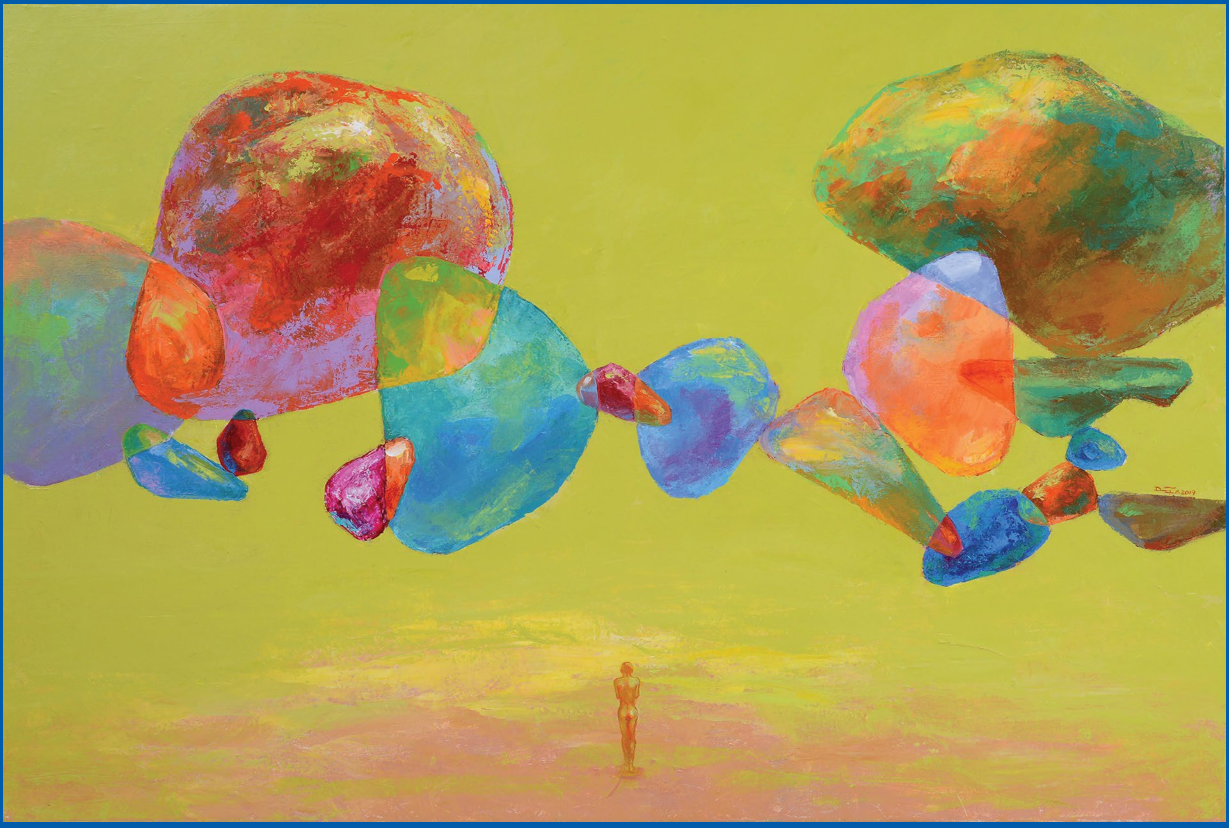
FUTURE JOBS

Robots, Artificial Intelligence, and Digital Platforms in East Asia and Pacific

Omar Arias, Daisuke Fukuzawa, Duong Trung Le, and Aaditya Mattoo



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About the artist: Mai Huy Dũng (b. 1974) is a Vietnamese artist creating independent art in a modernizing Viet Nam. With a unique, expressive style, Dũng’s work captures the color, rhythm, and evolving identity of contemporary life (https://www.maihuydung.com/c35/author.html).

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Foreword

Historically, technology has driven economic growth and transformed jobs. In a series of books, the East Asia and Pacific (EAP) region of the World Bank examines how technological advances today impact firm growth, productivity, jobs, services, and the transition to low-carbon economies. This book explores the profound labor market impacts of new technologies, such as industrial robots, artificial intelligence (AI), and digital platforms, in this dynamic region.

Over the past decade, new digital technologies have been reshaping the nature of work and the livelihoods of many people. In the EAP region, robot adoption has fortunately led to an increase in manufacturing employment. This is due in part to the region's comparative advantage in manufacturing. Higher productivity led to an expanded scale of production in global markets that outweighed the labor-displacing effects of automation technology. But the impacts of new technologies are being felt differently across population groups in the region. For instance, between 2018 and 2022, the introduction of industrial robots helped create jobs for an estimated 2 million (4.3 percent of) skilled formal workers but displaced an estimated 1.4 million (3.3 percent of) low-skilled formal workers in five Association for Southeast Asian Nations (ASEAN) countries.

While it is too early to assess the labor market effects of AI, and there is as yet no discernible impact on employment, AI, too, is likely to have both displacement and augmentation effects across occupations. While the region may be relatively less exposed to the displacement effects, it may also be less well placed to benefit from AI technology. Only about 10 percent of jobs in the EAP region involve tasks complementary to AI, which is comparable with the share in other emerging economies, but much lower than the 30 percent share in advanced economies.

Meanwhile, digital platforms are providing new opportunities for younger workers who possess digital skills and women who can benefit from more flexible work arrangements. The size of the digital platform economy reached between 5 percent and 7 percent of gross domestic product in most EAP countries in 2023.

This book explores both the technical feasibility and economic viability of these new technologies. While they can substitute for labor in an ever-widening range of activities, new technologies are economically feasible today only in the relatively high-wage sectors in more developed EAP countries. Looking ahead, with rising labor costs and declining technology prices, the reach of technology will expand. The book analyzes the interdependence of technology adoption and labor market impacts across sectors, providing insight into the economy-wide effects of adopting new technologies.

To address the challenges and opportunities presented by rapid technological change, the book proposes several policy actions. Besides reforms to create new opportunities, these actions include equipping the workforce with digital, socioemotional, and advanced technical skills that help them to work with the new technologies. At the same time, facilitating the mobility of workers and capital will lessen the costs of adjustment. Also, removing factor price distortions would reduce the risk of premature automation.

It is my hope that policy makers, researchers, and practitioners will find in this book insights and inspiration to devise and implement labor and economic policies that harness the potential of technology to create more and better-paying jobs in EAP countries.

Manuela V. Ferro
Vice President, East Asia and Pacific
The World Bank

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Overview

Introduction

This report analyzes the impact of new technologies, such as robots, artificial intelligence (AI), and digital platforms, on labor markets in the East Asia and Pacific (EAP) region. Technical feasibility and economic viability will determine the diffusion of these technologies. Apart from the overall impact on jobs, various population groups may be affected differently. And technological choices in one sector are likely to affect those in other sectors. The report also proposes policy reforms that can help turn technological change into a blessing.

Stylized facts about EAP labor markets

Overall employment in the labor markets in the EAP region remains high. Economic growth is driving wage increases that are outpacing labor productivity. However, demographic shifts are reshaping the dynamics of the workforce. In China, Mongolia, Thailand, and Viet Nam, populations are aging, leading to a shrinking available workforce. Trends in employment and earnings vary significantly across sociodemographic groups. While female labor force participation rates are higher in the region than in other developing regions, they still lag the rates among men and have exhibited limited progress, except in Indonesia, Malaysia, and the Philippines. The gender wage gap is narrowing. Yet, women continue to earn 10 percent to 15 percent less than men. Although the workforce is more well educated now than two decades ago, the quality of education is uneven, and only a third of workers have a college degree or higher educational attainment. Overall, youth unemployment is lower in the EAP region than in other developing regions, but, within the region, it is higher in China, Indonesia, Malaysia, and Mongolia. While older workers are experiencing lower unemployment rates, they are participating less in the labor force.

Alongside demographic shifts, sectoral employment patterns have also undergone significant transformation. Over the past decade, employment has primarily moved from low-productivity agriculture to low-productivity services and, to a lesser extent, into high-productivity manufacturing and services. The strongest wage growth has been in professional and information and communication technology (ICT) services. While informal employment has declined overall, it remains widespread, especially in low-productivity services and in the Pacific Islands, where it accounts for over half of employment.[1]

These trends raise important questions about the role of technology in shaping labor markets in developing EAP countries. Are new technologies likely to boost labor demand and labor earnings? Will the adoption of industrial robots and AI mitigate or exacerbate the challenge represented by a shrinking labor force in aging societies? Can digital technologies help narrow prevailing gaps in employment and wages or, instead, amplify them? What will the structural shifts in employment and earnings look like in EAP countries as they adopt new technologies? The report examines these and other related questions to gauge the impact of the diffusion of new technologies on employment, wages, and skill demand in the region.

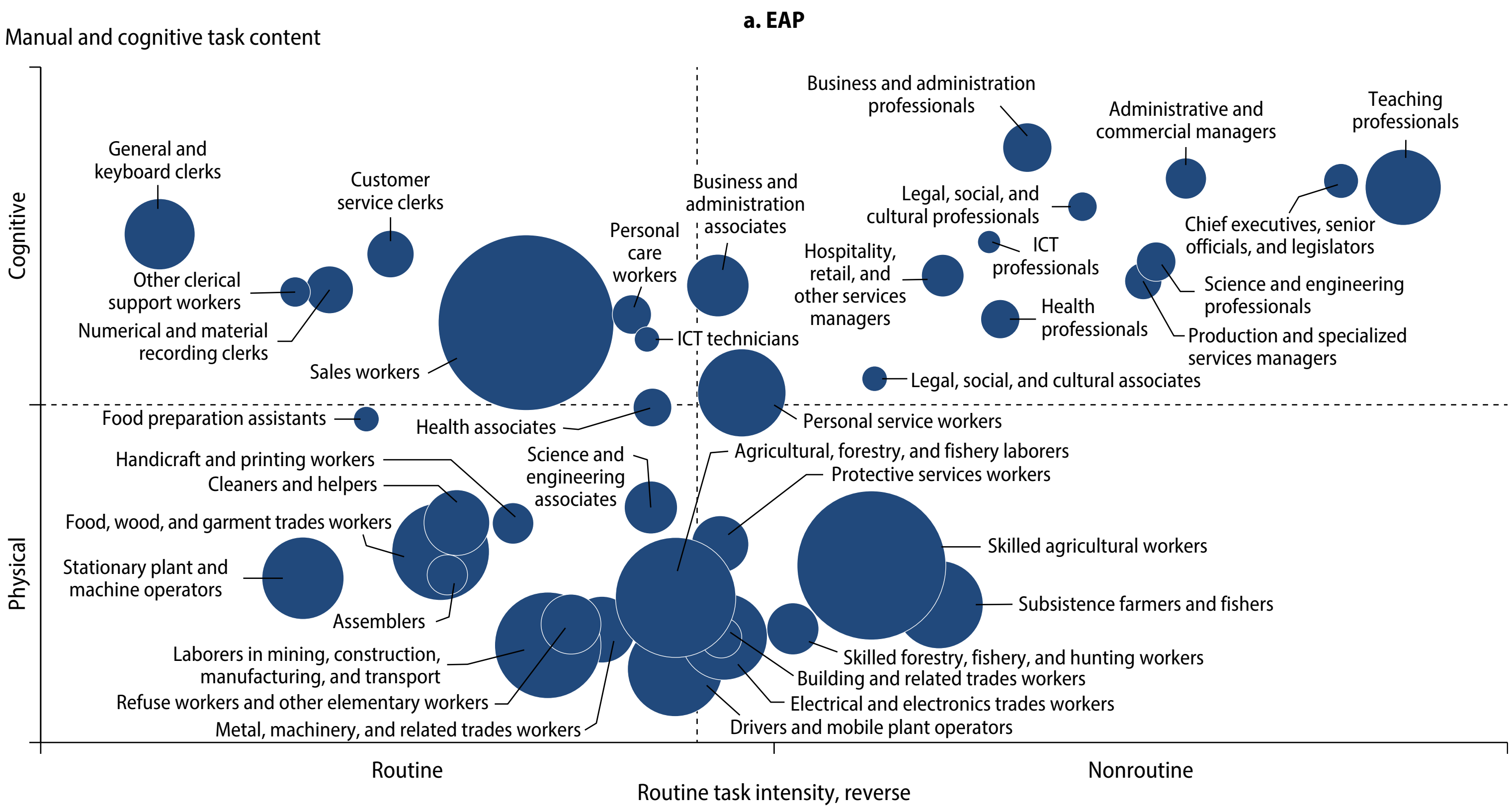
Technology diffusion in the EAP region

New technologies are affecting labor markets and the nature of work. Advances in technology are expanding the scope of tasks that machines can perform. Robots are already displacing industrial workers in routine manual task occupations. AI threatens to displace services workers not only in routine tasks but increasingly also in nonroutine cognitive task occupations. AI-empowered robots could also take over the tasks of workers in nonroutine manual occupations in both manufacturing and services. The extent to which this happens will depend on the technical feasibility and economic viability of new technologies within each country.

Based on *technical feasibility,* jobs in most EAP countries could be affected by robots and AI, although in ways that differ from the effects in advanced economies. EAP countries employ more people in routine manual task occupations and fewer people in cognitive task occupations relative to advanced countries (refer to figure O.1). This occupational structure reflects successful industrialization in countries such as China, Malaysia, Thailand, and Viet Nam and the relatively weaker condition of services in the region. Compared with workers in advanced countries, workers in EAP countries, similar to workers in other emerging market and developing economies, face a higher risk of job displacement by industrial robots than by AI. However, the share of EAP employment potentially exposed to AI is larger than the share exposed to robots. China and Malaysia stand out as countries with a relatively high share of people employed in nonroutine cognitive tasks who may be equipped to benefit from complementarities with AI.

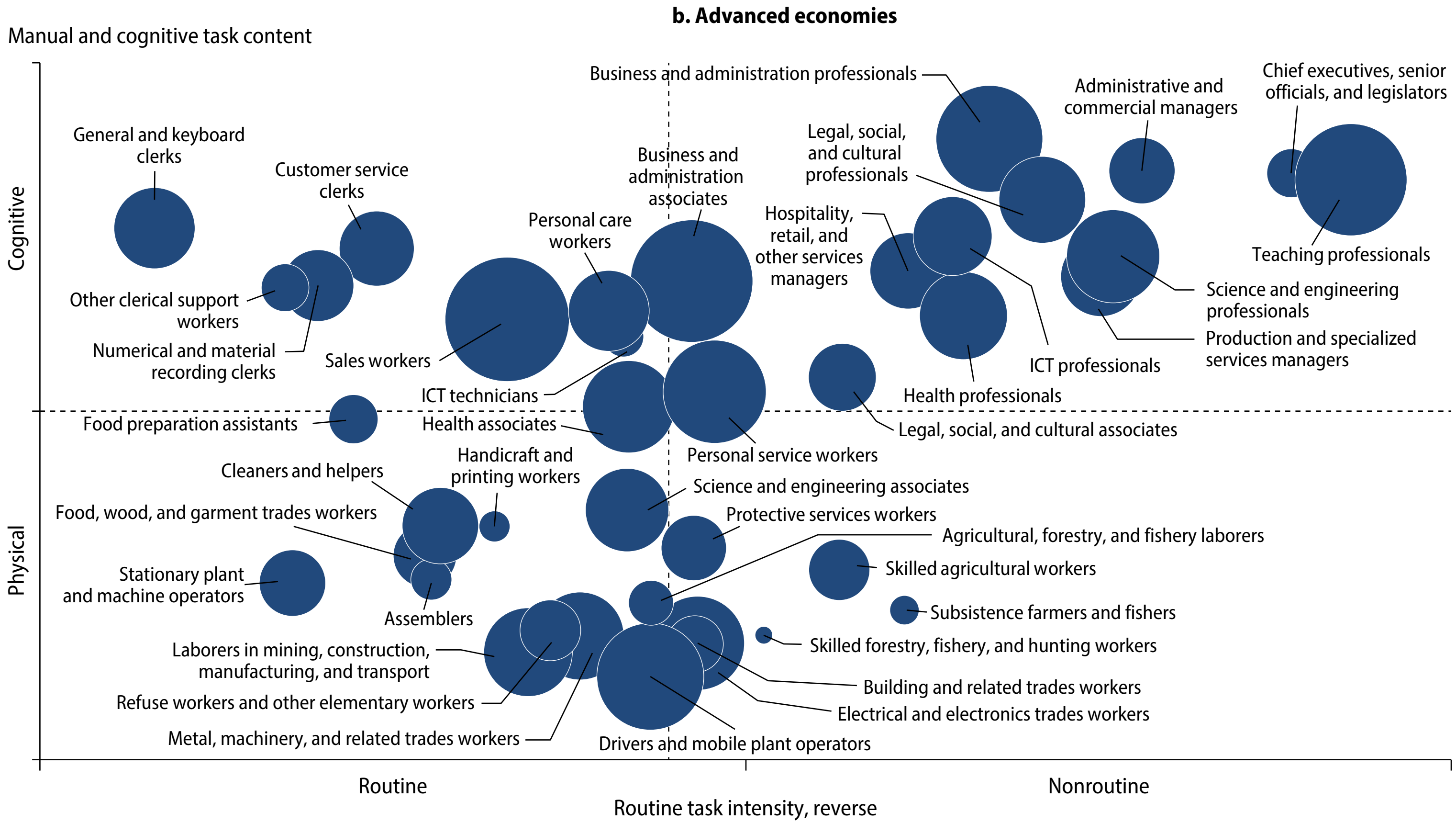
EAP: More jobs require physical tasks, and fewer jobs require nonroutine cognitive tasks.

FIGURE O.1 **The task structure of jobs, EAP and advanced economies**



(continued)

FIGURE O.1 The task structure of jobs, EAP and advanced economies *(continued)*



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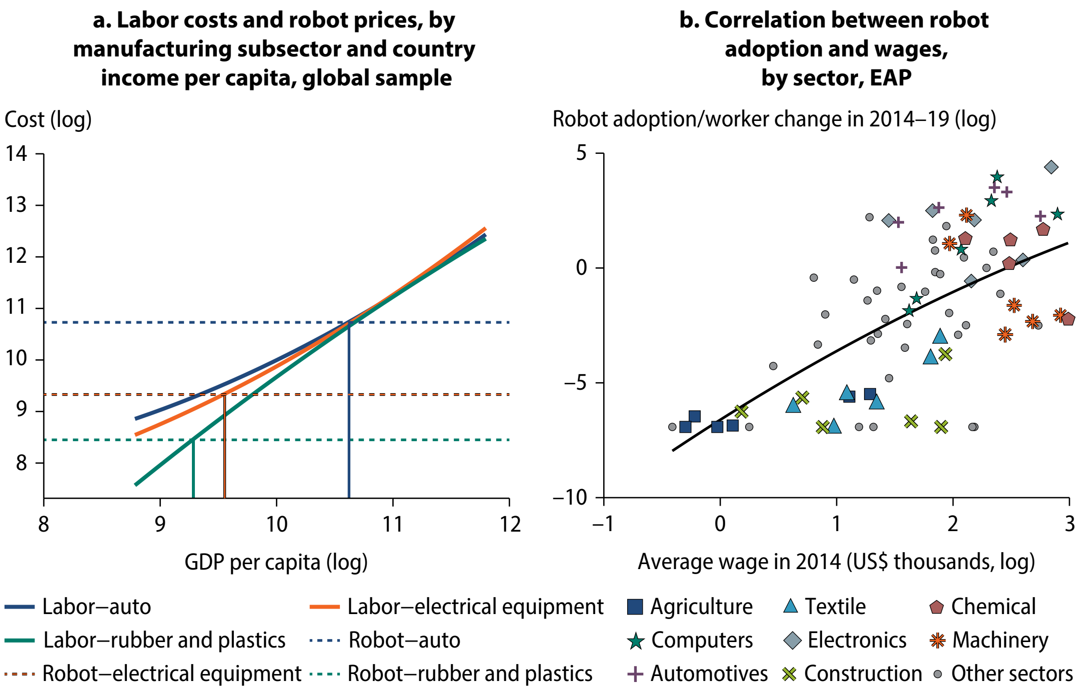
Note: The y-axis measures the relative cognitive versus manual content of job tasks (nonroutine physical task intensity). The x-axis measures routine task intensity computed following the methodology of Autor and Dorn (2013). The task intensity indicators are used to provide a relative ordering of occupations in the respective dimensions. Bubble size denotes the average occupation share in EAP (9 countries) and advanced economies (36 countries). Data are from the most recent year available. EAP = East Asia and Pacific; ICT = information and communication technology.

Economic viability also determines the adoption of new technologies. Technology diffusion varies across countries and sectors because of differences in the costs and benefits of adoption. These depend on the quality-adjusted cost of technology, the cost of local labor, and the responsiveness of product demand to price changes.

Consider the economics of robot adoption in three manufacturing subsectors: rubber and plastics, electrical equipment, and automotives. Figure O.2, panel a, shows estimates of the quality-adjusted robot costs per worker replaced (horizontal lines) and the potential labor cost savings (upward sloping curves) in each sector,

The economic viability of new technologies depends on the price of the technologies relative to labor costs.

FIGURE O.2 Correlation between labor costs and robot prices and labor costs and robot adoption, EAP and the world



Sources: Original figure for this publication based on data of TiM (Trade in Employment) (database), Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/data/datasets/trade-in-employment.html; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

Note: Panel a: The y-axis shows estimates of the average quality-adjusted, per worker robot price and total labor cost in three manufacturing subsectors. Labor cost curves are estimated in a global sample of countries. Panel b plots robot adoption rates against wages across different sectors in EAP countries and the estimated regression fit. For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search. Refer to chapter 2 for details on the methodology for estimating robot prices and the regressions.

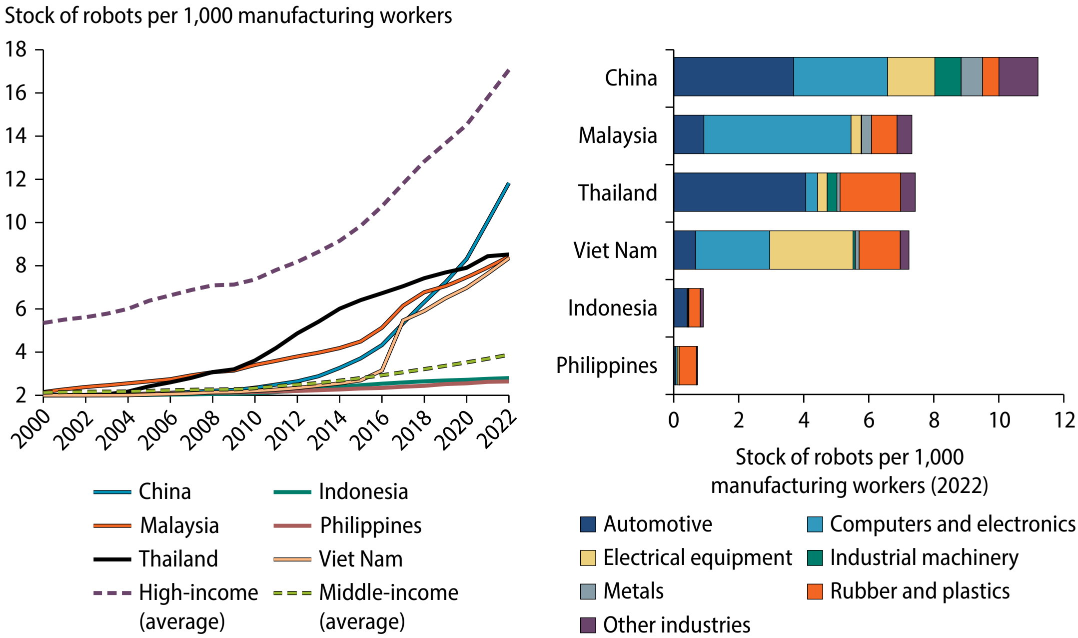
plotted against country income per capita worldwide. The intersections with the vertical lines denote the break-even points at which robots may be deemed economically viable to substitute for human labor. Robots are economically viable in lower-income countries only in sectors, such as rubber and plastics, that rely on cheaper, more-elementary robots. Figure O.2, panel b, plots the actual (average) robot adoption rates against wages across manufacturing sectors in EAP countries. As countries develop and labor costs rise, robot adoption rates increase in all sectors, but at a more rapid pace in the electrical equipment industry, which uses intermediate robots. Automotive robots are the most expensive and are used extensively only in EAP countries with higher labor costs.

The observed patterns of robot adoption across countries and sectors align with the predictions of the economic viability of the technology (refer to figure O.3).

Robot adoption is expanding in the EAP region, especially in computers and electronics, rubber and plastics, and automotives.

FIGURE O.3 The stock of industrial robots and trends in robot adoption, EAP, 2000–22

a. Trends in industrial robot adoption, 2000–22 **b. Industry composition of the stock of robots, 2022**



Sources: Original figure for this publication based on data of TiM (Trade in Employment) (database), Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/data/datasets/trade-in-employment.html; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

Note: Panel a: The manufacturing employment level is fixed in the baseline year (2000). Panel b: Industry composition of the stock of robots corresponds to the most recent year (2022).

Higher-income Malaysia and Thailand were the early adopters in the region, but China and Viet Nam have experienced a surge in robot adoption since 2010. By comparison, the level of robot adoption remains relatively low in Indonesia and the Philippines. In terms of industries, robot adoption in China, Malaysia, Thailand, and Viet Nam has been concentrated in sectors such as computers and electronics, automotives, and electrical equipment, while, in Indonesia and the Philippines, it has been concentrated in rubber and plastics.

Differences across EAP countries in the scope of automation arise because of differences in occupational structure and differences in labor costs. Relatively few jobs are susceptible to automation in countries such as the Lao People's Democratic Republic, Papua New Guinea, and Timor-Leste because many people are involved in nonroutine agricultural and services tasks, and wages are low (refer to figure O.4). More people work in routine manufacturing in Cambodia and Myanmar, but low wages reduce the economic benefits of automation. In contrast, in higher-wage countries, such as Malaysia and Thailand, many more people are susceptible to automation in manufacturing and services. Across EAP countries, some service jobs, such as customer services, involve routine tasks, pay relatively high wages, and are more likely to be automated than the nonroutine tasks performed by professionals and managers. As EAP countries develop and labor costs increase, a larger share of employment will become more exposed to new technologies.

The impact of new technologies

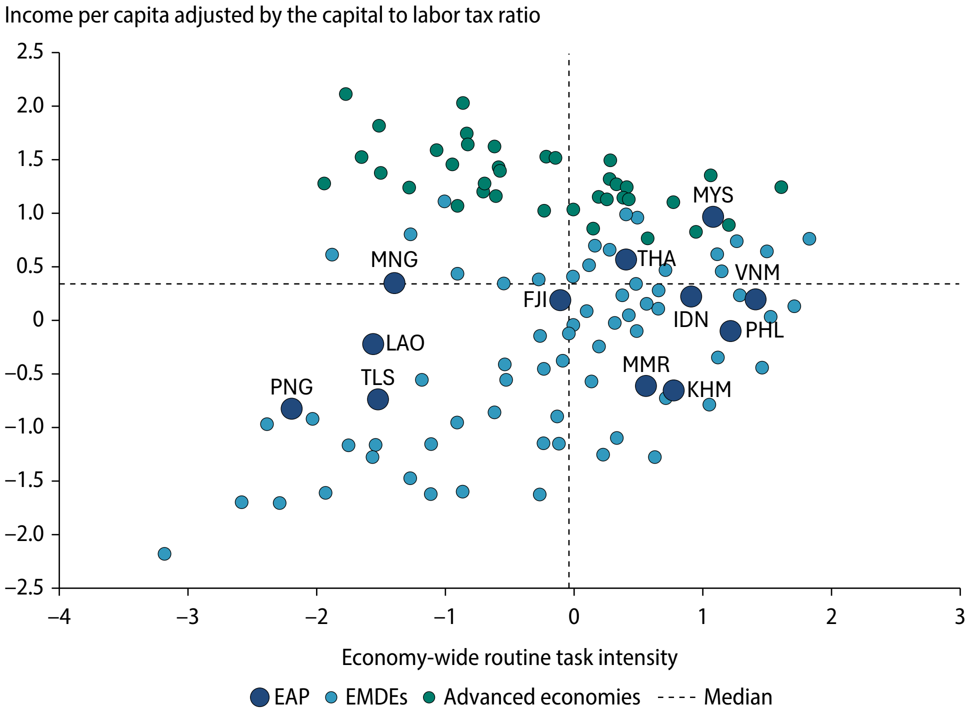
The adoption of new technologies is enhancing firm productivity and changing job opportunities. Because higher productivity leads to increased scales of production and growth, technological progress generally supports gains in jobs and wages. But, if technological progress involves labor savings, it can dampen growth in employment and wages. Because the effects of technology are heterogenous across age groups, sex, skills, and work status, technology can either exacerbate or ameliorate inequalities in EAP labor markets.

Robots

Rapid robot adoption is associated, on average, with expansions in employment and labor income in the EAP region. In Viet Nam, for instance, average employment and labor income gains were around 10 percent and 5 percent, respectively (refer to figure O.5). However, the effects are heterogenous. Medium- and high-skilled workers benefit, but low-skilled workers, especially those engaged in routine tasks, suffer reduced employment and are likely to be absorbed into the informal sector.

Economic viability rather than technical feasibility limits automation in the EAP region.

FIGURE O.4 Relative labor costs and employment, by routine task intensity and country



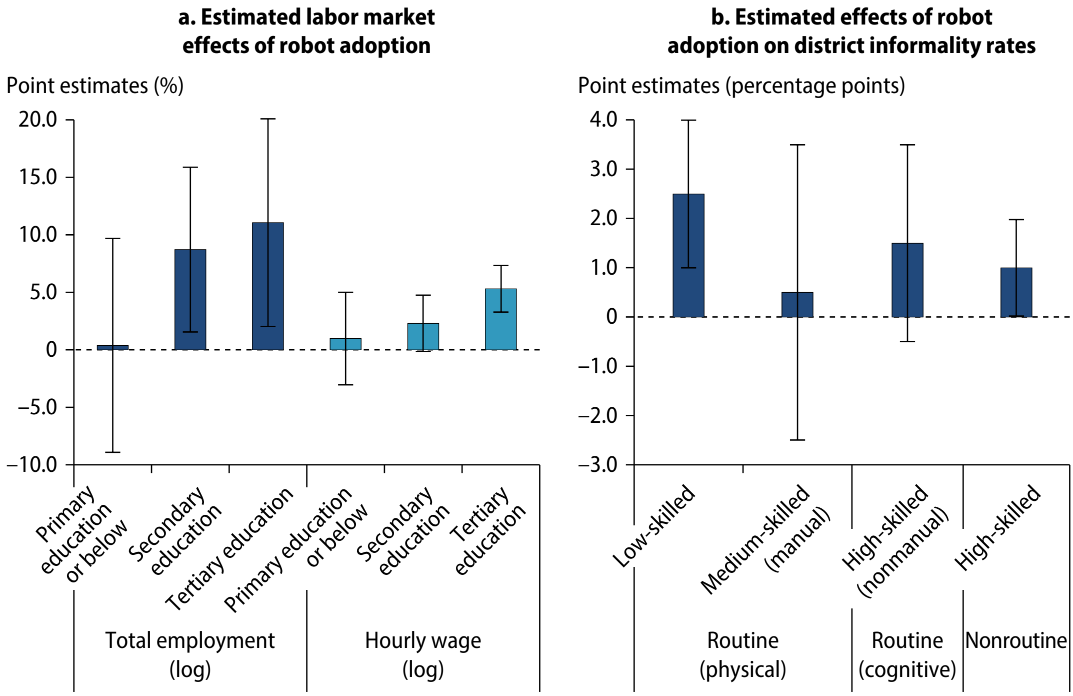
Sources: Original figure for this publication based on data from Bachas et al. 2022; ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; microdata from national labor force surveys: Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.

Note: Data from 2023 or most recent available year. The y-axis is a measure of economic viability based on the relative labor costs of a country (proxied by income per capita) and the taxation of capital relative to labor (proxied by the capital-labor tax ratio). The x-axis measures the routine task intensity of overall employment in a country by multiplying the labor share of occupations (ISCO08 2-digit level) and the routine task intensity of an occupation based on O*NET data. For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search. EMDEs = emerging market and developing economies. Refer to chapter 2 for details on the calculations.

In Indonesia, Malaysia, the Philippines, Thailand, and Viet Nam between 2018 and 2022, robots displaced an estimated 1.4 million (3.3 percent) low-skilled formal workers engaged in routine manual tasks. However, the productivity gains from automation and the resulting higher scale of production helped create an estimated 2 million jobs—4.3 percent of formal skilled employment—for skilled workers engaged in nonroutine manual and cognitive tasks. The labor gains derived

Robot adoption: Improved employment and earnings among the more educated and higher informality among the low-skilled.

FIGURE O.5 Effects of robot adoption on employment, wages, and informality, Viet Nam, 2014–20



Sources: Original figure for this publication based on data of 2011–20 Labor Force Survey, General Statistics Office, Hanoi, Viet Nam, https://www.gso.gov.vn/en/?s=Labour+force+survey&lang=en; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

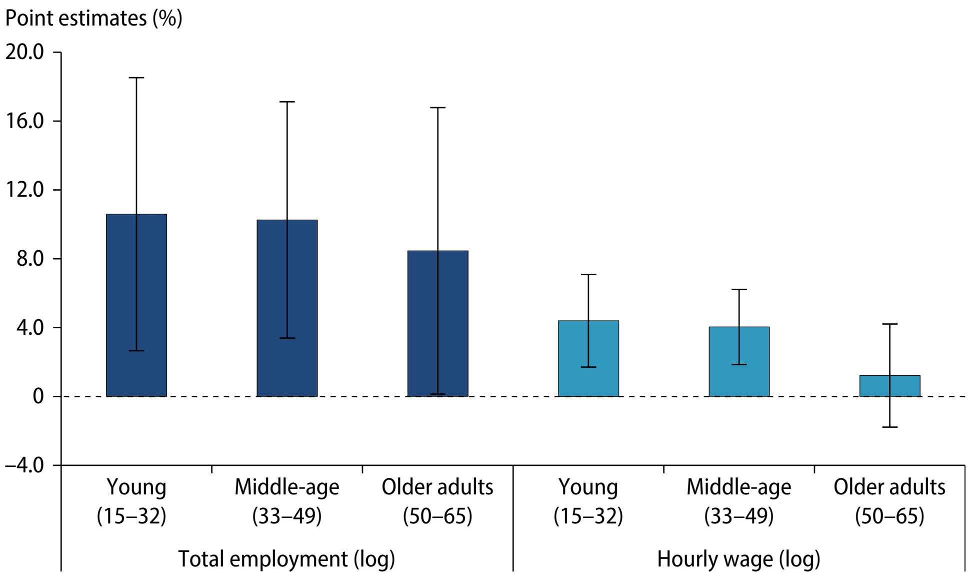
Note: The figure shows econometric estimates of the effects of exposure to robots on local labor market outcomes. Refer to chapter 3 for technical details.

from scale effects are observed especially in high–value added, trade-oriented manufacturing industries, such as computers and electronics or automotives.

Older workers benefit less in employment and earnings from robot adoption. Empirical evidence from Viet Nam shows that employment gains are positive among all age groups, but are less significant among older workers (refer to figure O.6). The positive effect of robot adoption on hourly wages, which may reflect the impact on labor productivity, is statistically significant only among the young and middle-age groups but not among workers over age 50. The findings suggest that robot adoption could help remedy the problem of the declining workforce in aging countries in the region but could also accelerate the exit of older workers from the workforce.

Younger workers benefit more in employment and wages from robot adoption.

FIGURE O.6 Estimated effects of robot adoption on district employment and wages, by age group, Viet Nam



Sources: Original figure for this publication based on data of 2011–20 Labor Force Survey, General Statistics Office, Hanoi, Viet Nam, https://www.gso.gov.vn/en/?s=Labour+force+survey&lang=en; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.
Note: Two-stage least squares estimates of the effects of exposure to robots on local labor market outcomes in Viet Nam during 2014–20. Refer to chapter 3 for technical details.

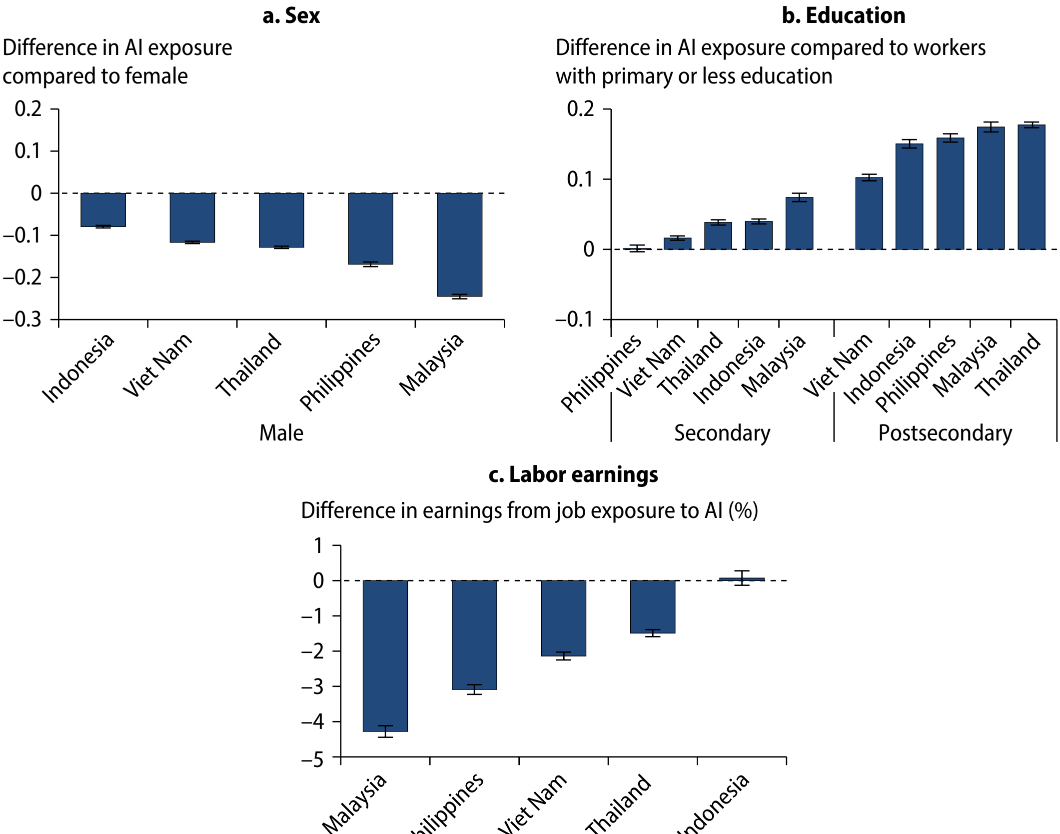
Artificial intelligence

The labor market impact of AI deployment cannot yet be estimated, but emerging evidence suggests that AI has both displacement and augmentation effects across occupations. Displacement effects are emerging in occupations primarily involving routine cognitive tasks that entail standard optimization and low social interaction (risk assessors) and more gradually in occupations involving nonroutine cognitive tasks (translation). Augmentation effects are appearing in occupations in which a significant subset of the tasks involving social interaction, creativity, or strategy can still be performed only by humans, but another subset of tasks can be delegated to AI (teachers, financial analysts). Only about 10 percent of jobs in the EAP region involve tasks complementary to AI. This is comparable with the share in other emerging economies but is much lower than the 30 percent share in advanced economies (refer to figure O.1). Moreover, empirical evidence suggests that the exposure of jobs to AI is likely to be lower in EAP countries compared with developed economies because jobs in the region, as in other developing economies, involve tasks that are less susceptible to AI.

