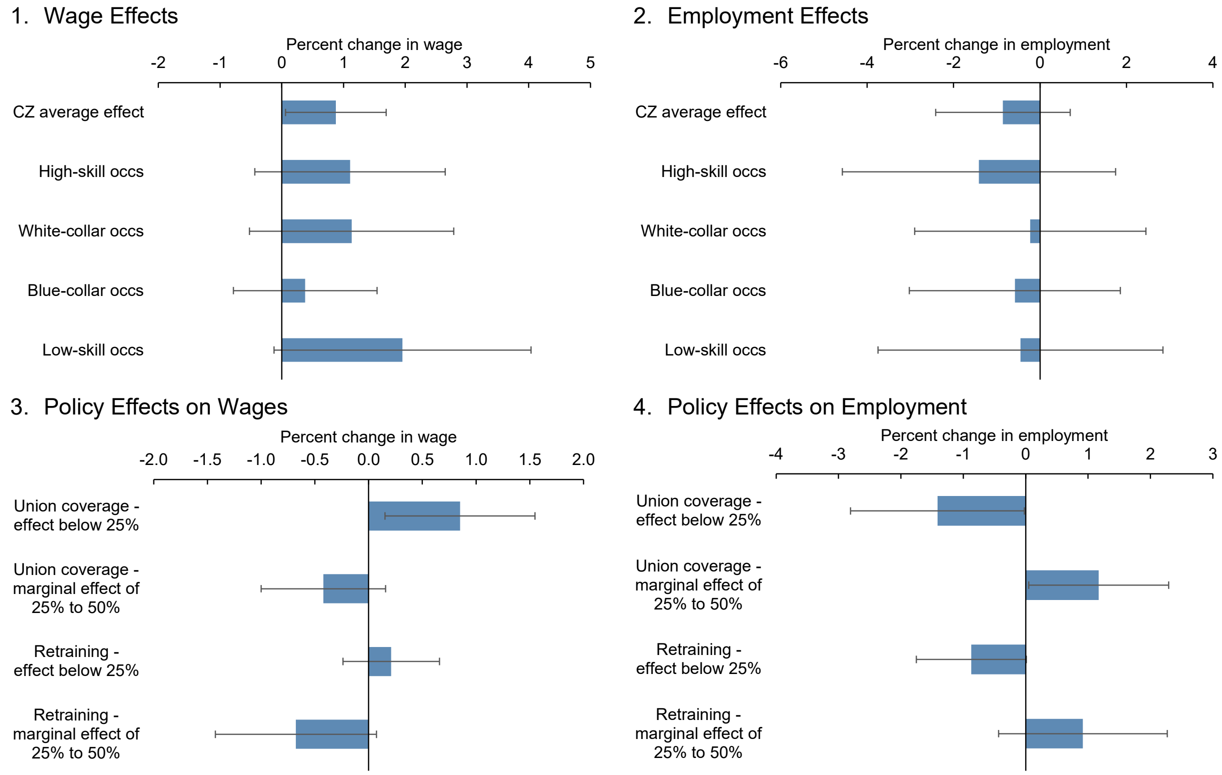
III.2 Germany

In German local labor markets new skills are associated with significant wage gains, although effects on employment are insignificant (Figure 7, panels 1 and 2). Because of data limitations in the Lightcast data, the analysis covers only the period 2019–23 and focuses on German regions. The econometric specification follows closely the described US setup allowing for a comparison between the two countries. To establish a causal relationship, the analysis employs two instruments in the shift-share design: first, the early adoption in the United States from 2014 and, second, the change in adoption in the United States between 2014 and 2018.[14] A 1 percentage point increase in vacancies requiring new skills significantly raises average wages at the local labor market by 0.9 percent. Wage gains appear to be concentrated more among high-skill, white-collar, and low-skill occupations, although the occupation-specific effects are measured insignificantly due to the smaller number of local labor markets in Germany implying lower statistical power. By contrast, employment is not impacted significantly, which may also reflect the relatively short time horizon of the data, as well as structural rigidities in Germany’s labor market that slow the adjustment of employment to new skill demand in a short period of time (see Coskun and others, forthcoming, for details).

The effects of new skills vary markedly with institutional features across German regions. The analysis considers initial union presence and opportunities for retraining (Figure 7, panels 3 and 4). In regions with weak initial union representation—those below the 25th percentile of union coverage, the adoption of new skills is associated with higher wages but lower employment, and both effects are statistically significant. By contrast, in regions with stronger union presence, the wage effect slightly decreases (though only to a marginally significant extent) compared to regions with low union presence. The employment effect increases significantly, suggesting that unions help mitigate displacement pressures by protecting existing jobs, potentially in exchange for some wage moderation. A similar pattern emerges with retraining intensity. In regions where the initial share of workers engaged in retraining or apprenticeship programs is below the 25th percentile, new skill adoption exerts a negative impact on employment, while the wage effect—though positive—is statistically insignificant. With increasing levels of retraining, however, the employment effect improves, yet insignificantly.

[14] The econometric setup closely resembles Dauth and others (2021). First-stage results confirm that the instruments are strong implying a high *F*-statistic and valid, with Hansen J-tests indicating exogeneity.

Figure 7. New Skills Impact on German Local Labor Markets



Sources: Lightcast; Sample of Integrated Labour Market Biographies (SIAB); and IMF staff calculations.
Note: This figure shows the estimation of wage and employment effects of new skill adoption across 96 German commuting zones. Panels 1 and 2 report the average effects of a 1 percentage point rise in new skill postings on wages and employment using a long-difference design (2019–23) with a shift-share measure of exposure, using an instrumental variable design based on past US changes (2014–18) and the initial past US level (2014). Panels 3 and 4 report heterogeneity results, where the effects of new skill adoption are interacted with local characteristics. To ensure a valid design, an additional instrument has been added, that is, the initial US level (2019). All local policies are measured prior to the diffusion of new skills: retraining by employment or by working-age population is measured between 2011–14 while the union share is measured in 1994 given data limitations. Occupational groups in all panels are defined following Acemoglu and Autor (2011). See Annex II.1 for details. occs = occupations; CZ = commuting zone.

III.3 Cross-Country Impact of New Tasks on Wages

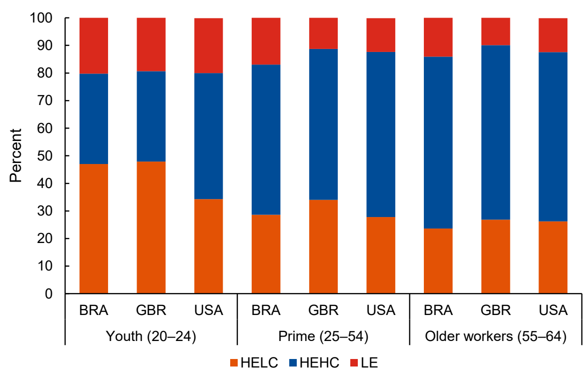
New task creation is associated with wage growth, even after accounting for productivity and market structure. To better understand the global relationship between new skills, wages, and productivity, a wage regression using country-level panel data from 2000 to 2023 is estimated. A macro measure of task creation is estimated—capturing the introduction of new tasks mapped across countries following Caunedo, Keller, and Shin (2022)—as a proxy for new skill adoption at the aggregate level. Task destruction measures capturing routine-biased displacement through robots and offshoring are also included (details in Annex II.3). The results indicate that task creation robustly predicts stronger wage growth, even conditional on productivity and institutional controls. In contrast, task destruction indicators—such as routine task intensity, offshorability, and robot penetration—are insignificant once conditioning on productivity. These findings underscore the importance of new tasks in explaining deviations between wage growth and productivity growth.

III.4 The Effect of AI Skills on Employment

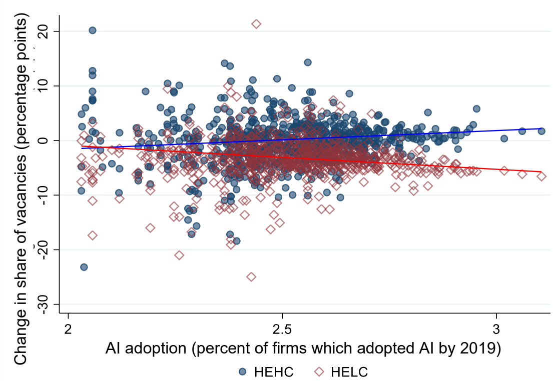
Although AI may create opportunities, especially for workers who develop the technology, it can also create risks for other workers. Young workers' employment is more concentrated in occupations with high exposure and low complementarity to AI, which carry a higher risk of being displaced by the technology than occupations typically held by prime-age and older workers (Pizzinelli and others 2023; Cazzaniga and others 2024; Renault 2025). These occupations often serve as steppingstones for young people in the career ladder. This pattern is even more accentuated for college-educated young workers, given their higher exposure to AI (Figure 8, panel 1). There is emerging evidence for the United States that generative-AI adoption has been reducing entry-level hiring—especially where tasks are automatable rather than complementary to humans (Brynjolfsson, Chandar, and Chen 2025; Hosseini and Lichtinger 2025). Brynjolfsson, Chandar, and Chen (2025) find that since the release of ChatGPT, early-career workers (ages 22-25) in the most AI-exposed occupations have experienced a 13 percent relative decline in employment. In contrast, employment has remained stable or continued to grow for workers in less exposed fields and for more experienced workers in the same occupations. Evidence from US vacancy data over 2019–23 confirms that local adoption of AI disproportionately weighs on vacancies in high-exposure, low-complementarity occupations (Figure 8, panel 2). After including controls, regression analysis in Pizzinelli and others (2023) shows that a one-standard-deviation higher adoption at the commuting-zone level in 2019[15]—about 0.18 percentage point, comparable to the gap between Boston, MA, and Portland, OR—is associated with a 0.4 percentage point lower vacancy share and 2.5 percent lower growth of high-exposure, low-complementarity vacancies, relative to high-exposure, high-complementarity occupations.

Figure 8. AI Exposure and Vacancy Impact

1. AI Exposure for College-Educated Workers by Age Group.



2. AI Adoption and Change in Share of Vacancies in the United States 2019–23



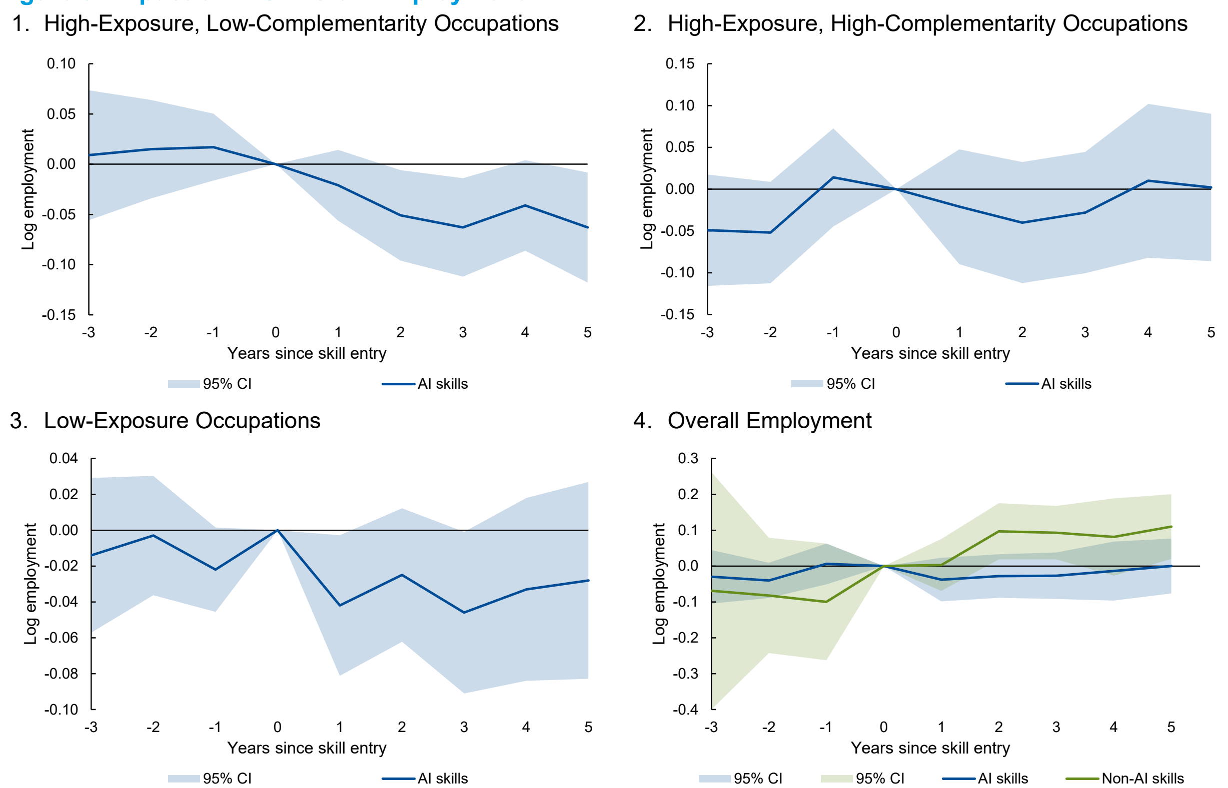
Sources: Cazzaniga and others 2024; Pizzinelli and others 2023; and IMF staff calculations.
Note: Panel 1 plots the estimated share of employment by age group for each exposure category for college-educated workers. Panel 2 plots the change in the share of vacancies of HEHC (blue circles) and HELC (red diamonds) occupations in each commuting zone between 2019 and 2023 against the industry-based measure of AI adoption. Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2). HEHC = high-exposure, high-complementarity; HELC = high-exposure, low -complementarity; LE = low-exposure.

