

Online Annex 2.1

This annex documents the data sources and methodologies used in the main text. Section 2.1.1 summarizes data sources. Section 2.1.2 describes how the new measure of emerging artificial intelligence skills is constructed. Section 2.1.3 provides regression specifications. Section 2.1.4 provides additional notes on figures in the main text.

2.1.1 Data

International Labour Organization Data

Figures 2.1–2.3 and 2.11 use the following International Labour Organization (ILO) databases:

- Figure 2.1: Unemployment rate by sex and age—ILO modeled estimates, November 2025 (%). Database ID UNE_2EAP_SEX_AGE_RT_A. The chart shows 25th, 50th, and 75th percentiles of unemployment rates across economies in each region.
- Figure 2.2: Unemployment rate by sex, age, and education (%) and Youth unemployment by sex, age and education (%) – Annual. Database ID UNE_DEAP_SEX_AGE_EDU_RT_A and UNE_3EAP_SEX_AGE_EDU_RT_A. The chart includes REO14 and program countries that have observations after 2023. Because of data limitations, for CHN, data from Haver Analytics are used. The average monthly urban unemployment rate in 2025 is shown for total unemployment, and the average monthly urban unemployment rate among people aged 16–24 (excluding students) in 2025 is shown for youth unemployment. No data are available for unemployment by age and education.
- Figure 2.3: Employment by sex, educational mismatch, and education—normative approach (thousands). Database ID EMP_TEMP_SEX_SKN_EDU_NB_A. The chart includes REO14 and program countries that have observations after 2023. See the ILO website (<https://ilostat.ilo.org/methods/concepts-and-definitions/description-education-and-mismatch-indicators/>) for a discussion of caveats to the measure of educational mismatch.
- Figure 2.11: Employment by sex and occupation—ISCO level 2 (thousands). Database ID EMP_TEMP_SEX_OC2_NB_A. The data are used to aggregate region-specific regression coefficients into aggregate impact of artificial intelligence (AI).

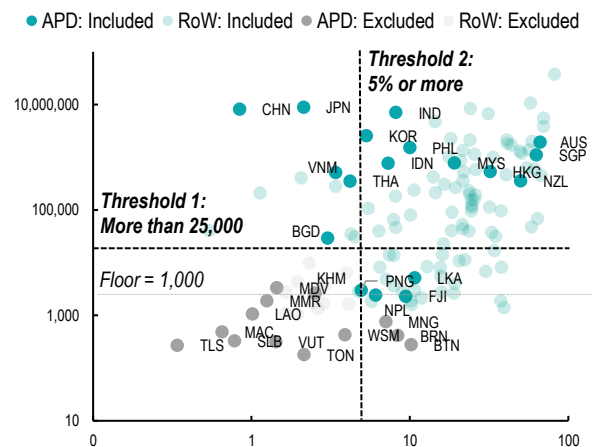
Job Posting and Worker Profile Data

Data on job postings and worker profiles are from Lightcast. Posting data include job descriptions, required skills, and other information available in job ads. Profile data include data on job histories, location of work, and other information in worker histories.

Regression analyses use postings from November 2021 onward to ensure sufficient coverage for Asia. The sample of economies is selected using data from May 2025 to April 2026. Economies enter the sample in two steps. Those with fewer than 1,000 postings over the window are excluded. Then, economies with active profiles (with locations updated within the last year) covering at least 5 percent of the 2025 labor force (ILO 2025 modeled estimates) or more than 25,000 postings

Online Annex Figure 2.1.1. Sample Selection

(x-axis: active profile, percent of 2025 labor force (log scale); y-axis: total postings in 2025, log scale)



Sources: April 2026 IMF World Economic Outlook; International Labour Organization; Lightcast; and IMF staff calculations.

Note: The sample comprises postings and active profiles between May 2025 and April 2026. Data labels in the figure use International Organization for Standardization (ISO) country codes. APD = Asia and Pacific Department; RoW = rest of the world.

are retained. The resulting sample covers 19 economies in Asia and the Pacific and 91 economies in the rest of the world (Online Annex Figure 2.1.1).

Staffing-agency postings are excluded throughout to limit double counting from vacancies reposted by intermediaries. Postings where the industry of the firm advertising the job cannot be identified are also excluded.

2.1.2 Emerging AI Skills

Emerging AI skills specific to generative AI are identified in four steps.

The first step identifies AI-related skills with names containing AI-related terms such as “AI,” “Generative,” “Agent,” “GPT,” “Language Model,” “LLM,” and “Prompt.” This initial step yields 1,411 skills from Lightcast’s skill taxonomy.

The second step constructs the time series of emergence for each skill. For each selected skill, the share of postings containing the skill is calculated for each year. The share is cumulated across years and normalized by the sum of the share over 2010–26, so that the resulting cumulative distribution function (CDF) ranges from 0 in 2010 to 1 in 2026.

The third step restricts attention to skills that emerged after 2022 following Atalay and others (2020). A skill is classified as emerging if its CDF is below 1 percent in 2010–11 and rises above 1 percent during 2023–26. This step identifies 39 skills.

Finally, all three steps are repeated using Lightcast’s taxonomy of AI skills, which contains 323 skills, and the taxonomy of AI skills developed by Jaumotte and others (2026), which contains 547 skills. Combining the skills identified here with the initial set of 39 skills leads to a final set of 51 emerging AI skills.

Examples of emerging AI skills are prompt engineering, vector databases, retrieval-augmented generation, agentic AI, LangChain, ChatGPT, Claude, and GitHub Copilot.