AI exposure is not uniform across groups. In the EAP region, women are more exposed than men to the AI displacement effect, especially in Malaysia and the Philippines. Higher educational attainment is also associated with greater AI exposure. Workers with tertiary education are more exposed than workers with secondary education. If one controls for the effect of broader occupational categories (1-digit occupations), exposure to AI is negatively correlated with earnings in most EAP countries (refer to figure O.7). This suggests that more highly AI-exposed occupations earn lower wages, potentially through the nature of the tasks involved (routine tasks, less social interaction, and so on). However, this may also reflect the level of penetration of AI, which is nascent in the region.

Women and the more highly educated are more likely to be in jobs exposed to AI.

FIGURE O.7 Exposure to AI: Correlation with sex, educational attainment, and wages, EAP, circa 2022



Sources: Original figure for this publication based on data from Felten, Raj, and Seamans 2021; microdata from national labor force surveys: Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; Pizzinelli et al. 2023.

Note: Data from 2022 or most recent year available. Panels a and b: the figure shows the coefficient from a regression of the complementarity-adjusted AI occupational exposure index (ISCO08 2-digit) on sex and educational attainment, respectively, controlling for age group and economic sectors. Panel c: the figure shows the coefficient from a regression of the log of annual earnings on the standardized complementarity-adjusted AI exposure measure. Regressions control for age, sex, education, 1-digit industry, and 1-digit occupation fixed effects.

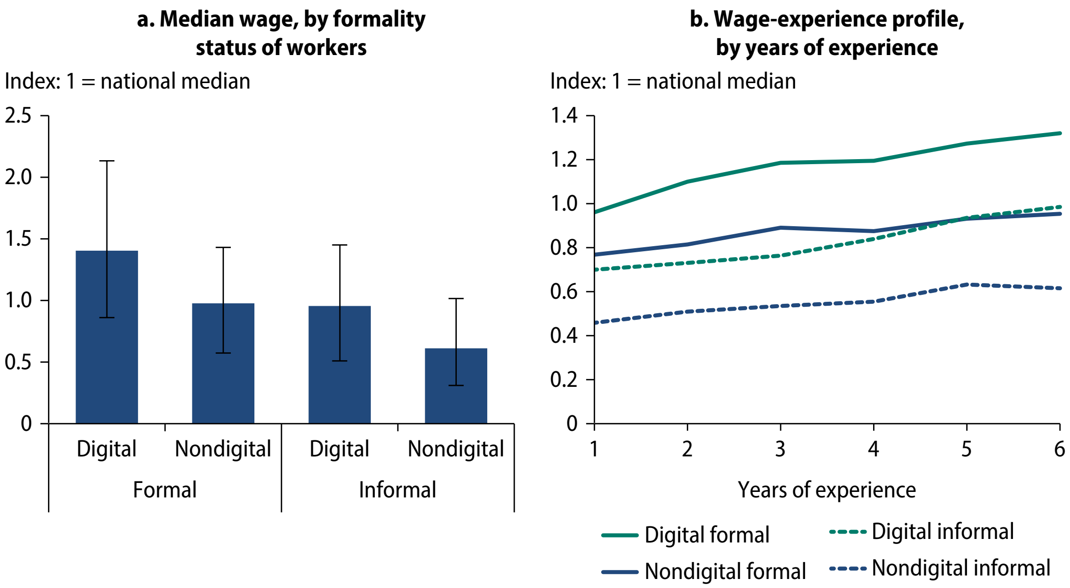
Digitalization and digital platforms

Work with digital technologies more broadly is also associated with positive labor outcomes, including higher wage premiums, for example, in Malaysia, the Philippines, and Thailand. The benefit tends to be larger among women in most EAP countries. For instance, the increase in wage premiums is twice as large among women than among men in Indonesia and Viet Nam. In Indonesia, workers in digital-intensive jobs in both the formal and informal sectors earn significantly more than workers in nondigital-intensive jobs. Workers in digital-intensive jobs in the informal sector earn almost as much as workers in nondigital-intensive jobs in the formal sector, suggesting that digitalization may shrink the wage gap between the formal and informal sectors (refer to figure O.8). The positive wage premium of digital-intensive jobs increases with job tenure.

New technologies have encouraged the emergence of new business models, including digital platforms. In general, digital platforms enhance the efficiency of intermediation and may thus also affect the number and nature of jobs. First, platforms operate on a large scale and may therefore accelerate automation and

Digital workers in the formal and informal sectors enjoy a wage premium.

FIGURE O.8 Wages and the digital intensity of jobs, by formality and work experience, Indonesia, 2023



Sources: Original figure for this publication based on data of 2018–24 rounds of Sakernas (Survei angkatan kerja nasional, National Labor Force Survey) (dashboard), Badan Pusat Statistik (Statistics Indonesia), Indonesian Statistics, MIT Dataverse, Massachusetts Institute of Technology, Cambridge, MA, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/OU8V2M.
Note: The figure shows real median wages. Panel a: Whiskers show the 25th and 75th wage percentiles.

AI adoption and hence the effects on employment. The size of the digital platform economy reached between 5 percent and 7 percent of gross domestic product in most EAP countries in 2023. The growth of digital platforms has raised firm productivity in downstream sectors in the Philippines and Viet Nam. Second, platforms facilitate labor force participation, task matching, and the emergence of new tasks, though, in some cases, this is accomplished by shifting tasks from formal to informal employment. Within the services sector where they operate, platforms are associated with lower employment in some enterprises but offer entrepreneurial opportunities for small businesses and self-employed workers, including women.

Digital platforms are turning some formal sector workers into informal workers but are encouraging the greater labor force participation of the more vulnerable population. The rollout of ride-hailing apps in Viet Nam did not durably benefit taxi drivers who were previously in the formal sector but led to a 20 percent increase in the earnings of motorbike drivers who were already in the informal sector.

Economy-wide impacts

To assess the overall impact of technology on jobs, it is essential to consider the interdependence and impact of technology choices across sectors. For example, the more rapid pace of adoption of labor-saving technologies in one sector, say, robots in manufacturing, could push down economy-wide wages and reduce the incentive to adopt technologies in other sectors, such as agriculture. If technological progress occurs simultaneously across sectors, the overall impact on jobs depends on the relative magnitude of three main effects: the jobs-displacing substitution effect (captured by the elasticity of substitution between labor and capital-embodied technology), the job-creating demand effect (captured by the product demand elasticity), and the cross-sector effects through which factors are reallocated across sectors.

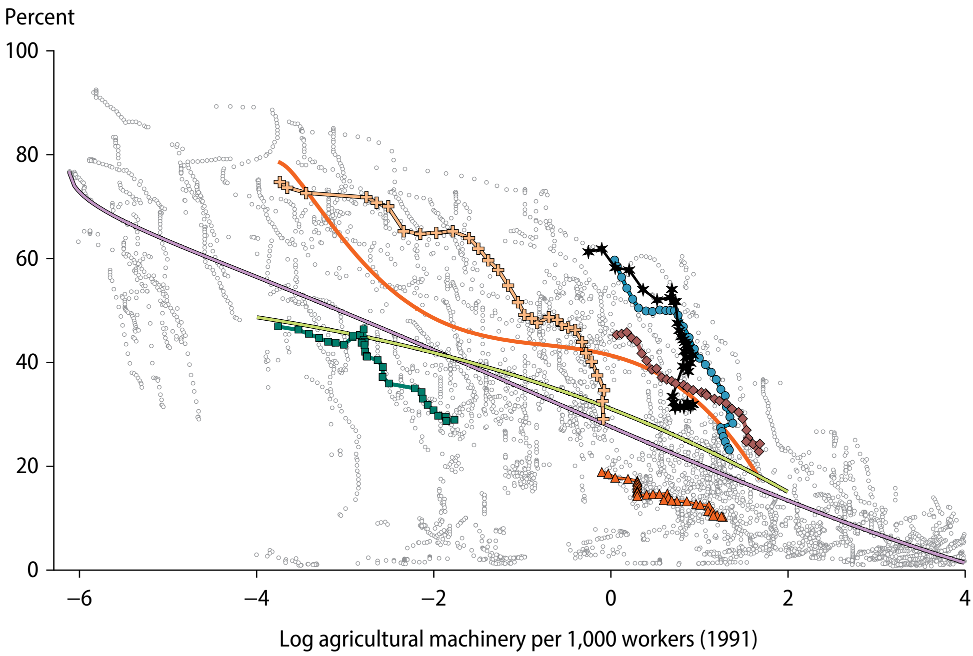
EAP resembles the rest of the world in the employment implications of agricultural mechanization, but the implications of industrial robotization in several EAP countries have so far been different. Mechanization per se has led to gains in farm productivity and little change in the level of agriculture employment. Nonetheless, mechanization in agriculture is associated with a shrinking share of farm employment globally and in EAP countries (refer to figure O.9), which, the findings suggest, is caused less by the labor displacement of mechanization in agriculture and more by the pull of higher manufacturing wages. Globally, the share of manufacturing employment tends to increase in the early stage of robot adoption and then begins to fall. This fall is sharp in middle-income economies outside the EAP region, which may help explain the phenomenon of premature deindustrialization. Developing EAP countries have, however, defied this pattern. The share of employment in industry has continued to rise even as countries deepen robot adoption. This is consistent with the evidence that the localities in EAP countries that experienced the more rapid adoption of robots also experienced more rapid growth in employment.

The comparative advantage of EAP countries in manufacturing, based in part on their relatively high endowment of middle-skilled workers, may have been enhanced by the productivity boost from the adoption of robots. The higher price elasticity of demand in global markets may have enabled an expansion in the scale of production that offset any negative substitution effects on the demand for labor. China and Viet Nam, which have seen the most rapid growth in robot penetration, have also seen the most rapid growth in the share of industrial employment. The other two

The share of employment in industry has continued to rise in some EAP countries, diverging from the global trend.

FIGURE O.9 Agricultural mechanization, robot adoption, and employment in agriculture and industry, EAP and the world, 1991–2021

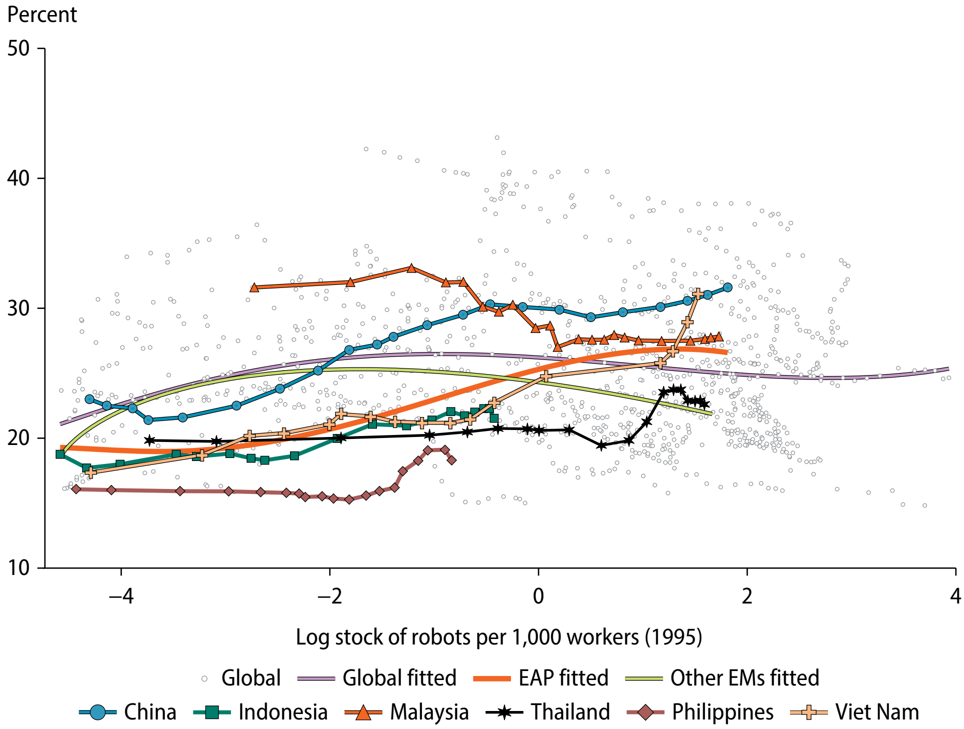
a. Agricultural employment share and mechanization



(continued)

FIGURE O.9 Agricultural mechanization, robot adoption, and employment in agriculture and industry, EAP and the world, 1991–2021 *(continued)*

b. Manufacturing employment share and robot adoption



Sources: Original figure for this publication based on data of TiM (Trade in Employment) (database), Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/data/datasets/trade-in-employment.html; USDA 2021; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.
Note: The fitted lines are drawn by using a third-degree polynomial. EMs = emerging markets.

countries with high penetration show mixed outcomes: Malaysia, a declining share from a high initial share followed by flattening, and Thailand, a greater share of industrial employment followed by flattening.

Having successfully relied on dynamic export-oriented manufacturing to sustain the transition of employment from agriculture to manufacturing, developing EAP countries need to ensure that, in the future, a dynamic services sector offers productive employment opportunities to those who leave agriculture and manufacturing. In China, Malaysia, Thailand, and Viet Nam, manufacturing dynamism has been driven by openness to trade and foreign direct investment (FDI) in manufacturing and investments in basic and intermediate skills. EAP countries need to harness the potential of AI, especially in the services sector. Such opportunities will materialize if countries undertake reforms to open their services sectors to trade and FDI and equip their workforce with the more advanced skills required by AI-powered technology. The broad services reforms are examined in World Bank (2024). Here, the focus is on a few areas.

The role of policy

EAP countries will need to implement reforms to turn technological change into a blessing rather than a curse. While trends in technology are difficult to predict, a few areas of reform should receive priority. The region must equip all its people with deeper technical, digital, and socioemotional skills that complement the new technologies; facilitate capital mobility and worker mobility across sectors, occupations, and space; remove factor price distortions that could lead to the adoption of inappropriate technologies; and encourage social insurance for workers in the new digital informal economy.

Equipping the workforce with the necessary skills

- Digital skills would equip people to engage with an increasingly digitalized workplace, using digital devices, applications, and digital platforms. In Japan, the Republic of Korea, and Singapore, teachers receive continuous professional development to enhance their digital pedagogic competencies. There is an emphasis on digital skills in the curriculum and on the use of digital textbooks, online learning platforms, and coding classes.
- Social and emotional skills would give people a comparative advantage over machines in tasks that involve social interactions, from education to health care. Research supports the notion that social and emotional skills are malleable and teachable through school interventions. In Indonesia, a large-scale intervention to develop a "growth mindset"—beliefs that intelligence and other socioemotional qualities are not fixed but develop with effort—through structured lessons had positive impacts on attitudes and test scores.
- Advanced technical skills would enable people to work in the use and creation of these new technologies. The supply of such skills is relatively scarce in developing EAP. In Korea, the Meister high schools address critical technical skill needs in priority sectors, including ICT, semiconductor manufacturing, and biotechnology, and offer a customized vocational training curriculum developed in collaboration with companies such as Hyundai Motor Company and Samsung Electronics.

Facilitating labor and capital mobility

- Labor mobility is impeded by market failures and policy distortions. The former include poor information about job opportunities, underdeveloped land and housing markets, and inadequate connectivity. The latter comprise rigid labor market institutions and the inadequate portability of benefits. For example, in China and Viet Nam, the household registration systems that regulate access to housing and public social services have curtailed rural-urban migration, trapping many farmers in low-productivity agricultural jobs. In Indonesia, reducing barriers to internal mobility could lead to productivity and labor income gains of around 20 percent. Private digital job intermediation platforms, such as online job boards and freelance marketplaces, can facilitate matches and mobility. Labor also requires capital to be mobile. Impediments to capital mobility, such as restrictions on firm entry and exit in the form of burdensome licensing requirements and bankruptcy procedures, also need to be addressed (refer to de Nicola, Mattoo, and Timmis 2025).

Removing factor price distortions

- Across a range of developed and developing economies, the stock of industrial robots (per 1,000 workers) is negatively associated with the relative taxation of capital and labor. Empirical evidence from the United States and other advanced economies shows that exemptions and allowances (for example, for depreciation) lead to higher effective tax rates on labor than on capital complementary to automation technologies and thus favor excessive automation and suboptimally lower employment. Removing these distortions would shift the adoption of automation technologies closer to what is socially optimal and raise employment levels. Technological progress can be steered through the right policy choices (refer to de Nicola, Mattoo, and Tran 2025).

Expanding social insurance for workers in the new digital informal economy

- Self-employed workers in Malaysia are willing to accept a slight reduction in their incomes in exchange for regular contributions to social insurance schemes, such as unemployment insurance and pensions. A range of schemes across the world, from public initiatives (in Colombia and India), public-private partnerships (in Malaysia), and purely private initiatives (in Denmark), have successfully applied relevant approaches, including informing workers about the existence and benefits of schemes (as in India), financial incentives (as in Colombia and Malaysia), and behavioral nudges to offer social insurance to informal workers.

Note

1. The World Bank EAP Pacific Island subregion includes Fiji, Kiribati, the Marshall Islands, the Federated States of Micronesia, Nauru, Palau, Samoa, the Solomon Islands, Tonga, Tuvalu, and Vanuatu.

References

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.

Bachas, Pierre, Matthew H. Fisher-Post, Anders Jensen, and Gabriel Zucman. 2022. "Capital Taxation, Development, and Globalization: Evidence from a Macro-Historical Database." NBER Working Paper 29819, National Bureau of Economic Research, Cambridge, MA.

de Nicola, Francesca, Aaditya Mattoo, and Johnathan Timmis. 2025. *Firm Foundations of Growth: Productivity and Technology in East Asia and Pacific*. East Asia and Pacific Development Studies. Washington, DC: World Bank.

de Nicola, Francesca, Aaditya Mattoo, and Trang Thu Tran. 2025. *Green Technologies: Decarbonizing Development in East Asia and Pacific*. East Asia and Pacific Development Studies. Washington, DC: World Bank.

Felten, Edward, Manav Raj, and Robert Seamans. 2021. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses." *Strategic Management Journal* 42 (12): 2195–217.

Pizzinelli, Carlo, Augustus J. Panton, Marina Mendes Tavares, Mauro Cazzaniga, and Longji Li. 2023. "Labor Market Exposure to AI: Cross-Country Differences and Distributional Implications." IMF Working Paper WP/23/216 (October), International Monetary Fund, Washington, DC.

USDA (United States Department of Agriculture). 2021. "International Agricultural Productivity Data Product." October, Economic Research, USDA, College Park, MD.

World Bank. 2024. *Services Unbound: Digital Technologies and Policy Reform in East Asia and Pacific*. East Asia and Pacific Development Studies. Washington, DC: World Bank.

Abbreviations

AE	advanced economies
AI	artificial intelligence
ASEAN	Association of Southeast Asian Nations
BPO	business process outsourcing
EAP	East Asia and Pacific
EM	emerging markets
EMDE	emerging market and developing economies
FDI	foreign direct investment
GDP	gross domestic product
IFR	International Federation of Robotics
IT	information technology
OECD	Organisation for Economic Co-operation and Development
O & M	operations and maintenance
RTI	routine task intensity
STEM	science, technology, engineering, and mathematics

Sectors

ACCOM	accommodation and food service activities
ADMI	administrative and support service activities
AGR	agriculture, forestry, and fishing
ARTS	arts, entertainment, and recreation

AUTO	manufacture of motor vehicles, trailers, semitrailers, and of other transport equipment
COM	manufacture of computer, electronic, and optical products
CONST	construction
EDU	education
ELEC	manufacture of electrical equipment
FINA	financial and insurance activities
FOOD	manufacture of food products; beverages and tobacco products
HEAL	human health and social work activities
ICT	information and communication technology
MACHINE	manufacture of machinery and equipment n.e.c. (National Electrical Code)
METAL	manufacture of basic metals and fabricated metal products, except machinery and equipment
MIN	mining and quarrying
MIN_CHEM	manufacture of chemicals and nonmetallic mineral products
O_MANU	manufacture of furniture; jewelry, musical instruments, toys, etc.; repair and installation of machinery and equipment
O_SRV	other service activities
PAPER	manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials; manufacture of paper and paper products; printing and reproduction of recorded media
PROF	professional, scientific, and technical activities
PUB	public administration and defense; compulsory social security
REAL	real estate activities
SELF	activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
TEX	manufacture of textiles, wearing apparel, leather, and related products
TRADE	wholesale and retail trade; repair of motor vehicles and motorcycles
TRANS	transportation and storage
UTIL	electricity, gas, steam, and air conditioning supply
WATER	water supply; sewerage, waste management, and remediation activities

Stylized Facts about EAP Labor Markets | 1

Introduction

Economic growth, technological advances, demographic change, and education have all affected labor markets in the East Asia and Pacific (EAP) region. The resulting shifts in the supply and demand of labor have had an impact on the level and structure of employment and the labor earnings of various groups. This chapter presents 10 stylized facts about trends in employment and labor earnings in the region. It sets the stage for an analysis of the observed and likely effects of emerging new technologies on work and an examination of the policies needed to ensure that economic growth continues to benefit workers.

The analysis is subject to data limitations. Many labor surveys in the region do not collect data on the earnings of self-employed workers, even though these workers account for roughly half of total employment. Surveys generally also do not collect data that facilitate a separate examination of informal salaried workers. Direct measures of worker skills are rare. Proxies, such as educational attainment, therefore need to be used. Comparable microdata for an investigation of longer-term trends in labor outcomes are only available in some countries. The following analysis thus focuses on labor market developments since 2010.

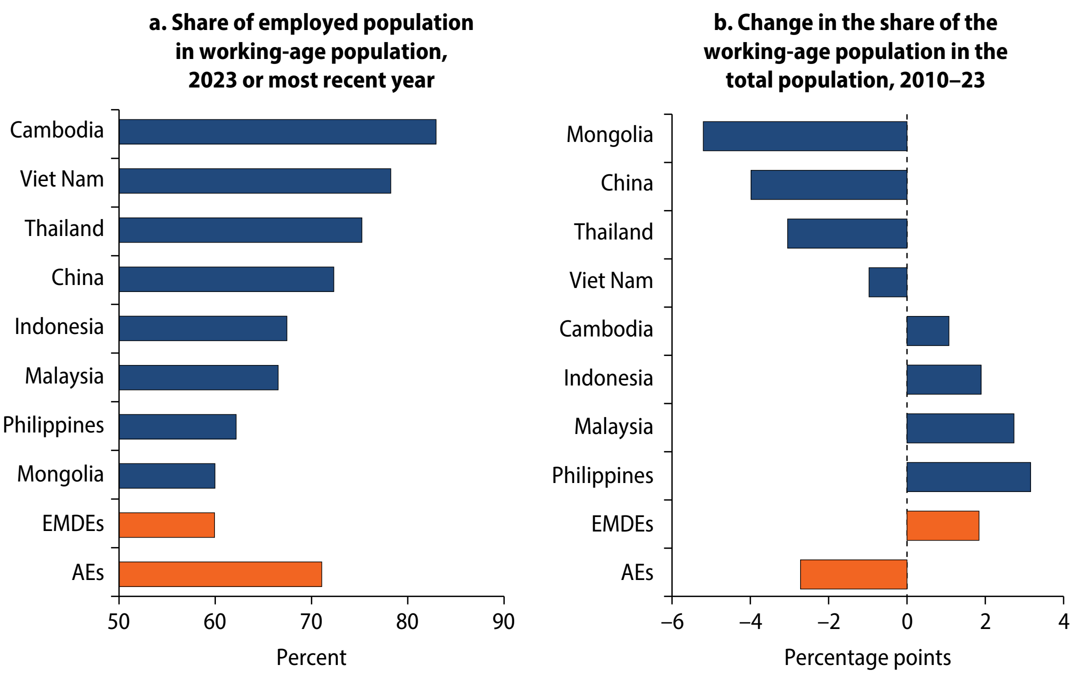
Overall employment and earnings

Fact 1: A larger share of the working-age population is employed in the EAP region than in most other developing economies, but the working-age population in the EAP region is aging and shrinking.

The ratio of employment to the size of the working-age population is higher in EAP countries than in other developing economies. The differences within the region are significant, however. From lowest to highest, the ratio is between 60 percent and 67 percent in Mongolia, the Philippines, Malaysia, and Indonesia and between 72 percent and 83 percent in China, Thailand, Viet Nam, and Cambodia (refer to figure 1.1, panel a). These differences partly reflect the lower labor force participation of women in the former group of countries (fact 5). The share of the working-age population in the total population has declined the most in aging Mongolia, China, Thailand, and Viet Nam, but has increased especially in the more youthful Philippines, Malaysia, Indonesia, and Cambodia.

A larger share of the working-age population is employed in the EAP region than in most other developing economies, but the share of the working-age population is shrinking in four EAP countries.

FIGURE 1.1 Share of the working-age population in the total population and ratio of employment to working-age population, by country or grouping, 2010–23



Sources: Original figure for this publication based on data of ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.

Note: The working-age population is the population ages 15–64. EMDEs and AEs show the median among emerging market and developing economies and among advanced economies, respectively. AEs = advanced economies; EMDEs = emerging market and developing economies.

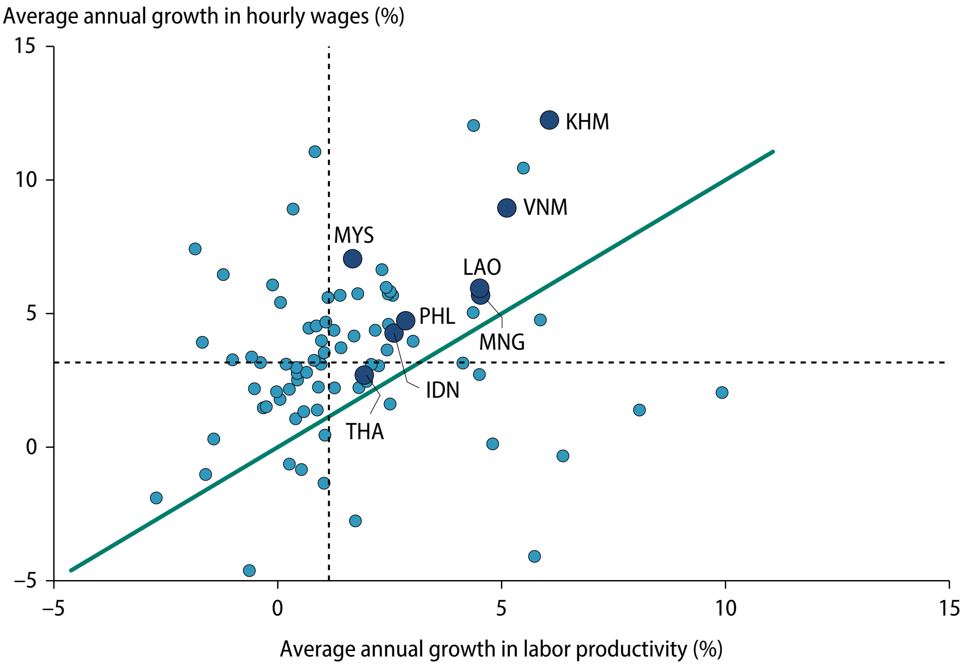
Fact 2: Wage growth has been robust and has outpaced labor productivity growth.

Overall, economic growth has benefited salaried workers in the region. Hourly wages increased more rapidly than labor productivity (refer to figure 1.2). Hourly wages rose more quickly in Cambodia, followed by Viet Nam and Malaysia.

These results do not give a complete picture of the trends in labor income because data on the earnings of the self-employed—accounting for roughly half of total employment—are not collected by most labor surveys in the EAP region. Global evidence indicates that growth in total labor income per person is closely associated with labor productivity growth. In a sample of 134 advanced and developing economies between 1990 and 2019, a study determined that average

Wage growth has been robust in EAP countries and faster than labor productivity growth.

FIGURE 1.2 Hourly wage and labor productivity growth, EAP, circa 2010–22



Sources: Original figure for this publication based on data of ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.
Note: The earliest data were available in 2010; the most recent, prior to 2022. Vertical and horizontal dashed lines indicate the global medians of hourly wages and labor productivity. The green line represents a 45-degree line. For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search.

labor productivity grew 2.5 percent a year, while labor income rose 2.4 percent (World Bank 2024b). The study found that labor productivity accounts for three-fourths of the variation in growth in labor income per person across countries.

The higher employment rates and steady wage growth in EAP countries reflect in large part the success of dynamic export-oriented and labor-intensive manufacturing sectors. Will new technologies increase or reduce labor demand and labor earnings? Will the adoption of industrial robots and artificial intelligence (AI) mitigate or exacerbate the challenge represented by a shrinking labor force in aging societies? The following chapters explore these questions, drawing on global and EAP-specific evidence.

Employment and earnings across sociodemographic groups

Fact 3: Younger workers are struggling to find jobs, especially in countries such as China and Indonesia; although unemployment rates are lower among older workers, fewer of these workers participate in the labor force.

Employment rates and labor force participation status differ across age groups. Relative to prime-age adults (ages 25–54) and older populations (ages 55–64), youth (ages 15–24) experience higher unemployment rates in all countries. The youth employment gap is more pronounced in China, Indonesia, Malaysia, and Mongolia (refer to figure 1.3, panel a). Youth unemployment rates in the Philippines, Thailand, and Viet Nam are below the levels observed in other developing and advanced economies. Unemployment rates are lowest among older workers (ages 55–64) compared with other age groups in all countries except Malaysia. However, labor force participation rates are also lower among older workers (refer to figure 1.3, panel b), which indicates that many older workers have stopped seeking employment.

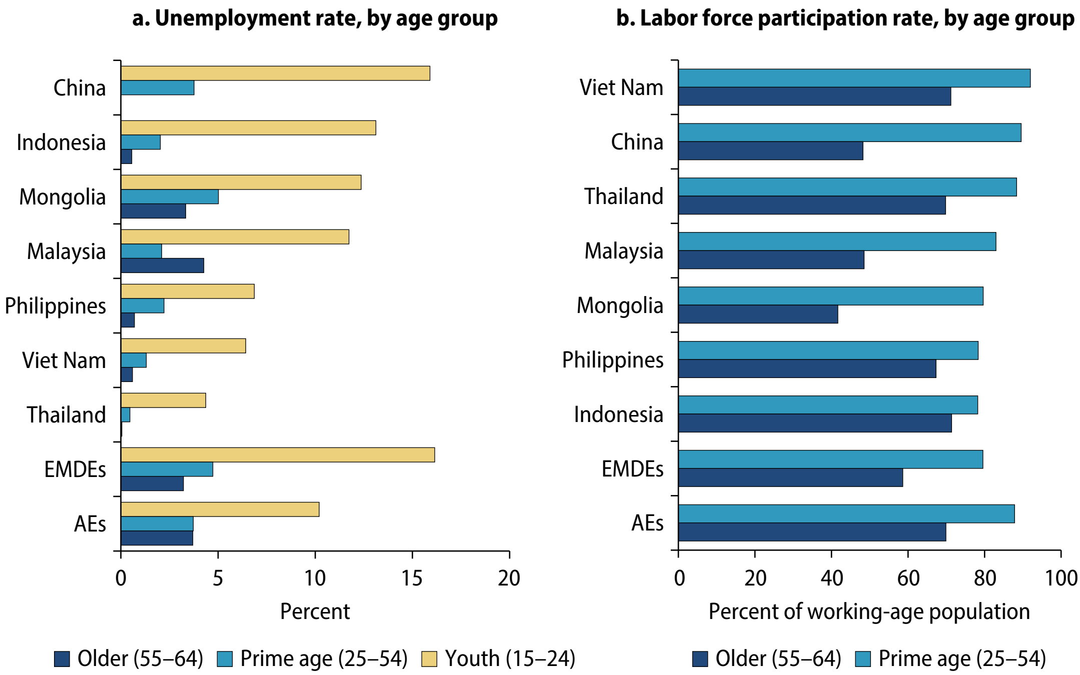
Fact 4: Wages grew more quickly among young and middle-age workers.

Wages rose more rapidly among young workers (ages 15–24) than among the 25–49 age group, while wages among workers ages more than 50 lagged, except in Viet Nam (refer to figure 1.4). Young workers experienced larger wage gains in Malaysia and the Philippines, while their wages rose at the same pace as the wages of middle-age workers in Viet Nam.

The wages workers earn typically increase as the workers age, consistent with the well-established premium associated with the experience and special knowledge people acquire on the job. The larger relative wage gains among younger workers may be

Youth are struggling more to find jobs, especially in China and Indonesia, while labor force participation rates are lower among older workers.

FIGURE 1.3 **Unemployment rates and labor force participation rates, by age group, circa 2023**



Sources: Original figure for this publication based on data of ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.
Note: Data refer to 2023 or the most recent year of data availability. Panel a: The prime-age estimate in China corresponds to ages 25+. Panel b: The youth labor force participation rate is not shown because many youth may still be in education or training. For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search. AEs = advanced economies; EMDEs = emerging market and developing economies.

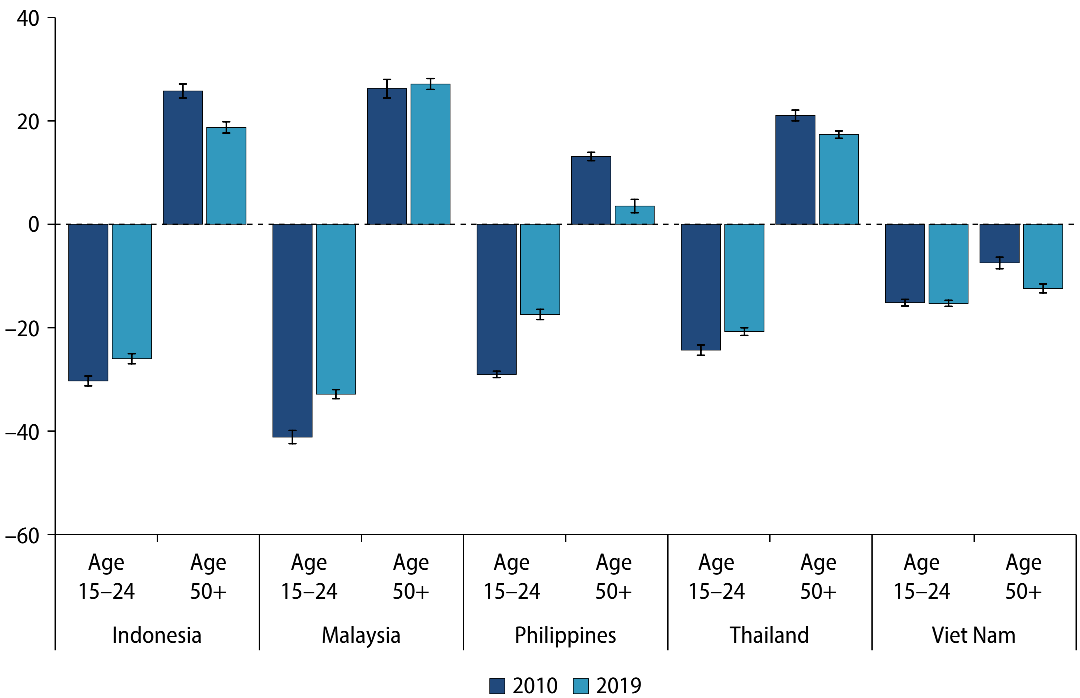
linked to the skills—such as digital literacy—they have acquired that are more highly aligned with the demands of occupations emerging in expanding sectors of the economy.

The penetration of new technologies is likely to influence the types of jobs available, the skills required, and the way work is performed—all of which have implications for the employability and productivity of younger versus older workers. How is new technology adoption affecting the employment and earnings of youth and of older workers in EAP? The report presents empirical evidence on the observed and predicted impacts of various technologies across age groups.

Fact 5: Labor force participation rates among women are higher in the EAP region than in other developing regions, but have risen little and are lower than the rates among men.

Wages rose more quickly among younger workers.

FIGURE 1.4 Wages: Youth and workers over age 50 relative to prime-age workers, five countries, 2010 or 2011 and 2019

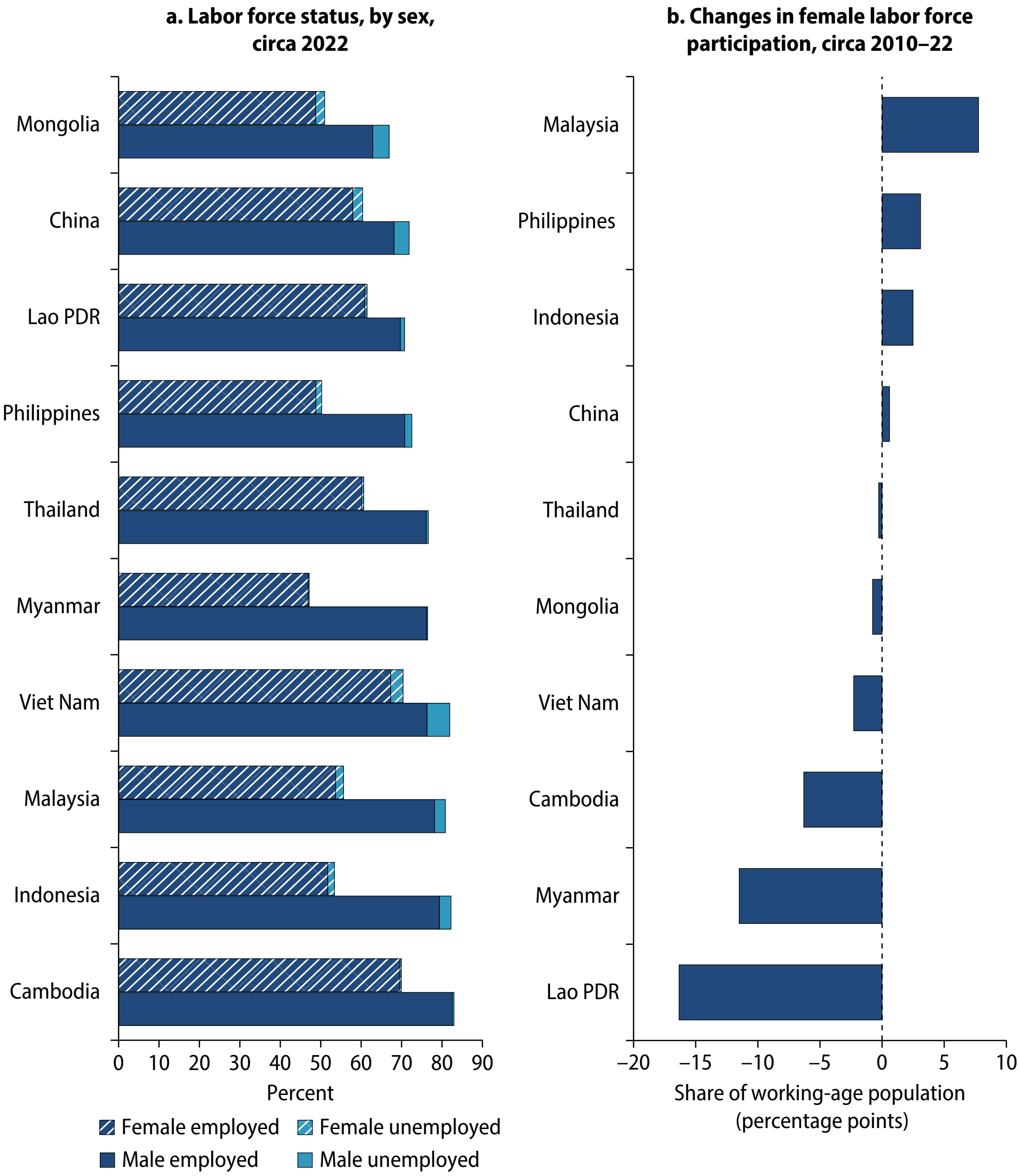


Source: Original figure for this publication based on data of Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/.
Note: The figure shows age coefficients from regressions of log annual wages of paid employees controlling for sex, educational attainment, and economic sector.