Although new non-AI skills benefit most workers, AI skills show a negative association with employment for groups of workers (Figure 9). On average, the demand for new AI skills has so far not boosted overall employment in US local labor markets. In contrast, the demand for non-AI skills is associated with significantly higher overall employment, corroborating the findings of the local labor market analysis in Section III.1. For workers in jobs with high exposure and low complementarity to AI—about 30 percent of total employment (Cazzaniga and others 2024)—a clear and sustained decline in employment growth is observed (Figure 9, Panel 1). In the medium term (after five years), regions with a 1 percentage point higher demand for

[15] AI adoption at the commuting-zone (CZ) level is estimated using the US Census Bureau's Annual Business Survey 2019 module on firms' AI use during 2016–18, which reports the share of firms using AI by the North American Industry Classification System. Industry-level adoption shares are employment-weighted by each CZ's 2019 industry composition to construct a CZ indicator of the presence of AI in local production activities.

AI-related skills show employment levels that are 6.3 percent lower than other regions for occupations that are highly exposed to AI with limited scope for complementarity. This translates into a predicted lower employment level of about 3.6 percent given the observed increase in new skill postings (which amounts to 0.57 percentage point for workers in high-exposure, low-complementarity occupations over the period considered).[16] Effects are insignificant for workers in high-exposure, high-complementarity occupations. For low-exposure occupations, employment levels are lower—by about 4 to 5 percent—in years one and three relative to other regions, possibly reflecting negative spillovers from declines in other occupations, but insignificant otherwise (Figure 9, panels 2 and 3). The impact on wages is overall insignificant. Yet workers in high-exposure, low-complementarity occupations experience modestly lower wages 2–3 years after the AI skill entry. These results resemble findings by others on AI (e.g., Huang 2024) and on previous episodes of technological change. For example, robot adoption has been found to reduce overall employment in the United States (Acemoglu and Restrepo 2020), while in Germany it mostly affected young workers entering the labor force (Dauth and others 2021). The fact that new skills appear to diffuse more rapidly in recent years also increases concerns about the capacity of workers and policymakers to adapt fast enough and minimize labor market disruptions.

Figure 9. Impact of AI Skills on Employment



Sources: Lightcast, American Community Survey; and IMF staff calculations.
Note: The figure shows the local employment effects of new AI skill adoption across different occupation groups. The panels present dynamic event study estimates of log employment following the entry of AI skills, disaggregated by occupations with high-exposure and low-complementarity (panel 1), high-exposure and high-complementarity (panel 2), and low-exposure (panel 3), along with a comparison of overall employment effects for AI versus non-AI skills (panel 4). Each panel plots employment changes relative to the year of skill entry (year 0), with shaded bands denoting 95 percent confidence intervals. The difference-in-differences estimator developed by De Chaisemartin and D'Haultfoeuille (2023, 2024) is applied to accommodate staggered, recurrent, and nonbinary treatments. See Annex II.2 for details.

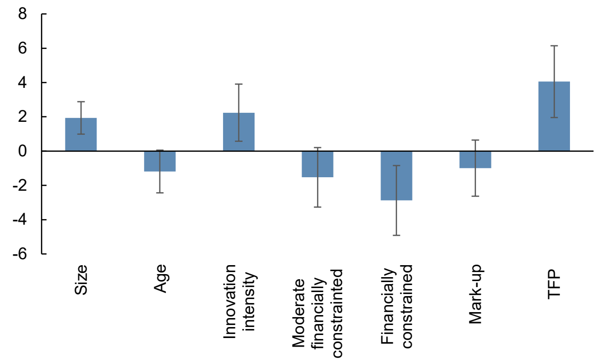
[16] Evidence at the firm level for France paints a different picture: AI-adopting firms are more likely to expand hiring across different types of workers (Aghion and others 2025). However, this does not provide a full picture of the employment effect at the commuting zone level as it does not account for potential employment losses in lagging firms whose market shares may be declining.

IV. The Demand and Supply of Skills

IV.1 Which Types of Firms Post New Skills?

The characteristics of firms that demand new skills are analyzed. US job vacancy data from Lightcast were matched to firm-level information from Compustat using company names. Because Compustat covers publicly listed companies, the analysis mainly covers larger firms. The match covers 83 percent of the total market capitalization of Compustat firms. Within this group, demand for new skills is concentrated in the technology, finance, and insurance sectors, including well-known innovators such as Salesforce and Cognizant in technology and JPMorgan Chase in finance.

Figure 10. The Demand of New Skills by Firm Characteristics in the United States



Sources: Compustat; Lightcast; and IMF staff calculations.
Note: The figure shows coefficients from multivariate regressions of the percentage change in new skills share (difference between period end and start) on firm characteristics measured at period start. TFP = total factor productivity.

Firms posting vacancies with new skills are larger, younger, more innovative, less financially constrained, and more productive (Figure 10). These correlations suggest that new skills complement innovation and productivity. In addition, an analysis of corporate earnings calls indicates that competition for workers with scarce, high-demand skills has intensified over time, fueling mergers and acquisitions aimed at acquiring talent (so-called “acquire-hire”) (see Box 1). Financial-press reporting indicates that Google’s purchase of DeepMind in 2014 and Apple’s acquisitions of Turi in 2016 and Xnor.ai in 2020 were motivated by not only product integration but also the race to secure cutting-edge AI talent (The Guardian 2014; Financial Times 2016, 2020). Unlike traditional mergers, acquire-hire transactions are followed by a slowdown in the acquirer’s external hiring for new skills, combined with increased patenting activity and value-added (Box 1). Although such acquisitions can benefit individual firms that want to acquire new skills, acquisitions may still carry broader economic costs associated with a potentially excessive increase in market power and thus merit oversight by competition authorities.

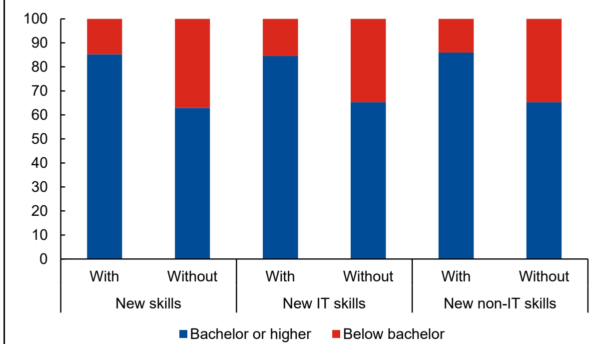
IV.2 What Types of Workers Have New Skills?

In the United States, workers who mention new skills in their curriculum vitaes are more likely to hold at least a bachelor’s degree. To assess worker characteristics associated with new skills, this section draws on Lightcast data covering nearly 18 million worker profiles in the United States. This data set provides information on education, field of study, skills, and employment history. Using AI-based text classification methods, the field of study was grouped into 16 categories and then combined with other profile characteristics. The evidence shows that 85 percent of workers listing new skills on their profiles have at least a bachelor’s degree, compared with 60 percent among workers who list only non-new skills (Figure 11, panel 1). A similar pattern emerges for new IT skills: 84.5 percent of workers reporting these skills hold at least a bachelor’s degree. Among new non-IT skills holders, the proportion of workers with at least a bachelor’s degree is similar, at 86 percent. Taken together, this evidence suggests that tertiary education is associated with a higher likelihood of workers being equipped with the new skills demanded by firms.

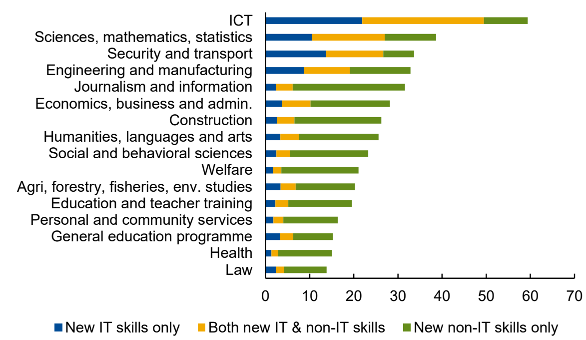
Workers with ICT degrees report the highest number of new skills. These workers are followed by those with backgrounds in natural sciences, mathematics, statistics, or security and transport (especially cyber-security) (Figure 11, panel 2). Although workers with education in ICT and STEM tend to report a higher share of new IT skills, workers in other fields are more likely to report more new non-IT skills than new IT skills. Interestingly, new IT skills are present in every area of study, and non-STEM workers who list IT skills are also more likely to report additional new non-IT skills. These findings suggest that, especially outside of STEM, the adoption of new IT skills often comes bundled with other emerging competencies. Turning to AI specifically, AI-developer skills are concentrated among workers with ICT and STEM backgrounds—accounting for nearly 60 percent of all AI-developer skills (Figure 11, panel 3). By contrast, AI-user skills are distributed far more broadly across fields, underscoring the general-purpose nature of AI.

Figure 11. Workers' Profile with New Skills in the United States

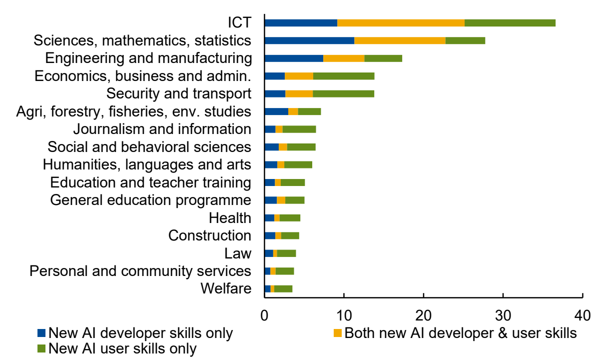
1. Workers with New Skills by Education
(Percent)



2. Share of New Skills by Field of Study
(Percent)



3. Share of AI New Skills by Field of Study
(Percent)



Sources: Lightcast; and IMF staff calculations.
Note: Calculations are based on Lightcast's US individual profile data with updated job information in 2024. Panel 1 shows the share of individuals with bachelor's or higher vs. below bachelor among those with/without new skills (first two), new IT skills (middle two), and new non-IT skills (last two). Panel 2 and 3 display the share of individuals with new skills and new AI skills, respectively, among all individuals within each field of study. Field of study classification is derived from the profile's degree information. ICT = information and communications technology.

IV.3 Skill Imbalance Index and Skill Readiness Index

This section combines cross-country data from several providers to assess the relative weight of demand and supply of new skills. One important caveat is that the analysis compares the intensity of demand for (or supply of) new skills across countries using the United States as the benchmark because it stands at the frontier of new-skill adoption (as shown by the diffusion analysis reported in Section II.3) and provides the most detailed vacancy data. While the analysis cannot quantify mismatches in terms of headcount, it nevertheless provides useful indicative evidence based on countries' relative position in the demand and supply of new skills. The main sources of data are Lightcast, the ILO, and the OECD. Using the ILO data set—which provides employment data by occupation for many countries—and the occupation-level demand for new skills in US vacancies, the potential future demand for new skills across countries is projected. Similarly, to estimate the potential supply of new skills, it is assumed that the share of new skills by field of study across countries is the same as in the United States. To broaden country coverage, a complementary analysis drawing on the United

Nations Educational, Scientific and Cultural Organization data is conducted for a larger set of countries and presented in Annex IV.3.