2.1.3 Regression Specifications

Monthly Specification

The month-by-month specification is as follows:

$$y_{eiot} = \sum_{k \neq -1} \beta_k (1_{o=\text{high exposure}} \times 1_{t=\text{AI Launch}+k}) + \alpha_{eit} + \alpha_{eio} + X_{eio} \sum_k \gamma_k 1_{t=k} + \epsilon_{eiot},$$

where e is the economy, i is the industry, o is the occupation, t is the year–month pair, and y_{eiot} is the log of postings. X_{eio} is the share of postings with remote work in all postings of economy e , industry i , and occupation o , averaged over $t = \text{AI launch} - 12$ to $\text{AI launch} - 1$. Standard errors are clustered at the occupation level. Occupations with above-median AI exposure are flagged with a dummy variable $1_{o=\text{high exposure}} = 1$, using the complementarity-adjusted AI Occupation Exposure constructed by Pizzinelli and others (2023).

Specification in AI Capability Time

Model Evaluation and Threat Research evaluates AI models using the software tasks performed by human experts and estimates the task duration for which the model achieves a 50 percent success rate. The resulting time horizon ranges from seconds to hours and beyond (METR 2026).

Let K_m be the set of year–month pairs where the length of software tasks successfully completed with 50 percent probability is m . For example, $K_{9 \text{ seconds}}$ covers May 2020 to February 2022:

$$y_{eiot} = \sum_{m \neq 36 \text{ seconds}} \beta_m (1_{o=\text{high exposure}} \times 1_{t \in K_m}) + \alpha_{eit} + \alpha_{eio} + X_{eio} \sum_k \gamma_k 1_{t=k} + \epsilon_{eiot},$$

where e is the economy, i is the industry, o is the occupation, and t is the year–month pair. Standard errors are clustered at occupation level.

Firm-Level Specification

The firm-level estimation calculates the growth rate of postings from $t - 1$ to t across different groups of firms and occupations, controlling for firm size as well as the economy and industry to which firms belong. The period of interest t is from May 2025 to April 2026, and $t - 1$ is from May 2024 to April 2025.

Let y_{eifo} denote the growth rate of postings by firm f for occupation o . Firm f has a unique economy e and industry i to which it belongs:

$$y_{eifo} = \beta_1 1_{o=\text{high exposure}} + \beta_2 1_{f=\text{adopt AI}} + \beta_3 1_{o=\text{high exposure}} \times 1_{f=\text{adopt AI}} + \alpha_{ei} + \gamma \text{firm_size}_f + \epsilon_{eifo},$$

where e is the economy, i is the industry, f is the firm, and o is the occupation. If firm f has postings that require emerging AI skills at $t - 1$, $1_{f=\text{adopt AI}} = 1$. Firm size is proxied by the log of postings by firm f at $t - 1$ for all occupations. α_{ei} is an economy–industry fixed effect.

Figure 2.9 shows the estimated growth rate for four firm–occupation groups, controlling for firm size and economy–industry fixed effects. Let $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ be the estimated coefficients.

- Postings by firms that do not adopt AI for low-AI-exposed occupation: 0
- Postings by firms that do not adopt AI for high-AI-exposed occupation: $\hat{\beta}_1$
- Postings by firms that adopt AI for low-AI-exposed occupation: $\hat{\beta}_2$
- Postings by firms that adopt AI for high-AI-exposed occupation: $\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3$

2.1.4 Additional Notes on Figures

Figure	Additional Notes
Figure 2.2	Youth is defined as people aged 15–29 years. Median values are used for the rest of the world (RoW). Data labels in the figure use International Organization for Standardization (ISO) country codes. The latest data vary by economy (see Online Annex 2.1.1). (*) Because of data limitations, total unemployment for CHN refers to urban unemployment, and youth unemployment for CHN refers to urban unemployment rate for 16–24 age group, excluding students. No data are available for unemployment by age and education.
Figure 2.3	Fraction of overeducated refers to workers in jobs that do not require their level of education. The latest data vary by economy (see Online Annex 2.1.1). Data labels in the figure use International Organization for Standardization (ISO) country codes
Figure 2.7	The sample comprises Asia and Pacific Department economies. The figure shows the share of postings that feature an emerging AI skill. Each dot represents an ISCO-08 4-digit occupation. Software developers correspond to ISCO-08 4-digit occupation group 2512 (“Software Developers”). Supply manager corresponds to ISCO-08 4-digit occupation group 1324 (“Supply, Distribution and Related Managers”). Standardized AI exposure index is the z-score of the C-AIOE measure for each ISCO-08 4-digit occupation from Pizzinelli and others (2023). AI = artificial intelligence; C-AIOE = complementarity-adjusted artificial intelligence occupational exposure; ISCO = International Standard Classification of Occupations.

Figure 2.11 Region-specific estimates of impact on labor demand (Figure 2.10) are scaled by the share of employment in highly exposed occupations in 2022 in each economy (occupational employment shares for Indonesia are from 2023). The impact on less-exposed occupations is assumed to be zero. Bubble sizes indicate working-age population size as of 2025. Working-age population growth and decline are measured as the percentage change in the projected population aged 15–64 between 2025 and 2035. Working-age population growth is capped at 20 percent. Data labels in the figure use International Organization for Standardization (ISO) country codes. AE = advanced economy; EM = emerging markets; LIC = low-income country; RoW = rest of the world.

Figure 2.12 The numerator counts profiles for workers that move across ISCO-08 4-digit occupations. The denominator counts all worker profiles excluding simultaneous employment across multiple employers. Ratios are calculated within each economy. RoW is the median across economies in each group. Transitions from higher- to lower-AI-exposure occupations are defined as a decline in AI exposure. AI = artificial intelligence; RoW = rest of the world.

References

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