Most of the EAP working-age population that is not employed is out of the labor force, that is, they are not actively seeking employment (refer to figure 1.5, panel a). Women participate in the labor market at higher rates in EAP countries than in other developing economies, although their participation rates are still below those of men. The gender gap in labor force participation in the EAP region is about 19 percentage points, below the global gender gap in labor force participation, which is estimated at 25 percentage points. However, female labor force participation has improved little in most EAP countries over the last decade, except in Indonesia, Malaysia, and the Philippines (refer to figure 1.5, panel b). Labor force participation is lower among women than men, especially in Indonesia, Malaysia, Myanmar, and the Philippines.

Labor force participation is lower among women, though to a lesser extent in Cambodia and Viet Nam, and has improved little except in Indonesia, Malaysia, and the Philippines.

FIGURE 1.5 **Labor force status and changes in female participation rates, by sex, EAP**



Source: Original figure for this publication based on data of ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/.

The region's success with labor-intensive manufacturing and the recent shift to services has helped facilitate women's integration into the labor force. Empirical studies show that firms that are integrated into global value chains employ a larger share of women and that trade expansion in unskilled manufacturing has had a positive impact on employment among women (World Bank and WTO 2020). Moreover, services tend to exhibit higher woman-to-man employment ratios, which also tend to rise as countries become more highly developed (Chiplunkar and Kleinberg 2025).

However, as in much of the world, female labor force participation is hindered by social and cultural norms (related, for instance, to family care), explicit or implicit bias, and regulations that restrict women's employment (Bertrand 2020; Klasen 2019; World Bank 2024a). For example, controlling for education and other socioeconomic characteristics, a recent study on the Philippines found that married women with young children are less likely to participate in the labor market (Belghith and Fernandez 2021). The survey data reveal that nearly 90 percent of economically inactive married women cited household and family duties as the main reason they do not seek work, while 75 percent of Philippine men and 80 percent of Philippine women respondents agreed with the statement: "A man's job is to earn money, while a woman's job is to look after home and family."

Facts 3 and 5 imply that there is room to expand the supply of labor in EAP countries through greater labor force participation among women and youth, especially in countries with aging populations. A recent analysis shows that closing the gaps in the labor participation of women and youth could raise the share of the employed in the working-age population in EAP countries by around 3–5 percentage points (World Bank 2024b).

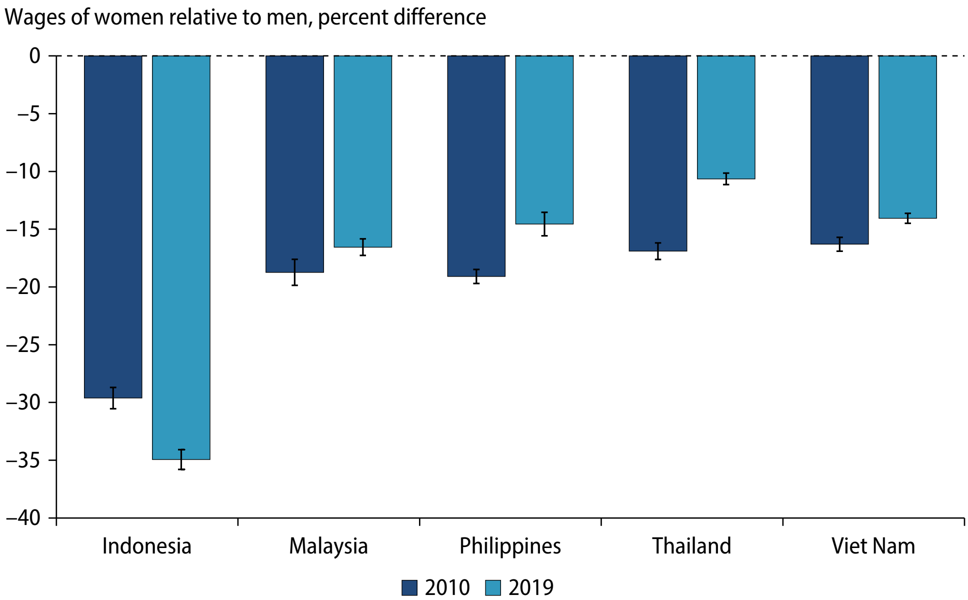
Fact 6: The gender wage gap has narrowed, except in Indonesia, but women still earn less than men.

Wages have grown more quickly among women than among men, especially in Thailand and the Philippines (refer to figure 1.6). However, women still earn 10 percent to 15 percent less than men in salaried jobs across countries, controlling for gender differences in education, age, and sector of employment. In Indonesia, this adjusted gender wage gap is much wider, reaching nearly 35 percent. The adjusted gap is somewhat smaller in most EAP countries than in other middle-income economies. In a 2018 report, the International Labour Organization estimates the gender wage gap globally and in middle-income countries at 21 percent (ILO 2018).

The gender wage gap may result from differences in skills (not captured by educational attainment), occupational segregation, the household division of labor,

Women still earn less than men, but the gender wage gap is narrowing in EAP countries except in Indonesia.

FIGURE 1.6 Changes in the gender wage gap in salaried jobs, five EAP countries, 2010 or 2011 and 2019



Source: Original figure for this publication based on data of Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/.
Note: The figure shows the gender coefficient (turned into a woman/man gap) from regressions of the log annual wages of paid employees after controlling for educational attainment, age group, and sector. Whiskers represent 95 percent confidence intervals.

and discrimination related to institutional, cultural, and social norms (Blau and Kahn 2017). Less is known about the impact of new technologies on the gender wage gap in the EAP region that may arise from differences in the tasks performed by men and women in similar jobs and the susceptibility of these tasks and jobs to automation (Cortés and Pan 2019).

Emerging technologies such as digital labor platforms allow flexible work, which may provide job opportunities among people who are unemployed or out of the labor force. Do new technologies help address the issues of limited female labor force participation and persistent gender wage gaps? This report presents new evidence on the ways these technologies are affecting employment and earnings among men and women in the EAP region.

Fact 7: Educational attainment among the workforce has improved, but a majority of the workforce in many countries lacks the skills needed in a modern economy.

Because of significant progress in access to basic education, a large share of the labor force in many EAP countries has completed secondary education (refer to figure 1.7). Notable exceptions include Cambodia, Lao People's Democratic Republic, Philippines, and some Pacific Islands countries.[1] In these countries, a majority of the workforce has attained only primary or some secondary education. Moreover, less than a quarter of the working-age population in the region has attained tertiary education, except in China, Malaysia, and Mongolia. While enrollment in tertiary education has risen significantly in most countries over the last decade, this expansion needs to be sustained because it takes time for new graduates to increase the stock of college-educated workers.

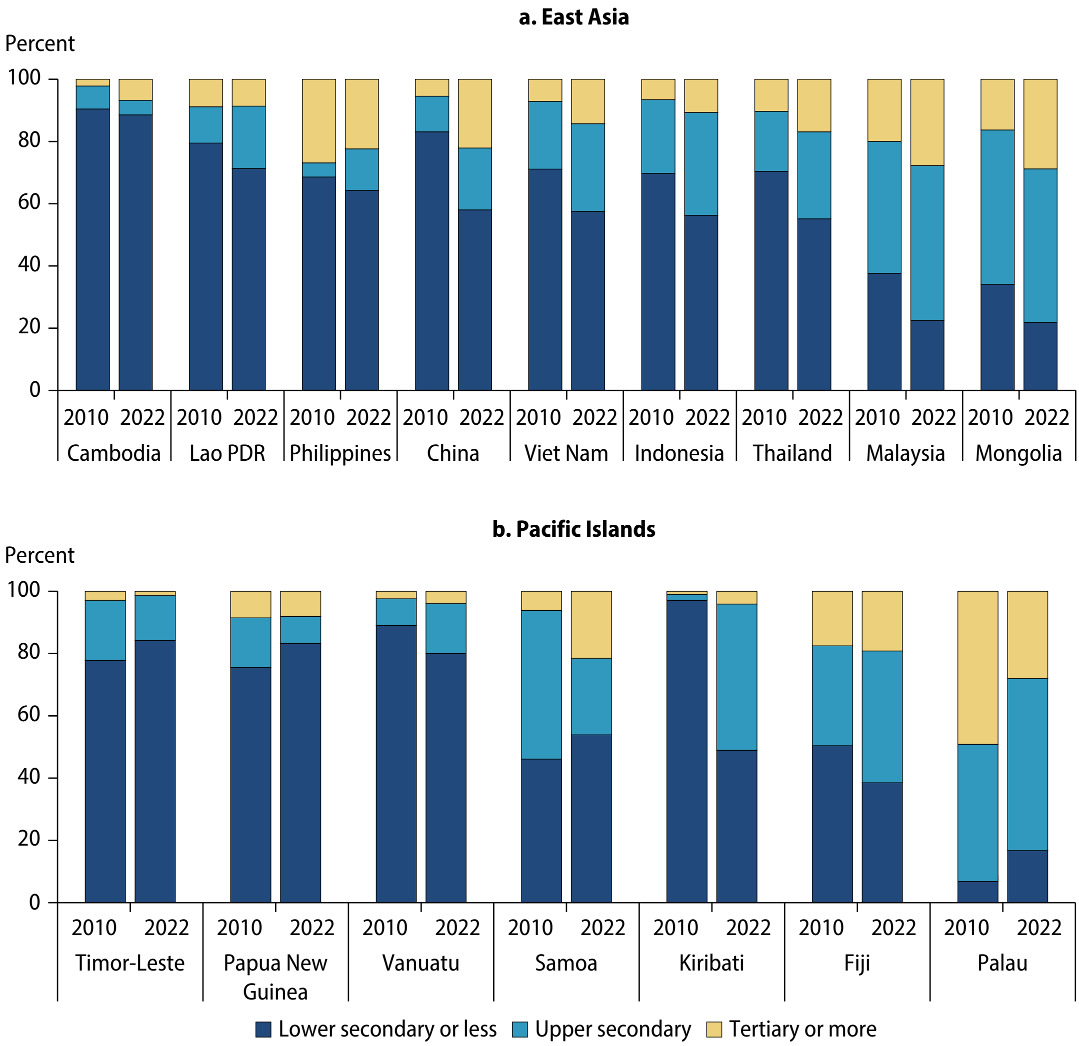
Years of schooling are an imperfect first pass measure of actual skills. Despite nearly universal access to basic education, many children and youth in EAP countries fail to acquire basic foundational skills (Afkar et al. 2023). In 14 of the region's 22 middle-income countries, more than half of all 10-year-olds experience learning poverty, that is, they are unable to read and understand age-appropriate reading material. According to the 2022 Program for International Student Assessment, even in Malaysia and the Philippines, countries with high secondary completion rates, only 24 percent and 16 percent of 15-year-olds, respectively, leave high school with basic literacy and numeracy skills (OECD 2024).

To the extent that individuals in the workforce have received low-quality basic education, they are likely to lack the foundational skills needed to acquire more advanced skills in tertiary education and on the job.

Data on adult skills in developing EAP countries are limited. Indonesia participated in the 2014–15 survey of the Organisation for Economic Co-operation and Development's (OECD) Program for the International Assessment of Adult Competencies, which determined that 69 percent of the 15- to 65-year-old respondents in Jakarta achieved at or below basic literacy proficiency (OECD 2016). Meanwhile, in urban areas of Viet Nam, a 2011–12 survey of the World Bank's Step Skills Measurement Program, which offers data comparable to the data of the OECD program survey, found that more than a quarter of adults lacked appropriate proficiency in literacy and numeracy (Bodewig and Badiani-Magnusson 2014). A recent assessment of skills in Thailand found that 65 percent of youth and adults lack basic reading literacy (World Bank 2024b).

The educational attainment of the workforce has increased, but only a small share has achieved tertiary education.

FIGURE 1.7 The educational attainment of the working-age population, East Asian countries and the Pacific Islands, circa 2010 and 2022



Source: Original figure for this publication based on data of ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/.

Note: Circa 2010 refers to 2000 for China and 2014 for Palau and the Philippines. Circa 2022 refers to 2016 for Fiji. The working-age population corresponds to ages 15–64.

In all three countries, the young population did relatively better than older individuals. In comparison, the 2022 Program for International Student Assessment showed that 75 percent, 65 percent, and 23 percent of 15-year-olds in Indonesia, Thailand, and Viet Nam, respectively, failed to acquire basic reading skills.[2] These results suggest that the basic skills of the current generation of children in school offer a good indication of the level of foundational skills of older cohorts in the workforce.

Another dimension of the skills gap emerges from the growing demand for digital and socioemotional skills. A good foundation of digital literacy and more advanced digital skills is essential for a workforce able to adopt new technologies and be competitive in services and advanced manufacturing. As documented by the World Bank (2023), the workforce, especially older adults, in developing EAP countries lags in both basic digital skills (such as processing documents or presentations) and more advanced digital skills (for example, coding). Jobs will increasingly require a good foundation of skills because of the expanding digitalization of working environments.

Strong socioemotional skills are also needed. These include grit (persistence in the pursuit of long-term goals despite challenges), self-regulation, creativity, curiosity, empathy, assertiveness, and cooperation. These skills are essential in tasks in which humans may have a particular comparative advantage over advanced digital technologies (for instance, in creative and social tasks) and in the constant need to learn and navigate changes throughout the working life.

Comparative data on socioemotional skills are limited even in developed economies. These skills are inherently difficult to measure and compare across countries because they are manifested differently across social and cultural contexts. The OECD Survey on Social and Emotional Skills is a first attempt to measure social and emotional skills consistently across countries (OECD 2024). It was used to collect data among 10- and 15-year-old students across cities in 25 countries in 2019 and 2023, including in Jinan and Suzhou in China and Kudus in Indonesia. The survey results reveal big gaps in these skills across socioeconomic groups within cities, which suggests that there is scope for developing the skills nationwide.

Fact 8: The skill wage premium is shrinking, but well educated workers still earn significantly more.

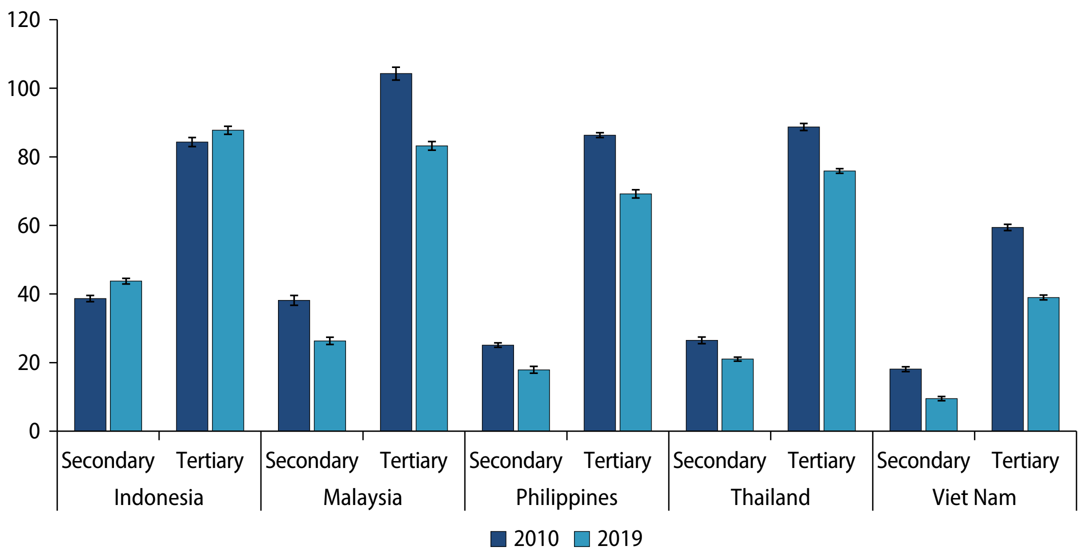
Wages have risen across all groups measured according to educational attainment over the last decade, but less well educated workers experienced larger gains. After controlling for age and sector of employment, the wage premium associated with secondary completion or tertiary educational attainment fell, except in Indonesia (refer to figure 1.8). The wage advantage of the more educated shrank, especially in Malaysia and Viet Nam and, to a lesser extent, in the Philippines and Thailand. However, workers with tertiary education were earning 40 percent to 80 percent more than workers with incomplete primary or secondary education. The wage premium of a high school diploma is much smaller, ranging from 10 percent to 40 percent.

The level of and trends in skill wage premiums reflect the interplay of shifts in the demand and supply of educated workers in the region. With nearly universal basic education and the recent rapid expansion in enrollment in tertiary education, the supply of more educated workers has grown over the past two decades. However, the supply shift has been relatively modest because it takes decades for

The wage premiums of secondary and tertiary education are significant, but have declined, except in Indonesia.

FIGURE 1.8 Wage premiums in secondary and tertiary education relative to primary education, five countries, 2010 or 2011 and 2019

Percent difference in wages compared with workers with primary education



Source: Original figure for this publication based on data of Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/.
Note: The figure shows age coefficients from regressions of log annual wages of paid employees controlling for gender, age, and economic sector.

educational expansion to affect the educational composition of the workforce. As cohorts of high school and college graduates enter the labor force, they are likely to exert an increasing downward pressure on the skill wage premium in the EAP region unless the demand for skills persists.

Structural transformation linked to trade and changes in technology has affected the demand for skills in the EAP region. Less skill-intensive manufacturing exports continue to sustain the demand for less-skilled workers in countries such as Cambodia, Indonesia, and Viet Nam, while more skill-intensive exports drive the demand for more highly educated workers in China, Malaysia, and Thailand. The shift to services is increasingly affecting the demand for skills in business services, finance, and communications, which are more skill-intensive, and traditional retail and transport, which predominantly employ less well educated workers. The diffusion of digital technologies is influencing the demand for skills across and within sectors through changes in comparative advantage and increased scale and through tradability (with the emergence of digital platforms).

Technology adoption can affect the demand for skills and, thus, the employment and wages of skilled and unskilled labor. As new technologies are diffused, the demand for workers proficient in these new technologies rises, resulting in improved job opportunities and higher earnings among this group. In contrast, unskilled labor may struggle in the face of automation and technological advances. What is the impact of new technologies on the labor market outcomes of skilled and unskilled workers in EAP countries? New evidence on this question is provided in subsequent chapters.

Trends in jobs and structural transformation

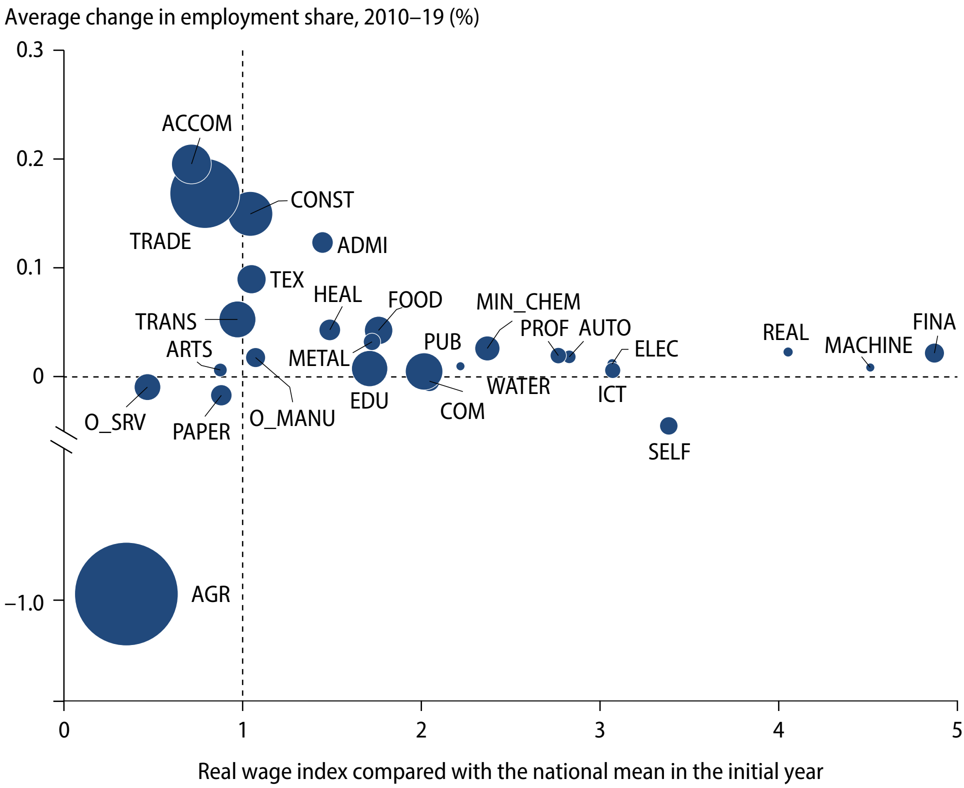
Changes in the structure of employment are inherent to the process of economic transformation as countries develop. The World Bank (2024b) distinguishes four dimensions to characterize the relationship between jobs and structural transformation: the sectoral, spatial, occupational, and organizational. Less productive jobs in agriculture (in rural areas) are replaced by more productive jobs in industry and services that are largely located in denser urban and rural areas. Jobs shift from self-employment or small firms with little physical or organizational capital to wage work in larger, more modern, and often formal firms producing higher value added products and services (often linked to trade). The variety and complexity of jobs increase and, along with these, the variety and sophistication of the skills required to perform the job tasks. The interplay of these transformations with demographic shifts and changes in the supply of skills drives changes in the composition of the workforce and employment.

Fact 9: Employment has shifted mostly from agriculture to low-earning sectors such as trade, hospitality, and construction, limiting the improvements in formal employment.

The EAP region has experienced a dramatic structural transformation whereby, following a period of rapid industrialization, less productive jobs in agriculture have been replaced by more productive jobs in industry and services (refer to figure 1.9).

Employment has moved mostly from agriculture to low-earnings sectors, such as trade, hospitality, and construction, and less to high-earnings sectors.

FIGURE 1.9 Changes in employment share and real wages, by sector, EAP, 2010–19



Sources: Original figure for this publication based on data of TiM (Trade in Employment) (database), Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/data/datasets/trade-in-employment.html; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.

Note: The figure shows the averages of China and five countries of the Association of Southeast Asian Nations (Indonesia, Malaysia, the Philippines, Thailand, and Viet Nam). Each bubble corresponds to different sectors (ISIC rev4, 2-digit level). Bubble size denotes relative employment size in the initial year. Refer to the TiM database for indicator definitions.

The strong integration of the EAP region into global manufacturing value chains has delayed the decline in the share of manufacturing employment observed in advanced economies and other middle-income economies. Cambodia and Viet Nam have even seen an increase in the share of manufacturing employment. Overall, during the last decade, employment increased in low-earnings services such as construction and trade, but changed little in high-earnings sectors such as business services, finance, and real estate.

The employment shifts from low-productivity agriculture to low-productivity services have restricted gains in formal employment. Measured by self-employment, the share of informal employment has fallen over the last decade largely because of the expansion in formal employment in both manufacturing and services. The informal employment rate is still higher in the EAP region than in other middle-income regions and is widely prevalent across most of the Pacific Islands (refer to figure 1.10). The decline in informal employment in agriculture across most EAP countries was partly offset by increases in services (refer to figure 1.11).

Fact 10: Wages have been converging across sectors, except in Thailand and Viet Nam, and across occupations, except in information and communication technology (ICT) and among technical professionals.

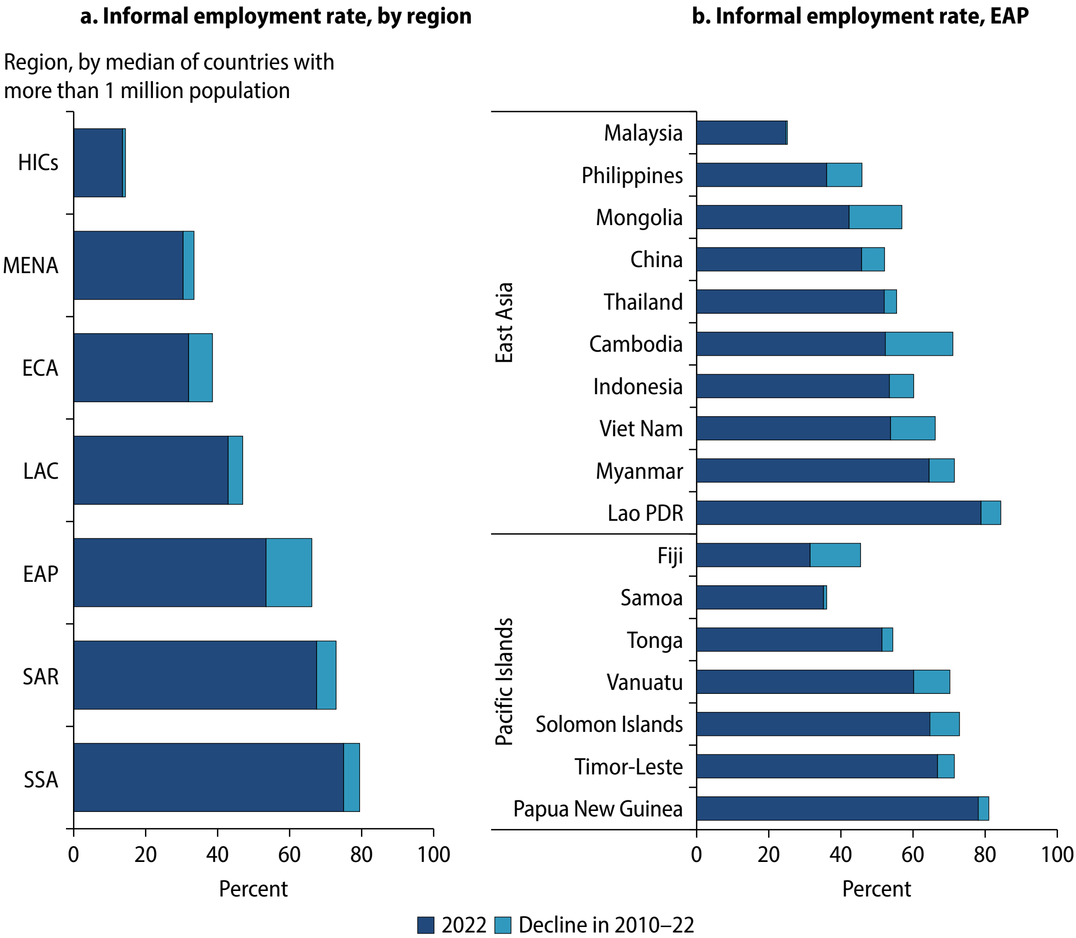
Wages rose across the board in services, manufacturing, and agriculture, but with distinctive patterns. Controlling for education and gender, the sectoral wage differentials that favor the higher-wage sectors shrank in Indonesia, Malaysia, and the Philippines and widened in Thailand and Viet Nam (refer to figure 1.12). The wage premium associated with working outside agriculture was highest in ICT and finance services (between 25 percent and 65 percent), followed by manufacturing and low-productivity services (for instance, retail trade).

Wage differentials have also shrunk across occupations over the past decade, except for the more highly paid technical and ICT-related jobs. Wages in these occupations—which were already two or three times above national averages—rose 2 percent to 4 percent a year over the decade, defying the broader trend of wage convergence across most occupations (refer to figure 1.13).

These patterns in wage differentials across sectors and occupations reflect the trends in the demand for skills in EAP countries. These changes in the demand for skills stem from the region's long-term structural transformation, trade patterns, and technological advances.

Informal employment has declined in the EAP region more than in other regions, but is still high in the Lao People's Democratic Republic, Myanmar, Papua New Guinea, Timor-Leste, and most Pacific Island countries.

FIGURE 1.10 Changes in the informal employment rate, by country and region, 2010–22



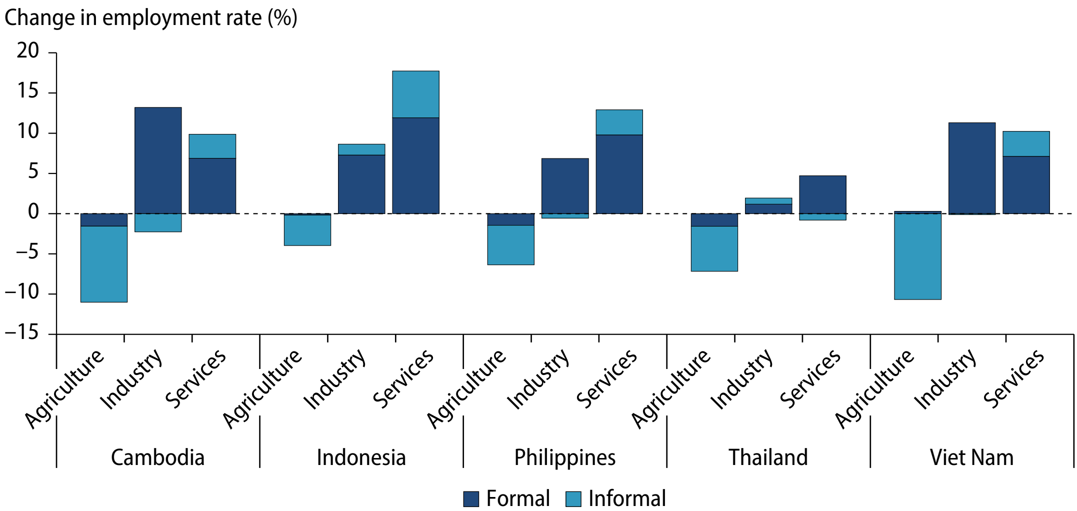
Sources: Original figure for this publication based on data of ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.

Note: The informal employment rate is proxied by the share of self-employment. Panel a: EAP includes 12 East Asian countries. ECA = Europe and Central Asia; HICs = high-income countries; LAC = Latin America and the Caribbean; MENA = Middle East and North Africa; SAR = South Asia; SSA = Sub-Saharan Africa.

The economic literature on structural transformation often emphasizes the role of technology in driving economic shifts (Rodrik 2018). Technologies such as automation, AI, and digital technologies are revolutionizing industries, often leading to increased productivity and efficiency. This causes shifts in employment patterns. What are the structural shifts in employment and earnings in EAP countries as

The decrease in informal employment in agriculture was partly offset by an increase in services.

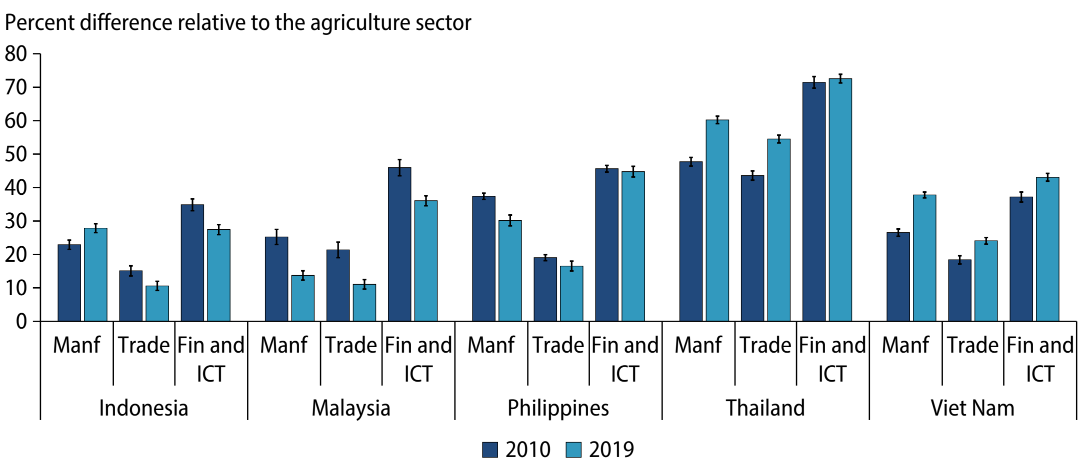
FIGURE 1.11 Changes in employment, by formal and informal status and type of work, five ASEAN countries, 2010–19



Source: Original figure for this publication based on data of ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/.
Note: The figure shows the changes in employment by type relative to total employment in 2010. ASEAN = Association of Southeast Asian Nations.

The highest wages are earned in skilled services, followed by manufacturing, low-skilled services, and agriculture.

FIGURE 1.12 Real wage growth, by sector, five ASEAN countries, 2010–circa 2019

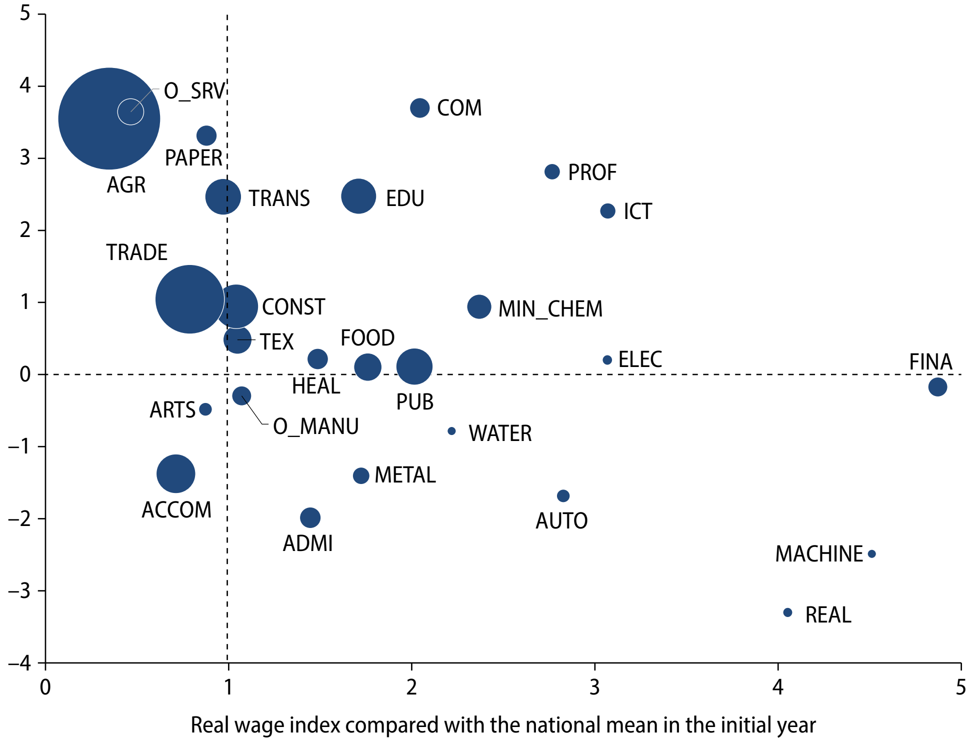


Source: Original figure for this publication based on data of Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/.
Note: The figure shows the coefficients of the employment sector from regressions of log annual wages of paid employees controlling for sex, age, and education. ASEAN = Association of Southeast Asian Nations; Fin and ICT = finance and information and communication technology; Manf = manufacturing.

Wages have been converging across sectors and occupations, except in ICT and among technical professionals, where already high wages rose even more quickly.

FIGURE 1.13 Average real wage growth, by occupation, EAP, 2010–19

Average change in real earnings, 2010 or most recent available year



Sources: Original figure for this publication based on data of TiM (Trade in Employment) (database), Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/data/datasets/trade-in-employment.html; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.

Note: The figure shows the averages of China and five countries of the Association of Southeast Asian Nations (Indonesia, Malaysia, the Philippines, Thailand, and Viet Nam). Each bubble corresponds to different occupations and sectors (ISIC rev4, 2-digit level). The bubble size denotes relative employment size in the initial year. Refer to the TiM database for indicator definitions.

they adopt new technologies? The next chapters offer evidence that addresses this question.

With the backdrop of the above 10 stylized facts on labor markets in the EAP region, the next chapters in the report examine the impact of the penetration of new technologies on employment and wages in the region.

Notes

1. The World Bank EAP Pacific Island subregion includes Fiji, Kiribati, the Marshall Islands, the Federated States of Micronesia, Nauru, Palau, Samoa, the Solomon Islands, Tonga, Tuvalu, and Vanuatu.
2. Refer to PISA (Programme for International Student Assessment) (dashboard), Organisation for Economic Co-operation and Development, Paris, http://www.oecd.org/pisa/pisaproducts/.

References

Afkar, Rythia, Tara Béteille, Mary E. Breeding, Toby Linden, Andrew D. Mason, Aaditya Mattoo, Tobias Pfutze, Lars M. Sondergaard, and Noah Yarrow. 2023. *Fixing the Foundation: Teachers and Basic Education in East Asia and Pacific*. World Bank East Asia and Pacific Regional Report. Washington, DC: World Bank.

Belghith, Nadia Belhaj Hassine, and Francine Claire Fernandez. 2021. "Women, Childcare, and Social Norms in the Philippines." Policy Brief (December), Philippine Women's Economic Empowerment Program, World Bank, Washington, DC.

Bertrand, Marianne. 2020. "Gender in the Twenty-First Century." *AEA Papers and Proceedings* 110 (May): 1–24. https://doi.org/10.1257/pandp.20201126.

Blau, Francine D., and Lawrence M. Kahn. 2017. "The Gender Wage Gap: Extent, Trends, and Explanations." *Journal of Economic Literature* 55 (3): 789–865.

Bodewig, Christian, and Reena Badiani-Magnusson. 2014. *Skilling Up Vietnam: Preparing the Workforce for a Modern Market Economy*. With Kevin Macdonald, David Locke Newhouse, and Jan Rutkowski. Directions in Development: Human Development Series. Washington, DC: World Bank.

Chiplunkar, Gaurav, and Tatjana Kleineberg. 2025. "Gender Barriers, Structural Transformation, and Economic Development." Policy Research Working Paper 11083, World Bank, Washington, DC.

Cortés, Patricia, and Jessica Pan. 2019. "Gender, Occupational Segregation, and Automation." Economics Studies (November), Brookings Institution, Washington, DC.

ILO (International Labour Organization). 2018. *Global Wage Report 2018/19: What Lies behind Gender Pay Gaps*. Geneva: ILO.

Klasen, Stephan. 2019. "What Explains Uneven Female Labor Force Participation Levels and Trends in Developing Countries?" *World Bank Research Observer* 34 (2): 161–97. https://doi.org/10.1093/wbro/lkz005.

OECD (Organisation for Economic Co-operation and Development). 2016. *Skills Matter: Further Results from the Survey of Adult Skills*. OECD Skills Studies Series. Paris: OECD.

OECD (Organisation for Economic Co-operation and Development). 2024. *Social and Emotional Skills for Better Lives: Findings from the OECD Survey on Social and Emotional Skills 2023*. Paris: OECD.

