Labor Markets in Asia: Challenges and Opportunities in the Age of AI[1]

This chapter will assess where Asian labor markets stand and examine how rapid technological change—particularly the rise of artificial intelligence—is reshaping the jobs landscape. It will highlight key labor market challenges in Asia, including significant demographic shifts, capital-intensive growth models, and high youth unemployment in some countries. Drawing on a rich cross-country dataset, it will then assess how AI is likely to interact with these existing challenges and reshape labor markets. It will emphasize that structural reforms to improve labor market outcomes are urgent throughout the region.

The first section (~3 pages) will present a backward-looking overview of labor markets in Asia. Building on the Asia in 2050 book, it will highlight that demographic trends vary significantly across countries. Labor forces are shrinking in some countries, while others are poised to benefit from demographic dividends—if new labor market entrants can be integrated successfully. Headline indicators such as unemployment suggest a relatively benign picture (Figure 1). *The key question for this section will be: despite low unemployment rates, are there important underlying challenges, including underemployment and skill mismatches?*

A set of complementary indicators will be used to highlight the main labor market challenges to date. From a macro perspective, the section will assess whether growth in the region has been 'job-scarce', by considering capital intensity, labor shares, and the extent to which employment in agricultural and informal sectors masks significant underemployment. At a micro level, drawing on granular, harmonized cross-country labor force survey data from the International Labor Organization, the section will evaluate the role of (i) high youth unemployment rates—particularly among well-educated youth—in several countries (Figure 1); (ii) skill mismatches (Figure 2); and (iii) the combination of significant informal employment and rigid formal labor markets. The section will end by noting that heterogeneity on these dimensions and in the extent of AI adoption (Figure 3) means that the starting point with respect to the anticipated AI shock varies widely across countries.

The second section (~3 pages) will assess the outlook for labor markets. It will note that the growing role of capital and technology—including digitalization, automation, and AI—in production has the potential to both boost productivity and threaten job creation. The section will ask whether contributions from capital have dominated contributions from labor in driving growth not only in aging economies with shrinking labor forces, but also in economies with significant job creation demands.

The impact of AI on the supply and demand sides of labor markets will be evaluated, using granular, high-frequency data from Lightcast. *On the supply side, the section will assess workers' readiness to adapt to the growing use of AI.* To do so, it will use worker profile data to quantify the prevalence of AI-related skills in each country and industry. *On the demand side, the section will ask: how has the rise of AI impacted labor demand at the occupation level?* To answer this question, the section will use data through early 2026 to empirically examine whether trends in postings already point to shifts in labor demand in occupations that are either highly substitutable with or strongly complementable by AI. The key empirical challenge—to separate

[1] This chapter will be prepared by Sakai Ando and Divya Kirti (lead), drawing on inputs from Willa Lin (Fund intern) and research assistance from Ilman Szami, under the guidance of Li Cui.

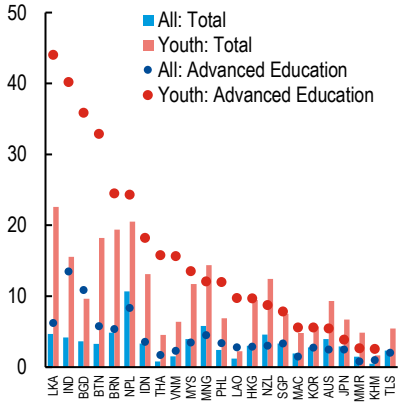
between the impact of AI and confounding factors—will be addressed using granular fixed effects. Annex A provides additional details on the dataset and proposed methodology.

This section will then synthesize the empirical findings to assess the impact of AI from a macro perspective. It will do so by asking two main questions. *First, what are the implications for aggregate labor demand at the country level and at the sector level? Second, how does this impact interact with supply considerations? More specifically, at the sectoral level, how is demand affected in industries that were previously labor intensive relative to others? And at the country level, how does the projected impact on demand relate to expected labor shortages or job creation needs going forward, the extent of underemployment, and the current prevalence of AI skills?*

The chapter will end with implications for how policies can help prepare for technological change (~1 page). It will highlight that structural fundamentals are essential to strong macroeconomic outcomes: in aging economies, to use AI to offset growth headwinds from shrinking workforces, and in economies with younger populations, to harness demographic dividends by ensuring that labor market entrants find employment in productive sectors. Specifically, the chapter is likely to argue that investing in digital infrastructure, facilitating worker mobility, and strengthening lifelong learning and education systems will be critical to help workers adapt to modern forms of production and working in new sectors. It could note that different responses may be needed if the impact of AI is significantly more disruptive than anticipated and flag fragmentation in access to frontier models as an important risk. The chapter is also likely to highlight the costs of high rigidity in small formal labor markets—protecting incumbent workers at the cost of reducing incentives to adapt and preventing new entrants from accessing high-quality employment—and barriers to growth in modern tradeable services.