Potential demand for new skills is generally higher in advanced economies than in emerging markets. It ranges from almost 5 percent of vacancies in Türkiye to 16 percent in Luxembourg (Figure 12, panel 1). This gap largely reflects the differences in occupational structure: advanced economies have a higher share of professional, managerial, and technical occupations, where new skills are more in demand. Across countries, IT skills account for the largest share of new skills sought by employers, followed by business and data analysis skills and social and administrative competencies. The high demand for new IT skills reflects the fast pace of technological change and associated turnover of skills, without implying a one-for-one rise in demand for IT specialists. It also reflects the growing demand for AI-user skills in many non-IT occupations. As AI automates many IT tasks, the impact on the demand for IT specialists remains ambiguous.

The potential supply of new skills also varies markedly across countries. It is estimated by using OECD data on graduates by field of study for each country between 2013 and 2021, combined with the prevalence of new skills by field of study observed in the United States. Assuming that graduates in each field across OECD countries can provide new skills in proportions similar to those of US graduates, cross-country estimates of potential supply are derived. Results point to wide differences: countries such as Ireland and Poland have a large share of recent STEM graduates with the potential to supply new skills, while Mexico and Brazil have only about one-third of that share and Luxembourg about one-fifth (Figure 12, panel 2).

Different world regions show different combinations of new skill demand and supply. These comparisons reflect the relative position of countries compared to the United States (normalized to 1) rather than absolute levels of skills or employment, which can vary widely with country size, sectoral structure, and data coverage (Figure 12, panel 3). Many northern and western European countries face relatively higher potential demand for new skills but can also leverage relatively strong domestic supply of recent graduates with the potential to provide relevant skills. On the other end of the spectrum, many emerging economies exhibit both weaker potential demand and more limited supply, while southern and eastern European economies fall somewhere in between.

A new Skill Imbalance Index captures the relative weight of new skill demand versus supply relative to the United States, suggesting policy priorities (Figure 12, panel 4).[17] In countries such as Luxembourg, Sweden, the Netherlands and Brazil, where potential demand is high relative to domestic supply, policy priorities should focus on expanding worker training, including IT training across all fields of study, strengthening STEM education, and potentially relying on outsourcing and foreign-born workers with such skills.[18] Countries such as Ireland, Poland and Australia, where supply capacity is relatively strong, but potential demand remains relatively modest, should prioritize stimulating firms' demand and helping companies absorb and deploy these skills—through innovation incentives, easier business creation, export promotion, and reduced financial constraints. Countries with smaller imbalances because both demand for and supply of new skills are more modest, such as Chile and Estonia, face less immediate urgency. However, as technological change advances, they may need policies on both sides of the skills market. Supporting the creation and growth of innovative firms, as well as broader investments in education to equip workers with new skills will be necessary to remain competitive and leverage new technologies to move up the value chains. Similar considerations apply to many emerging market economies and low-income countries, where a large share of workers is employed in the informal sector. New skills can still benefit informal workers through demand-

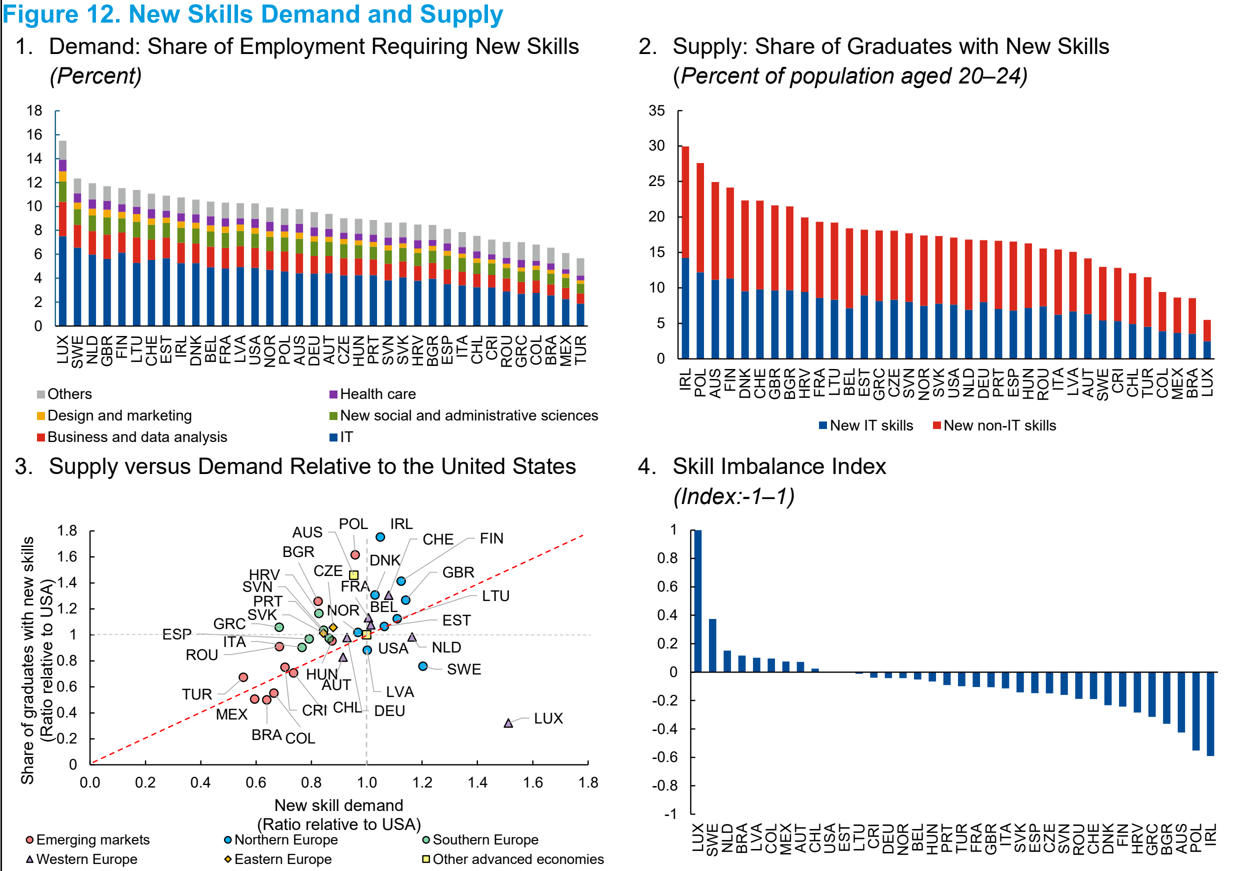
[17] The Skill Imbalance Index combines IT and non-IT skills. Annex Figure 4.1 shows that, when computing the index separately for IT and non-IT skills, a similar cross-country pattern emerges: countries abundant in the supply of new IT skills are also abundant in the supply of new non-IT skills, and likewise for IT and non-IT skills demand.

[18] Luxembourg, being a small country with a strong demand of new skills, already relies significantly on foreign-born workers to satisfy this demand.

induced channels akin to those observed for low-skilled workers in the United States. In these economies, governments should support the creation and growth of innovative firms and expand education and upskilling opportunities to prepare workers to supply new skills.

Retraining opportunities and the quality of education also shape a country's ability to supply new skills. To capture these dimensions, a new Skill Readiness Index covering 24 countries is developed, combining (1) the share of graduates able to supply new IT and non-IT skills, (2) an indicator that measures the share of adults aged 25–65 who participated in job-related learning, and (3) workforce proficiency measured by the OECD's Programme for the International Assessment of Adult Competencies literacy and numeracy scores. These three components are normalized and equally weighted to provide a single index of readiness, where higher values reflect a larger pool of graduates, more frequent retraining opportunities, and a workforce with stronger foundational skills. The broader nature of this index makes it suitable to assess countries' forward-looking adaptability to technological and social changes.

Figure 12. New Skills Demand and Supply

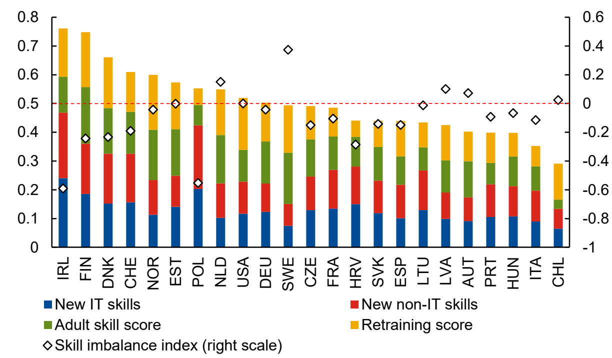


Sources: International Labour Organization; Lightcast; Organisation for Economic Co-operation and Development;; and IMF staff calculations.
Note: Panel 1 reports the share of employment requiring new skills, assuming the US occupational distribution of new skill requirements. For simplicity, job postings containing multiple new skills are classified according to the most common skill. For example, a posting listing both IT and business and data analysis is classified under IT new skills. Panel 2 shows the share of graduates with new skills among the population aged 20–24 from 2013 to 2021. For 2022 and 2023 the same graduation rates as those for 2021 are assumed, then the US distribution of graduates with new skills by field of study is applied. Since the numerator is an annual flow of graduates while the denominator is the size of the five-year cohort (ages 20–24), the ratio is multiplied by 5 to place on a comparable annual basis. Panel 3 shows the relationship between the share of graduates with new skills relative to the United States and new skill demand relative to the United States. Panel 4 presents the skill imbalance index, calculated as the difference between *x* axis values and *y* axis values in Panel 3, normalized by the maximum absolute value of these differences to range between –1 and 1. Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2).

The Skill Readiness Index shows that many northern European economies are well positioned to supply new skills going forward (Figure 13). This finding reflects strong investment in tertiary education, continuous learning, and adult training. Ireland, Finland, and Denmark top the ranking, with high shares of graduates in fields linked to both new IT and non-IT skills, strong performance in adult literacy and numeracy, and robust retraining systems. These are also countries where the demand for new skills is weak relatively to supply and, hence, policy priorities should focus on skills absorption. By contrast, countries such as Chile, Italy and Hungary, score at the lower end, reflecting weaker tertiary specialization in IT, fewer retraining opportunities, and lower adult skill levels. In countries where new skills demand is strong relative to supply—such as Sweden, Latvia and Austria—boosting skill readiness is of utmost importance. Additionally, the sub-indicators of the index are highly correlated: countries that score well in producing graduates with new skills also tend to invest more in lifelong learning and achieve higher adult skill levels. This finding suggests that readiness is not the result of isolated policies but rather of comprehensive education and training systems that reinforce one another.

Figure 13. Skill Readiness Index

(Index: 0–1)



Sources: International Labour Organization; Lightcast; Organisation for Economic Co-operation and Development (OECD); and IMF staff calculations.

Note: The left axis displays the Skill Readiness Index, the average of four normalized components: 1) graduates with new IT skills; 2) graduates with new non-IT skills; 3) average adult skills in literacy; numeracy, and adaptive problem-solving reported by OECD, and 4) adult participation in job-related learning reported by OECD. The right axis presents the skill imbalance index shown in panel 4 of Figure 12. Country labels use International Organization for Standardization (ISO) country codes.

The Skill Readiness Index and the Skill Imbalance Index complement the existing IMF AI Preparedness Index (Cazzaniga and others 2024). The three indices have different objectives. First, the AI Preparedness Index (AIPI) focuses exclusively on AI and covers four areas of preparedness, including not only human capital and labor market policies, but also digital infrastructure, innovation and economic integration, and regulation and ethics. The AIPI shares with the skill readiness index its human capital focus but the latter is more granular in its approach to calculating the availability of skills and also covers non-IT skills. The skill imbalance index compares supply and demand of new skills while the skill readiness index is an elaborate version of projected or potential supply of new skills. The AI Preparedness Index is correlated with both the demand and the supply measures of new skills that determine the skill imbalance index, but not with the skill imbalance index itself (see Annex IV.5).

V. Conclusions and Policy Considerations

The emergence of new skills is reshaping labor markets across advanced and emerging market economies. In advanced economies, roughly 1 in 10 job postings now requires at least one new skill, underscoring their macroeconomic relevance. The incidence is about half of that in emerging market economies. These skills are concentrated in professional, technical, and managerial occupations, with IT-related competencies—particularly AI—at the forefront. Their diffusion, however, is uneven: new skills demand originates mainly in advanced economies, especially the United States, and then spreads to other economies. Within countries, diffusion is also shaped by local educational attainment and labor market institutions that support technological change.