Rodrik, Dani. 2018. “New Technologies, Global Value Chains, and Developing Economies.” NBER Working Paper 25164 (October), National Bureau of Economic Research, Cambridge, MA.

World Bank. 2023. *Services for Development: East Asia and the Pacific Economic Update*. October. Washington, DC: World Bank.

World Bank. 2024a. *Firm Foundations of Growth: East Asia and the Pacific Economic Update*. April. Washington, DC: World Bank.

World Bank. 2024b. *Jobs and Technology: East Asia and the Pacific Economic Update*. October. Washington, DC: World Bank.

World Bank and WTO (World Trade Organization). 2020. *Women and Trade: The Role of Trade in Promoting Gender Equality*. Washington, DC: World Bank.

Technology and the Labor Market: Conceptual and Empirical Framework

2

Introduction

New technologies are reshaping the landscape of employment and the nature of jobs across the globe. Technological advancement is altering the fabric of existing jobs but also catalyzing the creation of new avenues of employment. This chapter presents a framework that, through the lens of the task content of occupations, allows an integrated examination of the influence of technologies on jobs. It relies on well-established frameworks in the empirical literature, for example, Acemoglu and Autor (2011), and in the economics of technology adoption. The chapter provides a conceptual foundation for the subsequent discussion on the impact of technology on jobs across sectors.

The chapter first examines the technical feasibility of reassigning some of the tasks of jobs from humans to technology. Technical feasibility provides a sense of the exposure of jobs to new technologies through the susceptibility of job tasks to the displacement or augmentation of human labor. The chapter investigates the transformation these technologies can generate in the nature of work through the assignment of tasks to machines. The chapter accomplishes this by building on prior studies, for instance, ADB (2018). It compares the East Asia and Pacific (EAP) region with other regions through the structure of employment by occupations and the resulting task content of jobs.

The chapter then explores the economic viability and the drivers of technology adoption. Economic viability determines the extent to which a given technology is adopted to replace or augment labor and, ultimately, the impact of the technology on jobs. If the benefits of the technology net of costs are positive, firms will find the substitution of capital for labor profitable in the relevant production tasks. The chapter illustrates the ways in which the potential costs and benefits of new technologies predict the adoption of the technologies across the development spectrum, and it summarizes the empirical literature on the macro drivers of technology adoption.

Technical feasibility: Tasks and job exposure to technology

The emergence of new technologies can both displace and augment the tasks performed by workers. Production requires the completion of a range of tasks that can be performed by a combination of human labor and machines. Technology affects the distribution of tasks between man and machine as well as the productivity of factors involved in economic activity (Acemoglu and Restrepo 2019a, 2019b, 2024).

Changes in the task content of jobs

- New technologies expand the tasks that may be performed by machines (including algorithms) rather than humans. If the machines are sufficiently cheap, automation can lead to the substitution of capital for labor in the associated tasks. Examples include software systems that can execute office tasks or robots able to carry out various welding, cutting, and assembly tasks.
- Technology can also create new tasks, some of which may be fulfilled most effectively by labor.[1] It can automate one or more tasks and leave other tasks to be completed by humans (for example, drones and drone operators). Some technologies, such as platforms and artificial intelligence (AI), may facilitate the creation of new tasks (for instance, AI trainers or prompt engineers). In the United States, the introduction and expansion of new tasks and job titles explain about half of employment growth between 1980 and 2010. In 1940–80, these new tasks were primarily in middle-wage production and clerical occupations, but, after 1980, job polarization occurred as new tasks were created mostly in high-paying professional occupations and in low-paying service jobs (Acemoglu and Restrepo 2018; Autor et al. 2024).

The productivity effect

The substitution of human labor by machines can lead to a productivity effect that reduces the unit cost of production. With lower unit costs, prices fall and the quantity demanded rises. This may boost the demand for labor in nonautomated tasks. For example, the introduction of ATMs increased the employment of bank tellers because the associated diminished costs encouraged banks to open more branches, raising the demand for bank tellers who then specialized in a range of tasks that ATMs did not automate (Bessen 2015). The productivity effect also leads to higher real incomes and thus to greater demand for all products, including those not directly affected by technology.

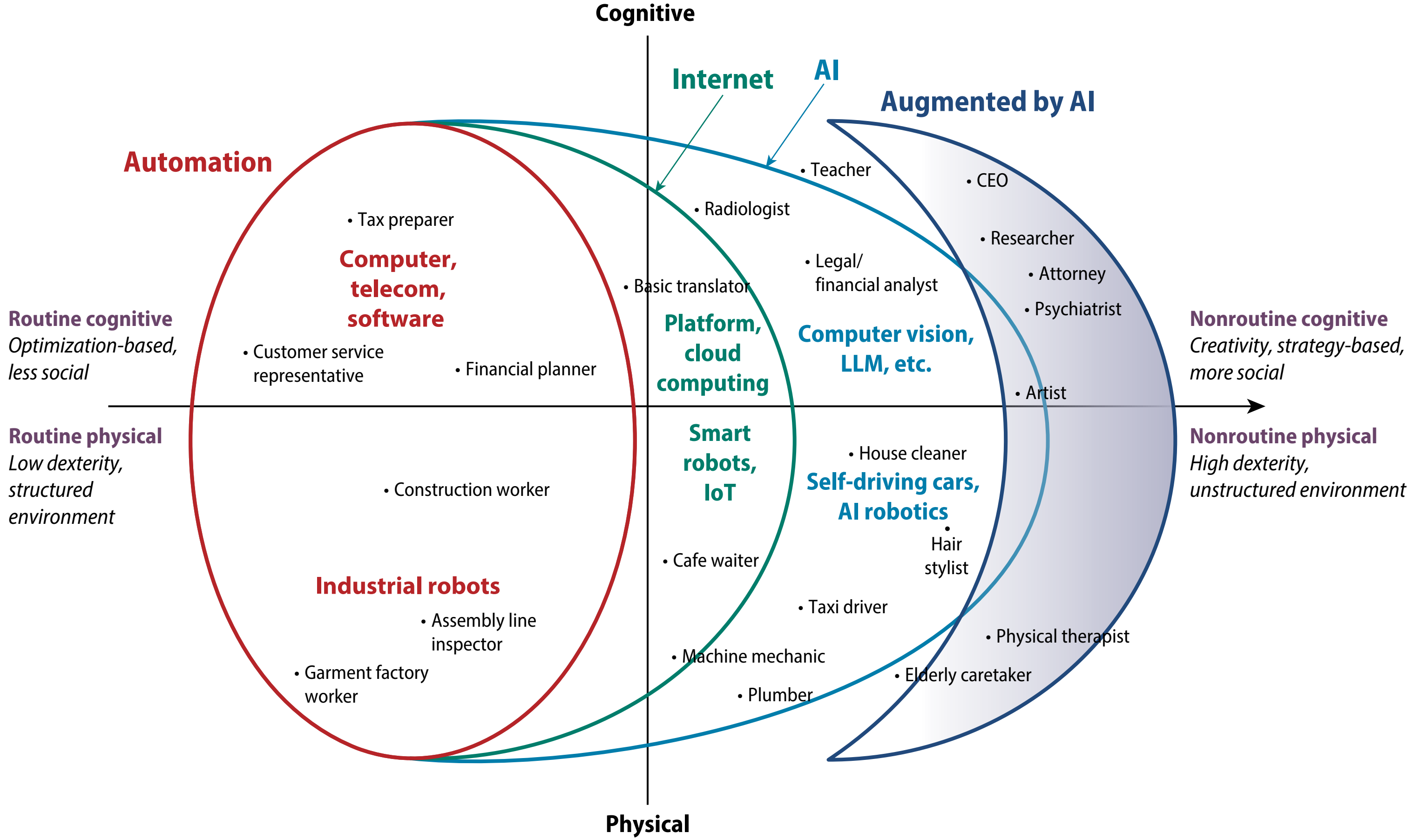
New technologies can thus spur a task enhancement effect that augments and creates new tasks for labor. The competing forces of task displacement and task enhancement determine the net effect of technological change on labor demand. If displacement outpaces enhancement, labor demand falls. Conversely, if enhancement outpaces displacement, labor demand rises.

Historically, technological progress has expanded the breadth of tasks that machines perform. Since the industrial revolution in the eighteenth century, mechanization in agriculture and technological advances have swelled the types of tasks machines perform. The first industrial revolution and the second in the nineteenth century, which added the power of electrical grid systems to allow mass production, mostly affected physical and routine tasks. The third industrial revolution in the twentieth century expanded the scope of technology to cognitive areas through advances in information technology, including computers and the internet. The fourth industrial revolution, which is under way, is characterized by a fusion of technologies that is blurring the borders among the physical, the digital, and the biological. AI is an important part of the current revolution because it relies on the combination of machine learning and computing power to allow machines to carry out increasingly complex nonroutine tasks.

The scope of labor displacement and enhancement has shifted from routine manual tasks to cognitive and nonroutine tasks. Depending on the bundle of tasks involved in each occupation, the emergence of new technologies could displace, augment, or create jobs (Acemoglu and Autor 2011). Previous automation technologies, including robots in industrial sectors and computer and digital software in information and communication technology (ICT) sectors, primarily affected routine cognitive and physical tasks (refer to figure 2.1). The introduction of the internet and advanced robotics allowed machines to perform more complex tasks. These digital technologies generate both labor displacement and enhancement effects on jobs. A more effective drill improves worker productivity (enhancement effect), but advanced robots may displace the worker in drilling.

New technologies expand the range of tasks performed by machines.

FIGURE 2.1 The effects of new technologies on routine and nonroutine tasks: An integrated view



Sources: Original figure for this publication based on Acemoglu and Autor 2011; Lee 2018.
Note: AI = artificial intelligence; IoT = internet of things; LLM = large language model.

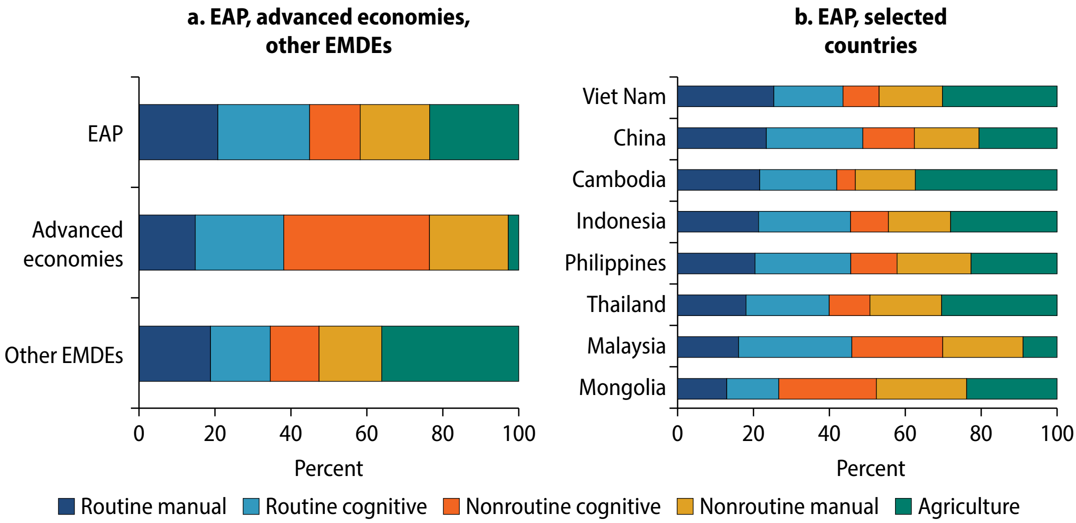
AI is poised to impact a wider spectrum of cognitive and nonroutine tasks relative to previous digital technologies. Displacement effects are becoming evident in occupations primarily involving routine cognitive tasks that entail standard optimization and low social interaction (risk assessors). Displacement is also gradually emerging in occupations involving nonroutine cognitive tasks (translation). The integration of AI into robotics could enhance the capabilities of robots, allowing them to perform a wider range of physical tasks with a larger cognitive component. For example, AI functionality is expanding to include physical tasks such as driving automobiles. Occupations in which a number of tasks can be delegated to AI, but a significant subset of tasks can still only be performed by humans (social interaction, creativity, or strategy) are likely to be augmented by AI (teachers, financial analysts).

Industrial robots and AI are affecting employment differently across economic sectors. Robots are already displacing industrial workers in occupations intensive in routine manual tasks. AI threatens to displace service workers in occupations that primarily involve routine cognitive tasks, but increasingly also in occupations involving nonroutine cognitive tasks. AI-empowered robots could also potentially take over the tasks of workers in nonroutine manual occupations in manufacturing and services, but that possibility seems to be more distant because of technological feasibility and economic viability.

The analysis of the exposure (technical susceptibility) of jobs to new technologies reveals that most EAP countries are likely to be affected by robots and AI in ways that differ from the impacts in advanced economies. Relative to advanced countries, EAP countries employ more people in occupations involving routine manual tasks and fewer people in cognitive tasks. The occupational structure in the EAP region reflects the successful industrialization in countries such as China, Malaysia, Thailand, and Viet Nam and the relatively weaker state of the regional services sectors. Similar to other emerging market and developing economies, EAP countries are thus more vulnerable than advanced countries to job displacement by industrial robots than to job displacement by AI (refer to figure 2.2; spotlight 2.1). However, in the EAP region, the share of employment potentially exposed to AI is larger than the share exposed to robots. China, Malaysia, and Mongolia have a relatively high share of people employed in nonroutine cognitive tasks who may be equipped to benefit from complementarities with AI. (The implications of differences in the task content of occupations across countries are summarized in spotlight 2.1.)

Relative to advanced economies, EAP countries employ more people in occupations intensive in routine manual tasks and fewer in occupations intensive in cognitive tasks.

FIGURE 2.2 Employment by job task content, EAP and other regions



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Note: Task content is measured based on the Autor and Dorn (2013) methodology and normalized at the ISCO08 2-digit level. Task intensity is based on the occupational share of dominant task categories. Task content in agriculture is not measured because of data limitations. Refer to spotlight 2.1 for methodological details. Data are from the most recent available year. Panel a: EAP = simple averages of the share of employment classified by the task intensity of occupations in China, Indonesia, Malaysia, the Philippines, Thailand, and Viet Nam. For the advanced economies and other emerging market and developing economies, the panel shows population-weighted averages. EMDEs = emerging market and developing economies.

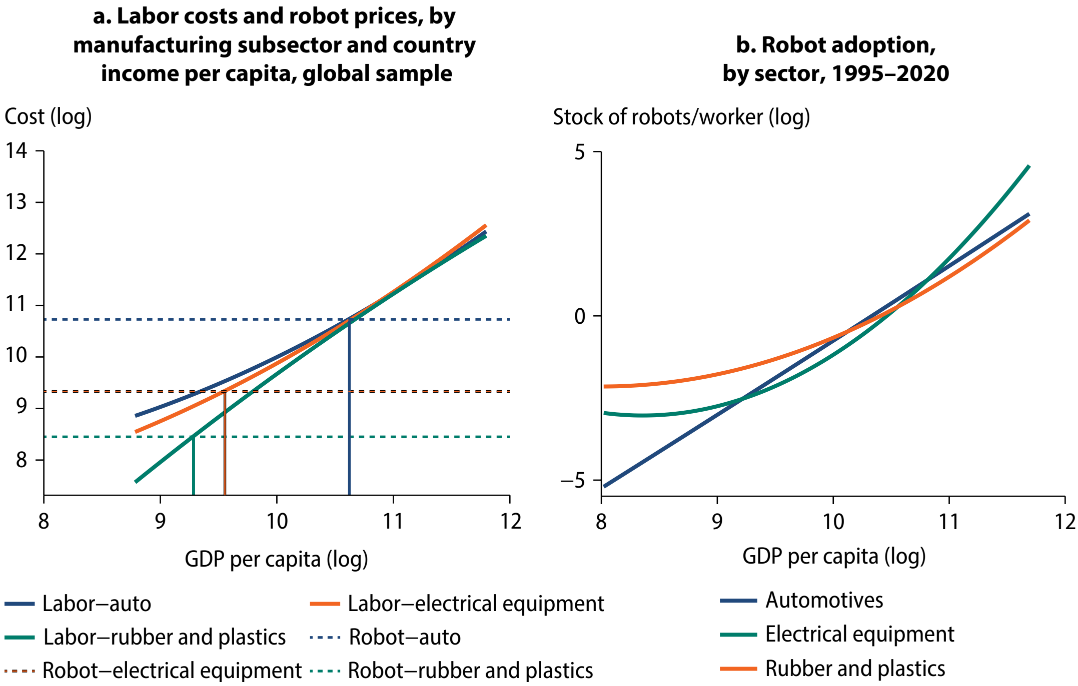
Economic viability: Drivers of technology adoption

The extent to which new technologies impact jobs depends not only on the technical feasibility but also on the economic viability of the technologies. Firms would likely adopt a given technology if the expected net return is positive, that is, if the cost of the technology is lower than the benefit derived from the technology. Among labor-saving technologies, a key component of any benefit is the reduction in the cost of the labor that would have been needed to perform the same tasks.[2]

Technology diffusion varies across countries and sectors because of differences in the costs and benefits of adoption. To illustrate, figure 2.3 presents a stylized example of the economics of robot adoption in three manufacturing subsectors: rubber

The economic viability of new technologies depends on the cost of the technologies relative to labor.

FIGURE 2.3 Economic viability of technology: Robot prices, labor costs, and robot adoption, the world



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Note: Gross domestic product income per capita at 2010 prices taken from WDI. Panel a: Labor cost curves are obtained from a quadratic fit of pooled country-year annual total wage income panel data for 2015–19 against country income per capita and adjusted upward by the share of nonwage costs in total labor costs (taken at 50 percent). The quality-adjusted per worker robot costs are calculated using World Robotics data estimates of the global value of robot stocks and the stock shares of different robot types. Refer to box 2.2 for methodological details. Panel b: The depicted curves (lines) are derived from a quadratic fit of the pooled country-year panel data on robot adoption in 1995–2020 against income per capita, controlling for industry and year fixed effects. GDP = gross domestic product.

and plastics, electrical equipment, and automotives. Figure 2.3, panel a, shows the potential labor cost savings (wage and nonwage costs) of replacing workers with robots in each sector (upward sloping curves) and the corresponding quality-adjusted robot prices (unit costs) per worker replaced (horizontal lines), both plotted against country income per capita. The labor cost profiles are estimated from annual wage income data from a global sample of countries in 2015–19 and empirical estimates of nonwage costs. The robot prices are estimated from the prices of robot types that are typically used in each of the three subsectors and assumed to be fixed across countries (refer to box 2.1 for details on the estimations).[3] The intersections with

Box 2.1. Estimating robot prices across manufacturing industries

To illustrate the economic viability of technology adoption, the prices of robots are estimated across three manufacturing subsectors: rubber and plastics, electrical equipment, and automotives. According to use-case descriptions of the International Federation of Robotics (IFR), these sectors typify the adoption of robots of varying degrees of sophistication, as follows:

- *Articulated robots* can be used for almost all applications, but they are mainly used for welding, handling, dispensing, and processing. The automotive industry is a major customer for this type of robot, accounting for roughly one-third of all articulated robot installations. About nine robots in 10 in the automotive industry are articulated robots.
- *SCARA robots* are mainly used in assembling tasks (especially fixing and press fitting) and handling operations, but also in cutting. The electrical and electronics industry is the largest customer for this type of robot, accounting for 59 percent of the demand. About 42 percent of the robots in this industry feature SCARA kinematics.
- *Cartesian robots* are mainly used for plastic molding, packaging, picking, and placing and for assembling tasks, such as fixing and press fitting. Cartesian robots are often found in the rubber and plastics industry (together with linear and gantry robots), which accounts for about 22 percent of the installations of this type of robot and 70 percent of the robots installed in this industry. They are also used in the electronics industry (33 percent of the installations of this type of robot; 11 percent of the installations in the industry).

For each robot type, the estimated global unit costs of robots are computed using IFR statistics on (a) the total value of global robot stocks, (b) the share of global robot stock by robot type, and (3) an adjustment for robot quality based on the average relative unit price across robot types. Because industrial robots are often produced in a small number of advanced countries and adopted globally through trade, the estimations assume that the global average unit price of each type of robot is the same across countries. The unit prices of robots are converted into per worker annual prices using the average lifetime of robots and the average number of workers a robot replaces, which is proxied by the midpoint estimate of the labor displacement effect reported by Acemoglu and Restrepo (2018). This displacement effect ranges between 3.0 and 6.2 workers.

(continued)

Box 2.1. Estimating robot prices across manufacturing industries *(continued)*

With these assumptions, table B2.3.1 shows estimated quality-adjusted per worker robot prices. The estimated average price of an articulated robot (regularly adopted in the automotive industry) is about four times the price of a SCARA robot (regularly used in the electrical equipment sector) and 10 times the price of a Cartesian robot (regularly used in the rubber and plastics industry).

TABLE B2.3.1 Estimation of global-average robot prices, by robot type

Robot types	Adoption industry, closest match by use-cases	Unit cost, quality-adjusted, 2015–19 average (constant 2010 US$)	Robot average lifetime (years)	Per worker robot price (constant 2010 US$)
Articulated	Automotives	21,407	9	41,883
SCARA	Electrical equipment	7,904	6	10,310
Cartesian	Rubber and plastics	3,293	6	4,296

Sources: Original estimates using data from Acemoglu and Restrepo 2018; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.
Note: The robot adoption industries are selected following IFR descriptions. The estimated unit prices of robots are computed using IFR statistics on (a) the total value of global robot stocks; (b) the share of global robot stocks by robot type, adjusted for robot quality and the average relative unit price across robot types; and (c) the assumption that a robot performs the work of 4.6 workers based on the median labor displacement estimate per robot of Acemoglu and Restrepo (2018). IFR = International Federation of Robotics.

the vertical lines denote the break-even points at which robots could be deemed economically viable to substitute for human labor. Figure 2.3, panel b, plots the actual (average) robot adoption profiles against country income per capita, estimated using actual adoption rates across manufacturing sectors worldwide with data from 1995–2020.

The results suggest that robot adoption is economically viable in lower-income countries only in sectors, such as rubber and plastics, that rely on cheaper, more-elementary robots. Robot adoption in more-sophisticated sectors, such as automotives and electrical equipment, only becomes economically viable in richer countries where labor is more expensive. Apart from the price of robots and the cost of labor, quality standardization and the more rapid turnaround times of production in these industries, especially if they are export-oriented, also tend to incentivize robot adoption (World Bank 2020).

The observed patterns of robot adoption across countries and sectors align with the predictions of the economic viability of robots. As shown in figure 2.3, panel b, more sophisticated robots are adopted at higher rates in sectors and countries with higher labor costs. Robot adoption in the automotive industry is low in low-income countries and increases as countries become richer and labor costs rise. Robots are adopted at higher rates in rubber and plastics at low-income levels, followed by the electrical equipment industry. As countries develop and labor costs rise, robot adoption rates increase in all sectors, but at a faster pace in the electrical equipment industry. The need for quality standardization at scale may also be driving the higher robot adoption in this sector.

The technical feasibility and economic viability of technology

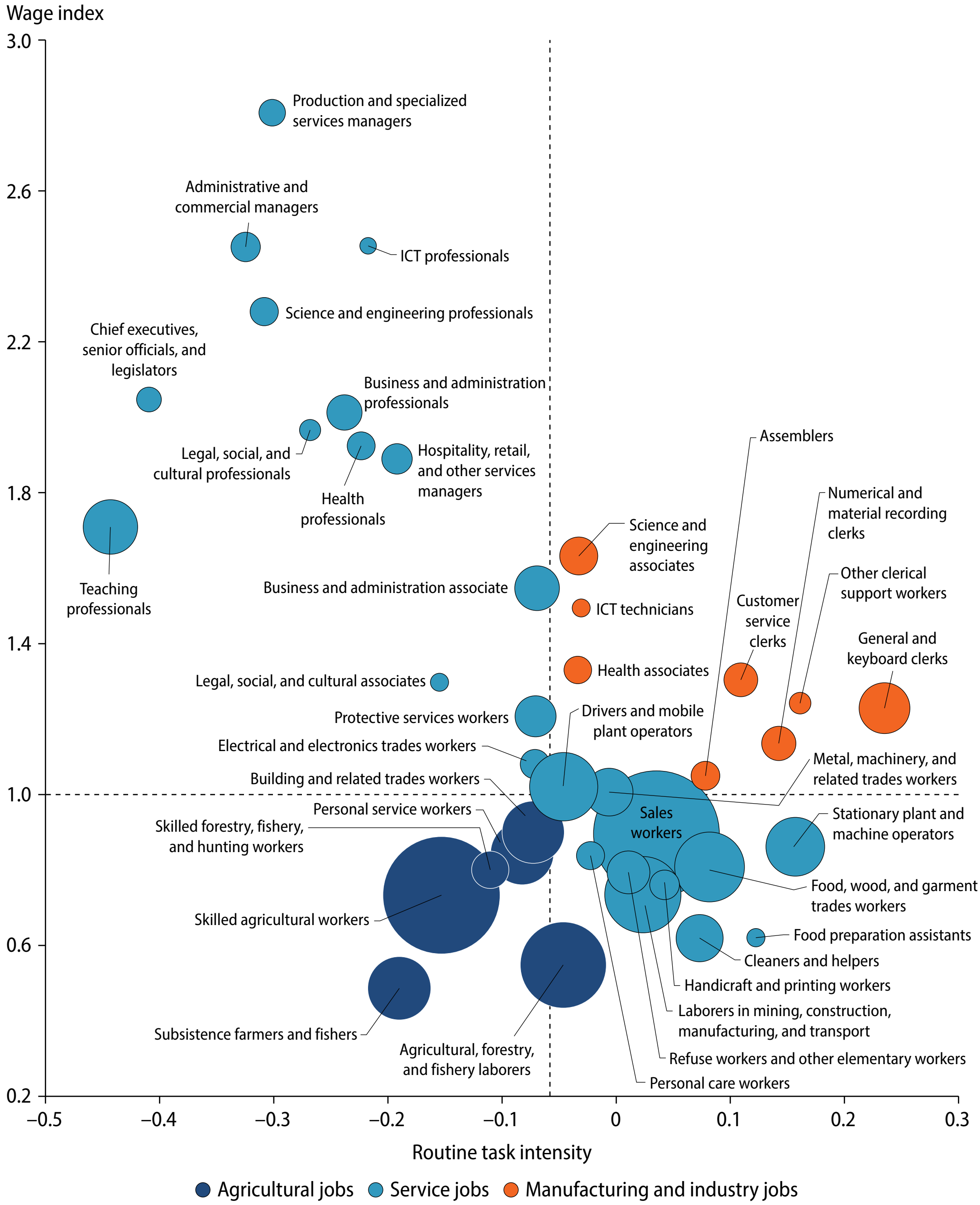
Technical feasibility and economic viability jointly determine the likely impact on jobs of technology adoption in the EAP region. Figure 2.4 maps the occupational structure of five economies of the Association of Southeast Asian Nations and the United States in terms of their routine task index (RTI) and relative wage costs. Wages in an occupation influence the economic viability of technology adoption, along with the quality-adjusted cost of the relevant technology. Comparable data on the costs of different types of technology are not available, but are likely to be correlated with RTI because the performance of more complex (less routine) tasks requires costlier technology (refer to spotlight 2.1).

Jobs with high RTI and high wages are most susceptible to automation. In the United States, jobs are largely concentrated in the top-left and bottom-right quadrant of the occupational distribution (refer to figure 2.4, panel b). This means that jobs are either less routine with higher pay (top-left quadrant) or more routine with lower pay (bottom-right quadrant). There are few jobs remaining in occupations that involve routine work and high pay (top-right quadrant) where automation has greatly advanced. In the EAP region, while overall wages are lower than in the United States, there is still a sizable share of routine jobs in (a) the top-right quadrant, such as customer services and other clerks and ICT and science and engineering associates, and (b) the border between the top and lower-right quadrants, such as manufacturing assemblers, machine mechanics, and operators. These categories of routine jobs with relatively high or average pay are more susceptible to automation (services jobs by AI, and manufacturing jobs by robots) as wages increase in the region.

Routine jobs in the EAP region are increasingly at risk of automation as wages rise.

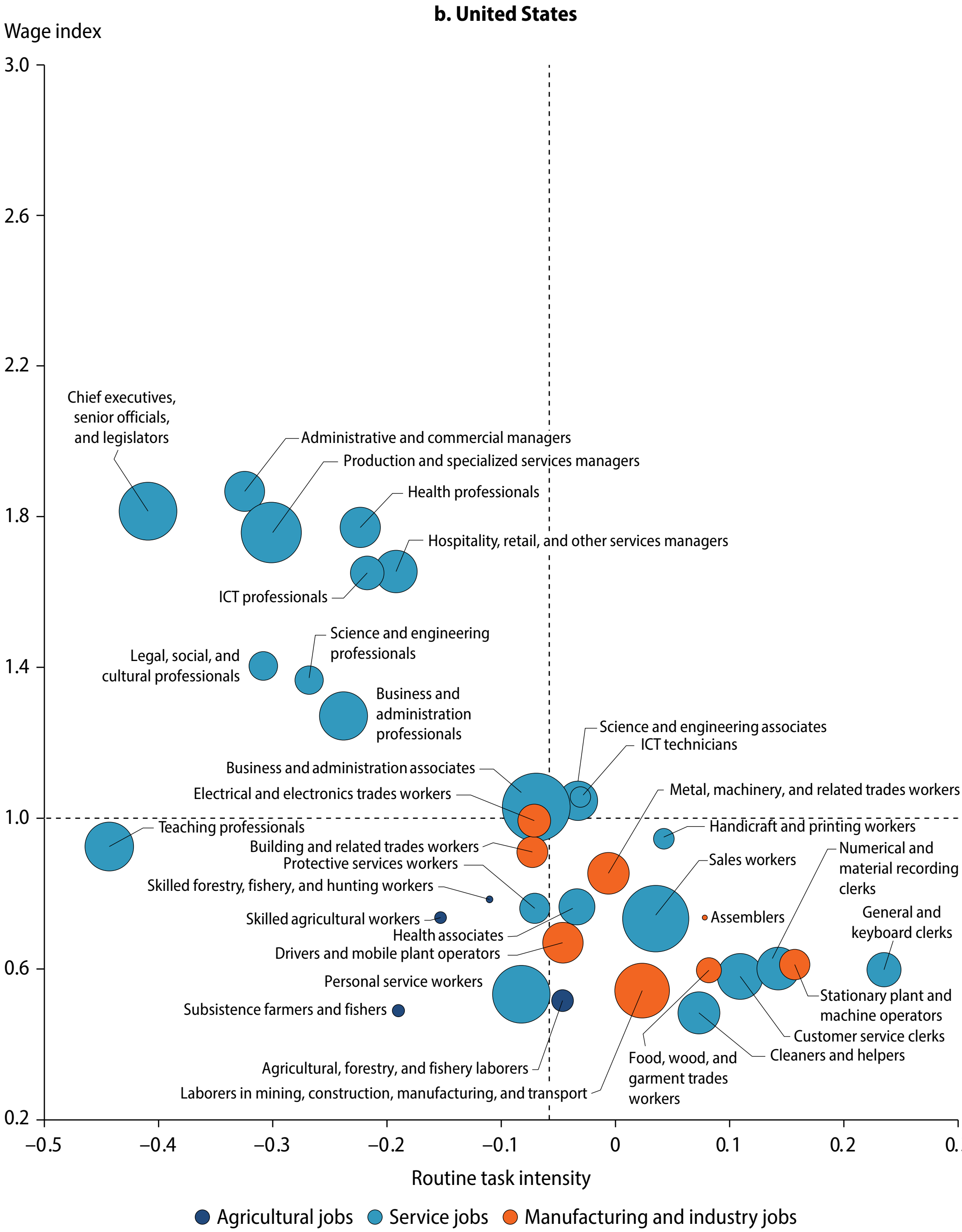
FIGURE 2.4 Jobs and technology in the EAP region: Technical susceptibility and economic viability

a. Average: Indonesia, Malaysia, Philippines, Thailand, and Viet Nam



(continued)

FIGURE 2.4 Jobs and technology in the EAP region: technical susceptibility and economic viability *(continued)*



(continued)

FIGURE 2.4 Jobs and technology in the EAP region: technical susceptibility and economic viability *(continued)*

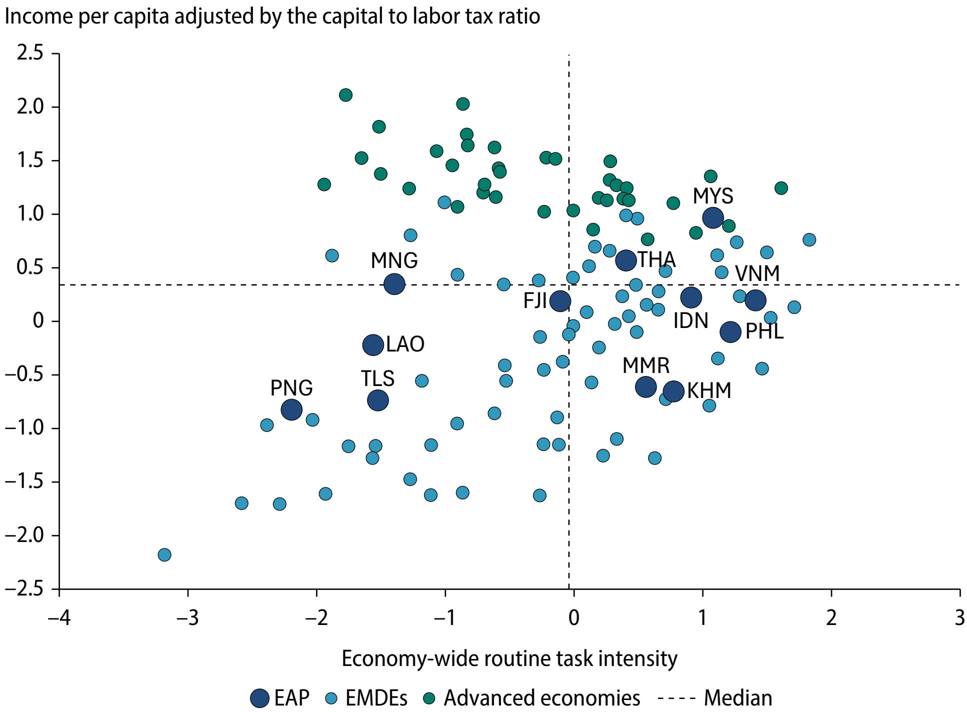
Sources: Original figure for this publication based on data of ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; microdata from national labor force surveys: Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/; OOH (Occupational Outlook Handbook) (portal), Office of Occupational Statistics and Employment Projections, Bureau of Labor Statistics, US Department of Labor, Washington, DC, https://www.bls.gov/ooh/.
Note: The figure shows the US average and the average for five ASEAN economies (Indonesia, Malaysia, the Philippines, Thailand, and Viet Nam) in the most recent year available of (a) the RTI of jobs (x-axis) measured at the ISCO08 2-digit level using US O*NET task content measures (except for agriculture) and (b) an index of average wages (y-axis) for each occupational category relative to the national average wage. Bubble size denotes the employment share of each occupational group. The horizontal and vertical dashed lines denote an index of 1 for wages and the median RTI across occupations, respectively. In the case of agriculture, the assumption that the task intensity of jobs is the same as in the United States is less adequate given that, in heavily mechanized US agriculture, the remaining agricultural tasks are classified as nonroutine manual, which is unlikely to be the case in developing EAP (refer to box 2.1). ASEAN = Association of Southeast Asian Nations; ICT = information and communication technology; RTI = routine task intensity.

Differences across EAP countries in the scope of automation arise because of differences in both occupational structure and labor cost. Relatively few jobs are susceptible to automation in countries such as the Lao People's Democratic Republic, Papua New Guinea, and Timor-Leste because many people are involved in nonroutine agricultural and services tasks, and wages are low (refer to figure 2.5). More people work in routine manufacturing in Cambodia and Myanmar, but low wages reduce the economic benefits of automation. In contrast, in higher-wage countries, such as Malaysia and Thailand, many more people are susceptible to automation in manufacturing and services. Across EAP countries, some services jobs, such as customer service clerks, involve routine tasks, pay relatively high wages, and are more likely to be automated than the nonroutine tasks performed by professionals and managers. As EAP countries develop and labor costs increase, a higher share of employment will become more exposed to new technologies.

The following chapters explore the impact of various technologies on EAP labor markets. The main focus is on the adoption of two new key technologies: industrial robots and AI. Chapter 3 examines the drivers of the use of industrial robots in manufacturing, and chapter 4 focuses on AI. The analysis of industrial automation follows the established scholarly literature to estimate empirically the causal impact of robots, which have been adopted rapidly and steadily in several EAP countries since as early as the 2000s. In spotlight 3.1 that follows chapter 3, the report examines the first wave of technology adoption in agriculture through the diffusion and impacts of mechanization on agricultural employment and productivity. While it is too early to estimate the impact of nascent AI technologies, correlational

Economic viability rather than technical feasibility limits the extent of automation in the EAP region.

FIGURE 2.5 Relative labor costs and employment routine task intensity, by country



Sources: Original figure for this publication based on data of Bachas et al. 2022; ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; microdata from national labor force surveys: Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.

Note: Data from 2023 or most recent available year. The horizontal and vertical dashed lines denote the median values across the sample of countries. The y-axis is a measure of economic viability based on the relative labor costs of a country (proxied by income per capita) and the relative taxation of capital versus labor (proxied by the capital-labor tax ratio). The x-axis measures the RTI of overall employment in a country by multiplying the labor share of occupations (ISCO08 2-digit level) by the RTI of an occupation based on O*NET data. For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search. EMDEs = emerging market and developing economies; RTI = routine task index. The horizontal and vertical dash lines denote the median values across the sample of countries.

evidence suggests that AI can have both displacement and augmentation effects across occupations. Chapter 5 investigates the implications of working with digital technologies, focusing on the digital intensity of jobs, that is, the digital skills and knowledge required for a job. Digital platforms as a distinct and significant technological development are also examined. Chapter 6 takes an integrated view of the impact of technology adoption across occupations and sectors, and chapter 7 presents policy implications of the findings.

Notes

1. The productivity effect and the displacement of labor-intensive tasks both cause the production process to become more capital intensive and tend to raise productivity more than wages, thereby reducing the share of labor in national income. Only the creation of new tasks increases the demand for labor and the share of labor in national income (Acemoglu and Restrepo 2019b).
2. The empirical literature points to several factors that influence the returns to technology adoption (and thus the diffusion of the technology), including a country's level of economic development, complementarities with human capital and other factors, trade openness, and competition (Caselli and Coleman 2001; Cirera and Maloney 2017; Comin and Hobijn 2004; Lee 2001).
3. The price of technology can be considered similar across countries, although the actual costs would differ across countries because of tariffs, other taxes, and exemptions. Prices do fall significantly over time (refer to appendix, figure A.2), which accelerates the economic viability of technology adoption.

References

Acemoglu, Daron, and David H. Autor. 2011. "Skills, Tasks, and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, vol. 4, part B, edited by Orley C. Ashenfelter and David E. Card, 1043–171. San Diego: North-Holland.

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review* 108 (6): 1488–542.