Unemployment rates are high for highly educated youth in several Asian countries.

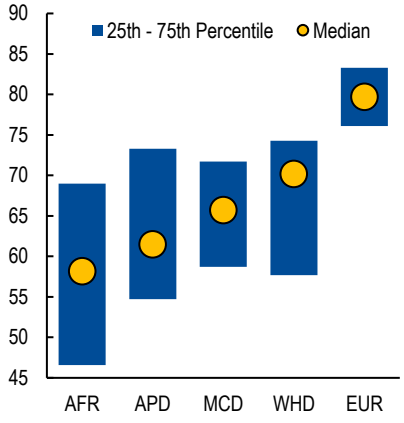
Fig 1. Unemployment Rate by Age and Education
(percent, 2025 or the latest)



Source: International Labor Organization; IMF staff calculations.
Notes: Youth unemployment is defined as unemployed people aged 15-24 years old. Advanced Education is unemployed person with tertiary education.

Advanced education is less likely to translate to high skill jobs in Asia.

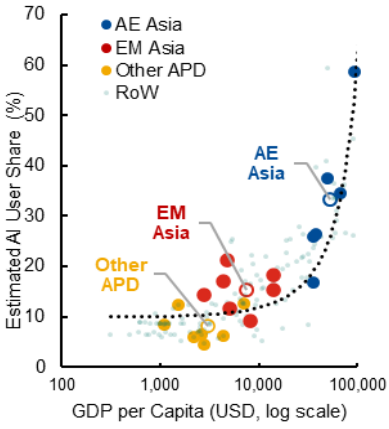
Fig 2. Share of High Skill Jobs Among Workers with Advanced Education
(percent, 2024 or the latest)



Sources: International Labor Organization; IMF staff calculations.
Notes: Numerator is employment of those with college or higher education and high skill jobs (managers, professionals, technicians and associate professionals). Denominator is employment of those with above-college education.

Growth of AI could worsen inequality, with more adoption in higher income economies.

Fig 3. AI Usage and GDP per Capita
(Percent of estimated AI users in 2025, 2024 GDP per capita)



Source: Misra et al. (2025), IMF World Economic Outlook; IMF Staff Calculations Notes: Misra et al. (2025) use data from devices using Microsoft software to estimate the share of working-age population that actively use AI tools over 2025. Values for AE Asia, EM Asia, and Other APD are averages.

ANNEX A

For APD countries, Lightcast's raw dataset includes roughly 30 million postings annually with coverage through March 2026 and 122 million individual profiles.

On the supply side, the team will look at the fraction of worker profiles with AI skills (separately for producer and user skills) by country and industry. It will draw on a detailed classification of worker skills provided by Lightcast and a taxonomy of AI skills constructed by Jaumotte and others (2026).

On the demand side, the team will begin with the following specification:

$$y_{c,i,o,t} = \alpha_{c,i,t} + \alpha_{c,i,o} + \sum_{h} \beta_h \, Expected\ AI\ impact_o \times 1_{t=AI\ Launch+h} + \epsilon_{c,i,o,t},$$

$$c = country, i = industry, o = occupation, t = time$$

The dependent variable could be based on postings in levels, logs, or shares of postings within country, industry and time, building on Bastos and others (2026).

The AI exposure and complementarity indices constructed by Felton and others (2021) and Pizzinelli and others (2024) offer natural starting points for occupation-level measures of the expected impact of AI. The analysis could use the launch of Chat GPT or other impactful AI events to date the 'launch' of AI. The analysis could separately consider occupations where AI could largely substitute for labor and occupations where AI is more likely to complement labor, as in Goldman Sachs (2026). The chapter could explore whether the coefficients of interest (β_h) differ for a sample restricted to APD countries, and whether they vary across individual APD countries. If so, the analysis could relate such variation to differences in labor market rigidity across countries.

Country x industry x time fixed effects should absorb shifts in industry-specific final demand and dynamics related to the post-pandemic reopening. Country x industry x occupation fixed effects should absorb industry-occupation traits including differences in the mix of tasks within occupation across industries. Work on the impact of AI on labor demand has largely focused on the US, debating the extent of impact so far and the relative importance of cyclical and structural shifts (see e.g., Brynjolfssen and others, 2025, Jaumotte and others, 2026, Liu and Webber, 2026, Liu and others, 2025, Gimbel and others, 2025). If data quality permits, the analysis could also be conducted within geographic regions within countries.

The team plans to translate occupation-level estimates of the impact of AI on labor demand into sector and country-level estimates using the pre-existing distribution of occupations in each sector and country.

If feasible, the analysis could also consider whether trends differ for more junior roles and explore differential effects for AI-adopting firms. Wages could also be considered, subject to data availability.