New skills carry significant economic benefits but also risks. Wage and employment analyses show that many new skills are associated with higher wage offers and local employment and wage gains, particularly benefiting high- and low-skill workers. This finding echoes past technological shifts, where rapid productivity growth in some sectors also boosted job creation in slower-productivity, more labor-intensive activities in services. At the same time, these dynamics may reinforce job polarization and the shrinking of the middle class, and risk amplifying inequalities if adoption remains concentrated in certain sectors, firms, or regions. Although vacancies demanding AI skills post higher wages, so far the rise in demand for new AI skills has not generated an increase in economywide employment. Moreover, in the medium term, regions with greater demand for AI-related skills show lower employment levels than other regions for occupations that are highly exposed to AI with limited scope for complementarity, posing challenges especially for young workers. In contrast, new non-AI skills do boost overall employment.

There is considerable variation among countries in both the demand for new skills and their capacity to provide them. On the demand side, a country's economic structure plays a critical role in shaping its need for emerging skill sets. Economies with high shares of employment in professional, technical, and managerial occupations are likely to experience higher demand for new skills. On the supply side, the development of new skills relies substantially on individuals with tertiary education, especially those with backgrounds in information technology. However, IT competencies are present across a broad range of academic disciplines. Importantly, the rise of AI and the high demand for IT skills does not necessarily imply a broad surge in demand for AI or IT specialists. Many firms will adopt AI through ready-made tools or outsourcing rather than by expanding in-house technical teams. Moreover, a large share of the demand for IT skills relates to AI-user skills demanded across a wide range of non-IT roles, indicating the importance of disseminating IT skills broadly, across many fields of study.

Policy responses must be tailored to each country's conditions, as captured by the new Skill Imbalance Index. Although the analysis covers a limited number of countries, notable examples shed light on policy priorities. In economies where demand for new skills is already relatively high but domestic supply remains constrained—such as Sweden, the Netherlands and Brazil—policies should focus on expanding lifelong training opportunities, integrating IT skills into all fields of study, and strengthening STEM education. In economies where supply capacity is relatively strong but demand is more modest—such as Ireland, Poland and Australia—the priority should be to stimulate firm demand through innovation incentives, easier business creation, and improved access to finance. Emerging market economies and low-income countries, where both demand and supply remain relatively limited, will need both sets of policies and more fundamental investment in human capital, including enhanced education systems, adult learning, and retraining programs, supported also by international cooperation. The IMF AI Preparedness Index can help policymakers identify the policy areas where to focus their efforts to enhance their economy's readiness to benefit from recent AI developments.

Five broader recommendations emerge. First, policies that support worker mobility across occupations and regions—including active labor-market policies, potentially organized in collaboration with unions, affordable housing, and remote work—are essential to accelerate diffusion and ensure that new skills are broadly adopted and workers can access the new opportunities. Second, competition policies should safeguard against excessive concentration, by restricting the use of non-compete agreements and monitoring mergers and acquisitions, targeting cases likely to lead to excessive concentration and weakened skill diffusion across firms. Third, building effective lifelong learning systems is critical: governments must ensure that retraining is widely accessible and aligned with emerging skill needs, enabling workers to adapt as labor markets evolve. Fourth, education systems need to be rethought to prepare the workforce for the AI era. This means equipping young people with cognitive, creative, and technical skills that complement AI and allow them to use it effectively, while also providing reskilling opportunities for workers whose tasks are most at risk of automation. Policies should support younger workers by improving career guidance, expanding apprenticeships and internship programs, and strengthening transitions from school to work. Fifth, stronger social protection and unemployment insurance systems are needed to support those who may face longer job transitions or struggle to re-enter the labor market. Ultimately, this also calls for examining the role of AI in society, acknowledging that work provides not only income but also dignity and purpose.

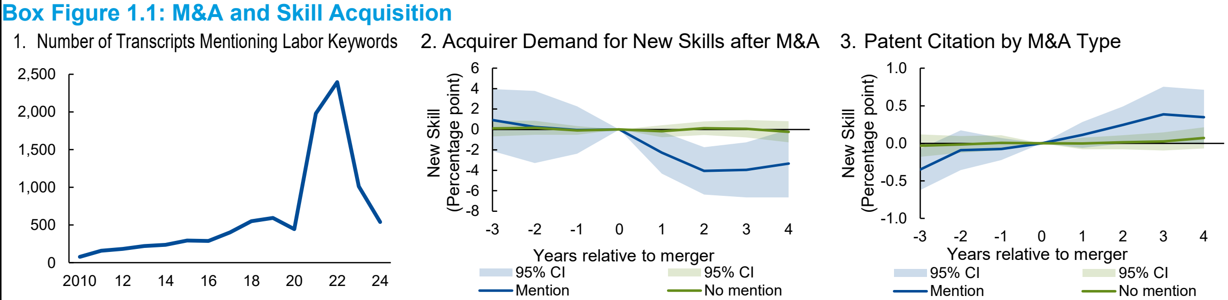
Box 1. The Impact of Mergers and Acquisitions on New Skills Demand[1]

Acute shortages of specialized skills can shape firms' behavior. In US technology-intensive sectors, heightened competition for AI-related talent has coincided with a rise in mergers and acquisitions (M&A) meant to internalize tacit know-how (acqui-hiring), echoing patterns observed in the early 2010s (for example, Business Insider 2010; McGregor 2012; Needleman 2012; Coyle and Polsky 2013). Although many transactions are framed as genuine talent acquisitions, concerns persist that some deals reflect more traditional motives—acquiring intellectual property, reinforcing market positions, or limiting antitrust scrutiny (Kanter 2025).

This recent acqui-hiring wave may carry broader implications for market power and innovation. Some acquisitions can consolidate innovation capacity within incumbents, limiting skill diffusion and reducing competitive pressure (Kamepalli, Rajan, and Zingales 2020; Cunningham, Ederer, and Ma 2021; Berger and others 2025). At the same time, binding frictions—such as caps on skilled immigration and the use of non-compete agreements—can push firms toward M&A as an alternative channel to access talent (Chen, Hshieh, and Zhang 2024), with potential benefits for firm capabilities but adverse side effects for competition.

To gauge the prevalence of talent-motivated M&A, listed-firm earnings and M&A call transcripts from Capital IQ are analyzed in the United States from 2010 to 2024. References to "labor shortages," "talent acquisition," and related terms have become materially more common in recent years, with a marked increase around the pandemic (Box Figure 1.1, panel 1). The potential impact of talent-motivated M&A on firms' demand for new skills is examined by merging firm-level data from Compustat with Lightcast job postings, Capital IQ transcripts, and a database of completed M&A. Acquirers are split into two groups based on whether labor/talent keywords are mentioned in the three years prior to a given deal. Results indicate that acquirers whose pre-deal calls highlighted labor/talent issues subsequently reduce their demand for new skills in job postings, whereas acquirers without such mentions show no material change (Box Figure 1.1, panel 2). This pattern is consistent with substitution away from external hiring once specialized teams are internalized. On average, post-deal patenting levels and patent value are higher among the labor-mentioning group; however, the differences are not statistically significant at conventional levels, and this group also seems to already be engaging in more innovation activities prior to the M&A as the pre-trend indicates Although talent-driven M&A may help firms navigate skill shortages, it can also concentrate market power which has been associated with higher markups and profitability alongside a slowing in business dynamism (Akcigit and others 2021), heightening concerns that similar forces could impede the spread of new skills.

Box Figure 1.1: M&A and Skill Acquisition



Sources: Kogan and others 2017; Lightcast; and IMF staff calculations.
Note: The figure shows the impact of talent-motivated mergers and acquisitions (M&As). Panel 1 plots the number of earnings call transcripts mentioning talent-related keywords over time. Panels 2 and 3 present event-study estimates for acquirers in talent-motivated versus other M&As, controlling for industry-year and firm fixed effects, where –1 represents the effective completion year of the M&A deal. Panel 2 shows changes in acquirers' demand for new skills (percentage points), while panel 3 shows changes in the forward patent citations (in logs), following the method of Kogan and others (2017).

[1] Prepared by Elmer Zongyang Li, Alina Song, and Marina M. Tavares

Annex I. Data

I.1. Data Description

Annex Table 1.1. Data Sources for Stylized Facts

Figures	Sources	Economies
Figure 1. A Dynamic Labor Market	Lightcast	USA, GBR, BRA, ZAF, DEU, DNK
Figure 2. New Skills	Lightcast	USA, GBR, BRA, ZAF, DEU, DNK
Figure 3. AI-Related New Skills	Lightcast	USA, GBR, BRA, ZAF, DEU, DNK
Figure 4. Skill Diffusion across Countries and within the United States	Lightcast, American Community Survey (ACS), Current Population Survey (CPS, via UnionStats), Wharton Residential Land Use Regulatory Index, Opportunity Lab, PIACC, Reinmuth and Rockall (2023)	USA, GBR, BRA, ZAF, DEU, DNK
Figure 5. The Return of New Skills	Lightcast	USA, GBR
Figure 6. New Skills Impact on US Local Labor Markets	Lightcast, American Community Survey, Current Population Survey (CPS, via UnionStats), Wharton Residential Land Use Regulatory Index, Opportunity Lab, PIACC, Reinmuth and Rockall (2023)	USA
Figure 7. New Skills Impact on Germany Local Labor Markets	Lightcast, Sample of Integrated Labour Market Biographies,	DEU
Figure 8. AI Exposure and Vacancy Impact	Cazzaniga and others (2024), Pizzinelli and others (2023)	USA, GBR, BRA
Figure 9. Impact of AI Skills on Employment	Lightcast, American Community Survey	USA
Figure 10. The Demand of New Skills by Firm Characteristics in the United States	Compustat, Lightcast	USA
Figure 11. Workers' Profile with New Skills in the United States	Lightcast	USA
Figure 12. New Skills Demand and Supply	Lightcast, OECD, ILO, PIACC	36 countries
Figure 13. Skill Readiness Index	Lightcast, OECD, ILO, PIACC	23 countries
Box Figure 1.1. M&A and Skill Acquisition	Kogan and others 2017, Lightcast	USA
Annex Figure 1.1. Job Posting and Employment Reweighted	Lightcast; ILO	USA, GBR, BRA, ZAF, DEU, DNK
Annex Figure 1.2 Distribution of Country-Specific Pure New Skills	Lightcast	USA, GBR, BRA, ZAF, DEU, DNK
Annex Figure 2.1 Skill Appearance Time Lag Relative to California (In months)	Lightcast	USA
Annex Figure 4.1. Skill Imbalance Index Distinguishing by IT and Non-IT Skills	Lightcast, OECD, ILO	36 countries
Annex Figure 4.2. Skill Imbalance Index – Extended Country Sample	Lightcast, OECD, UNESCO UIS, ILO, PIACC	54 countries
Annex Figure 4.3. Relation with AI Preparedness Index	Lightcast, OECD, UNESCO UIS, ILO, PIACC, Cazzaniga and others (2024)	54 countries

Note: All analyses are based on Lightcast job postings and profile data published in June 2025. The coverage period for each country in the analyses is as follows: 2010–25 for the United States; 2012–24 for the United Kingdom; 2018–24 for Germany; and 2021–24 for Brazil, Denmark, and South Africa. Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2). ILO = International Labour Organization; M&A = mergers and acquisitions; OECD = Organisation for Economic Co-operation and Development; PIACC = Programme for the International Assessment of Adult Competencies; UNESCO UIS = United Nations Educational, Scientific and Cultural Organization, Institute for Statistics.

I.2. Country Coverage

Annex Table 1.2. Country Sample Coverage

ISO3	Country	Income Group	ISO3	Country	Income Group	ISO3	Country	Income Group
AUS	Australia	AE	EST	Estonia	AE	MEX	Mexico	EM
AUT	Austria	AE	FIN	Finland	AE	NLD	The Netherlands	AE
BEL	Belgium	AE	FRA	France	AE	NOR	Norway	AE
BGR	Bulgaria	EM	GBR	United Kingdom	AE	POL	Poland	EM
BRA	Brazil	EM	GRC	Greece	AE	PRT	Portugal	AE
CHE	Switzerland	AE	HRV	Croatia	AE	ROU	Romania	EM
CHL	Chile	EM	HUN	Hungary	EM	SVK	Slovak Republic	AE
COL	Colombia	EM	IRL	Ireland	AE	SVN	Slovenia	AE
CRI	Costa Rica	EM	ISR	Israel	AE	SWE	Sweden	AE
CZE	Czech Republic	AE	ITA	Italy	AE	TUR	Türkiye	EM
DEU	Germany	AE	LTU	Lithuania	AE	USA	United States	AE
DNK	Denmark	AE	LUX	Luxembourg	AE	ZAF	South Africa	EM
ESP	Spain	AE	LVA	Latvia	AE			

Note: Country labels use International Organization for Standardization (ISO) country codes. AE = advanced economies; EM = emerging market economy.