Acemoglu, Daron, and Pascual Restrepo. 2019a. "Artificial Intelligence, Automation, and Work." In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay Agrawal, Joshua Gans, and Avi Goldfarb, 197–236. Cambridge, MA: National Bureau of Economic Research; Chicago: University of Chicago Press.

Acemoglu, Daron, and Pascual Restrepo. 2019b. "Automation and New Tasks: How Technology Displaces and Reinstates Labor." *Journal of Economic Perspectives* 33 (2): 3–30.

Acemoglu, Daron, and Pascual Restrepo. 2024. "Automation and Rent Dissipation: Implications for Wages, Inequality, and Productivity." NBER Working Paper 32536 (June), National Bureau of Economic Research, Cambridge, MA.

ADB (Asian Development Bank). 2018. *Asian Development Outlook 2018: How Technology Affects Jobs*. April. Manila: ADB.

Autor, David H., Caroline Chin, Anna Salomons, and Bryan Seegmiller. 2024. "New Frontiers: The Origins and Content of New Work, 1940–2018." *Quarterly Journal of Economics* 139 (3): 1399–465.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.

Bachas, Pierre, Matthew H. Fisher-Post, Anders Jensen, and Gabriel Zucman. 2022. "Capital Taxation, Development, and Globalization: Evidence from a Macro-Historical Database." NBER Working Paper 29819, National Bureau of Economic Research, Cambridge, MA.

Bessen, James. 2015. *Learning by Doing: The Real Connection Between Innovation, Wages, and Wealth*. New Haven, CT: Yale University Press.

Caselli, Francesco, and Wilbur John Coleman II. 2001. "Cross-Country Technology Diffusion: The Case of Computers." *American Economic Review* 91 (2): 328–35.

Cirera, Xavier, and William F. Maloney. 2017. *The Innovation Paradox: Developing-Country Capabilities and the Unrealized Promise of Technological Catch-Up*. Washington, DC: World Bank.

Comin, Diego A., and Bart Hobijn. 2004. "Cross-Country Technology Adoption: Making the Theories Face the Facts." *Journal of Monetary Economics* 51 (1): 39–83.

Lee, Jong-Wha. 2001. "Education for Technology Readiness: Prospects for Developing Countries." *Journal of Human Development and Capabilities* 2 (1): 115–51.

Lee, Kai-Fu. 2018. *AI Superpowers: China, Silicon Valley, and the New World Order*. Boston: Houghton Mifflin Harcourt.

World Bank. 2020. *World Development Report 2020: Trading for Development in the Age of Global Value Chains*. Washington, DC: World Bank.

SPOTLIGHT 2.1

Measuring the Task Content of Jobs

Classifying jobs by task content

Mapping the occupational structure of countries along the physical-cognitive and routine-nonroutine spectrum helps in understanding the distribution of employment by the nature of the tasks involved in jobs. The analysis here relies on the methodology of Acemoglu and Autor (2011) based on the O*NET classification of tasks performed in various occupations in the United States.[1] Each occupational category at the ISCO08 2-digit level is assigned ratings for job task content based on O*NET and then classified based on its relative task intensity (that is, the dominant task categories). The results are summarized in figures 2.2 and S2.1.1. One important qualification of this exercise is that the nature of tasks in specific occupations in the United States is likely to be different from the nature of tasks performed in the same occupation in a developing country. For example, in heavily mechanized US agriculture, the remaining agricultural tasks are classified as nonroutine manual, whereas, in most low-wage developing countries, a significant share of agricultural tasks are still likely to be routine manual. For this reason, the task content of employment in agriculture in EAP and other developing economies is not estimated here, and agricultural employment is reported separately in figure 2.2.

In the EAP region, a large share of workers are engaged in jobs that primarily involve physical tasks such as in agriculture, assembly lines, machine operations, and construction. Routine-cognitive jobs also account for a significant share of the labor market in the region. Meanwhile, in advanced economies, fewer workers are in jobs intensive in physical tasks and more workers perform a wider range of cognitive tasks (refer to figures 2.2 and S2.1.1).

Nearly half of jobs in the EAP region are primarily routine task–based, a higher share than in advanced economies and other emerging market and developing economies. About 21 percent of jobs in the EAP region involve routine manual tasks, which exceeds the share in advanced economies (15 percent) and is slightly higher than the share in other emerging market and developing economies. This is because of the large share of labor-intensive manufacturing and service jobs involving manual and routine tasks in the region. The share of jobs that primarily involve routine cognitive tasks is 24 percent in the EAP region, higher than the share in other emerging market and developing economies (16 percent) and similar to the share in advanced economies. Within the EAP region, Cambodia, China, and Viet Nam exhibit a relatively high share of routine manual-based jobs because of their large share of labor-intensive manufacturing, while China, Indonesia, Malaysia, and the Philippines have a relatively high share of routine cognitive-based jobs, reflecting their relatively high share of jobs in the services sector.

Jobs involve more physical and routine cognitive tasks in the EAP region than in advanced economies; nonroutine cognitive jobs are relatively scarce in the EAP region.

FIGURE S2.1.1 Occupational structure by the task intensity of jobs, EAP and advanced economies

a. EAP

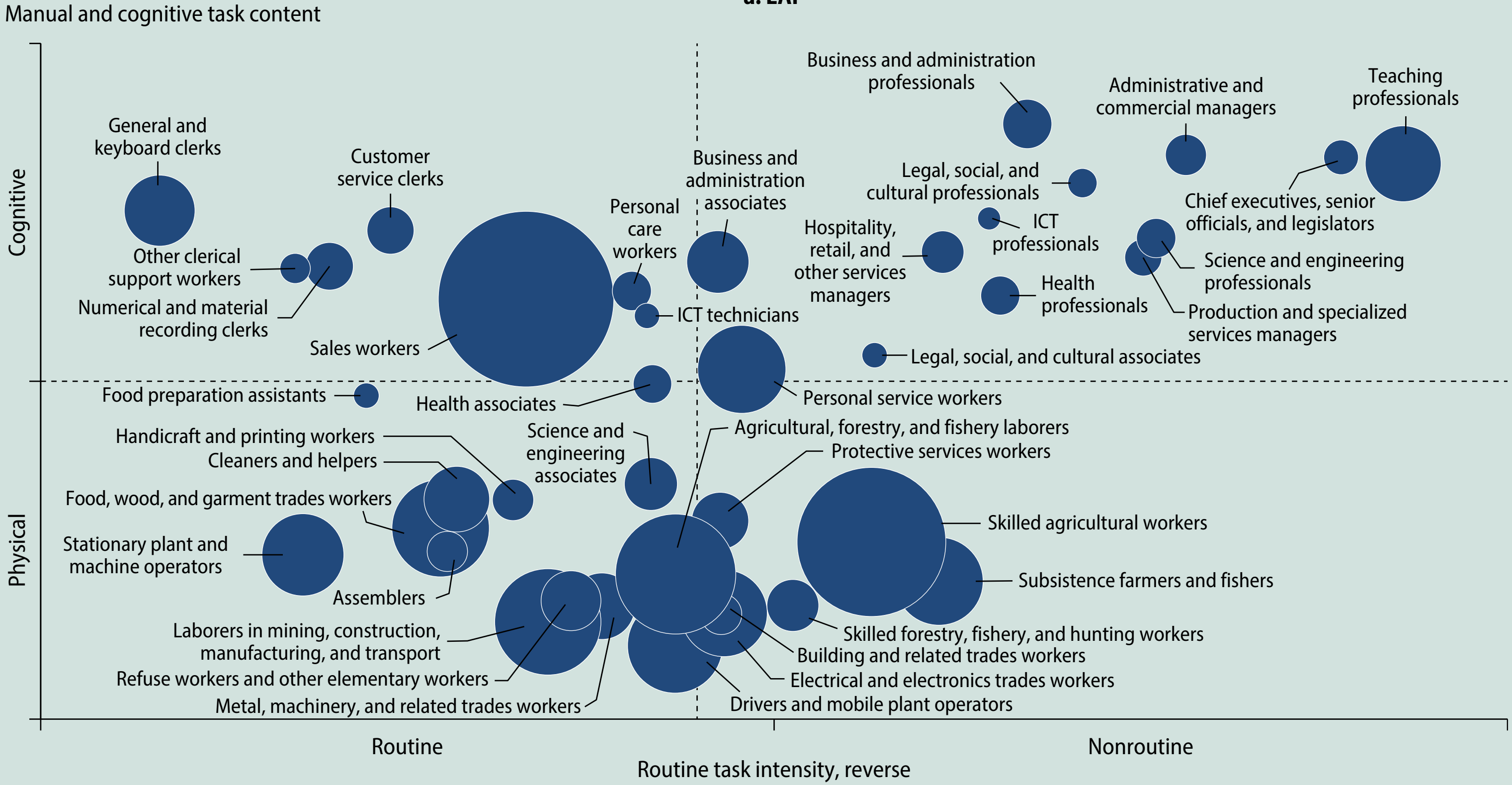


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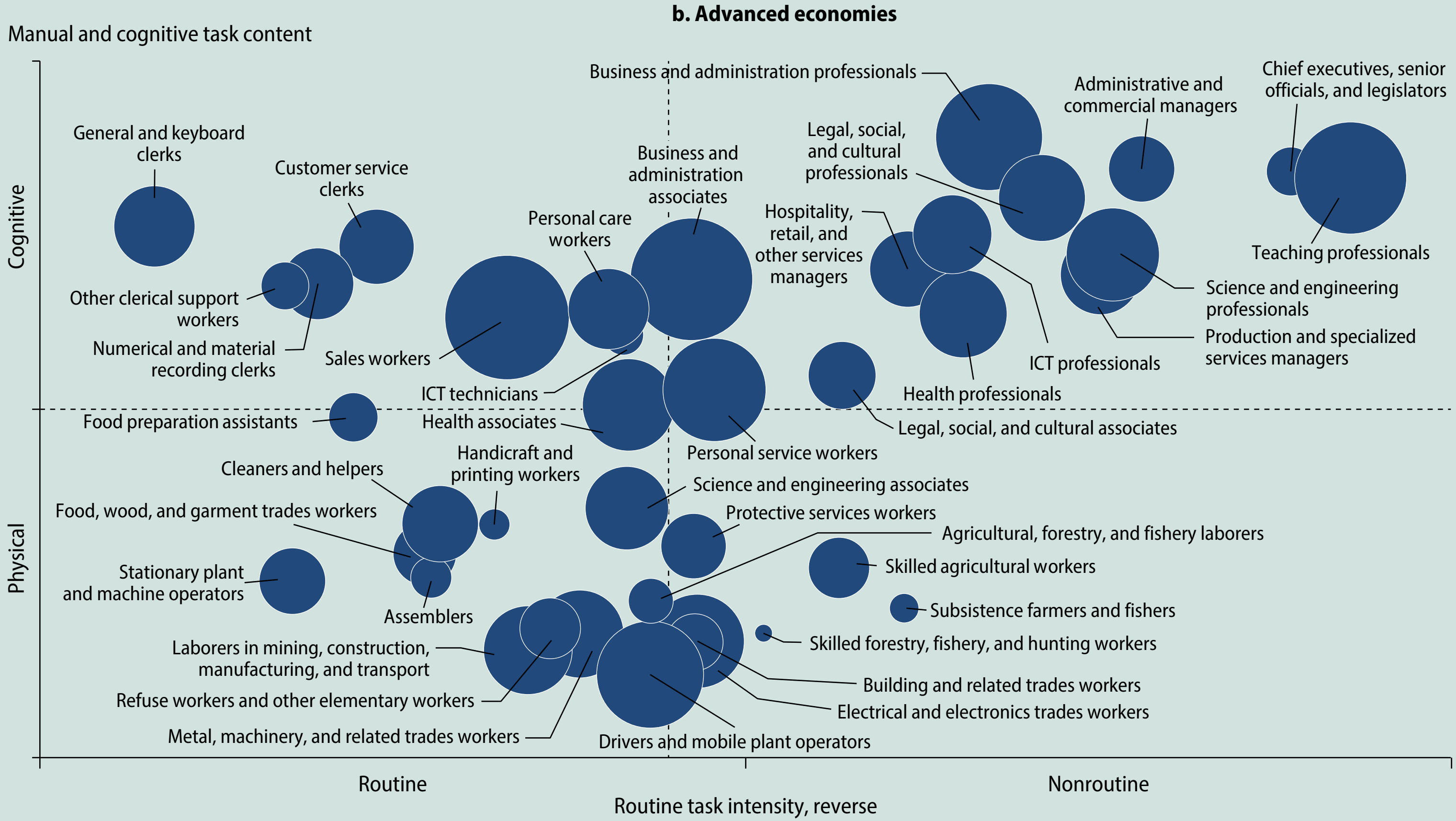
FIGURE S2.1.1 Occupational structure by the task intensity of jobs, EAP and advanced economies *(continued)*



Sources: Original figure for this publication based on data of ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; microdata from national labor force surveys: Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/.

Note: The y-axis measures the relative cognitive versus manual content of job tasks (nonroutine physical task intensity). The x-axis measures routine task intensity computed following the methodology of Autor and Dorn (2013). The task intensity indicators are used to provide a relative ordering of occupations in the respective dimensions. Bubble size denotes the average occupation share in EAP (9 countries) and advanced economies (36 countries). Data are from the most recent year available. EAP = East Asia and Pacific; ICT = information and communication technology.

Less than 15 percent of jobs in the EAP region are nonroutine cognitive task–based, significantly fewer than in other regions. Jobs in advanced economies tend to be more cognitive (both routine and nonroutine) than manual, reflecting the services-led economies. However, in advanced economies, the share of nonroutine cognitive-based jobs (38 percent) is higher than the share of routine cognitive-based jobs (23 percent), unlike in the case of EAP and other emerging market and developing economies. In EAP, only 13 percent of jobs primarily involve nonroutine cognitive-based tasks. In the region, Malaysia and Mongolia have a relatively high share of nonroutine cognitive-based jobs.

Survey-based versus O*NET-based routine task intensity measures

The task content of an occupation may be different across countries because of differences in worker skills, how firms organize production, and the requirements of the job market. Few labor surveys in developing countries collect data on the tasks performed in jobs. For this reason, most of the empirical literature has relied on the task content measures collected in the United States through O*NET to analyze the implications of technological change on the nature of jobs.[2]

A few studies use the limited available survey data to examine the implications of differences in the tasks of an occupation across the country-development spectrum. These studies document significant cross-country and within-occupation variations in the task content of jobs between developed and developing economies. Lewandowski, Park, and Schotte (2023) and Lewandowski et al. (2022) use adult skills surveys—the China Urban Labor Survey, the Program for the International Assessment of Adult Competencies surveys, and the Skills toward Employability and Productivity Program surveys—to construct measures of routine task intensity (RTI).[3] These survey-based RTI measures reveal larger cross-country differences in the routine tasks involved in jobs (standard deviation of 0.27) compared with the O*NET-based measures (standard deviation of 0.19). The correlation between the survey-based RTI and country income per capita is stronger than in the case of the O*NET-based measures. Thus, the latter underestimate the true RTI of jobs in developing countries. Caunedo, Keller, and Shin (2022) examine survey-based task intensity by distinguishing granular task dimensions (routine-nonroutine and manual-cognitive). They find that any given occupation in developing countries generally involves more routine tasks and fewer nonroutine tasks than in developed countries. The gap between survey-based measures and O*NET-based measures is larger in nonroutine tasks. Compared with the O*NET-based measures, the task intensity of jobs in terms of nonroutine cognitive and interpersonal tasks is somewhat lower in developed countries, while, in developing countries, jobs have a much lower intensity of nonroutine tasks and a higher intensity of routine manual and cognitive tasks.

Figure S2.1.2 illustrates the relationship between RTI and a country's development level found by Lewandoski et al. (2022) using O*NET and survey-based measures. The negative correlation is stronger in the survey-based measures than in the O*NET-based measures.

Across both O*NET and survey-based measures, EAP countries generally exhibit a higher RTI compared with economies at similar per capita income. The EAP average survey-based RTI is 0.52, and the average O*NET-based RTI is 0.46, indicating that the task structure is in fact more routine in the EAP region than in advanced economies. For instance, compared with the O*NET-based measure, Mongolia's RTI is significantly higher on the survey-based measure, while jobs in the Philippines are less routine.

The cross-country variation in RTI is explained by task differences within occupations or by differences in occupational structures. Lewandowski et al. (2022) find that only one-fifth of the variation may be attributed to occupational structures. Their assessment of the determinants of task differences reveals that technology (computer use) is the most important factor. The supply of skills is the next most important factor, especially among workers in high-skilled occupations, while globalization is more important than skills among workers in low-skilled occupations (refer to figure S2.1.3). In the EAP countries covered in the analysis, the supply of skills is the largest contributor to the RTI gap with the United States, indicating that low skill levels correlate with a higher degree of RTI in occupations.

The same job involves more routine tasks in developing countries than in advanced economies.

FIGURE S2.1.2 Routine task intensity, survey versus O*NET measures, EAP and other economies

a. Survey-based routine task intensity measures

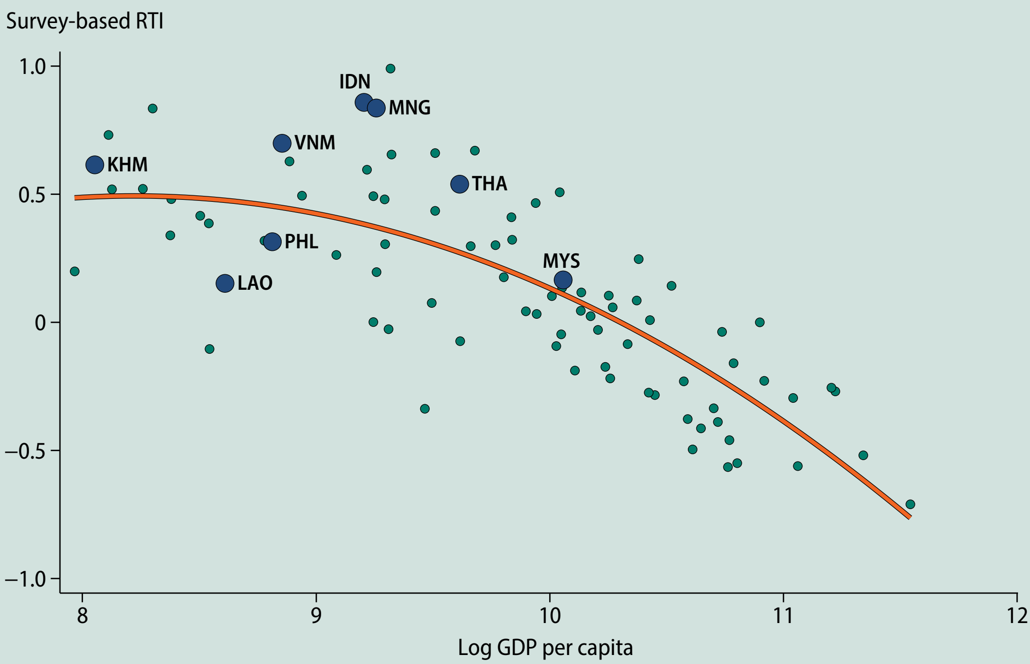


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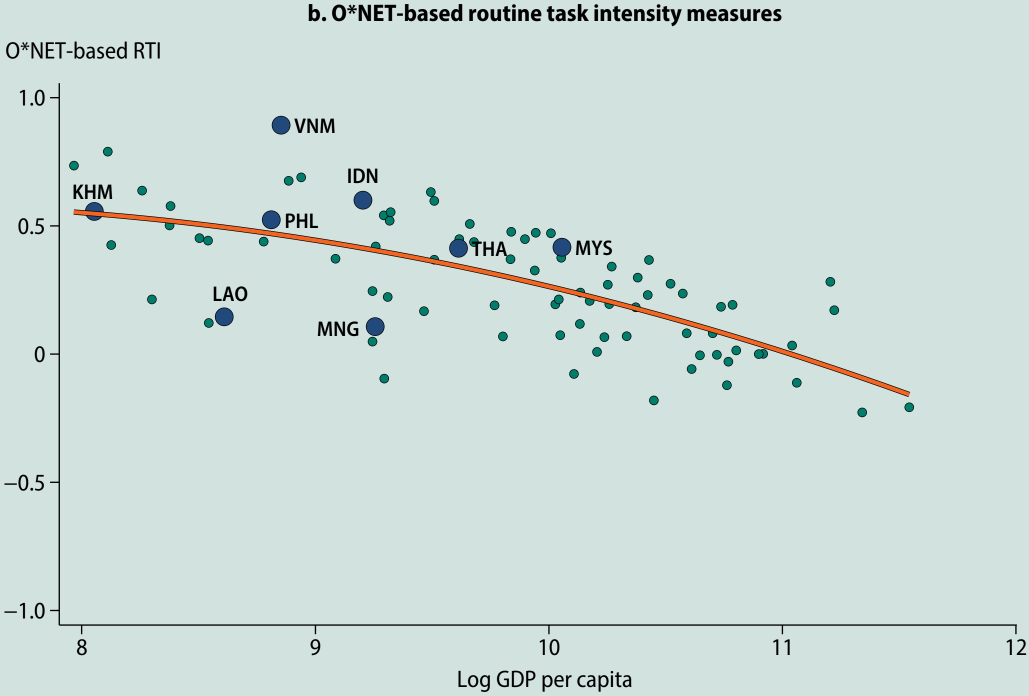
FIGURE S2.1.2 Routine task intensity, survey versus O*NET measures, EAP and other economies *(continued)*

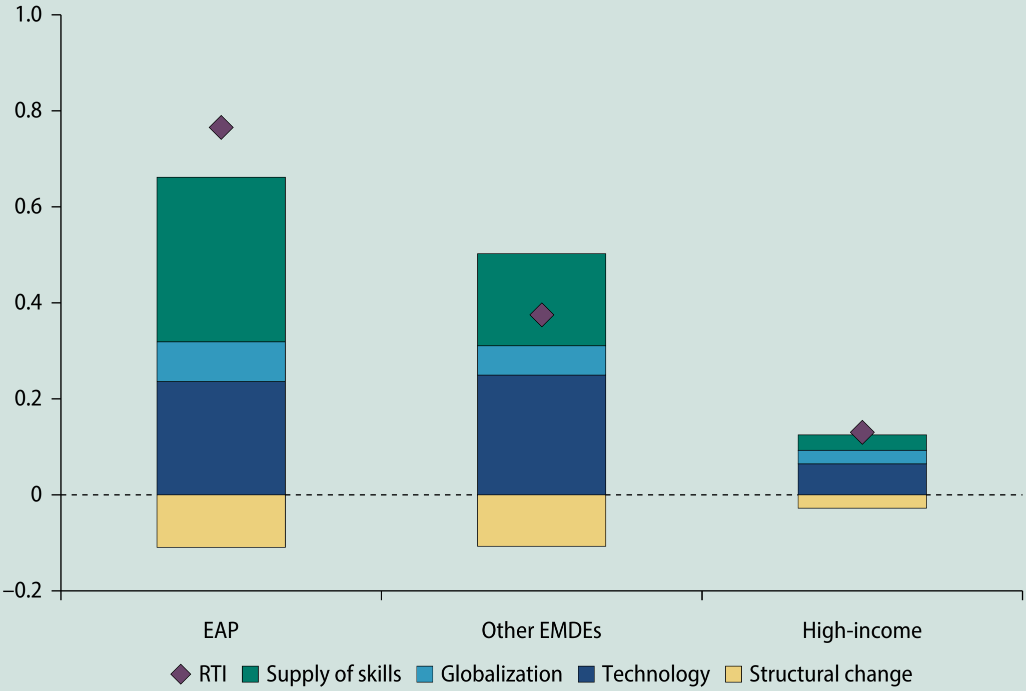


Sources: Original figure for this publication based on ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; the methodology and data of Lewandowski et al. 2022; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.

Note: Calculations are based on ISCO08 2-digit occupation shares. For each task content, the 0 is set at the US average value, and 1 corresponds to one standard deviation from this particular task content value in the United States. GDP per capita is in current international purchasing power parity (US dollars), country averages for 2011–16. For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search. GDP = gross domestic product; RTI = routine task intensity.

The higher routine task intensity of employment in EAP is mainly driven by technology use and workforce skills.

FIGURE S2.1.3 The drivers of differences in routine task intensity across economies



Source: Original figure for this publication based on Lewandowski et al. 2022.
Note: The figure illustrates the simple average of the country-level decomposition of the RTI gap with the United States. EAP includes China, Indonesia, and the Lao People's Democratic Republic. EMDEs = emerging market and developing economies; RTI = routine task intensity.

Notes

1. Refer to O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/.
2. Refer to O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/.
3. Refer to CULS (China Urban Labor Survey), Institute for Population Studies, Chinese Academy of Social Sciences, Beijing, https://doi.org/10.18170/DVN/XMFDUI; PIAAC Data and Methodology (dashboard), Program for the International Assessment of Adult Competencies, Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/about/programmes/piaac/piaac-data.html; STEP Skills Measurement (dashboard), World Bank, Washington, DC, https://microdata.worldbank.org/index.php/collections/step. The China Urban Labor Survey was conducted in 2001, 2005, and 2010. Only data on the 2001 round are readily available.

References

Acemoglu, Daron, and David H. Autor. 2011. "Skills, Tasks, and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, vol. 4, part B, edited by Orley C. Ashenfelter and David E. Card, 1043–171. San Diego: North-Holland.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.

Caunedo, Julieta, Elisa Keller, and Yongseok Shin. 2022. "Technology and the Task Content of Jobs across the Development Spectrum." Economic Research Working Paper 2022-035 (September), Federal Reserve Bank of St. Louis, St. Louis.

Lewandowski, Piotr, Albert Park, Wojciech Hardy, Yang Du, and Saier Wu. 2022. "Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work Using Survey Data." *World Bank Economic Review* 36 (3): 687–708.

Lewandowski, Piotr, Albert Park, and Simone Schotte. 2023. "Global Divergence in the De-routinization of Jobs." In *Tasks, Skills, and Institutions: The Changing Nature of Work and Inequality*, edited by Carlos Gradín, Piotr Lewandowski, Simone Schotte, and Kunal Sen, 33–51. UNU-WIDER Studies in Development Economics. Helsinki: United Nations University–World Institute for Development Economics Research; New York: Oxford University Press.

Automation in Manufacturing: Industrial Robots

3

Introduction

This chapter examines the determinants and consequences of the adoption of industrial robots. There is sufficient variation in the diffusion of robots in the East Asia and Pacific (EAP) region to enable a relatively rigorous analysis across countries and over time, especially in the case of Viet Nam, on which detailed subnational data are available. The chapter also places the findings on the region within the global context by drawing on a meta-analysis of existing research.

While the focus is on industrial automation, spotlight 3.1 examines the implications of technology adoption (mechanization) for agricultural productivity and employment across EAP countries and the world. The interplay between technology adoption in agriculture and the expansion of manufacturing has historically been a major driver of overall employment. The economy-wide analysis in chapter 6 draws on the assessment of technological progress in agriculture and the associated changes in agricultural productivity and employment.

Technical and economic drivers of the adoption of robots

Given the relatively high employment in industry in the region, a significant concern from the perspective of job displacement or job opportunity is the rapid adoption of robots. Modern industrial robots perform a wide range of tasks at high speed and with precision, such as material handling, labeling, packaging, assemblage, painting, welding, and mechanical cutting. Most of these tasks are usually performed by low-skilled or medium-skilled workers. Developing EAP countries host a large share of such workers.

Technological advances have expanded the scope of tasks that machines can perform. Besides this technical viability, the adoption of robots is also affected by economic viability, which depends on the quality- and scope-adjusted costs of robots, the local labor costs, and the responsiveness of product demand to price changes (refer to box 3.1).

Box 3.1. Empirical evidence on the determinants of the adoption of robots

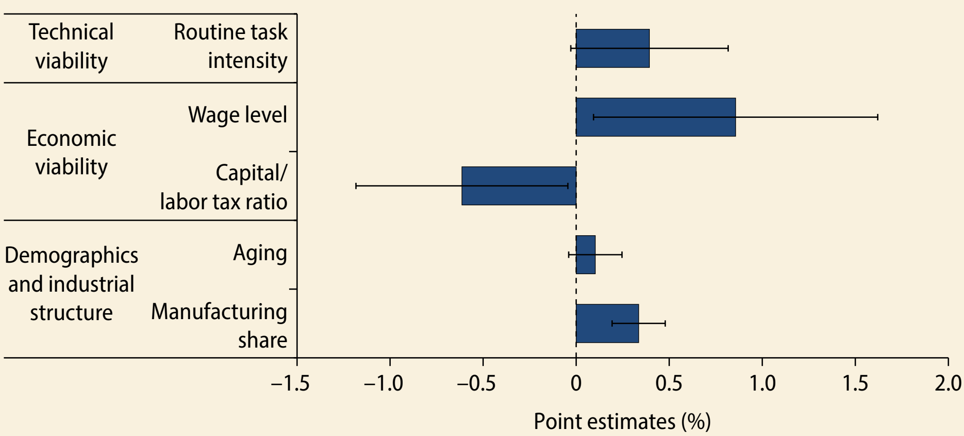
The adoption of robots is influenced by both technical viability and economic viability. For example, in the textile industry in developing economies, where automation is technically achievable, the actual deployment of robots may be limited because of the relatively low cost of labor compared with the cost of acquiring, operating, and maintaining robots.

Countries with higher routine task intensity tend to adopt more robots (Artuc, Christiaensen, and Winkler 2019) (refer to figure B3.1.1). Robot adoption is dominant in manufacturing industries, such as automotives, computers and electronics, and electrical equipment, where the production tasks are more amenable to automation and the need for product standardization is greater.

The adoption of robots is influenced by both technical viability and economic viability.

FIGURE B3.1.1 Robot adoption: Determinants and correlation with sectoral wage

a. Determinants of robot adoption



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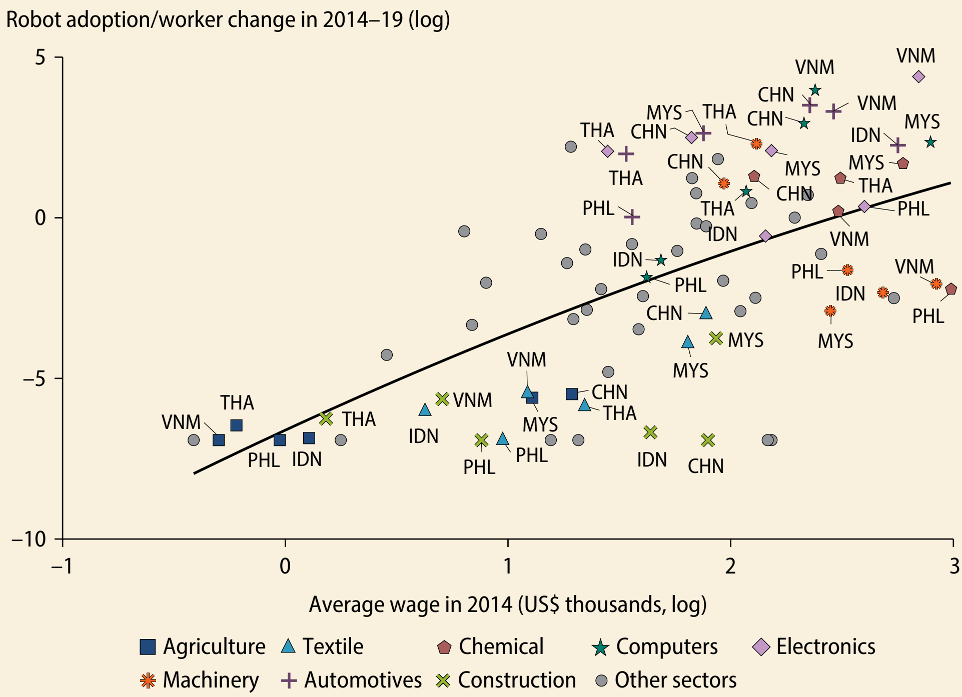
Box 3.1. Empirical evidence on the determinants of the adoption of robots *(continued)*

FIGURE B3.1.1 Robot adoption: determinants and correlation with the sectoral wage *(continued)*

b. Correlation between robot adoption and wages, by sector, EAP



Sources: Original figure for this publication based on ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; TiM (Trade in Employment) (database), Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/data/datasets/trade-in-employment.html; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

Note: Panel a shows the coefficients and 90 percent confidence intervals of country-sector-level panel regressions where the dependent variable is the stock of robots per 1,000 workers in 1995 and the independent variables are routine task intensity (standardized), log of earning level, the tax ratio of capital to labor, the share of the population ages 65 or more, and the share of manufacturing in gross domestic product. Regression controls are applied for country-sector and sector-year fixed effects. The sample period is 1995–2021. Panel b, y-axis: to include 0 changes, 0.001 is added to the change in the robot stock. For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search. GDP = gross domestic product.

(continued)

Box 3.1. Empirical evidence on the determinants of the adoption of robots *(continued)*

Country per capita income, a proxy of labor cost, is positively associated with robot adoption, while the tax ratio of capital to labor is negatively associated with robot adoption (Acemoglu, Lelarge, and Restrepo 2020; Acemoglu and Restrepo 2019a, 2019b; Atkinson 2019; Graetz and Michaels 2018). The empirical literature suggests that factors of economic viability are the main determinants of robot adoption in emerging market and developing economies. In East Asia and Pacific (EAP), robot adoption is greater in sectors with higher labor costs, such as computers, automotives, and machinery (refer to appendix, figure A.3). In advanced economies, in which firms face high domestic labor costs, decisions by firms about robot adoption also weigh the costs of investment in robots at home relative to the costs associated with offshoring production to low-wage countries (Carbonero, Ernst, and Weber 2018; De Backer et al. 2018; Krenz, Prettner, and Strulik 2018).

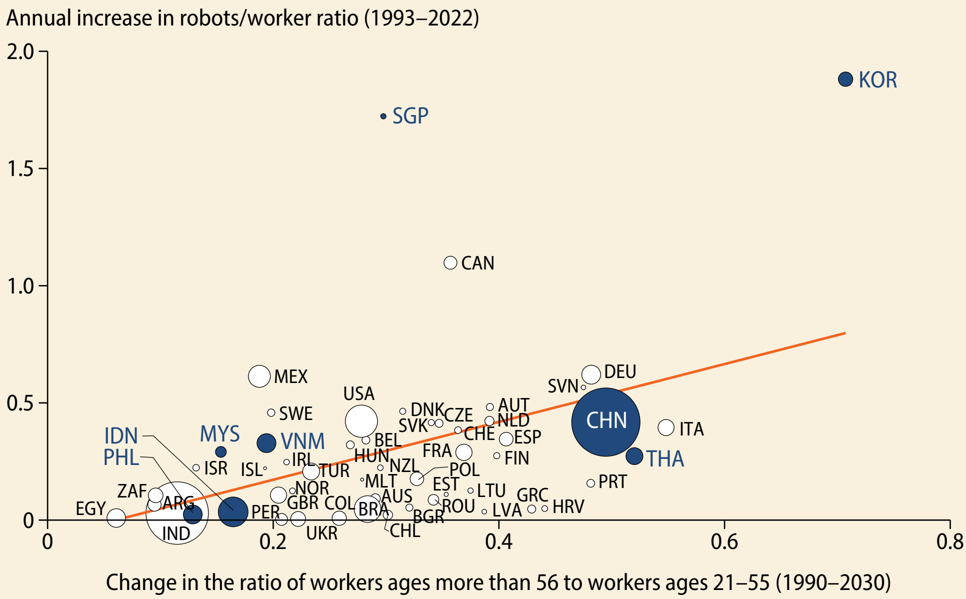
Robot adoption is also associated with workforce aging and skills. Studies find that countries with a higher share of workers with at least secondary educational attainment are more likely to adopt robots (Calì and Presidente 2021). Acemoglu and Restrepo (2022a) find that population aging—measured by the share of the population ages 65 or more—is strongly correlated with increased robot adoption. Countries with more rapidly aging populations tend to adopt more robots. Aging explains about 35 percent of the cross-country variation in robot adoption. This trend is more pronounced in industries that rely heavily on middle-age workers and those with greater opportunities for automation. In EAP, two advanced countries—the Republic of Korea and Singapore—adopt robots much more intensively than would be expected based on their aging populations. This is also true of Malaysia and Viet Nam, but to a much lesser extent. Other EAP countries, such as China, Indonesia, the Philippines, and Thailand, exhibit adoption rates somewhat below what might be expected based on population aging (refer to figure B3.1.2).

(continued)

Box 3.1. Empirical evidence on the determinants of the adoption of robots *(continued)*

Aging is associated with greater robot adoption across countries.

FIGURE B3.1.2 Correlation between robot adoption per worker and population aging



Sources: Original figure for this publication following and extending Acemoglu and Restrepo 2022a based on data of TiM (Trade in Employment) (database), Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/data/datasets/trade-in-employment.html; World Population Prospects (dashboard), Population Division, Department of Economic and Social Affairs, United Nations, New York, https://population.un.org/wpp/; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

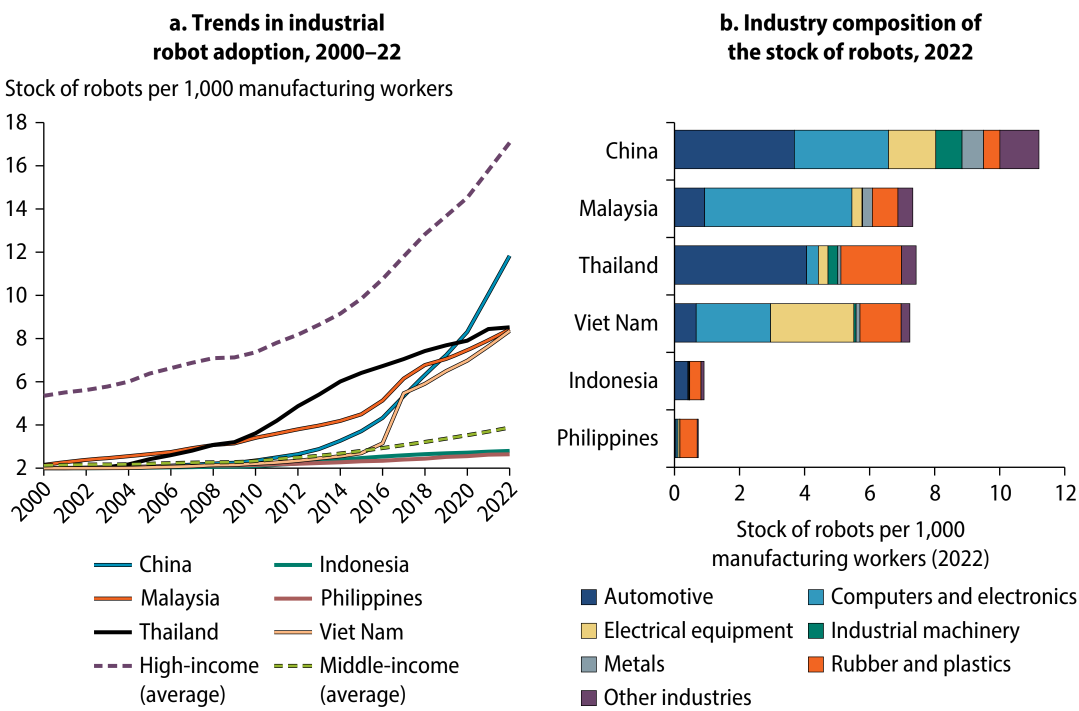
Note: The country sample is based on Acemoglu and Restrepo (2022a) and extended to include other EAP and developing countries as well as more recent data. The change in ratio of workers was calculated as $y = 1.234x + -0.075 + \varepsilon$, with R-squared = 0.1929. Bubble size shows the relative population. For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search.