I.3. Top Skills Demanded

Annex Table 1.3. Top 10 Growing New Skills, 2024

	USA	*GBR*	*DEU*	*DNK*	*BRA*	*ZAF*
1	Generative Artificial Intelligence	Generative Artificial Intelligence	Generative Artificial Intelligence	Generative Artificial Intelligence	CI/CD	CI/CD
2	Microsoft Edge	TikTok	Milling Cutters	Continuous Deployment	Kubernetes	Vue.js (JavaScript Library)
3	Social Media Management	Site Reliability Engineering	Express.js (JavaScript Library)	Canva (Software)	Docker (Software)	Containerization
4	Google Cloud Platform (GCP)	Social Media Management	SAP S/4HANA	Large Language Modeling	Microsoft Azure	Google Cloud Platform (GCP)
5	Power BI	Large Language Modeling	Industrial Dishwashers	Microsoft Copilot	Apache Kafka	Cloud Technologies
6	General Data Protection Regulation (GDPR)	Applications Of Artificial Intelligence	QR Codes	Vulkan Graphics API	Terraform	Generative Artificial Intelligence
7	Registered Behavior Technician (RBT)	PyTorch (Machine Learning Library)	Social Media Management	Instagram Marketing	Amazon Web Services	Apache Flink
8	Large Language Modeling	Trauma Informed Approaches	Large Language Modeling	Circular Solutions	TypeScript	Social Media Management
9	Preparer Tax Identification Number	IAM Certificate In Asset Management	Canva (Software)	Applications Of Artificial Intelligence	Google Cloud Platform (GCP)	Xero (Accounting Software)
10	Amazon Web Services	OutSystems	POCO (C++ Library)	Milling Cutters	Data Pipelines	Canva (Software)

Source: Lightcast; and IMF staff calculations.
Note: The table presents the 10 new skills with the largest increase in job postings for each country in 2024. Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2). CI = Continuous Integration; CD = Continuous Delivery/Deployment.

I.4. Skill Taxonomy

Annex Table 1.4. Lightcast Skill Taxonomy and Skill Fields

Lightcast Skill Taxonomy	Skill Fields	Lightcast Skill Taxonomy	Skill Fields
Administration	Social and Administrative	Design	Design and Marketing
Economics, Policy, and Social Studies	Social and Administrative	Marketing and Public Relations	Design and Marketing
Human Resources	Social and Administrative	Education and Training	Education, Public
Sales	Social and Administrative	Environment	Education, Public
Social and Human Services	Social and Administrative	Public Safety and National Security	Education, Public
Agriculture, Horticulture, and Landscaping	Service and Vocational Studies	Transportation, Supply Chain, and Logistics	Education, Public
Customer and Client Support	Service and Vocational Studies	Energy and Utilities	Energy and Utilities
Hospitality and Food Services	Service and Vocational Studies	Performing Arts, Sports, and Recreation	Arts, Sports, and Recreation
Personal Care and Services	Service and Vocational Studies	Engineering	Engineering
Physical and Inherent Abilities	Service and Vocational Studies	Finance	Finance
Property and Real Estate	Service and Vocational Studies	Health Care	Health Care
Analysis	Business and Data Analysis	Information Technology	Information Technology
Business	Business and Data Analysis	Law, Regulation, and Compliance	Law, Regulation, Compliance
Architecture and Construction	Architecture and Facilities	Manufacturing and Production	Manufacturing and Production
Maintenance, Repair, and Facility Services	Architecture and Facilities	Media and Communications	Media and Communications
		Science and Research	Science and Research

Source: Lightcast; and IMF staff calculations.

I.5. Lightcast Data

I.5.1 Job Postings Data

Vacancy postings data provided by Lightcast are obtained by scraping more than 220,000 websites globally, including job advertisement boards and company career pages. To ensure data quality and eliminate duplication, Lightcast employs a two-step algorithm which, first, detects whether an ad is new directly when scraping the source, and second, compares fields such as the job title, company, location, etc. across job postings of the last 60 days, since the same posting might appear in multiple places. The data provided by Lightcast for this analysis include postings for six countries and contains the raw text of each job posting. In addition, Lightcast enhances each posting with additional inferred information such as standardized job titles and company names, extracted skills according to the Lightcast skill taxonomy, assignment of occupations and industry, determination of education and experience requirements, information on salaries/wages, location, among others. Lightcast does not consistently identify whether a position is remote; therefore, it is not possible to distinguish between remote and on-site job postings.

I.5.2 Job Profiles Data

The Job Profiles data set provides information on individual workforce profiles, which includes information about a person, such as their job title, employer, skills, and educational background listed in their online profiles. The profiles data are collected from publicly accessible online sources, resume repositories, applicant information systems, among others. The database currently contains more than 100,000,000 unique individuals. As for the postings data, machine learning methods are used to identify duplicates, apply the Lightcast skill taxonomy, and add information on standardized job titles, skills, company names, and educational achievements.

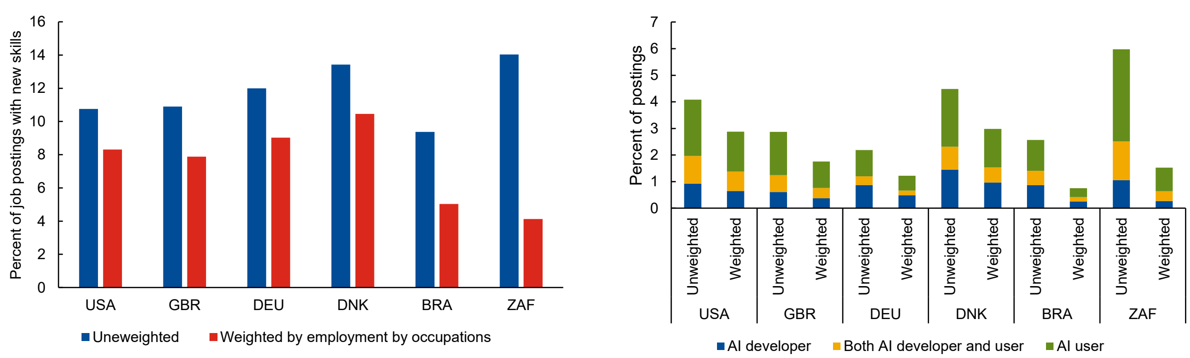
I.5.3 Data Comparison

Because postings are sourced primarily from online ads, coverage is tilted toward formal, urban, and higher-skill occupations. As a result, especially in emerging market economies, Lightcast postings may not mirror the full universe of vacancies. To mitigate composition bias, the occupational shares of postings with new skills for Brazil and South Africa are reweighted according to each country's employment structure using International Labour Organization (ILO) employment data at the ISCO 2-digit level. Note that for South Africa ILO only provides data at the ISCO-88 2-digit level while for Brazil ISCO-08 data exists. Annex Figure 1.1. compares the share of postings requiring new skills in the raw Lightcast series with an employment-reweighted series. In advanced economies, the employment-reweighted series lies about 2 percentage points below the raw postings on average—implying that employment weights may understate measured demand for new skills. This gap can arise because vacancy postings need not match the employment distribution (for example, higher turnover in certain occupations, or structural change concentrating vacancies in expanding sectors). The divergence is larger in emerging market economies—about 3 percentage points in Brazil and roughly 10 percentage points in South Africa—consistent with heavier online-coverage bias in those countries. Accordingly, Figures 2.1, 2.3, and 3.1 report the employment-reweighted (more conservative) measures of new-skill incidence (Figure 2.1), new-skill incidence by 1-digit occupation (Figure 2.3), and the new AI skill incidence (Figure 3.1), rather than the raw posting-based measures for these two emerging economies.

Similar data coverage concerns also exist for identifying new skills. The baseline definition uses US data, which offer longer historical coverage and consistent taxonomy. Nevertheless, to test robustness, alternative country-specific definitions identify skills absent in 2021 but emerging after 2022. Results are reported in Annex Figure 1.2. These independently identified skills show similar occupational distributions, with strong concentration in IT and professional fields, in line with the US-based classification. The share of country-specific new skills that match those identified in the United States, weighted by posting counts varies by country. Exact overlap is very high for the United Kingdom, moderate for Germany, and lower for other countries, reflecting differences in labor market composition.

Annex Figure 1.1. Job Postings and Employment Reweighted

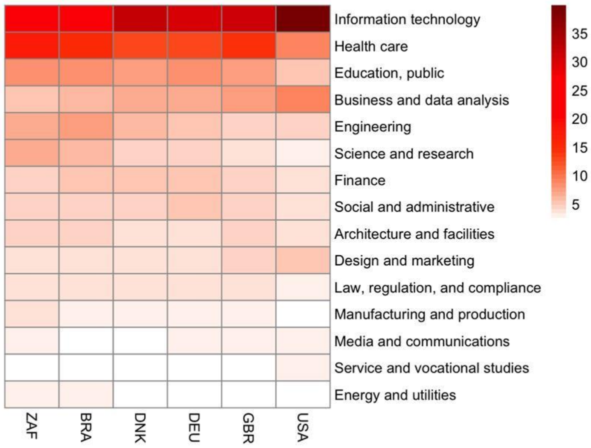
1. Job Posting Comparison 2. AI Exposure Comparison



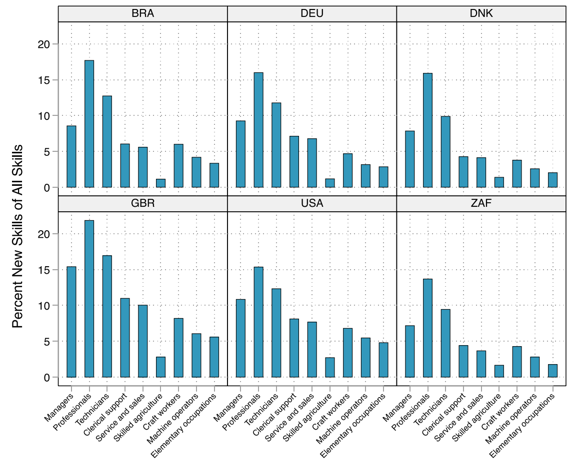
Sources: International Labour Organization; Lightcast; and IMF staff calculations.
Note: The figure shows the share of job postings requiring new skills (panel 1) or AI-related new skills (panel 2) relative to total postings. The weighted bar represents the weighted average of these shares, using the latest employment data by 2-digit ISCO code from the International Labour Organization. Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2).

Annex Figure 1.2. Distribution of Country-Specific Pure New Skills

1. Distribution of New Skills by Fields



2. Distribution of New Skills by Occupations



Sources: Lightcast; and IMF staff calculations.
Note: A "pure" new skill measure identifies any skill absent in all previous years. Panel 1 plots the distribution of new skills across broad fields using a heatmap, where each cell presents the proportion of posted new skills in that field compared to the total number of new skills posted across all fields. Panel 2 shows the share of new skills—measured consistently as in Panel 1—across major occupational groups. Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2).

Annex II. Data and Methodology

II.1. Local Labor Market Analysis

II.1.1 United States Data

This part of the analysis uses individual-level labor market data from the American Community Survey (ACS) and job postings data from Lightcast, covering the years 2013 to 2023. The ACS provides detailed information on worker demographics and earnings. Real wages are constructed by dividing total annual income by reported hours and weeks worked. The primary unit of analysis is the commuting zone (CZ), a stable and economically meaningful geographic unit based on commuting patterns, following the approach of Autor and Dorn (2013), Autor, Dorn, and Hanson (2013), and Acemoglu and Restrepo (2020). ACS microdata are assigned to CZs using PUMA-to-CZ crosswalks (that is, mapping between data sets) from Autor and Dorn (2013), allowing for consistent aggregation of worker outcomes over time. Similarly, Lightcast job postings are mapped to CZs using county-to-CZ crosswalks.

Control variables follow Autor and Dorn (2013) and Acemoglu and Restrepo (2020), including lagged measures of educational attainment (college vs. non-college share), immigration (non-college immigrant share), industrial structure (manufacturing share), labor market slack (unemployment rate), demographic structure (female employment share, share of population aged 60 and older), and low-wage employment prevalence (defined using the deflated state-level minimum wage). All regressions include state fixed effects and are estimated with standard errors clustered at the CZ level.

Union membership and coverage are obtained from www.unionstats.com, which is an Internet data resource providing private and public sector labor union membership, coverage, and density estimates compiled from the monthly household Current Population Survey (CPS) using Bureau of Labor Statistics methods. State-level non-compete indexes come from Reinmuth and Rockall (2023). Educational attainment is captured using the college share in 2010 derived from American Community Survey data. The housing supply elasticity is measured using the 2008 Wharton Residential Land Use Regulatory Index. Early childhood educational quality is proxied by third-grade math test scores obtained from the Opportunity Lab (Chetty and others 2014). Adult skill levels are measured using literacy and numeracy scores from the 2012 Programme for the International Assessment of Adult Competencies (PIACC) administered by the Organisation for Economic Co-operation and Development.

II.1.2 German Data

This part of the analysis uses the Lightcast job postings data for Germany covering the years 2019 and 2023 and all years for the United States data. In addition, the Sample of Integrated Labour Market Biographies is used. The authors use a 2 percent random sample which is drawn from the Integrated Employment Biographies (IEB) hosted by the Institute for Employment Research. The IEB consists of all individuals in Germany who are subject to social security, have at least a marginal part-time employment, receive benefits, registered as a job seeker, or participated in programs of active labor market policies. The administrative nature of the data allows tracking the daily employment status and wages of individuals as well as region, industry, occupation, age, and education. The analysis relies on real daily wages of full-time and part-time workers as determined on June 30 of the respective year. The authors apply the standard procedure introduced by Card and others (2013) to impute censored daily wages. The authors build on the code provided by Stueber, Dauth, and Eppelsheimer (2023) to clean and structure the data. As part-time work constitutes a substantial part of the German workforce, following the convention in the literature, daily wages of part-time workers are multiplied by a factor of two. Employment is determined by the number of workers in full-time or part-time employment on June 30 of the respective year. The regional unit of analysis is called "Raumordnungsregion," of which 96 exist in Germany. The analysis relies on a crosswalk to map the German 5-digit occupational classification KldB into the 4-digit ISCO classification used in Lightcast. Data are aggregated to the region and region by occupation level and only cells with at least five observations are included in the analysis. The definition of the control variables at the local labor market level follows Dauth and others (2021) by using employment shares at the 1-digit industry level as well as demographic controls such as employment shares of female, foreign, age older than 50, medium-skilled (apprenticeship), and high-skilled (university degree) individuals. All covariates are measured as averages of the base years 2011–14.

The policy heterogeneity exercise first uses the administrative record to calculate the ratio of the number of individuals who are in active labor market policies on June 30 over the number of individuals who are employed on June 30 (retraining share). Second, the regional union coverage created by Dauth and others (2021) for the year 1993 are used. They built these shares by using the German Socio-Economic Panel that surveys households in Germany and calculated the share of workers who are members of trade unions in 1993. Regions are then ranked according to their union shares (retraining shares) and the regression estimates a baseline effect for regions with low union shares (retraining shares), that is, those in the lowest quartiles (below 25th percentile), and additional marginal effects for regions in the second, third, and fourth quartile of union shares (retraining shares).

II.1.3 Methodology

The analysis relies on long-difference regressions following the setup of Acemoglu and Restrepo (2020) and Dauth and others (2021) who estimate the effect of robot exposure on wages and employment (and population) denoted by Y in the local labor market:

$$\Delta\, ln(Y)_{c,d} = \delta\, \Delta\, share\ of\ job\ postings\ with\ new\ skill_c + X_c' \gamma + \delta_d + \delta_s + \epsilon_{c,d}$$

where c denotes the local labor market (or commuting zone) and d denotes the demographic group which is a combination of gender by education group by age group. The long-difference denoted by Δ is taken between 2019–23 for Germany, given the limited time span of the Lightcast data in the case of Germany, and 2013–23 for the United States. Following the seminal work of Acemoglu and Restrepo (2020), X_c' captures initial local characteristics in the base year. In addition, the regression setup includes fixed effects δ_d and δ_s for the demographic group d and for the state s. All regressions use robust standard errors (clustered at the commuting zone-level in the United States).

Parameter δ is the coefficient of interest representing the effect of a one percentage point increase in the share of job postings with new skills on average wages or employment in the local labor market. $\Delta\, share\ of\ job\ postings\ with\ new\ skill_c$ represents the adoption of new skills: it is the percentage point change in the share of job postings with any new skill at the local labor market c.

This change might be endogenous to local shocks, demand conditions, or policies. In addition, simultaneity issues might arise where local labor market conditions could accelerate or slow down the adoption of new skills. To tackle these issues, the analysis uses a shift-share approach which explores pre-period employment shares of occupations and instruments the shift component which is the change in job postings with new skills at the occupational level for each local labor market level ($\Delta\, share\ of\ job\ postings\ with\ new\ skill_{o,c}$). Instrumenting also alleviates concerns of measurement error in the shift component and reduces the related bias.

The non-instrumented shift-share variable can be represented as:

$$\Delta\, share\ of\ job\ postings\ with\ new\ skill_c = \sum_o \frac{Emp_{c,o,baseyear}}{Emp_{c,baseyear}} \Delta\, share\ of\ job\ postings\ with\ new\ skill_{c,o}$$

The instrumented shift-share variable for the United States using the 2000 as the base year is given by:

$$\begin{aligned} &\Delta\, share\ of\ job\ postings\ with\ new\ skill_c^{IV} \\ &= \sum_o \frac{Emp_{c,o,baseyear}}{Emp_{c,baseyear}} share\ of\ job\ postings\ with\ new\ skill_{California\ 2013,o} \\ &+ \sum_o \frac{Emp_{c,o,baseyear}}{Emp_{c,baseyear}} share\ of\ job\ postings\ with\ new\ skill_{United\ Kingdom\ 2013,o} \end{aligned}$$

The instrumented shift-share variable for Germany using the average of 2011–14 as the base years is:

$$\begin{aligned} &\Delta\, share\ of\ job\ postings\ with\ new\ skill_c^{IV} \\ &= \sum_o \frac{Emp_{c,o,baseyear}}{Emp_{c,baseyear}} \Delta\, share\ of\ job\ postings\ with\ new\ skill_{United\ States\ 2014-2018,o} \\ &+ \sum_o \frac{Emp_{c,o,baseyear}}{Emp_{c,baseyear}} share\ of\ job\ postings\ with\ new\ skill_{United\ States\ 2014,o} \end{aligned}$$

Policy setup. The following regressions are deployed to determine the heterogenous effects of new skill adoption by ex ante differences in policy exposure of the local labor market c:

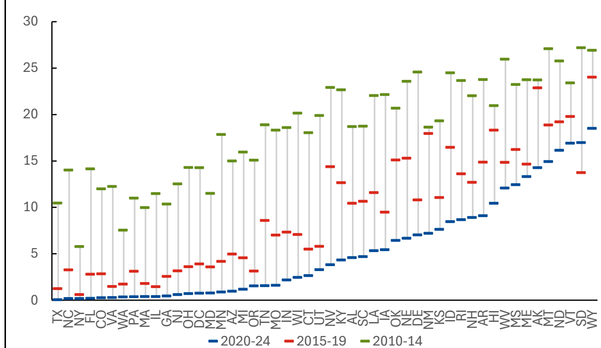
$$\begin{aligned}\Delta\, ln(Y)_{c,d} = {} & \delta_1\, \Delta\, share\ of\ job\ postings\ with\ new\ skill\ _c^{IV} \\ & + \ \delta_2\, \Delta\, share\ of\ job\ postings\ with\ new\ skill\ _c^{IV} \times high\ Policy\ exposure_c \\ & + \delta_3\ high\ Policy\ exposure_c + \ X_c'\gamma + \delta_d + \delta_s + \epsilon_{c,d}\end{aligned}$$

- Baseline effect of new skills (δ_1): the effect of a change in new skill exposure in a region with low policy exposure.
- Marginal effect (δ_2): additional effect of new skill adoption on wages in regions with high policy exposure. For example, in a region with a higher minimum wage, a significantly positive δ_2 would imply that the effect of new skill adoption on wages is significantly higher in regions with a higher minimum wage compared to regions with a lower minimum wage.
- Baseline effect of high policy exposure on wages (δ_3).

II.1.4 Additional Analysis

To investigate how new skills diffusion is changing over time, in this Annex, the Lightcast data for the United States is divided into three subperiods—2010–14, 2015–19, and 2020–24—and the diffusion of new skills from California to other states is estimated for each subperiod. The results indicate that the diffusion of new skills has been noticeably faster in the most recent period than in earlier periods (Annex Figure 2.1). In the most recent period, many states see new skills appear only a few months after California, whereas earlier periods often show lags on the order of one to two years or more.

Annex Figure 2.1. Skill Appearance Time Lag Relative to California (In months)



Sources: Lightcast; and IMF staff calculations.
Notes: This figure shows the distribution of time lags in new skill appearance across U.S. states over the three sample periods. Time lags are measured in months relative to California. States are ordered by their diffusion lag in the 2020–24 period. Positive values indicate slower appearance relative to California.

II.2. Event Study Analysis

II.2.1 Data

The study uses the same data as that of the United States local labor market analysis (Annex II, Section II.1.1).

II.2.2 Methodology

To estimate the dynamic employment effects of new skill entry at the county level, the Difference-in-Differences (DID) estimator developed by De Chaisemartin and D'Haultfoeuille (2023, 2024) is applied. This method extends standard DID to accommodate staggered, recurrent, and nonbinary treatments—specifically, cases where treatment intensity (for example, number or share of new AI-related skills adopted) varies over time and across units. Rather than estimating a single average treatment effect, it identifies dynamic treatment effects relative to the timing and intensity of exposure. For each treated cohort, the estimator compares outcomes at different event times (relative to skill entry) against a relevant comparison group of not-yet-treated or never-treated counties. This allows us to recover a time path of effects surrounding the treatment event, providing both pre-trend checks and post-treatment responses.

This methodology offers clear advantages over traditional two-way fixed effects event studies, which can be biased when treatment effects vary across cohorts or over time. The DID estimator avoids such contamination by constructing valid group-time contrasts and aggregating them with appropriate weights. It also handles recurrent treatment exposure without requiring right-censoring after the first treatment or restricting analysis to single-entry events. For our application, this means that counties experiencing multiple waves of AI skill diffusion remain usable in the analysis, and the estimator correctly attributes marginal employment responses to each incremental increase in skill exposure.

The actual estimator estimates cohorts-by-time effects and then aggregates to different time periods. A simplified representation is provided as follows:

$$Y^{o}_{cs,t} = \sum_{l=-L}^{P} \beta_l \Delta PostAISkill^{o}_{cs,t-l} + \delta_s + \delta_t + \epsilon_{csd,t},$$

where c represents a commuting zone, s denotes a state, and t indicates time. The regression is estimated at the (c,s,t) level, separately for each occupation group. The coefficient β_l captures the dynamic response to a one-unit change in exposure l periods ago and is the primary object of interest.

II.3. Macro-Regression

II.3.1 Data

The data are an unbalanced country-year panel for 2000–23 covering real hourly wages, labor productivity (GDP per hour), task content measures, product market institutions, and globalization variables. The wage–productivity block follows the long-run pass-through literature (Elsby, Hobijn, and Şahin 2013, Karabarbounis and Neiman 2014, IMF 2017) and is constructed from World Bank World Development Indicators for GDP (and price deflators) combined with harmonized hours/employment from OECD (advanced economies) and IMF staff calculations elsewhere. Task destruction is proxied by (1) robot penetration from the International Federation of Robotics and (2) offshorability indices mapped from occupations to national employment in the spirit of Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018), using published measures compiled by Brookings and IMF staff. Task creation is measured using O*NET "emerging tasks," aggregated to country–year employment shares (Acemoglu and Restrepo 2019). Institutional controls include product market concentration (HHI) from Brookings series and IMF Structural Reforms Database. All monetary series are deflated with national consumer price indexes, and shares/indices are standardized.

II.3.2 Methodology

The wage pass-through of new task content is estimated. using a country–year panel estimation for 2000–23, following Elsby, Hobijn, and Şahin (2013), Karabarbounis and Neiman (2014), and IMF (2017):

$$\ln w_{ct} = y + \delta \ln LP_{ct} + \Psi'[X_{ct}, M^{P}_{ct}, M^{L}_{ct}] + \Theta'[\Gamma^{D}_{ct}, \Gamma^{C}_{ct}] + \mu_c + \tau_t + \epsilon_{ct}.$$

Here, w_{ct} is the real hourly wage; LP_{ct} is labor productivity (GDP per hour); X_{ct} captures worker composition (education, age, sector shares); M^{P}_{ct} and M^{L}_{ct} are product- and labor-market institutions (Herfindahl-Hirschman Index, product market reform index; union density and collective-bargaining coverage). Task "destruction" (Γ^{D}_{ct}) is proxied by robot penetration and offshorability (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018). Task "creation" or new tasks (Γ^{C}_{ct}) is the incidence of O*NET emerging tasks (Acemoglu and Restrepo 2019). Estimation uses country and year fixed effects, employment weights, one-year lags for task variables, and standard errors clustered by country.