There is wide variation across industries and over time in robot adoption in the large developing EAP countries. Malaysia and Thailand were the early adopters in the region, the countries in which annual stocks of robot imports have been tracked across broad industries by the International Federation of Robotics over the past three decades.[1] Robot adoption, measured as the stock of robots per 1,000 manufacturing workers, picked up in these countries in the early 2000s, and adoption growth has been sustained (refer to figure 3.1, panel a). China and Viet Nam started importing robots during the early 2010s, and both countries have experienced a surge in robot adoption since then, mimicking the growth in industrial output in these countries. By comparison, the level of robot adoption remains relatively low in Indonesia and the Philippines. A linear projection assuming robot adoption continues at the average pace observed in 2018–22 suggests that it would take Viet Nam, Malaysia, and Thailand approximately 13, 19, and 28 years, respectively, to reach the current average adoption level in high-income countries (around 17 robot units per 1,000 manufacturing workers). China would reach this level in 2026.

Robot adoption in the EAP region has been concentrated and increasing in computers and electronics, automotives, and electrical equipment. In 2022, robot imports accounted for major shares of the adoption of robots in computers and

Robot adoption has risen in automotives and in computers and electronics, but also in rubber and plastics.

FIGURE 3.1 Adoption trends and the composition of industrial robots, EAP, 2000–22



Source: Original figure for this publication based on data of TiM (Trade in Employment) (database), Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/data/datasets/trade-in-employment.html; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

electronics in China, Viet Nam, and Malaysia (25 percent, 32 percent, and 60 percent, respectively), in the automotive sector in China, Indonesia, and Thailand (32 percent, 45 precent, and 54 percent, respectively), and in electrical equipment in Viet Nam (35 percent) (refer to figure 3.1, panel b). Besides high–value added sectors, robot adoption in light manufacturing, such as rubber and plastics, also accounted for a significant share in Thailand, Indonesia, and the Philippines (24.6 percent, 38.0 percent, and 72.5 percent, respectively).

Labor market impacts of robot adoption

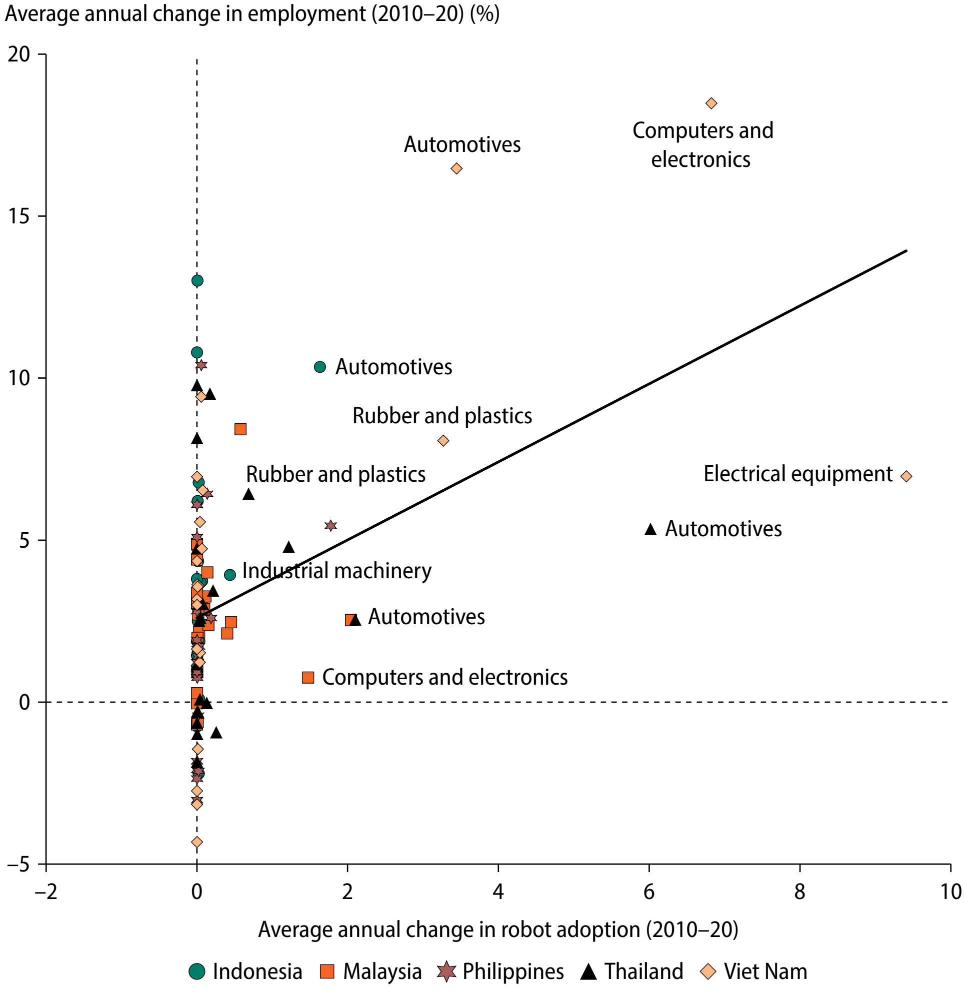
Theoretically, industrial automation has ambiguous effects on employment and wages. A useful framework for analyzing these effects is the task model (Acemoglu and Autor 2011; Acemoglu and Restrepo 2022b; Autor, Levy, and Murnane 2003). Robots perform tasks previously carried out by workers, thereby reducing labor demand and generating a displacement and substitution effect. Simultaneously, robots reduce production costs and raise total factor productivity, thereby increasing labor demand and wages, that is, the scale effect. These two countervailing forces depend on the degree of labor-robot substitutability, the productivity gains from automation technologies, and the responsiveness of demand to price reductions (Gregory et al. 2021).

In the EAP region, descriptive evidence suggests there is a positive correlation between robot penetration and overall employment growth in high-adoption industries across five countries of the Association of Southeast Asian Nations (ASEAN). The data in figure 3.2 suggest that the labor displacement effect associated with robotization at the industry-level in EAP countries is limited. All industries that experienced greater robot penetration exhibited positive average annual growth in employment in 2010–20.

Robot adoption in the EAP region is associated with increased employment and income, especially among more highly educated workers. Following Acemoglu and Restrepo (2020) and Brambilla et al. (2023), the link between robot adoption and local labor market outcomes can be examined by exploiting the variability of industrial composition across administrative divisions in the five ASEAN countries, along with temporal trends in robot adoption across industries in each country. Such empirical analysis accounts for the potential endogeneity in robot adoption intensity by instrumenting for robot adoption across industries and over time in each country with a measure of global exposure to robots that relies on the average robot adoption by each industry across 54 countries in every year. The estimation also controls for potential confounding factors by including administrative-location, country-by-time fixed effects, and baseline demographic and socioeconomic characteristics in each administrative unit.

Among industries in the EAP region, high rates of robot adoption is positively correlated with overall employment growth.

FIGURE 3.2 Robot adoption and employment growth across industries, EAP, 2010–20

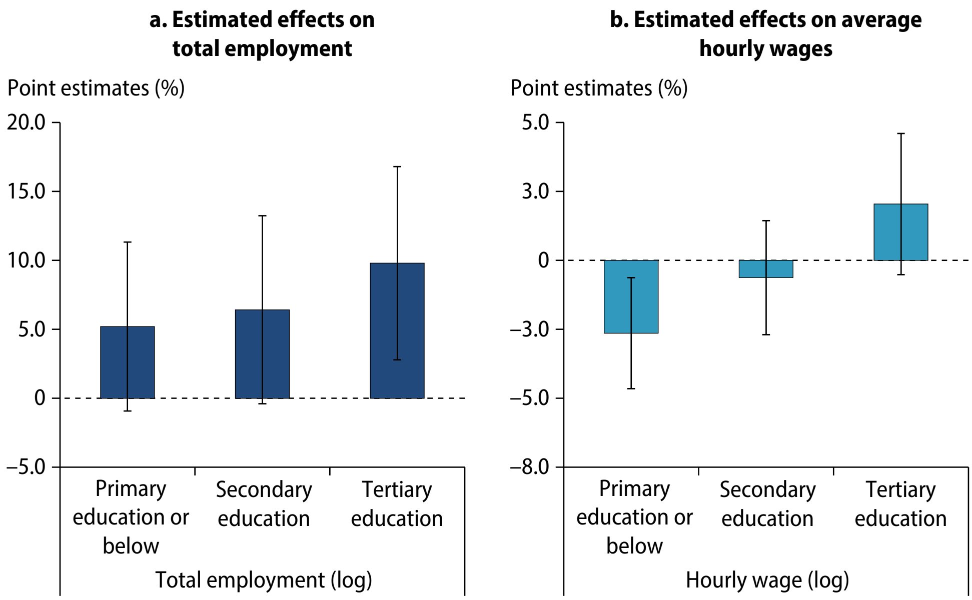


Source: Original figure for this publication based on data of TiM (Trade in Employment) (database), Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/data/datasets/trade-in-employment.html; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.
Note: The figure depicts manufacturing industries on which data on robot adoption are available. The black line represents the linear fit.

The findings suggest that administrative divisions across the five ASEAN countries exposed to greater robot penetration have experienced significant increases in overall employment and in the average wages of workers. These positive effects are concentrated among more highly educated workers, that is, those workers who have attained tertiary education (refer to figure 3.3). The estimated employment effects among workers at low educational attainment are smaller in magnitude and less statistically significant. A wage-reduction effect is observed among the least well educated group; workers who have attained only primary education or less experienced a significant contraction in average hourly wages in locations more highly exposed to robots.

In the five ASEAN countries showing greater robot adoption, employment and earnings rose among the more highly educated, but average wages fell among the least well educated.

FIGURE 3.3 Total employment and average wage effects of robot adoption, five ASEAN countries



Sources: Original figure for this publication based on data of Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

Note: The figure shows two-stage least squares estimates of the effects of exposure to robots on local labor market outcomes in five ASEAN countries (Indonesia, Malaysia, the Philippines, Thailand, and Viet Nam). Exposure to robots is measured as the interaction between the baseline employment composition by industry in each administrative division and robot adoption by industry-year in each country and is instrumented by global exposure to robots, which relies on average robot adoption across 54 countries by industry-year (following Acemoglu and Restrepo 2020). Based on data availability, an administrative division is defined at the district level in Indonesia (pre-2015) and Viet Nam and at the province level in Malaysia, the Philippines, and Thailand. Low-skilled = primary education (or less). Middle-skilled = secondary education or high school. High-skilled = vocational, college, or higher education. All regressions are weighted by the baseline population in each administrative division. The controls are for location fixed effects and country × year fixed effects, baseline demographic characteristics in each division (log population; share of urban population; share of migrants; shares of population with primary, secondary, and tertiary education; shares of population under ages 21–55 and ages 56 or more; and share of women), the division baseline industry shares (employment in primary, manufacturing, services, and the female share of manufacturing employment), and baseline economic characteristics (employment rate, unemployment rate, labor informality rate, share of salaried employment, share of self-employment, female employment rate, exposure to job routinization, log average hourly wage, log average labor income, and log total labor income).

The cross-country estimates of the employment effect of robotization in the five ASEAN countries suggest that approximately 1.67 million jobs occupied by workers with tertiary education were created by robots between 2018 and 2022 in these countries (or 3.5 percent of employment among workers with tertiary education in 2022). It is noted that a cross-country analysis is subject to the inconsistencies in data coverage and data availability across EAP countries as well as the influence of unobservable time-varying country-specific variables. The next section presents a discussion of the impact of robotization across sectors and demographic groups in Viet Nam, a country in which more disaggregated labor force survey data are generally available.

Global evidence suggests that the employment impact of robotization is more pronounced in developed countries than in developing countries. Box 3.2 provides a literature review on the employment effects of industrial robots outside the EAP region. A follow-up meta-analysis also suggests that the impact of robotization is more pronounced in developed countries. Studies covering the early adoption period are more likely to find negative employment effects.

Box 3.2. The employment effects of industrial robots across the world: A literature review

Studies on the effects of robotization on labor markets have focused primarily on developed countries largely because robots are predominantly adopted in these economies. Firms report that they invest in industrial robots mainly to improve process quality, upgrade existing processes, and automate tasks performed by labor (Acemoglu et al. 2022). There are concerns that automation technologies may displace a significant share of workers from the labor market (Brynjolfsson and McAfee 2014; Frey and Osborne 2017). Studies mostly using robot exposure measures derived from data of the International Federation of Robotics suggest that robots have reduced the wages of low-skilled workers engaged in routine manual tasks or have replaced such workers.[a] Chen and Frey's (2024) comparative assessment of the impact of robots on local labor markets across eight European countries reveals employment losses in the manufacturing sector, while the impact on total employment is more ambiguous.

The negative displacement effects of robotization may be surpassed by productivity and reallocation effects, leading to positive effects on employment after a certain level of robot penetration has been reached (Sequeira, Garrido, and Santos 2021). Among the positive effects, robotization has been shown to increase total factor

(continued)

Box 3.2. The employment effects of industrial robots across the world: A literature review *(continued)*

productivity and value added per worker, lower output prices, augment product quality, raise the demand for skilled labor, and boost the production, export, and import of intermediate inputs.[b] Antón et al. (2022) show that the impact of robotization may depend on the period of analysis. While the results in 1995–2005 are ambiguous, the positive effects of robots on employment seemed to prevail in 2005–15.

Compared with the evidence on developed countries, studies on the impact of automation in developing countries are limited and less conclusive. Automation may reduce the importance of low labor costs as a determinant of international competitiveness, thereby undermining the prospects for industrialization, participation in global value chains, and export-led growth in developing countries as production reshores back to host countries.[c] Nonetheless, robot adoption in developed countries may increase both the imports from low-income countries and the number of developed-country affiliates in low-income countries (outward foreign direct investment), in line with the fact that a firm's offshoring and automation decisions may be complementary (Artuc, Bastos, and Rijkers 2023; Stapleton and Webb 2020). Moreover, if automation technologies have diminishing returns, marginal productivity gains may be larger in developing countries (which are generally at an earlier stage of automation) than in industrialized economies (Calì and Presidente 2021; Ing and Zhang 2023; Serrano 2024). If productivity gains translate into higher wages and greater demand for goods and services, the result will be greater economic growth, employment creation, and improved welfare. Ultimately, the effects of automation technologies on employment, wages, and well-being in developing countries are highly context-dependent.

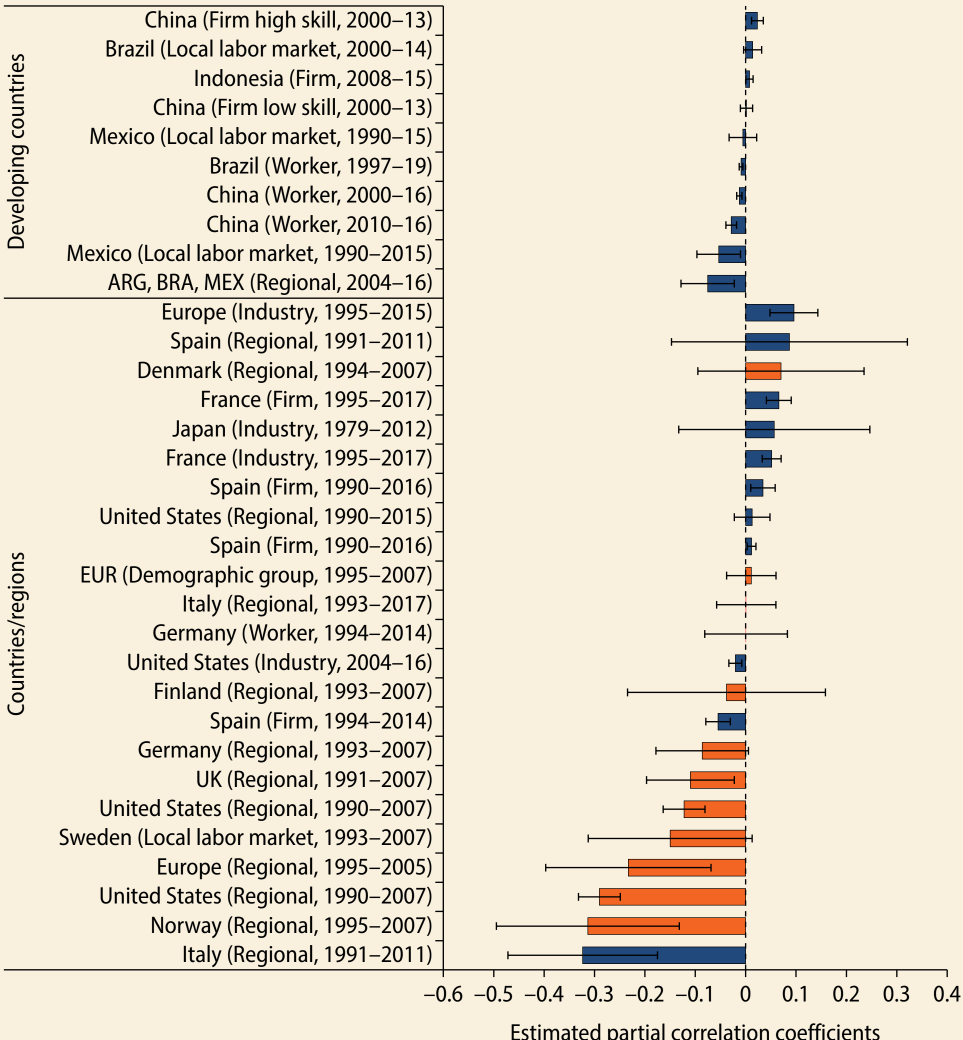
Reflecting a meta-analysis methodology introduced by Guarascio, Piccirillo, and Reljic (2024), figure B3.2.1 presents the comparative employment effects documented in the existing literature through a process of converting the estimates of all individual studies into a homogenous metric, namely, partial correlation coefficients. As may be seen in the figure, the magnitude of the impact of robotization is more pronounced in developed countries than in developing countries. Furthermore, the majority of the studies documenting a negative employment effect in developed countries involve early-adoption periods (for example, up to circa 2007; orange bars). In contrast, studies involving more recent analysis periods appear to show overwhelmingly positive estimated effects (blue bars).

(continued)

Box 3.2. The employment effects of industrial robots across the world: A literature review *(continued)*

Documenting the estimated employment effects of robotization.

FIGURE B3.2.1 Meta-analysis of estimates on the employment effects of robotization



Source: Original figure for this publication.

Note: ARG = Argentina; BRA = Brazil; EUR= Europe; MEX = Mexico; UK = United Kingdom.

a. Refer to Acemoglu and Restrepo (2020); Aghion, Antonin, and Bunel (2019); Albinowski and Lewandowski (2024); Bonfiglioli et al. (2023); Borjas and Freeman (2019); Chiacchio, Petropoulos, and Pichler (2018); Graetz and Michaels (2018); Humlum (2020); and Webb (2020).

b. Refer to Acemoglu and Restrepo (2021); Acemoglu et al. (2022); Aghion et al. (2020, 2023); Alguacil, Lo Turco, and Martínez-Zarzoso (2022); Artuc, Bastos, and Rijkers (2023); Dauth et al. (2021); Dekle (2020); DeStefano and Timmis (2024); Dottori (2021); Graetz and Michaels (2018); Ing and Zhang (2023); Klenert, Fernández-Macías, and Antón (2020); Koch, Manuylov, and Smolka (2021); Lin, Adey, and Harris (2022); and Stapleton and Webb (2020).

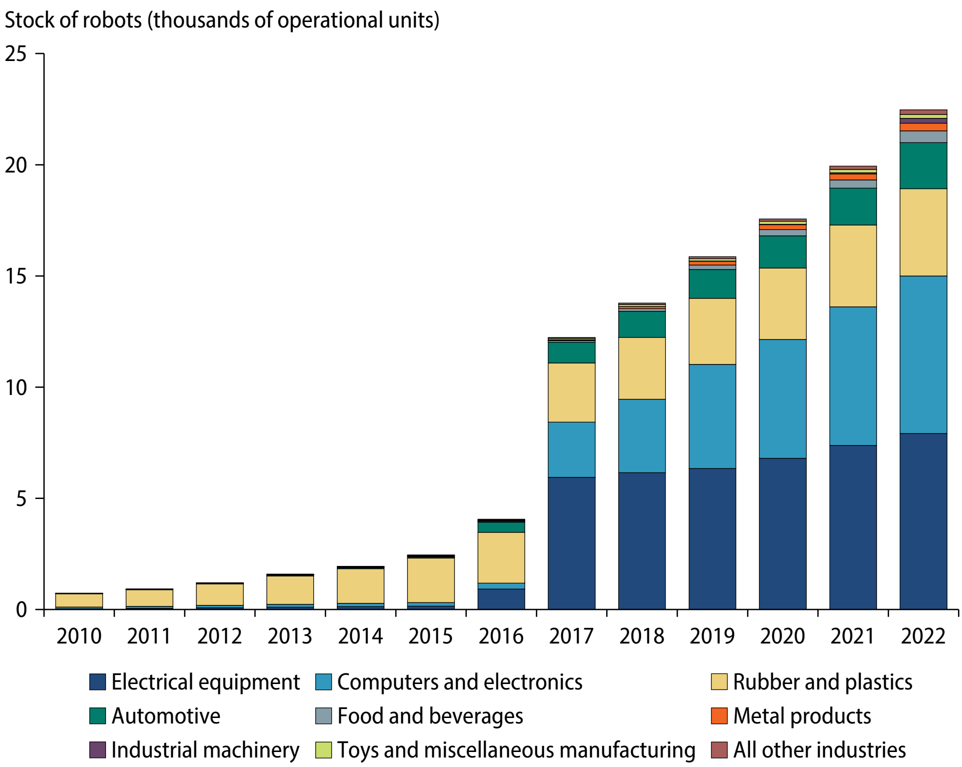
c. Refer to Díaz Pavez and Martinez-Zarzoso (2024); Faber (2020); Gravina and Pappalardo (2022); Krenz, Prettner, and Strulik (2018); Kugler etal. (2020); and Rodrik (2018).

Robots and jobs in Viet Nam

Robot adoption has rapidly increased in high–value added, trade-oriented manufacturing industries in Viet Nam especially since 2016. During this period, there has been significant government policy effort to incentivize domestic and foreign investments in key industrial sectors, such as electrical equipment and computers and electronics (refer to figure 3.4). This period has also witnessed the accelerated integration of Viet Nam in global value chains through participation in free trade agreements, promotion of foreign direct investment, and so on and through trade diversion stemming from China–United States trade tensions. While current data do not allow robot adoption to be tracked at the firm level, statistics on imports of industrial robots by industries suggest that robot adoption is concentrated in industrial zones where there is a dominant presence of foreign-owned enterprises (refer to map 3.1).

Robot adoption has rapidly increased in Viet Nam since 2016, driven by the electrical equipment and computers and electronics sectors.

FIGURE 3.4 Industry composition of the stock of robots, Viet Nam, 2010–22

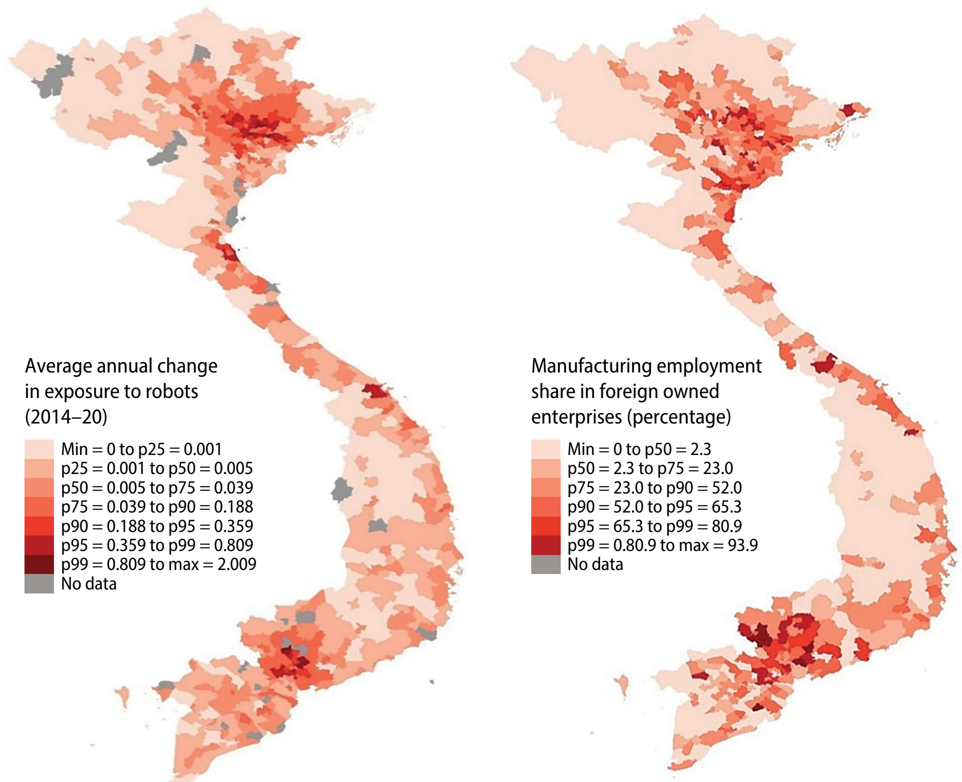


Source: Original figure for this publication based on data of World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

Robot adoption is concentrated in industrial zones where there is a dominant presence of foreign-owned enterprises.

MAP 3.1 Robot penetration and employment share of foreign-owned manufacturers, Viet Nam, annual averages, by district, 2014–20

a. Change in industrial robot penetration **b. Foreign enterprise share in employment**



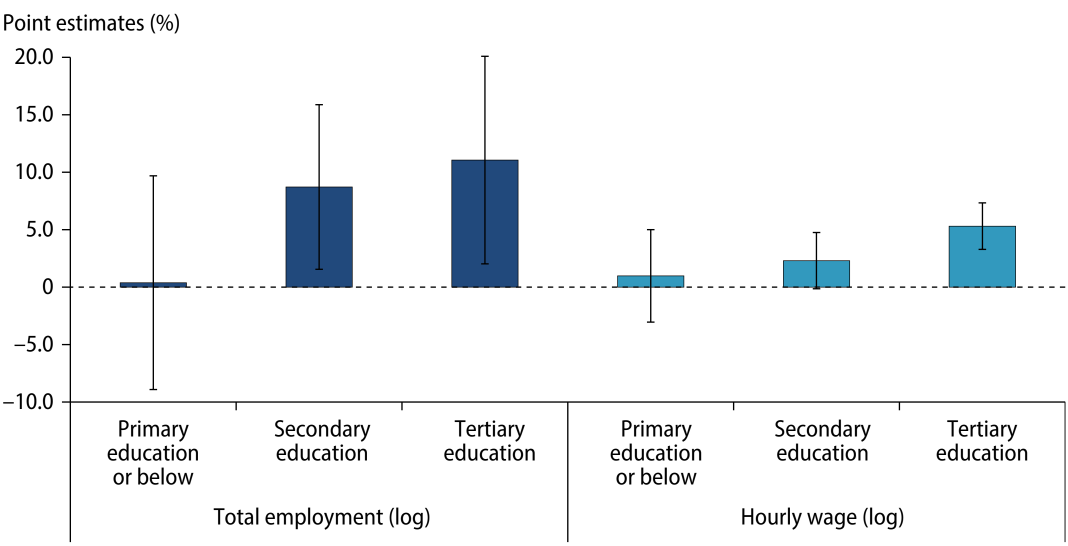
Sources: Original map for this publication based on data of 2014–20 Enterprise Surveys, National Statistics Office, Hanoi, Viet Nam, https://www.gso.gov.vn/en/?s=enterprise+survey&lang=en; 2014–20 Labour Force Survey, National Statistics Office, Hanoi, Viet Nam, https://www.gso.gov.vn/en/?s=Labour+force+survey&lang=en; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

Note: Panel a: Exposure to robots per 1,000 workers at the district level is constructed as the interaction between 2011 industry shares in district employment and robot adoption at the industry-year level. Panel b: Locations in continental Viet Nam in which data have been collected on robot adoption and employment.

Rapid robot adoption in Viet Nam is associated with increased employment and income, especially among more educated workers. Following the same approach introduced in the previous section, the causal impact of robot adoption on local labor markets can be estimated by exploiting the variability in industrial composition across Vietnamese districts and the temporal trends in robot adoption among Vietnamese industries. The findings of an instrumental variables estimation exercise suggest that Vietnamese districts with greater robot adoption have experienced differentially greater increases in overall employment and average worker wages. Both positive effects, in overall employment and in wages, are driven by the significant positive impact on more educated workers, that is, workers with at least secondary educational attainment. The analysis finds no significant effects on less well educated workers (refer to figure 3.5).

Districts with more robot adoption exhibit increases in the employment and earnings of the more educated workers.

FIGURE 3.5 Estimated effects of robot adoption on employment and wages, by educational attainment, Viet Nam, 2014–20



Sources: Original figure for this publication based on data of 2011–20 Labour Force Survey, National Statistics Office, Hanoi, Viet Nam, https://www.gso.gov.vn/en/?s=Labour+force+survey&lang=en; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

Note: The figure shows two-stage least squares estimates of the effects of the exposure to robots on local labor market outcomes in Viet Nam during 2014–20. Exposure to robots is measured as the interaction between the 2011 employment composition by industry in each district and robot adoption by industry-year in Viet Nam, and it is instrumented by global exposure to robots, which relies on average robot adoption by industry-year across 54 countries (following Acemoglu and Restrepo 2020). Low-skilled = primary education (or less). Middle-skilled = secondary education or high school. High-skilled = vocational, college, or higher education. All regressions are weighted by the population in 2011 (baseline year). The controls are for district and subregion × year fixed effects, baseline demographic characteristics in each district (log population; share of urban population; share of migrants; shares of population with primary, secondary, and tertiary education; shares of population under ages 21–55 and age 56 or more; and share of women), district baseline industry shares (employment in primary, manufacturing, services, and the female share of manufacturing employment), and district baseline economic characteristics (employment rate, unemployment rate, labor informality rate, share of salaried employment, share of self-employment, female employment rate, exposure to job routinization, log average hourly wage, log average labor income, and log total labor income).

Greater exposure to robot adoption in Viet Nam negatively affects employment among low- and middle-skilled wage workers in jobs requiring routine physical tasks, and such workers who become displaced are likely absorbed into the informal sector. A heterogeneity analysis across the skill spectrum of the workforce, made feasible thanks to granular data coverage of the Vietnamese labor force surveys, helps unpack the employment effect of robot exposure, especially among less-skilled workers, who, it has been shown, are more vulnerable to robot displacement (Acemoglu and Restrepo 2019b; Autor and Dorn 2013; Autor, Dorn, and Hanson 2015). Figure 3.6, panel a, suggests there is a negative and significant effect of robotization on the employment of low-skilled and middle-skilled salaried workers who mostly perform routine physical tasks. Based on the occupational classifications of the International Labour Organization, these negatively exposed jobs include elementary occupations (low-skilled), plant and machine operators and assemblers, and craft and other trade-related workers (middle-skilled, manual).[2]

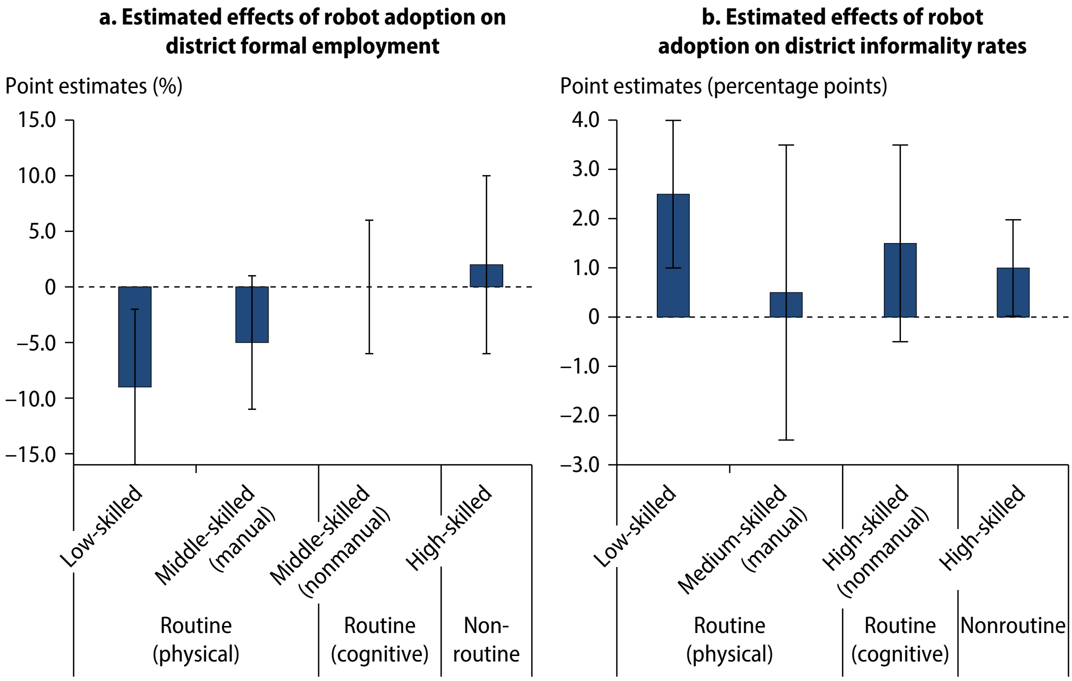
Figure 3.6, panel b, suggests that workers who are likely to have been displaced by robots find shelter in the informal sector. Districts with greater robot penetration exhibit a significantly larger increase in the labor informality rate strictly in low-skilled employment. The spillover of low-skilled, routine formal employment into the informal sector may explain why robot adoption has no substantial impact on the aggregate employment of less educated workers (refer to figure 3.5). Along the gender dimension, the analysis shows that men and women workers in districts with greater robot adoption experience similar employment and wage gains (refer to figure 3.7).

Older workers in Viet Nam benefit less from robot adoption through gains in employment and labor productivity. The empirical analysis of the case of Viet Nam shows that employment gains are positive across all age groups, but weaker and less significant among older workers (refer to figure 3.8). The positive effect of robot adoption on hourly wages among workers, which is likely to reflect an impact on labor productivity, is statistically significant only among the young and the middle-aged, but not among workers over age 50.

That older workers in Viet Nam tend to benefit less from automation aligns with findings in other developing EAP countries. In China, robot adoption is associated with lower wages and greater employment loss among older workers, especially among low-skilled (Giuntella, Lu, and Wang 2022). Notably, these findings differ from evidence found in developed countries, such as the United States, which suggests that the robot displacement effect is more pronounced among middle-age workers, especially in manufacturing (Acemoglu and Restrepo 2022a). This difference

The displacement effect of robotization may be observed among low- and middle-skilled workers, who are likely to be absorbed into the informal sector.

FIGURE 3.6 Estimated effects of robot adoption on formal employment and the informality rate, Viet Nam, 2014–20



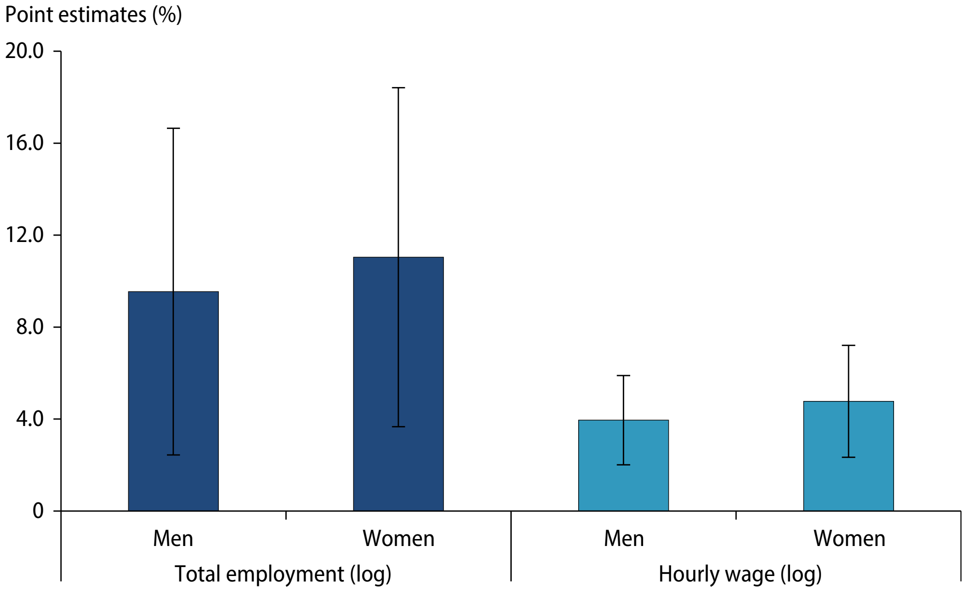
Sources: Original figure for this publication based on data of 2011–20 Labour Force Survey, National Statistics Office, Hanoi, Viet Nam, https://www.gso.gov.vn/en/?s=Labour+force+survey&lang=en; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

Note: The figure shows two-stage least squares estimates of the effects of the exposure to robots on local labor market outcomes in Viet Nam during 2014–20. Exposure to robots is measured as the interaction between the 2011 employment composition by industry in each district and robot adoption by industry-year in Viet Nam, and it is instrumented by global exposure to robots, which relies on average robot adoption by industry-year across 54 countries (following Acemoglu and Restrepo 2020). Skill levels are based on International Labour Organization ISCO08 1-digit occupational classifications. All regressions are weighted by the population in 2011 (baseline year). The controls are for district and subregion × year fixed effects, baseline demographic characteristics in each district (log population; share of urban population; share of migrants; shares of population with primary, secondary, and tertiary education; shares of population under ages 21–55 and age 56 or more; and share of women), district baseline industry shares (employment in primary, manufacturing, services, and the female share of manufacturing employment), and district baseline economic characteristics (employment rate, unemployment rate, labor informality rate, share of salaried employment, share of self-employment, female employment rate, exposure to job routinization, log average hourly wage, log average labor income, and log total labor income). Panel a: Formal employment indicates salaried workers. Panel b: The labor informality rate is defined to cover workers who do not receive employment pensions.

may derive from the sorts of tasks that older workers tend to perform in EAP, which are often performed by middle-age workers in more developed countries: routine manual tasks that are more amenable to automation. This difference could stem in part from the fact that the current cohort of older workers in EAP countries tends to be less well educated than their counterparts in more developed

Men and women workers in districts with greater robot adoption experience similar employment and wage gains.