II.3.3 Results

The macro-level regression results indicate that new task creation consistently predicts higher wages across countries. Column (1) of Annex Table 2.1 uses the full sample of countries with available productivity data and shows a positive relationship between productivity and wages. Column (2) limits the analysis to countries with complete information on task creation and destruction. The positive relationship between productivity and wage growth remains and becomes stronger in magnitude. Columns (3) and (4) examine the relationship between task creation and log wages, controlling for a range of factors, including productivity, product market concentration, business regulation, automation, offshoring, trade openness, and financial integration. In these specifications, task creation shows a positive and statistically significant association with wage growth. The estimated coefficients suggest that a one standard deviation increase in task creation correlates with approximately 18 percent higher wages. These findings highlight that the emergence of new tasks—serving here as a macro-level counterpart to new skills—plays a central role in shaping wage dynamics.

Annex Table 2.1. Cross-Country Analysis of Task Creation and Wages

Dep: ln(wage)	(1)	(2)	(3)	(4)
ln(Productivity)	0.668	1.642**	1.851**	1.857**
	[0.492]	[0.701]	[0.774]	[0.849]
HHI			0.799	0.818
			[0.919]	[0.954]
Business regulation			-0.071	-0.073
			[0.141]	[0.153]
Robot exposure			-0.181	-0.182
			[0.380]	[0.390]
Offshoring			-0.016	-0.026
			[0.354]	[0.383]
Task creation			0.182***	0.178**
			[0.435]	[0.450]
Import/GDP				-0.003
				[0.009]
Financial integration				0.000
				[0.000]
Year fixed effects	X	X	X	X
Country fixed effects	X	X	X	X
Observations	812	426	426	416
R-squared	0.607	0.657	0.661	0.657

Source: Brookings Institution, IMF Structural Reforms Database, International Federation of Robotics, OECD, O*NET, World Bank World Development Indicators, and IMF staff calculations.
Note: HHI = Herfindahl-Hirschman Index.

Annex III. Wage Regression

III.1. Job Postings Data

This part of the analysis relies on job postings data from Lightcast restricted to the United Kingdom and the United States between 2020 and 2024. The data set includes detailed information on occupations (4-digit ISCO), industry (6-digit North American Industry Classification System – NAICS), geographic location (county or local authority), hourly wage, and salary type (annual, monthly, weekly, daily, hourly). The sample is restricted to postings with non-missing information on all these dimensions. Hence, the US sample comprises 54.3 million postings, while the UK sample contains 5.6 million postings. If the wage in the job posting is specified as an interval, the authors take the midpoint. The outcome variable is the log of posted hourly wages, constructed by harmonizing all salary frequencies into hourly units. The share of job postings with any new skill is 9.2 percent in the United States and 8.8 percent in the United Kingdom.

III.2. Methodology

The analysis relies on fixed-effect regressions to estimate the effect of a new skill being included in a job posting on the posted wage. The following regression constitutes the baseline setup:

$$\log(wage)_j = \beta * I(any\ new\ skill)_j + \delta_{o,i,c,y} + \delta_{st,y} + \delta_{\#\ skills} + \epsilon_j$$

where j denotes the job posting and $I(any\ new\ skill)_j$ is an indicator equal to one if at least one new skill is listed in the job posting. The granularity of the data allows to control for detailed fixed effects: $\delta_{o,i,c,y}$ represents the fixed effects combining 4-digit ISCO occupations o, 6-digit industry i, country c, and year y. The fixed effect absorbs substantial variation allowing the resulting wage premium of new skills to be determined within a narrow definition of job postings: it is identified by comparing job postings within cells with the same occupation, the same industry, the same county and the same year. Hence, the setting is more conservative compared to using fewer fixed effects. In addition, the analysis includes fixed effects for salary types of posted wages which are allowed to change with the year of posting ($\delta_{st,y}$). This captures, first, inherent job differences expressed through the salary type and, second, measurement error that might occur by reporting the salary for a specific pay period (hourly, daily, weekly, monthly, annually). The coefficient of interest β represents the percentage difference in posted wages between job postings that list a new skill instead of an existing skill. This comparison relies on controlling in the regression for the number of skills listed in the job posting, that is, including the fixed effect $\delta_{\#\ skills}$. Robust standard errors are clustered at the occupational level. Results are qualitatively robust to other specifications with fewer fixed effects or more detailed occupations.

The following additional specifications are estimated to determine heterogeneous effects of new skills. First, to capture the wage premium by the number of new skills, a separate regression includes four indicators capturing if (1) one new skill is present, (2) two new skills are present, (3) three new skills are present, or (4) four or more new skills are present in the job posting. Second, an adjusted specification captures the heterogeneous effects of at least one new skill listed in a job posting by skill category, for example, IT, business and data analysis, etc. Third, wage premiums stemming from the presence of at least one new skill are determined by the type of occupation (high-skill, white-collar, blue-collar, and low-skill). Four and finally, new skills are classified into AI Developer skills, AI User skills, and non-AI skills, and three indicators for the presence of these types of skills are added in an additional specification to determine AI skill specific wage premiums.

Annex IV. Demand and Supply of New Skills

IV.1. Demand of New Skills

The demand of new skills is estimated under the assumption that the US occupational distribution of new skill requirements applies to all countries. Specifically,

$$Demand\ of\ new\ skill_{c,s} = \frac{\sum_o Emp_{c,o} \times \frac{Postings\ with\ new\ skill_{USA,o,s}}{Emp_{USA,o}}}{\sum_o Emp_{c,o} \times \frac{Postings_{USA,o}}{Emp_{USA,o}}}$$

where *c* denotes the country, *s* the skill category (for example, IT, business analysis, etc.), and *o* is occupation. $Postings_{USA,o}$ represents the number of US job postings from the Lightcast database, and

$Emp_{c,o}$ represents employment by occupation and country, sourced from the International Labour Organization.

IV.2. Supply of New Skills

The share of graduates with new skills among the population aged 20–24 is estimated assuming the US distribution of graduates with new skills by field of study applies to all countries. The value reflects the average share of graduates between 2013 and 2023, calculated as:

$$Share\ of\ graduates\ with\ new\ skills_{c,y} = \frac{\left(\sum_f Share\ of\ graduates\ with\ new\ skill_{USA,f,y} \times Graduates_{c,f,y}\right) \times 5}{Pop_{20-24,c,y}}$$

where *c* denotes the country, f the field of study, and y the year.

$Share\ of\ graduates\ with\ new\ skill_{USA,f,y}$ represents the share of US graduates with new skills in field f and year y, estimated as follows:

1. Using degree information from Lightcast US profiles graduating in 2022–24, the field of study was inferred using the ChatGPT-4o-mini model to derive the distribution of graduates with new skills by field.
2. For earlier years, the distribution was adjusted by the ratio of graduates with new skills relative to 2023, to reflect temporal changes.

$Graduates_{c,f,y}$ denotes the number of graduates in country *c* from OECD data. Since the numerator reflects an annual flow of graduates while the denominator captures the size of a five-year age cohort (ages 20–24), the ratio is multiplied by five to ensure comparability on an annual basis.

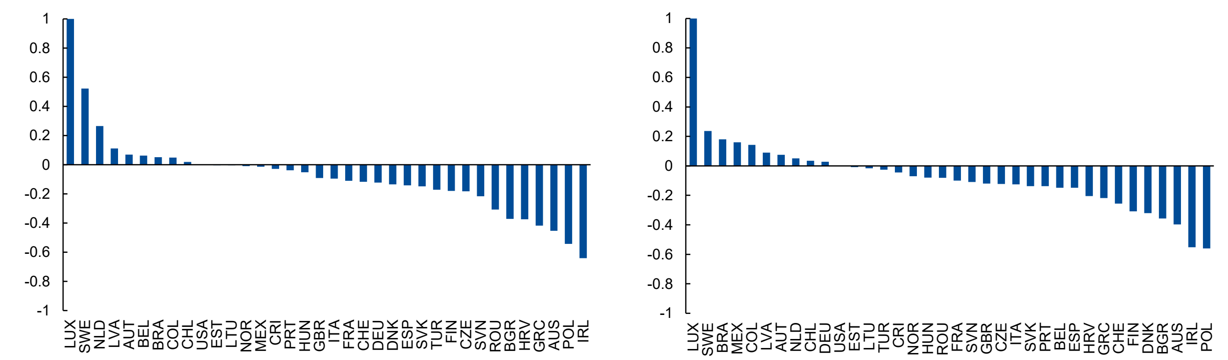
IV.3. Skill Imbalance Index

To calculate the skill imbalance index, the demand and supply of new skills are benchmarked to the United States, because it stands at the frontier of new-skill adoption (as shown by the diffusion analysis reported in Section II.3) and provides the most detailed vacancy data. The normalization is done by expressing both demand and supply as ratios relative to the values for the United States. In a subsequent step, the imbalance is calculated as the difference between the demand and the supply ratios and normalized by the maximum absolute value of these differences to range between –1 and 1.

Annex Figure 4.1. extends the Skill Imbalance Index to focus separately on granular new IT and new non-IT skills.

Annex Figure 4.1. Skill Imbalance Index Distinguishing by IT and Non-IT Skills

1. IT Skills 2. Non-IT Skills



Sources: International Labour Organization; Lightcast; Organisation for Economic Co-operation and Development; and IMF staff calculations.
This figure shows the relationship between the share of graduates with new skills relative to the United States and new skill demand relative to the United States. Panel 1 presents the skill imbalance index focusing on new IT skills only which is calculated as the difference of the new IT skill demand relative to the United States minus the new IT skill supply relative to the United States, normalized by the maximum absolute value of these differences to range between –1 and 1. Panel 2 shows the same relationship for new non-IT skills. The construction of both indices follows the construction of the general Skill imbalance index (see Figure 12). Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2).

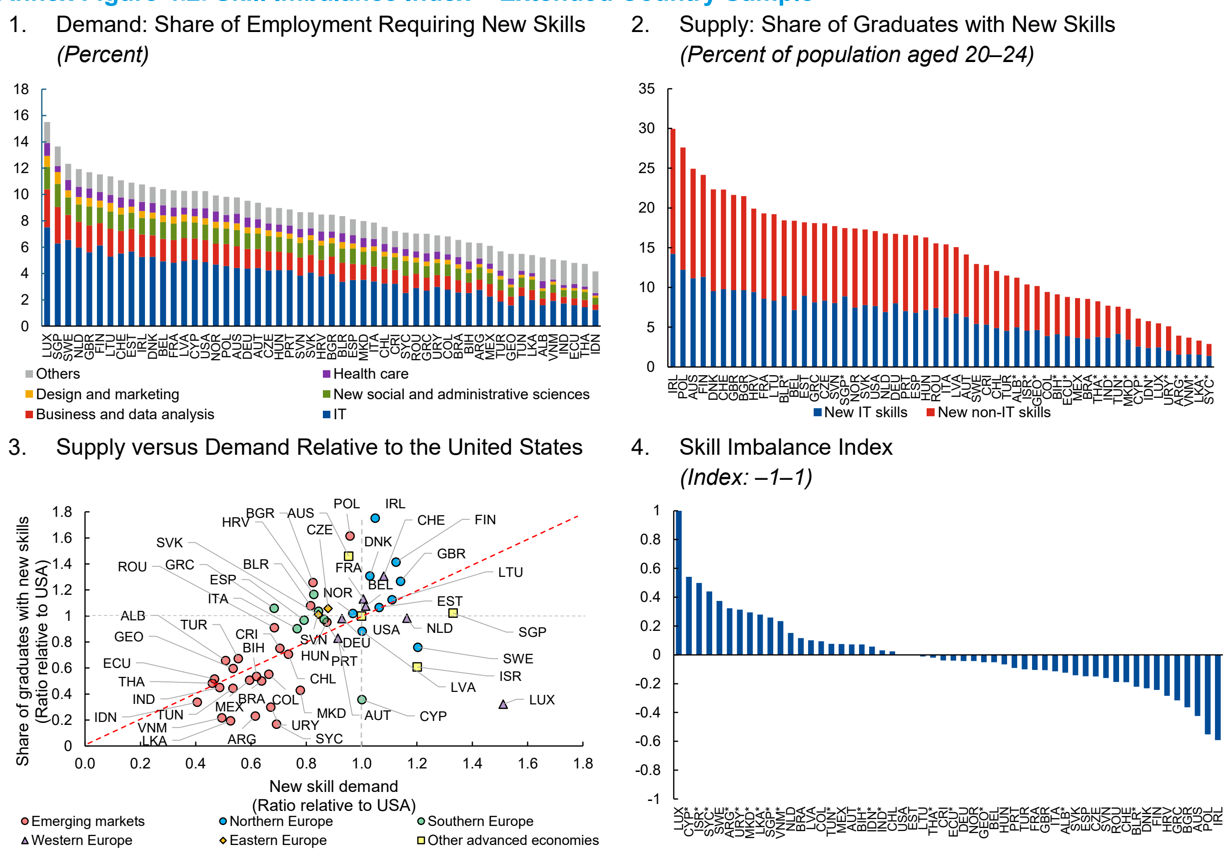
To extend the coverage of the skill imbalance index to a larger set of countries, the OECD data are complemented by using data from UNESCO UIS on the distribution of graduates by field of study and gross graduation ratios for countries not covered by the OECD. This comes at the expense of lower comparability to the main results which use OECD data on graduates by field of study as UNESCO covers fewer years and the fields of study are broader (moving from 16 fields in OECD to 11 fields using a many-to-one mapping). In addition, gross graduation rates in the UNESCO data cover only bachelor's and master's degrees (ISCED 6 and 7) and not all levels of tertiary education as in the OECD data. Results are shown in Annex Figure 4.2 The use of UNESCO UIS data is restricted to countries which (1) were not covered by using the OECD data, (2) for which ILO provides occupational employment distributions at the 2-digit ISCO level, (3) for which UNESCO UIS covered at least four years between 2013–24 and the latest year is 2022 or later, and (4) which are not low-income countries because assuming that graduates have the same level of new skills as in the United States might be less reasonable for such countries. This adds 18 additional countries to the Skill Imbalance Index.