FIGURE 3.7 Estimated effects of robot adoption on district employment and wages, by sex, Viet Nam, 2014–20



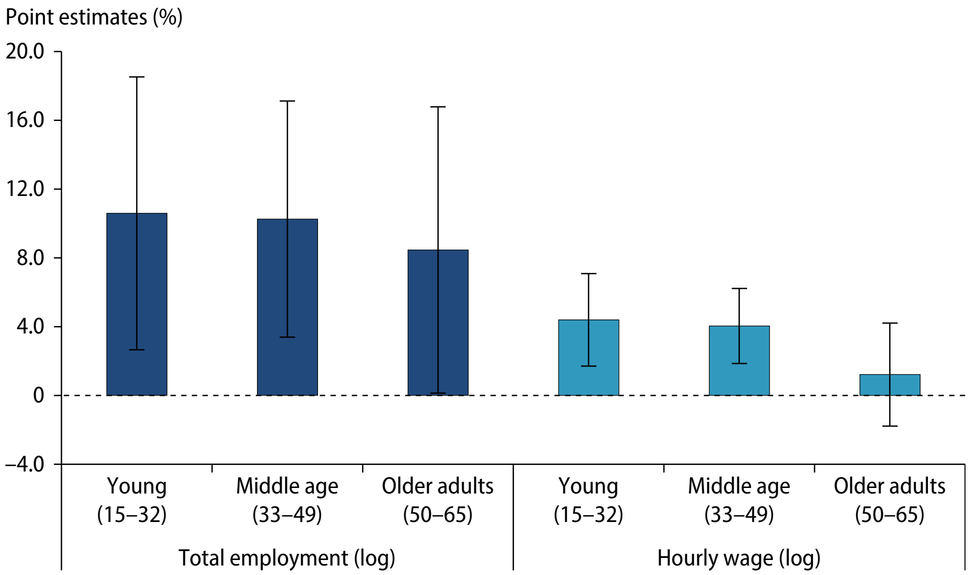
Sources: Original figure for this publication based on data of 2011–20 Labour Force Survey, National Statistics Office, Hanoi, Viet Nam, https://www.gso.gov.vn/en/?s=Labour+force+survey&lang=en; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.
Note: The figure shows two-stage least squares estimates of the effects of the exposure to robots on local labor market outcomes in Viet Nam during 2014–20. Exposure to robots is measured as the interaction between the 2011 employment composition by industry in each district and robot adoption by industry-year in Viet Nam, and it is instrumented by global exposure to robots, which relies on average robot adoption by industry-year across 54 countries (following Acemoglu and Restrepo 2020). All regressions are weighted by the population in 2011 (baseline year). The controls are for district and subregion × year fixed effects, baseline demographic characteristics in each district (log population; share of urban population; share of migrants; shares of population with primary, secondary, and tertiary education; shares of population under ages 21–55 and age 56 or more; and share of women), district baseline industry shares (employment in primary, manufacturing, services, and the female share of manufacturing employment), and district baseline economic characteristics (employment rate, unemployment rate, labor informality rate, share of salaried employment, share of self-employment, female employment rate, exposure to job routinization, log average hourly wage, log average labor income, and log total labor income).

countries. The finding that older workers in the EAP region tend to benefit less from automation also suggests that robot adoption in the region could help remedy the problem of the shrinking workforce in aging countries, but might also magnify the problem by accelerating the exit of older workers from the workforce.

A quantification of the estimated effects of robot adoption in Viet Nam indicates that the number of high-skilled jobs created by robots in the formal sector was

Older workers in Viet Nam benefit less than younger workers from robot adoption through employment gain and labor productivity.

FIGURE 3.8 Estimated effects of robot adoption on district employment and wages, by age group, Viet Nam, 2014–20



Sources: Original figure for this publication based on data of 2011–20 Labour Force Survey, National Statistics Office, Hanoi, Viet Nam, https://www.gso.gov.vn/en/?s=Labour+force+survey&lang=en; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

Note: The figure shows two-stage least squares estimates of the effects of the exposure to robots on local labor market outcomes in Viet Nam during 2014–20. Exposure to robots is measured as the interaction between the 2011 employment composition by industry in each district and robot adoption by industry-year in Viet Nam, and it is instrumented by global exposure to robots, which relies on average robot adoption by industry-year across 54 countries. All regressions are weighted by the population in 2011 (baseline year). The controls are for district and subregion × year fixed effects, baseline demographic characteristics in each district (log population; share of urban population; share of migrants; shares of population with primary, secondary, and tertiary education; shares of population under ages 21–55 and age 56 or more; and share of women), district baseline industry shares (employment in primary, manufacturing, services, and the female share of manufacturing employment), and district baseline economic characteristics (employment rate, unemployment rate, labor informality rate, share of salaried employment, share of self-employment, female employment rate, exposure to job routinization, log average hourly wage, log average labor income, and log total labor income).

greater than the number of low-skilled jobs displaced. Based on the empirical results shown in figures 3.6 and 3.7 and the statistics on robot adoption in Viet Nam (figure 3.1, panel a), an estimated 66,800 low-skilled workers in the formal sector were displaced by robots in 2018–22 (or 2 percent of low-skilled formal employment in 2022; with a 90 percent confidence interval ranging between 14,900 and 118,800 workers). The estimated displacement effect of robots is likely smaller than the employment creation effect. In contrast, robot adoption is estimated to have led to the creation of 254,700 formal jobs occupied by workers with tertiary educational attainment in 2018–22 (or 2.7 percent of formal employment with tertiary education in 2022; with a 90 percent confidence interval ranging between 38,500 and 471,000 workers).

Studies on the employment and wage impacts of robotization in other EAP countries offer a mixed picture. Guintella, Lu, and Wang (2022) use individual longitudinal data to find a large negative impact of robot exposure on employment and wages among nonagricultural salaried workers in China. Similar to evidence on the formal sector in Viet Nam, the study shows a significant displacement impact of robot exposure on employment and wages among the least well educated. The skill-bias effect of robot adoption on employment is also documented by Tang, Huang, and Liu (2021), who use firm-level data on China to find that robot adoption encourages firms to hire more skilled workers. Also aligning with the quantification of job displacement and displacement effects in Viet Nam, Calì and Presidente (2021) find that the productivity-enhancing effect of robots in Indonesia prevails over the replacement effect. Similarly, Jongwanich, Kohpaiboon, and Obashi (2022) find a limited displacement effect of automation in Thailand. Instead, robot exposure tends to promote upskilling among the workforce.

Notes

1. Refer to World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.
2. Refer to ISCO (International Standard Classification of Occupations) (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/methods /concepts-and-definitions/classification-occupation/.

References

Acemoglu, Daron, and David H. Autor. 2011. "Skills, Tasks, and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, vol. 4, part B, edited by Orley C. Ashenfelter and David E. Card, 1043–171. San Diego: North-Holland.

Acemoglu, Daron, David H. Autor, Jonathon Hazell, and Pascual Restrepo. 2022. "Artificial Intelligence and Jobs: Evidence from Online Vacancies." *Journal of Labor Economics* 40 (S1): S293–S340.

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo. 2020. "Competing with Robots: Firm-Level Evidence from France." *AEA Papers and Proceedings* 110 (May): 383–88.

Acemoglu, Daron, and Pascual Restrepo. 2019a. "Artificial Intelligence, Automation, and Work." In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay Agrawal, Joshua Gans, and Avi Goldfarb, 197–236. Cambridge, MA: National Bureau of Economic Research; Chicago: University of Chicago Press.

Acemoglu, Daron, and Pascual Restrepo. 2019b. "Automation and New Tasks: How Technology Displaces and Reinstates Labor." *Journal of Economic Perspectives* 33 (2): 3–30.

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy* 128 (6): 2188–244.

Acemoglu, Daron, and Pascual Restrepo. 2021. "Tasks, Automation, and the Rise in US Wage Inequality." NBER Working Paper 28920 (June), National Bureau of Economic Research, Cambridge, MA.

Acemoglu, Daron, and Pascual Restrepo. 2022a. "Demographics and Automation." *Review of Economic Studies* 89 (1): 1–44.

Acemoglu, Daron, and Pascual Restrepo. 2022b. "Tasks, Automation, and the Rise in U.S. Wage Inequality." *Econometrica* 90 (5): 1973–2016.

Aghion, Philippe, Céline Antonin, and Simon Bunel. 2019. "Artificial Intelligence, Growth, and Employment: The Role of Policy." *Economics and Statistics* 510-511-5: 149–64.

Aghion, Philippe, Céline Antonin, Simon Bunel, and Xavier Jaravel. 2020. "What Are the Labor and Product Market Effects of Automation? New Evidence from France." Sciences Po OFCE Working Paper 01/2020, Observatoire Français des Conjonctures Économiques, Paris.

Aghion, Philippe, Céline Antonin, Simon Bunel, and Xavier Jaravel. 2023. "The Effects of Automation on Labor Demand: A Survey of the Recent Literature." In *Robots and AI: A New Economic Era*, edited by Lili Yan Ing and Gene M. Grossman, 15–39. Routledge-ERIA Studies in Development Economics Series. New York: Routledge.

Albinowski, Maciej, and Piotr Lewandowski. 2024. "The Impact of ICT and Robots on Labour Market Outcomes of Demographic Groups in Europe." *Labour Economics* 87 (April): 102481.

Alguacil, Maite, Alessia Lo Turco, and Inmaculada Martínez-Zarzoso. 2022. "Robot Adoption and Export Performance: Firm-Level Evidence from Spain." *Economic Modelling* 114 (September): 105912.

Antón, José-Ignacio, David Klenert, Enrique Fernández-Macías, Maria Cesira Urzì Brancati, and Georgios Alaveras. 2022. "The Labour Market Impact of Robotisation in Europe." *European Journal of Industrial Relations* 28 (3): 317–39.

Artuc, Erhan, Paulo S. R. Bastos, and Bob Martinus Johannes Rijkers. 2023. "Robots, Tasks, and Trade." *Journal of International Economics* 145 (November): 103828.

Artuc, Erhan, Luc Jozef Christiaensen, and Hernán Jorge Winkler. 2019. "Does Automation in Rich Countries Hurt Developing Ones? Evidence from the U.S. and Mexico." Policy Research Paper 8741, World Bank, Washington, DC.

Atkinson, Robert D. 2019. "Robots and International Economic Development." *Georgetown Journal of International Affairs* 20 (Fall): 170–78.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.

Autor, David H., David Dorn, and Gordon H. Hanson. 2015. "Untangling Trade and Technology: Evidence from Local Labour Markets." *Economic Journal* 125 (584): 621–46.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–333.

Bonfiglioli, Alessandra, Rosario Crinò, Gino Gancia, and Ioannis Papadakis. 2023. "Robots, Offshoring, and Welfare." In *Robots and AI: A New Economic Era*, edited by Lili Yan Ing and Gene M. Grossman, 40–81. Routledge-ERIA Studies in Development Economics Series. New York: Routledge.

Borjas, George J., and Richard B. Freeman. 2019. "From Immigrants to Robots: The Changing Locus of Substitutes for Workers." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 5 (5): 22–42.

Brambilla, Irene, Andrés César, Guillermo Falcone, and Leonardo Carlos Gasparini. 2023. "The Impact of Robots in Latin America: Evidence from Local Labor Markets." *World Development* 170 (October): 106271.

Brynjolfsson, Erik, and Andrew McAfee. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W. W. Norton & Company.

Calì, Massimiliano, and Giorgio Presidente. 2021. "Automation and Manufacturing Performance in a Developing Country." Policy Research Working Paper 9653, World Bank, Washington, DC.

Carbonero, Francesco, Ekkehard Ernst, and Enzo Weber. 2018. "Robots Worldwide: The Impact of Automation on Employment and Trade." Research Department Working Paper 36 (October), International Labour Office, Geneva.

Chen, Chinchih, and Carl Benedikt Frey. 2024. "Robots and Reshoring: A Comparative Study of Automation, Trade, and Employment in Europe." *Industrial and Corporate Change* 33 (6): 1331–77.

Chiacchio, Francesco, Georgios Petropoulos, and David Pichler. 2018. "The Impact of Industrial Robots on EU Employment and Wages: A Local Labour Market Approach." Bruegel Working Paper 2018/02 (April 18), Bruegel, Brussels.

Dauth, Wolfgang, Sebastian Findeisen, Jens Südekum, and Nicole Wößner. 2021. "The Adjustment of Labor Markets to Robots." *Journal of the European Economic Association* 19 (6): 3104–53.

De Backer, Koen, Timothy DeStefano, Carlo Menon, and Jung Ran Suh. 2018. "Industrial Robotics and the Global Organisation of Production." OECD Science, Technology, and Industry Working Paper 2018/03, Organisation for Economic Co-operation and Development, Paris.

Dekle, Robert. 2020. "Robots and Industrial Labor: Evidence from Japan." *Journal of the Japanese and International Economies* 58 (December): 101108.

DeStefano, Timothy, and Jonathan David Timmis. 2024. "Robots and Export Quality." *Journal of Development Economics* 168 (May): 103248.

Díaz Pavez, Luis R., and Inmaculada Martínez-Zarzoso. 2024. "The Impact of Automation on Labour Market Outcomes in Emerging Countries." *World Economy* 47 (1): 298–331.

Dottori, Davide. 2021. "Robots and Employment: Evidence from Italy." *Economia Politica* 38 (2): 739–95.

Faber, Marius. 2020. “Robots and Reshoring: Evidence from Mexican Labor Markets.” *Journal of International Economics* 127 (November): 103384.

Frey, Carl Benedikt, and Michael A. Osborne. 2017. “The Future of Employment: How Susceptible Are Jobs to Computerisation?” *Technological Forecasting and Social Change* 114 (January): 254–80.

Giuntella, Osea, Yi Lu, and Tianyi Wang. 2022. “How Do Workers and Households Adjust to Robots? Evidence from China.” NBER Working Paper 30707 (December), National Bureau of Economic Research, Cambridge, MA.

Graetz, Georg, and Guy Michaels. 2018. “Robots at Work.” *Review of Economics and Statistics* 100 (5): 753–68.

Gravina, Antonio Francesco, and Maria Rosaria Pappalardo. 2022. “Are Robots in Rich Countries a Threat for Employment in Emerging Economies?” *Economics Letters* 221 (December): 110888.

Gregory, Robert Wayne, Ola Henfridsson, Evgeny Kaganer, and Harris Kyriakou. 2021. “The Role of Artificial Intelligence and Data Network Effects for Creating User Value.” *Academy of Management Review* 46 (3): 534–51.

Guarascio, Dario, Alessandro Piccirillo, and Jelena Reljic. 2024. “Will Robots Replace Workers? Assessing the Impact of Robots on Employment and Wages with Meta-Analysis.” GLO Discussion Paper 1395, Global Labor Organization, Essen, Germany.

Humlum, Anders. 2020. “Essays on Automation and Labor Markets.” PhD dissertation, Princeton University, Princeton, NJ.

Ing, Lili Yan, and Rui Zhang. 2023. “Automation in Indonesia: Productivity, Quality, and Employment.” In *Robots and AI: A New Economic Era*, edited by Lili Yan Ing and Gene M. Grossman, 275–309. Routledge-ERIA Studies in Development Economics Series. New York: Routledge.

Jongwanich, Juthathip, Archanun Kohpaiboon, and Ayako Obashi. 2022. “Technological Advancement, Import Penetration and Labour Markets: Evidence from Thailand.” *World Development* 151 (March): 105746.

Klenert, David, Enrique Fernández-Macías, and José-Ignacio Antón. 2020. “Do Robots Really Destroy Jobs? Evidence from Europe.” *Economic and Industrial Democracy* 44 (1): 280–316.

Koch, Michael, Ilya Manuylov, and Marcel Buus Smolka. 2021. “Robots and Firms.” *Economic Journal* 131 (638): 2553–84.

Krenz, Astrid Martina, Klaus Prettner, and Holger Strulik. 2018. “Robots, Reshoring, and the Lot of Low-Skilled Workers.” CEGE Discussion Paper 351 (July), Center for European, Governance and Economic Development Research, University of Göttingen, Göttingen, Germany.

Kugler, Adriana D., Maurice David Kugler, Laura Ripani, and Rodimiro Rodrigo. 2020. “U.S. Robots and Their Impacts in the Tropics: Evidence from Colombian Labor Markets.” NBER Working Paper 28034 (October), National Bureau of Economic Research, Cambridge, MA.

Lin, Weiqiang, Peter Adey, and Tina Harris. 2022. "Dispositions towards Automation: Capital, Technology, and Labour Relations in Aeromobilities." *Dialogues in Human Geography* 14 (1): 51–70.

Rodrik, Dani 2018. "New Technologies, Global Value Chains, and Developing Economies." NBER Working Paper 25164 (October), National Bureau of Economic Research, Cambridge, MA.

Sequeira, Tiago Neves, Susana Garrido, and Marcelo Serra Santos. 2021. "Robots Are Not Always Bad for Employment and Wages." *International Economics* 167 (October): 108–19.

Serrano, Joaquín. 2024. "Do Robots Necessarily Displace Workers? Evidence from Mexican Local Labor Markets." Job market paper, May 30, 2024, Department of Economics, University of California–Los Angeles, Los Angeles.

Stapleton, Katherine, and Michael Webb. 2020. "Automation, Trade, and Multinational Activity: Micro Evidence from Spain." CSAE Working Paper 2020-16 (September), Department of Economics, Centre for the Study of African Economies, Oxford University, Oxford, UK.

Stemmler, Henry. 2019. "Does Automation Lead to De-Industrialization in Emerging Economies?—Evidence from Brazil." CEGE Discussion Paper 382 (September), Center for European, Governance and Economic Development Research, University of Göttingen, Göttingen, Germany.

Tang, Chengjian, Keqi Huang, and Qiren Liu. 2021. "Robots and Skill-Biased Development in Employment Structure: Evidence from China." *Economics Letters* 205 (August): 109960.

Webb, Michael. 2020. "The Impact of Artificial Intelligence on the Labor Market." Unpublished working paper, Department of Economics, Stanford University, Stanford, CA.

SPOTLIGHT 3.1

Technology, Agricultural Productivity, and Jobs in EAP and the World

Any discussion of jobs in an economy must also consider the implications of technological change in agriculture. Agricultural employment comprises a sizable, albeit declining share of total employment in the East Asia and Pacific (EAP) region. While the focus of this report is on new technologies, examining the impacts on jobs of the first wave of labor automation through agricultural mechanization is a useful exercise. Digital technologies are also being diffused and affecting jobs in agriculture. However, the lack of suitable data limits the scope for systematic analysis of the labor market impacts in the case of the EAP region. Nonetheless, illustrative examples are available of the way these technologies are being applied and the potential impacts on agricultural productivity and employment.

Agricultural mechanization

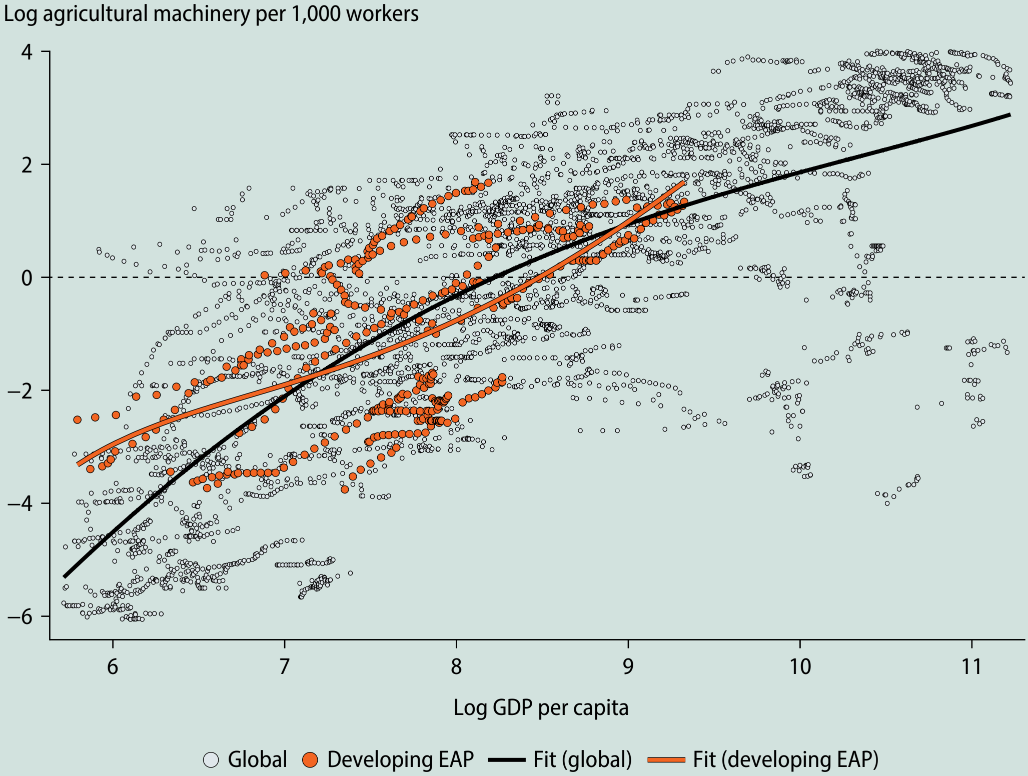
To examine how mechanization has affected productivity and employment in agriculture, the brief analysis presented here draws on global data on the diffusion of the earlier wave of agricultural automation, proxied by the adoption of tractors and other machinery relative to the baseline (1991) size of agricultural employment. The data cover around 100 countries, including most developing EAP countries, and span from 1991 to 2021.

Over the last three decades, agricultural automation has advanced in developing EAP countries and in other economies at a similar pace (refer to figure S3.1.1). There is significant variation in the expansion of mechanization across countries. In the EAP region, the mechanization of agriculture expanded the most in China, Malaysia, the Philippines, Thailand, and Viet Nam, in some cases approaching the level of the expansion in the Republic of Korea. Agricultural mechanization has also advanced in Cambodia, Indonesia, the Lao People's Democratic Republic, Myanmar, and Papua New Guinea, though these countries trail far behind.

Historically, agricultural mechanization is associated with higher farm productivity, and EAP is no exception. Rapidly mechanizing countries, such as China, the Philippines, and Viet Nam, have experienced larger gains in farm productivity (measured as agricultural value added per hectare), while agricultural productivity has lagged in countries where agriculture is less mechanized (refer to figure S3.1.2).

In the EAP region, farm employment has declined steadily in most countries, but the decline may not be attributable to mechanization. China, Thailand, and, more recently, Myanmar and Viet Nam have experienced sustained declines in the level of agricultural employment (refer to figure S3.1.3, panel a). Chapter 6 shows that these declines are

FIGURE S3.1.1 Log agricultural machinery versus log gross domestic product per capita, EAP and the world, 1991

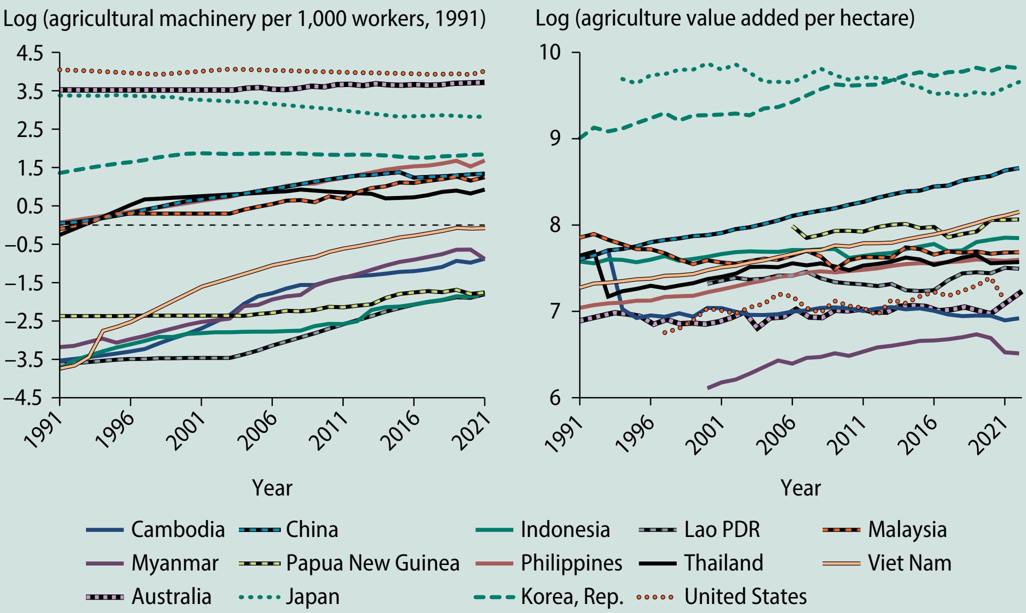


Source: Original figure for this publication based on data of USDA 2023.
Note: Fit corresponds to the third-degree polynomial. For both variables, 1 percent of the data on the lower end and 1 percent on the upper end were trimmed. The countries trimmed on the lower end for log GDP per capita include Burundi, Ethiopia, Mozambique, and Myanmar, while the upper end includes Ireland, Luxembourg, Norway, and Switzerland. Machine quantity is adjusted using 1991 data on employment in agriculture. Per capita gross domestic product is measured in 2015 constant prices. EAP = East Asia and Pacific; GDP = gross domestic product.

likely to be the result of a positive pull from expanding manufacturing rather than a negative push from increasing agricultural mechanization. Within agriculture, advances in mechanization are associated with increasing levels of productivity and employment (refer to figure S3.1.3, panel b). The relationship among automation, productivity, and employment in agriculture remains robust after accounting for other confounding factors. These results suggest that the productivity gains from agricultural automation in EAP, which can spur lower prices and boost demand, tend to offset the displacement effect from replacing human labor with machinery. Econometric evidence suggests that the strength of the positive productivity and employment effects increases as the share of agriculture in total employment declines.

FIGURE S3.1.2 Trends in agricultural machinery and farm labor productivity, EAP, 1991–2022

a. Trends in agricultural machinery **b. Trends in farm labor productivity**



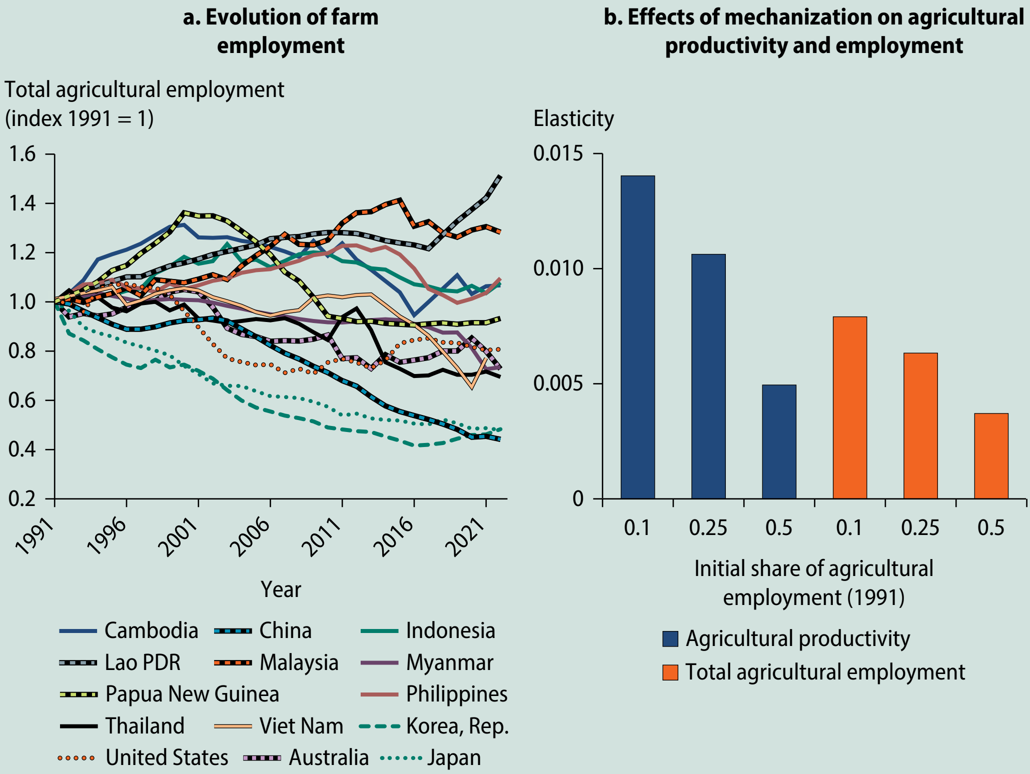
Source: Original figure for this publication based on data of USDA 2023.

Digital technologies

Digital technologies are also penetrating agriculture. They are enabling farmers to participate in markets, improve efficiency, and achieve economies of scale (Deichmann, Goyal, and Mishra 2016). Their use includes mobile technology to obtain better information on weather, prices, and input costs and to facilitate payments. Internet of things technology connects agricultural tools and machinery over the internet or mobile networks, thereby automating and optimizing activities, such as irrigation and fertilizer application, according to precise schedules and quantities. Artificial intelligence (AI) sensors that measure soil moisture and nutrients help detect disease and pest infestations and improve the efficiency of input use. AI-empowered robots have the potential to improve productivity and the quality of products (Sparrow and Howard 2021). Drones and satellites provide more accurate weather information for better planning (Wolfert et al. 2017). While systematic evidence on the effects of these technologies on jobs in agriculture is not yet available, some studies find significant impacts on farm productivity.

Agricultural employment in the EAP region includes many smallholder farmers. Small farms are often poorly integrated into markets where the products of the smallholder farmers may be sold, and the farmers often lack information on effective harvesting

FIGURE S3.1.3 Trends in farm employment and the mechanization effect



Source: Original figure for this publication based on data of USDA 2023.
Note: Panel b presents a summary of the results of cross-country panel data regressions (1991–2022) of agricultural productivity and employment on mechanization, controlling for cross-country differences in the levels of and trends in income per capita, population size, arable land area, the share of agricultural production more susceptible to mechanization (proxied by the share of cereals), country and year fixed effects, and country-specific (linear) time trends (to capture country heterogeneity and economy-wide trends and shocks). Full results are reported in the appendix.

techniques and inputs. Traditional agricultural extension services have not proven cost-effective at scale to provide information and support to improve the agricultural practices of smallholder farmers (Fabregas, Kremer, and Schilbach 2019).

The productivity of and returns to the self-employed farmer are enhanced by new digital technologies. Mobile technology is now used regularly to provide smallholder farmers with timely, relevant, and actionable information at lower cost than traditional agricultural extension services. Research in Bangladesh, China, India, and Viet Nam finds that 80 percent of farmers regularly use mobile phones to connect with agents and traders to estimate market demand and prices (Reardon et al. 2012). Digital Green, the Grameen Foundation, ReutersMarket Light, Technoserve, and other organizations are using digital tools (such as voice, text, videos, and the internet) to provide farmers with information and support in Latin America, South Asia, and Sub-Saharan Africa (Nakasone, Torero, and Minten 2014). Similarly, governments are partnering with mobile operators to use telephones to manage the distribution of improved seeds and subsidized fertilizers in remote areas and to coordinate and relay information on transport and logistics, as exemplified by Nigeria's large-scale e-vouchers initiative and Zambia's SMS-based service that provides information on the arrival and delivery times of transporters (van Rensburg 2004).

The evidence highlights the positive impacts of the use of mobile technology in improving the productivity and earnings of smallholder farmers. For instance, Jensen's (2007) study of sardine fishermen and wholesalers in Kerala, India, revealed that the regular use of mobile phones substantially reduced product price discrepancies and waste, thereby improving earnings. Similar impacts have been found in the case of other commodities, such as cereals and cash crops, based on other communication platforms, including Esoko in Ghana, e-choupals in India, telecenters in Peru, farmers in the Philippines, and grain traders in Niger.[1]

Some emerging uses of big data platforms are promising. Indonesia has implemented the information and communication technology digital ecosystem model to enhance agricultural productivity through digital technologies. The model includes the use of sensors to measure soil health, drone cameras for medium-range data collection, and satellite images for long-range data collection. In Thailand, big data are used to provide detailed information on topography, weather conditions, and farming practices to help farmers plan better, as well as internet of things technology to connect agricultural tools and machinery. In Viet Nam, AI and block chain technologies are being applied to improve productivity and control product quality throughout the supply chain by optimizing the application of resources and ensuring food quality and the traceability of inputs.

Note

1. Refer to Aker (2010); Beuermann, McKelvey, and Vakis (2012); Goyal (2010); Labonne and Chase (2009); Nyarko et al. (2013).

References

Aker, Jenny C. 2010. "Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger." *American Economic Journal: Applied Economics* 2 (3): 46–59.

Beuermann, Diether W., Christopher McKelvey, and Renos Vakis. 2012. "Mobile Phones and Economic Development in Rural Peru." *Journal of Development Studies* 48 (11): 1617–28.

Deichmann, Uwe, Aparajita Goyal, and Deepak Mishra. 2016. "Will Digital Technologies Transform Agriculture in Developing Countries?" *Agricultural Economics* 47 (S1): 21–33.

Fabregas, Raissa, Michael R. Kremer, and Frank Schilbach. 2019. "Realizing the Potential of Digital Development: The Case of Agricultural Advice." *Science* 366 (6471): eaay3038.

Goyal, Aparajita. 2010. "Information, Direct Access to Farmers, and Rural Market Performance in Central India." *American Economic Journal: Applied Economics* 2 (3): 22–45.

Jensen, Robert T. 2007. "The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector." *Quarterly Journal of Economics* 122 (3): 879–924.

Labonne, Julien Bernard, and Robert S. Chase. 2009. "The Power of Information: The Impact of Mobile Phones on Farmers' Welfare in the Philippines." Policy Research Working Paper 4996, Impact Evaluation Series 33, World Bank, Washington, DC.

Nakasone, Eduardo, Maximo Torero, and Bart Minten. 2014. "The Power of Information: The ICT Revolution in Agricultural Development." *Annual Review of Resource Economics* 6 (1): 533–50.

Nyarko, Yaw, Nicole Hildebrandt, Giorgia Romagnoli, and Emilia Soldani. 2013. "Market Information Systems for Rural Farmers Evaluation of Esoko MIS: Year 1 Results." Center for Technology and Economic Development, New York University Abu Dhabi, Abu Dhabi, United Arab Emirates.

Reardon, Thomas A., Kevin Z. Chen, Bart Minten, and Lourdes Adriano. 2012. *The Quiet Revolution in Staple Food Value Chains: Enter the Dragon, the Elephant, and the Tiger*. Manila: Asian Development Bank and International Food Policy Research Institute.

Sparrow, Robert, and Mark Howard. 2021. "Robots in Agriculture: Prospects, Impacts, Ethics, and Policy." *Precision Agriculture* 22: 818–32.

USDA (United States Department of Agriculture). 2023. "International Agricultural Productivity Data Product." September, Economic Research Service, USDA, College Park, MD.

van Rensburg, Johann (Rensie) Janse. 2004. "The Infopreneur Concept Document and the Supportive Role of ICTs." Council for Scientific and Industrial Research, Pretoria, South Africa.

Wolfert, Sjaak, Lan Ge, Cor Verdouw, and M. J. Bogaardt. 2017. "Big Data in Smart Farming—A Review." *Agricultural Systems* 153: 69–80.

Artificial Intelligence and Jobs 4

Introduction

The diffusion of artificial intelligence (AI) in the East Asia and Pacific (EAP) region and the consequences are still difficult to measure. One methodology, adopted in this chapter, is to rely on measures of the occupational exposure to AI and analyze the associated risks of labor displacement and the benefits of labor augmentation and the creation of jobs. Using the exposure to AI measure, the chapter also presents preliminary evidence on the correlation of AI exposure with wages and employment.

Exposure to AI

The literature suggests that AI, including generative AI, affects a wide range of cognitive tasks by exploiting big data on the internet (Felten, Raj, and Seamans 2021; Gmyrek, Berg, and Bescond 2023; Webb 2020). Similar to other technologies, AI can automate certain tasks, complement other tasks, and create new tasks. A recent study suggests that complementarity with AI is influenced by the social, ethical, and physical context of occupations, along with the required skill levels (Pizzinelli et al. 2023). Chapter 2 discusses the effect of AI on jobs that require cognitive tasks and on the expansion of the scope of jobs from routine to more nonroutine tasks. At the same time, complementarity with AI is high if the tasks in a job are less routine (refer to appendix, box A.1).

With its wide-ranging capabilities, AI has been rapidly and extensively adopted by individuals and firms. Large firms in technology-intensive sectors were the initial adopters. Generative AI tools, such as ChatGPT, have enabled individuals to benefit from the state-of-the-art technology. AI adoption at work has been rapidly increasing, outpacing the earlier adoption rates of the internet and personal computers (box 4.1).

While it is too early to estimate causally the impact of nascent AI technologies, analyzing which jobs are exposed to AI can help in assessing the implications of AI adoption. In the EAP region, many jobs require manual tasks. Overall AI exposure is therefore relatively low. However, there are also many jobs that require routine cognitive tasks that could potentially be negatively affected by AI. These jobs exhibit high AI exposure and low complementarity. Nonroutine cognitive task-intensive jobs that are potentially complementary to AI are more limited in the EAP region than in advanced economies (refer to figure 4.1). These findings are derived from the assumption that specific jobs require the same tasks across countries, but cross-country differences in AI exposure may appear more substantial if the differences in the tasks are considered (refer to box 4.2). For example, the task structure of lower-income countries may mean these countries are less exposed to AI in terms of both substitutability and complementarity.

Box 4.1. Who is adopting artificial intelligence? The correlates of AI adoption by individuals and firms

Understanding which individuals and firms are adopting artificial intelligence (AI) is vital to the analysis of the economic impact of AI, the design of targeted interventions, and the identification of policies to address the associated challenges. Evidence is limited on the situation in developing countries, but large-scale firm surveys in the United States have provided insights that can be useful in determining the path developing countries are likely to take.