IV.4. Skill Readiness Index

The skill readiness index is calculated as the simple average of four normalized components: 1) graduates with new IT skills; 2) graduates with new non-IT skills; 3) adult participation in job-related learning (OECD 2023);[19] and 4) average adult skills in literacy, numeracy, and adaptive problem-solving score (OECD 2023). Each component is normalized by converting values into standard scores, adding 3, and dividing by 6, thereby rescaling the distribution such that values between the 0.1^{st} and 99.9^{th} percentiles correspond to a range from 0 to 1.

[19] Adult participation in job-related learning refers to the share of adults who engaged in formal or non-formal job-related adult learning as reported in *Trends in Adult Learning: New Data from the 2023 Survey of Adult Skills* published by the OECD. Box 1.1 in the same report provides details on the types of learning and survey questions included in the 2023 Survey of Adult Skills.

Annex Figure 4.2. Skill Imbalance Index – Extended Country Sample



Sources: International Labour Organization; Lightcast; Organisation for Economic Co-operation and Development (OECD); Programme for the International Assessment of Adult Competencies; United Nations Educational, Scientific and Cultural Organization, Institute for Statistics (UNESCO UIS); and IMF staff calculations.

Note: The figure is an extension of Figure 12 in the main text. Figure 12 relies on the sample of countries for which OECD data on graduates by field of study are available. The figure includes countries based on available UNESCO UIS data on the field of study of university graduates and the gross graduation rate, adding them to the previous set of countries covered in Figure 12.

*The share of graduates with new skills is calculated based on UNESCO UIS data, otherwise it is calculated using OECD data.

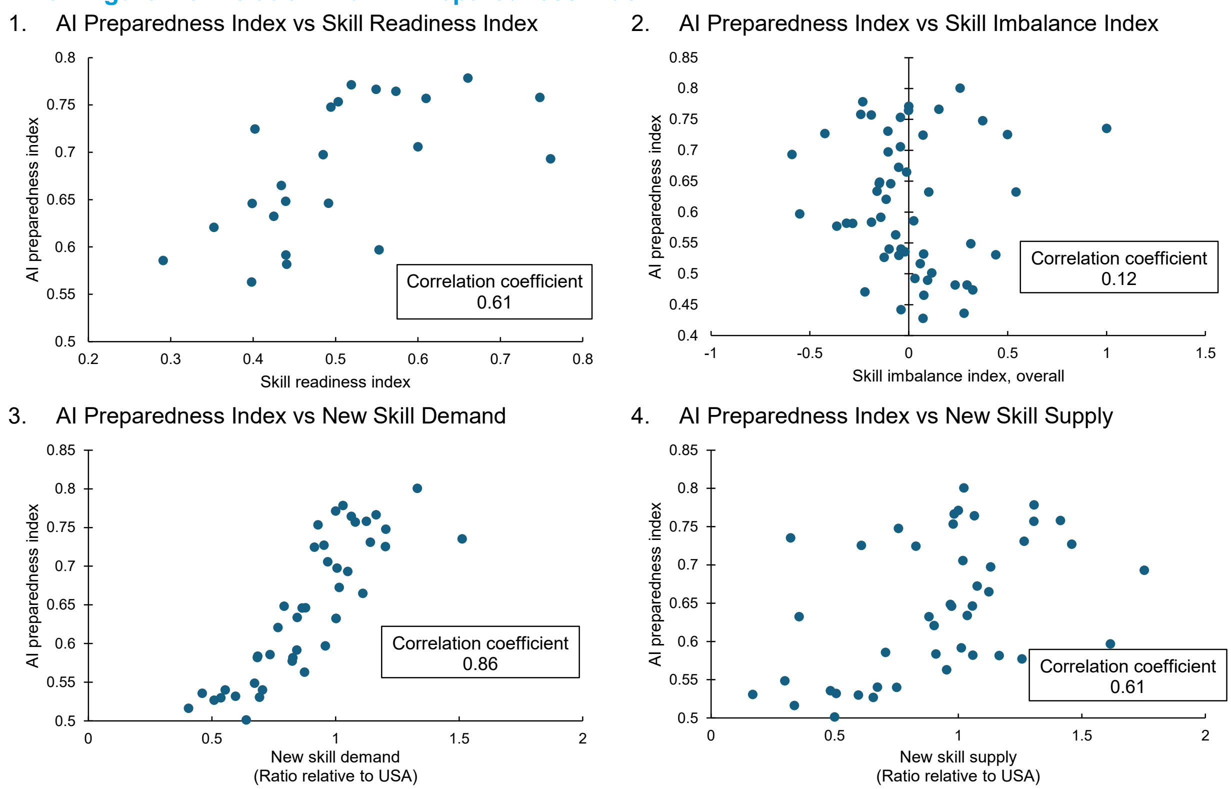
Panel 1 reports the share of employment requiring new skills, assuming the US occupational distribution of new skill requirements. For simplicity, job postings containing multiple new skills are classified according to the most common skill. For example, a posting listing both IT and business and data analysis is classified under IT new skills.

Panel 2 shows the share of graduates with new skills among the population aged 20–24 from 2013 to 2021. For 2022 and 2023 the same graduation rates as that of 2021 are assumed, then the US distribution of graduates with new skills by field of study is applied. Since the numerator is an annual flow of graduates while the denominator is the size of the five-year cohort (ages 20–24), the ratio is multiplied by 5 to place on a comparable annual basis. If no education data from the OECD are available (indicated by *), the analysis uses UNESCO UIS data: first, the percent graduates by field of study and second, the gross graduation ratio of the respective graduation cohort and multiplies both with the US distribution of graduates with new skills by field of study to achieve a measure, which is comparable to using the OECD data. Panel 3 shows the relationship between the share of graduates with new skills relative to the United States and new skill demand relative to the United States. Panel 4 presents the skill imbalance index, calculated as the difference between *x* axis values and *y* axis values in Panel 3, normalized by the maximum absolute value of these differences to range between –1 and 1. Country labels use International Organization for Standardization (ISO) country codes (see Annex Table 1.2). The coverage of UNESCO UIS data differs by country: Albania 2015–24, Argentina 2018–23, Bosnia and Herzegovina 2018–23, Belarus 2018–24, Cyprus 2013–23, Ecuador 2014–16 and 2023, Georgia 2016–22, India 2013–23, Indonesia 2015–18 and 2022–23, Israel 2020–23, North Macedonia 2013–15, 2017–18, 2020–22, Singapore 2016–23, Seychelles 2015–16 and 2020–24, Sri Lanka 2015 and 2021–23, Thailand 2015 and 2022–24, Tunisia 2015–16 and 2020–23, Uruguay 2020–23, Vietnam 2015–16 and 2021–22.

IV.5. Relating the Skill Indices to the AI Preparedness Index

The Skill Readiness Index and the Skill Imbalance Index complement the AI Preparedness Index (AIPI) introduced by Cazzaniga and others (2024). The three indices have different objectives. The AI Preparedness Index focuses exclusively on how well countries are prepared to adopt AI technologies. It covers four areas of preparedness, such as human capital and labor market policies, digital infrastructure, innovation and economic integration, and regulation and ethics. Like one of the areas covered by the AIPI, the skill readiness index has a human capital focus. But both the skill readiness index and the skill imbalance index are based on a more granular set of new skills covering not only skills and technologies related to AI but also new non-IT skills and non-AI related IT skills. The skill imbalance index compares projected supply and demand of new skills relative to the United States, while the skill readiness index can be viewed as an elaborate version of the projected potential supply of new skills. Both skill indices are inherently forward-looking as they assume for all countries the same intensity of new skill demand by occupation and the same intensity of new skill supply by field of study as found in the United States. Panel 1 of Annex Figure 4.3 shows that the AI Preparedness Index is correlated with the skill readiness index with a correlation coefficient of 0.61. The demand and supply measures of new skills that determine the skill imbalance index are also found to be correlated with the AI Preparedness Index (Annex Figure 4.3, panel 3 and 4). But the skill imbalance index itself—shown for the extended sample of countries—is uncorrelated with the AI Preparedness Index (Annex Figure 4.3, panel 2).

Annex Figure 4.3. Relation with AI Preparedness Index



Sources: Lightcast, OECD, UNESCO UIS, ILO, PIACC, Cazzaniga and others (2024), and IMF staff calculations.
Notes: This figure presents scatter plots of the AI Preparedness Index (Cazzaniga and others, 2024) against four different Indexes with each dot representing a country: the Skill Readiness Index (panel 1), the Skill Imbalance Index (panel 2), New Skill Demand (panel 3), and New Skill Supply (panel 4). The country coverage in panels 2, 3, and 4 is the same as in Annex Figure 4.2.

Annex V. Mergers and Acquisitions Analysis

V.1. Data

The analysis combines four US firm-level sources during 2010–24: (1) Capital IQ earnings and M&A call transcripts to identify talent-motivated deals; (2) Compustat North America for fundamentals and identifiers; (3)

Lightcast job-posting microdata to measure firms' demand for "new skills"; and (4) a database of completed M&As with effective completion year and acquirer identifiers. Transcripts are tokenized and searched for a curated dictionary of labor/talent terms (for example, "talent acquisition," "hiring freeze," "labor shortage," "skills gap," "acqui-hire"), and an indicator is set to one if any acquirer mentions these terms in the three years preceding deal completion. Lightcast postings are de-duplicated at firm–occupation–location–date and mapped to SOC codes; the new-skills index follows the definition discussed in Annex III, and is aggregated to firm-year shares. Firms are linked across data sets via gvkey/ticker and name-matching with manual resolution of large mergers. Outcomes include (1) the change in the firm's new-skills share in postings (percentage points), and (2) innovation outcomes using patent value and forward citations (Kogan and others 2017, log values).

V.2. Methodology

The empirical framework used to analyze the behavior of acquirers is based on a standard event-study approach, in which firm-level outcomes are regressed on a series of relative-year indicators around the completion of each M&A deal, controlling for firm and industry-year fixed effects. Specifically, for each deal, the empirical specification is as follows:

$$y_{it} = \sum_{r=-3}^{4} \beta_r \cdot rel\_year_{r,it} + \alpha_i + \gamma_{n,t} + \epsilon_{it}$$

y_{it} denotes the outcome variable for firm i in year t, which can be the percentage of postings requiring new skills, the log real value of patents, or the log forward citations of patents. *rel_year*$_{r,it}$ represents the number of years before or after the effective completion of the M&A deal. α_i captures firm fixed effects, and $\gamma_{n,t}$ captures industry-by-year fixed effects.

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