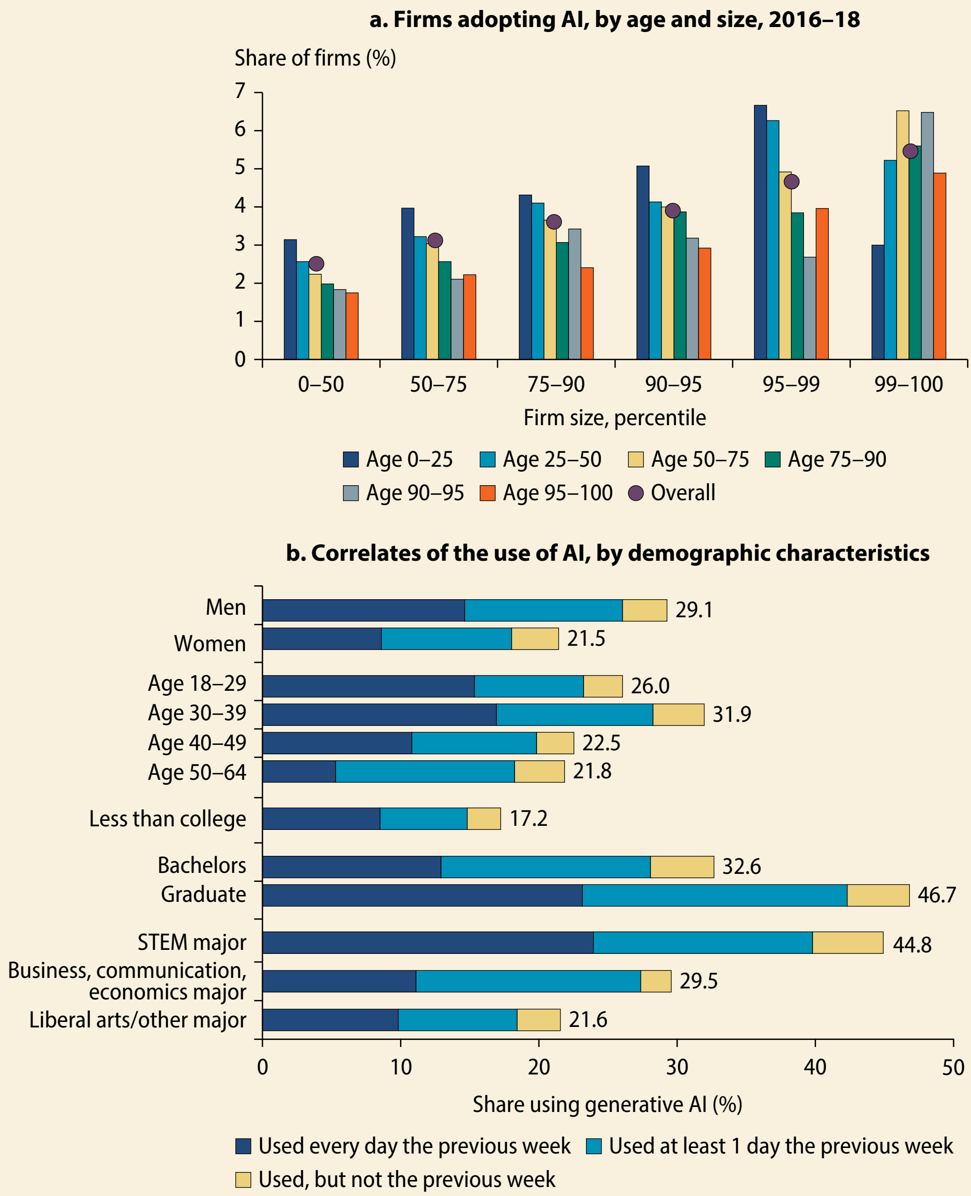
AI adoption in the United States is most prevalent among large firms, technology-intensive sectors (such as information and professional services), and young, dynamic start-ups (Acemoglu et al. 2023; Bonney et al. 2024; McElheran et al. 2023) (refer to figure B4.1.1, panel a). Start-ups adopting AI often feature younger, highly educated founders, innovative business strategies, and venture capital backing. These firms rely on AI primarily for applications—for example, marketing automation, data analytics, and chatbots—and often integrate AI through complementary changes in, for instance, employee training or new workflows. The combined use of AI and robotics is also observed in large firms.

(continued)

Box 4.1. Who is adopting artificial intelligence? The correlates of AI adoption by individuals and firms *(continued)*

Use of artificial intelligence is heterogenous across firms by size and age and across individuals by demographic characteristics.

FIGURE B4.1.1 The correlates of AI adoption, by the characteristics of firms and individuals



Sources: Acemoglu et al. 2023; Bick, Blandin, and Deming 2025.

Note: AI = artificial intelligence; STEM = science, technology, engineering, and mathematics.

(continued)

Box 4.1. Who is adopting artificial intelligence? The correlates of AI adoption by individuals and firms *(continued)*

AI adoption has significant implications for firm performance. Adopters often experience enhanced productivity and improved business outcomes (Bonney et al. 2024; McElheran et al. 2023). Despite widespread fears about the job replacement effect of AI, most firms adopting AI have not experienced significant changes in employment, nor are they expecting changes in the future. Nonetheless, the benefits of AI adoption are not uniformly distributed, leading to concerns about a widening digital divide. The geographic and sectoral clustering of AI adoption—concentrated in tech hubs and among larger, well-resourced firms—risks the exclusion of smaller firms and rural firms from the benefits of AI.

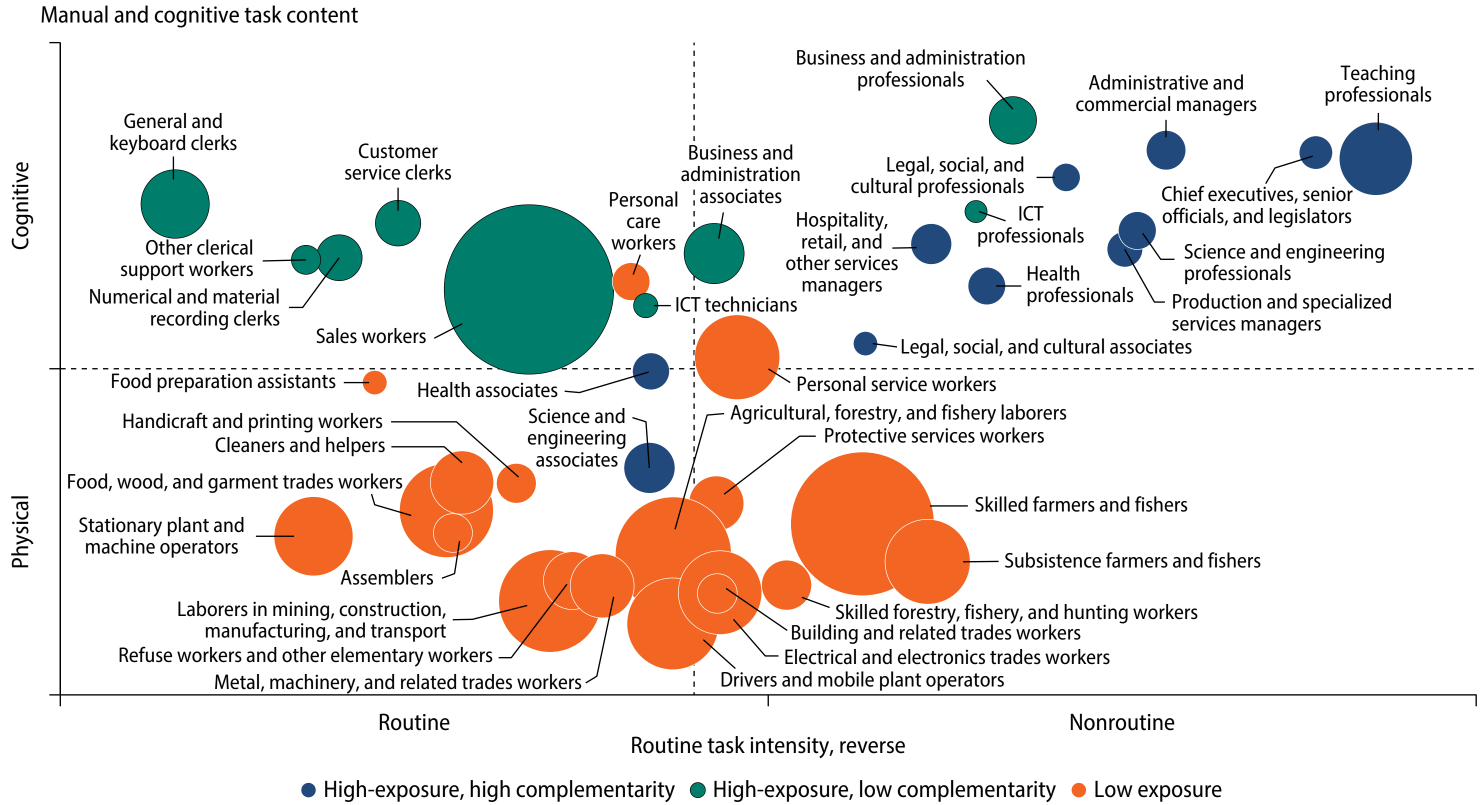
Generative AI tools, such as ChatGPT, have enabled individuals to benefit from state-of-the-art technologies. Nearly 40 percent of US adults ages 18–64 had used generative AI by August 2024; 28 percent of employed individuals were using it for work-related tasks (Bick, Blandin, and Deming 2025). Adoption rates are particularly high among younger, more well educated, and higher-income workers, and use is concentrated in management, computer and calculation, and business and finance functions (refer to figure B4.1.1, panel b). Significant use is also observed among blue-collar and less well educated workers, highlighting the versatility of generative AI as a general-purpose technology. The adoption of generative AI in the workplace is outpacing the adoption rates of the internet and personal computers in earlier periods (Bick, Blandin, and Deming 2025).

Individuals use generative AI primarily in writing, administrative support, data analysis, and coding. Bick, Blandin, and Deming (2025) estimate that 0.5 percent–3.5 percent of all US work hours are currently being supported by generative AI, with a potential productivity boost of 0.125 percent–0.875 percent based on existing experimental evidence. While these productivity gains are promising, adoption patterns may mirror those of prior technologies, potentially exacerbating inequalities if adoption remains concentrated among advantaged groups.

AI mainly affects cognitive tasks, but it may support some nonroutine cognitive tasks. The EAP workforce is less exposed to AI because of the high concentration of physical tasks in the region.

FIGURE 4.1 Exposure and complementarity with AI, by routine task intensity of physical and cognitive jobs, EAP and advanced economies

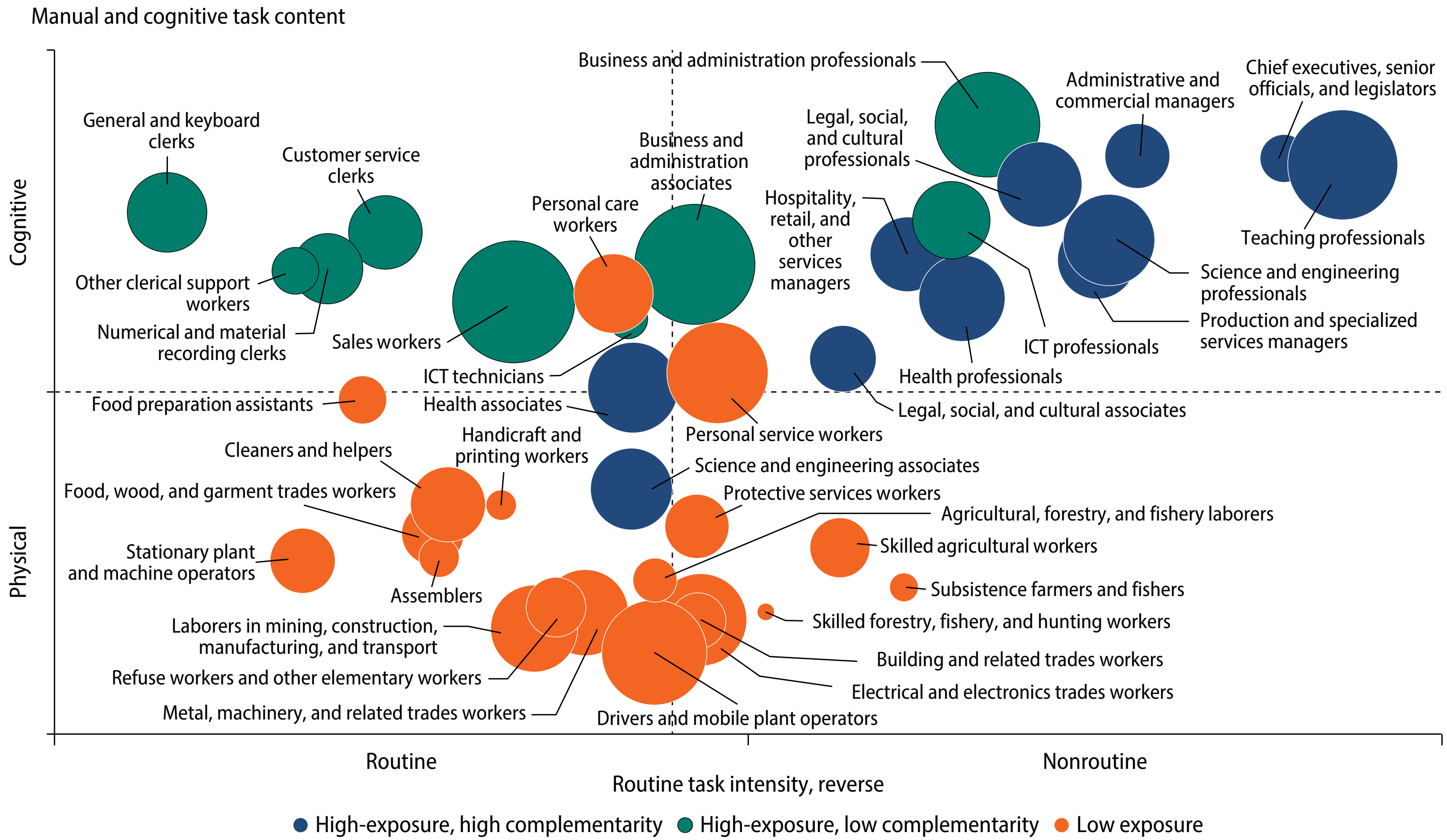
a. EAP



(continued)

FIGURE 4.1 Exposure and complementarity with AI, by routine task intensity of physical and cognitive jobs, EAP and advanced economies *(continued)*

b. Advanced economies



Sources: Original figure for this publication based on data of Autor and Dorn 2013; Felten, Raj, and Seamans 2021; ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; microdata from Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; Pizzinelli et al. 2023.

Note: Bubble size denotes average employment share. Advanced economies = simple average of 36 countries. EAP = simple average of 9 countries. Data refer to the most recent available year. EAP = East Asia and Pacific; ICT = information and communication technology.

Box 4.2. AI exposure and differences in the tasks within occupations

Cross-country differences in tasks may affect the extent of exposure to artificial intelligence (AI) in the labor market. Lewandowski, Madoń, and Park (2024), in a background paper for this report, utilize country-specific surveys of job tasks to create a more realistic measure of AI. They combine the well-established United States–based AI occupational exposure measure of Felten, Raj, and Seamans (2021) with worker-level survey data on the United States from the Program for the International Assessment of Adult Competencies of the Organisation for Economic Co-operation and Development (OECD).[a] They then use these data and data of the World Bank's Skills toward Employment and Productivity Program surveys and the China Urban Labor Survey to create country-specific measures of the AI exposure of each occupation.[b]

The results reveal profound differences across countries at different stages of development. The original Felten, Raj, and Seamans (2021) measures of AI exposure across countries reveal a positive association between country income and the average AI exposure (refer to figure B4.2.1, panel a). Based on the Felten et al. (2021) measure, the average AI exposure is lower in the least developed countries than in the United States by about 0.5 US standard deviation. The differences originate entirely in the distinct occupational structures of the countries. Adjusting the AI exposures by differences in the task content of occupations across countries strengthens the comparison (refer to figure B4.2.1, panel b). With these adjustments, the difference between the least developed countries and the United States in the average AI exposure of employment becomes about one US standard deviation.

Differences in the nature of tasks contribute more than occupational differences to the cross-country variations in AI exposure. The task-related differences in AI exposure contribute 58.5 percent of the cross-country variation (refer to figure B4.2.2). The task component is most pronounced in low-income countries. Task-related differences in AI exposure are greatest at the two tails of the skill distribution (high and low). These findings demonstrate the importance of measuring the differences in both occupational structure and the nature of tasks associated with occupations to measure AI exposure correctly.

(continued)

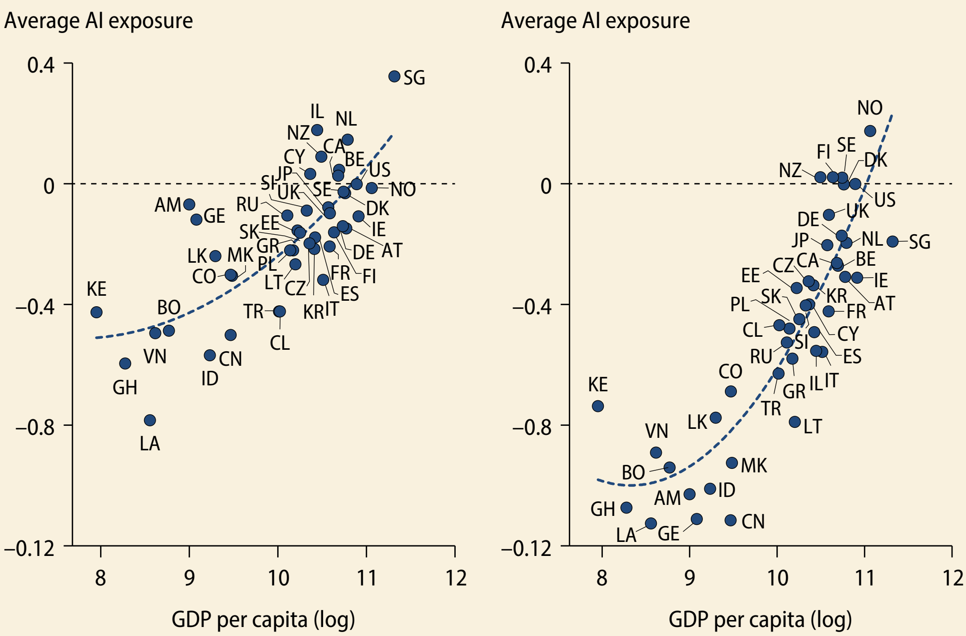
Box 4.2. AI exposure and differences in the tasks within occupations *(continued)*

Country-specific AI exposure measures suggest there is a starker association between country income and AI exposure.

FIGURE B4.2.1 A comparison of AI exposure estimates, by country

a. Felten, Raj, and Seamans (2021) measures

b. Country-specific AI exposure



Sources: Original figure for this publication based on data of Felten, Raj, and Seamans 2021; PIAAC Data and Methodology (dashboard), Program for the International Assessment of Adult Competencies, Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/about/programmes/piaac/piaac-data.html; STEP Skills Measurement (dashboard), World Bank, Washington, DC, https://microdata.worldbank.org/index.php/collections/step.

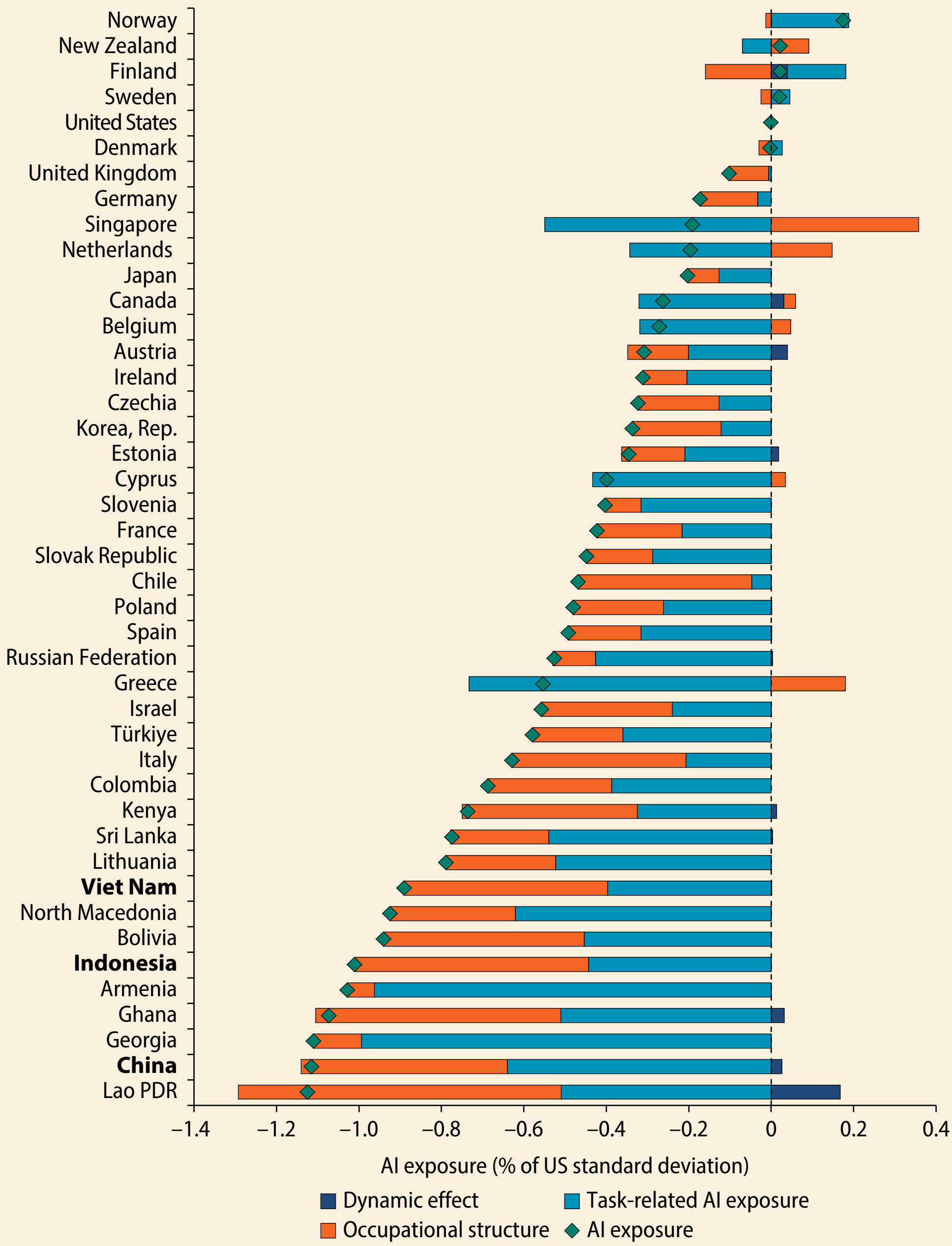
Note: Spearman (1904) correlations of AI exposure calculated with the most detailed information available in the Program for the International Assessment of Adult Competencies and the STEP Skills Measurement Program and exposure calculated only with the set of questions and answers as available in STEP are 74 percent (country average) and 81 percent (country occupation level). The dashed lines are the medians. The values of the AI exposures are standardized with the US mean and standard deviation. For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search. GDP = gross domestic product; STEP = Skills toward Employment and Productivity.

(continued)

Box 4.2. AI exposure and differences in the tasks within occupations *(continued)*

Task-related differences contribute more than occupational differences to the cross-country variations in AI exposure.

FIGURE B4.2.2 Decomposition of the differences in average AI exposure, by country



(continued)

Box 4.2. AI exposure and differences in the tasks within occupations *(continued)*

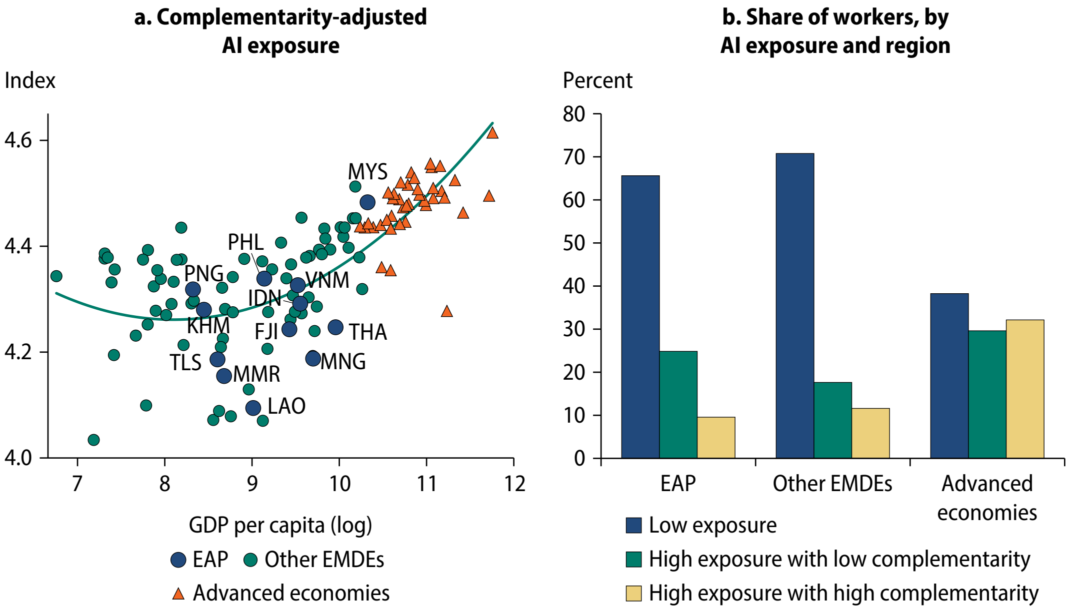
Source: Original figure for this publication based on data of PIAAC Data and Methodology (dashboard), Program for the International Assessment of Adult Competencies, Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/about/programmes/piaac/piaac-data.html; STEP Skills Measurement (dashboard), World Bank, Washington, DC, https://microdata.worldbank.org/index.php/collections/step.
a. Refer to PIAAC Data and Methodology (dashboard), Program for the International Assessment of Adult Competencies, Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/about/programmes/piaac/piaac-data.html.
b. Refer to CULS (China Urban Labor Survey), Institute for Population Studies, Chinese Academy of Social Sciences, Beijing, https://doi.org/10.18170/DVN/XMFDUI; STEP Skills Measurement (dashboard), World Bank, Washington, DC, https://microdata.worldbank.org/index.php/collections/step. The China Urban Labor Survey was conducted in 2001, 2005, and 2010. Only data from the 2001 round are readily available.

EAP countries are less exposed than advanced economies to AI but are also less well equipped to benefit from it (refer to figure 4.2, panel a). The limited exposure to AI in the EAP region derives from the relative dominance of manual task–based occupations. Within EAP, Malaysia, the Philippines, and Thailand are relatively more highly exposed than other EAP countries to AI because of their greater engagement with cognitive services. The share of AI exposed occupations with high complementarity potential is about 10 percent, less than a third of the share in advanced economies (refer to figure 4.2, panel b). The relative shortage of jobs that would benefit from AI complementarity may become a challenge in the region.

AI exposure is not uniform across demographic profiles and economic sectors. In EAP, women, the more highly educated, and workers in commerce and trade sectors are more exposed to AI.[1] Women are more highly exposed than men to AI because their jobs involve more cognitive and routine tasks, especially in Malaysia and the Philippines. Higher educational attainment is associated with greater AI exposure. In particular, workers with tertiary education are more highly exposed than workers with secondary education. Furthermore, workers in nonagriculture sectors, especially workers in the commerce sectors, are much more exposed than agricultural workers to AI (refer to figure 4.3). These findings correspond to evidence in the literature on other developing countries (Demombynes, Langbein, and Weber 2025; Gmyrek, Berg, and Bescond 2023; Pizzinelli et al. 2023).

EAP countries are relatively less exposed than advanced economies to the labor displacement effects of AI and also have fewer jobs that are complementary to AI.

FIGURE 4.2 Exposure and complementarity with AI, EAP and other country groups

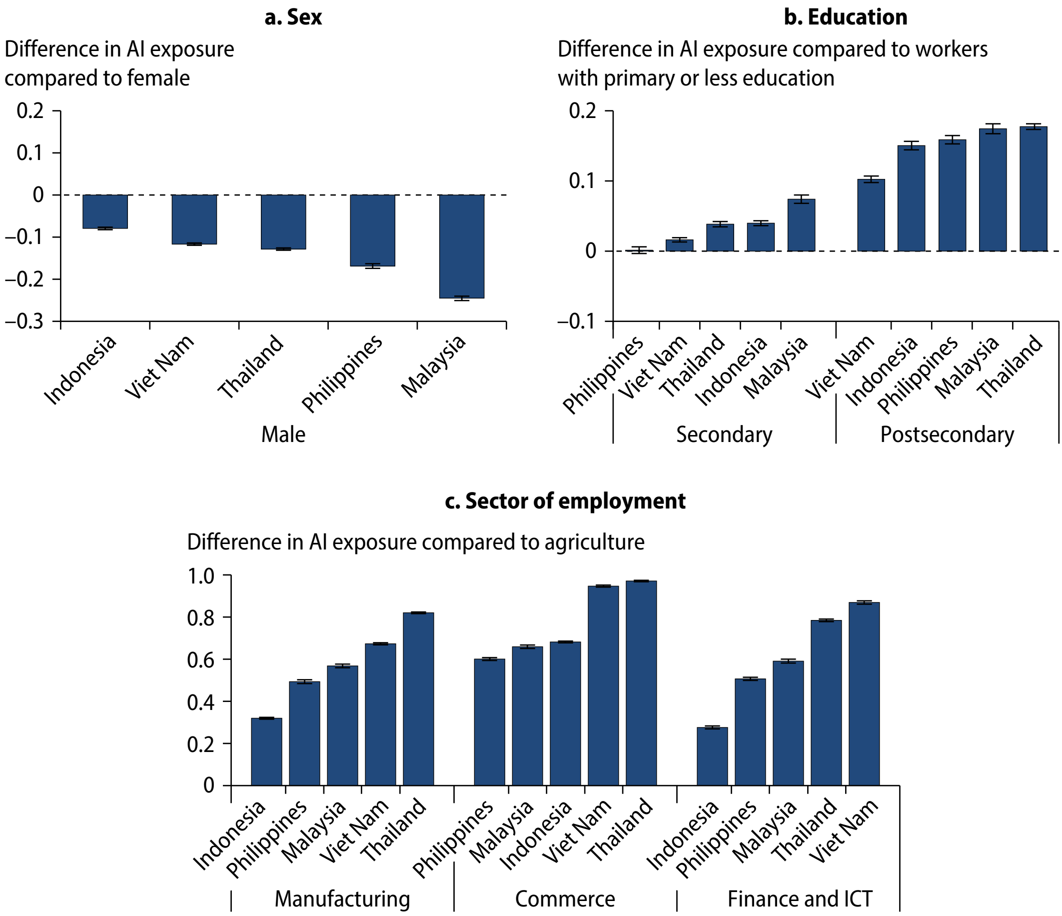


Sources: Original figure for this publication based on data of Felten, Raj, and Seamans 2021; Pizzinelli et al. 2023; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.
Note: Panel a: A higher value of exposure corresponds to high exposure with low complementarity. Panel b: The figure shows the share of workers in occupations under each category of exposure. The categorization is based on the median threshold of the AI exposure measure (Felten, Raj, and Seamans 2021) and the AI complementarity measure (Pizzinelli et al. 2023). For country abbreviations, see International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search. AI = artificial intelligence; EMDEs = emerging market and developing economies; GDP = gross domestic product.

Older workers in EAP countries are more highly exposed than younger workers to automation, but less exposed to AI. There is a mild U-shape relationship between automation exposure and age in the region, suggesting that older workers are more highly exposed than middle-age workers to automation, except in the Philippines (refer to figure 4.4). Meanwhile, the intensity of AI exposure in the EAP region declines with age because older workers tend to work less in AI-exposed occupations relative to younger and middle-age workers. These results may be associated with the large share of older workers in the region who are engaged in routine manual tasks, and the smaller share of such workers engaged in cognitive tasks. This pattern is opposite to the pattern observed in more developed countries, where older workers engage more frequently in cognitive tasks.

Women, the more highly educated, and workers in commerce are more likely to be in jobs exposed to AI in the EAP region.

FIGURE 4.3 Exposure to AI: Correlation with sex, educational attainment, and sector of employment, EAP



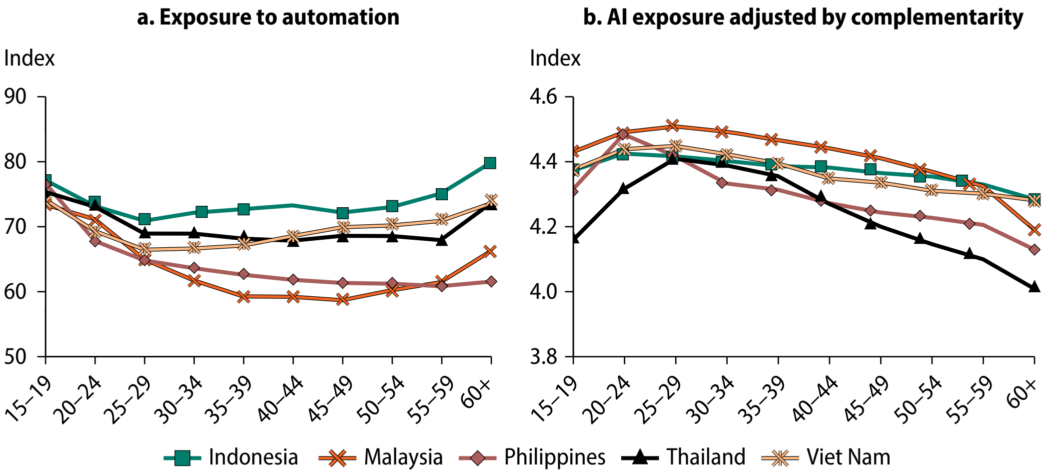
Sources: Original figure for this publication based on data of Felten, Raj, and Seamans 2021; Microdata Library (database), World Bank, Washington, DC, http://microdata.worldbank.org/index.php/home; Pizzinelli et al. 2023.
Note: The figure shows the regression coefficient of complementarity-adjusted AI index controlling for sex, educational attainment, and employment sector. ICT = information and communication technology.

AI exposure and labor market outcomes

Evidence on advanced economies suggests that AI is already affecting workers whose tasks are highly exposed. Businesses in the United States with task structures exposed to AI experienced a sharp rise in AI-related job postings throughout the 2010s, while simultaneously reducing hires for non-AI–related roles (Acemoglu et al. 2022). Freelancers working on online platforms in highly

In EAP countries, relative to younger workers, older workers are more highly exposed to automation and less exposed to AI.

FIGURE 4.4 Exposure to automation and AI, by age group, five EAP countries



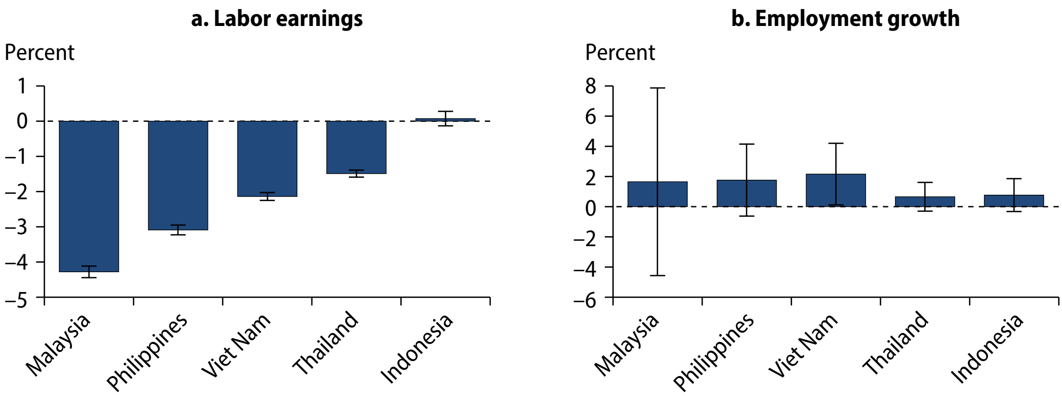
Sources: Original figure for this publication based on data of Felten, Raj, and Seamans 2021; Frey and Osborne 2017; ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; Microdata Library (database), World Bank, Washington, DC, http://microdata.worldbank.org/index.php/home; O*NET Online, Occupational Information Network, Employment and Training Administration, US Department of Labor, Washington, DC; National Center for O*NET Development, Raleigh, NC, https://www.onetonline.org/; Pizzinelli et al. 2023.
Note: The index of the y-axis is calculated by the occupational composition (ISCO08 2-digit level).

exposed occupations are experiencing reductions in both employment and earnings following the introduction of generative AI (Hui, Reshef, and Zhou 2024). Other studies on generative AI have demonstrated that, for a given task, productivity gains are primarily observed among less-experienced low-skilled workers (Brynjolfsson, Li, and Raymond 2023; Noy and Zhang 2023). These findings suggest that AI is already driving a combination of complementarity and substitution in the workforce in advanced economies.

AI exposure in the EAP region has not yet translated into significant employment impacts, but it is associated with lower earnings. Controlling for the effect of broader occupational categories (1-digit-level occupations), one finds that exposure to AI is negatively correlated with earnings in most EAP countries (refer to figure 4.5, panel a). This suggests that AI-affected occupations are already experiencing negative impacts mediated through the nature of the associated tasks (routineness, fewer social interactions, and so on) even though the penetration of AI in the region is still nascent. The largely insignificant correlation between AI and aggregate changes in employment is also observed in advanced economies (Acemoglu et al. 2022) (refer to figure 4.5, panel b).

Greater exposure to AI is associated with lower earnings in most EAP countries, but it is not significantly correlated with employment change.

FIGURE 4.5 The correlation of exposure to AI with earnings and employment growth, five countries in EAP



Sources: Original figure for this publication based on data from Felten, Raj, and Seamans 2021; Pizzinelli et al. 2023.
Note: The coefficients in each panel correspond to the percent difference in earnings (panel a) and change in employment (panel b) associated with a 1 standard deviation change in the AI exposure measure. The regressor is the standardized complementarity-adjusted AI exposure measure (ISCO08 2-digit). Panel a: The dependent variable is log of annual earnings in the latest survey year. Regressions control for age, gender, education, 1-digit industry, and 1-digit occupation fixed effect. Panel b: The dependent variable is average employment growth from 2010–19 at the 2-digit occupation level.

Note

1. The AI exposure measure used in the analyses is based on the complementarity-adjusted AI exposure proposed by Pizzinelli et al. (2023).

References

Acemoglu, Daron, Gary Anderson, David Beede, Catherine D. Buffington, Eric Childress, Emin Dinlersoz, Lucia Smith Foster, et al. 2023. "Advanced Technology Adoption: Selection or Causal Effects?" *AEA Papers and Proceedings* 113 (May): 210–14.

Acemoglu, Daron, David H. Autor, Jonathon Hazell, and Pascual Restrepo. 2022. "Artificial Intelligence and Jobs: Evidence from Online Vacancies." *Journal of Labor Economics* 40 (S1): S293–S340.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.

Bick, Alexander, Adam Blandin, and David J. Deming. 2025. "The Rapid Adoption of Generative AI." Economic Research Working Paper 2024-027 rev. (February), Federal Reserve Bank of St. Louis, St. Louis. https://doi.org/10.20955/wp.2024.027.

Bonney, Kathryn, Cory Breaux, Cathy Buffington, Emin Dinlersoz, Lucia S. Foster, Nathan Goldschlag, John C. Haltiwanger, Zachary Kroff, and Keith Savage. 2024.

"Tracking Firm Use of AI in Real Time: A Snapshot from the Business Trends and Outlook Survey." NBER Working Paper 32319 (April), National Bureau of Economic Research, Cambridge, MA.

Brynjolfsson, Erik, Danielle Li, and Lindsey R. Raymond. 2023. "Generative AI at Work." NBER Working Paper 31161 rev. (November), National Bureau of Economic Research, Cambridge, MA.

Demombynes, Gabriel, Jörg Langbein, and Michael Weber. 2025. "The Exposure of Workers to Artificial Intelligence in Low- and Middle-Income Countries." Policy Research Working Paper 11057, World Bank, Washington, DC.

Felten, Edward, Manav Raj, and Robert Seamans. 2021. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses." *Strategic Management Journal* 42 (12): 2195–217.

Frey, Carl Benedikt, and Michael A. Osborne. 2017. "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change* 114 (January): 254–80.

Gmyrek, Pawel, Janine Marie Berg, and David Bescond. 2023. "Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality." ILO Working Paper 96 (August), International Labour Organization, Geneva.

Hui, Xiang, Oren Reshef, and Luofeng Zhou. 2024. "The Short-Term Effects of Generative Artificial Intelligence on Employment: Evidence from an Online Labor Market." *Organization Science* 35 (6): 1977–89.

Lewandowski, Piotr, Karol Madoń, and Albert Park. 2024. "Workers' Exposure to AI across Development." Background paper for this report, World Bank, Washington, DC.

McElheran, Kristina, J. Frank Li, Erik Brynjolfsson, Zachary Krof, Emin Dinlersoz, Lucia Smith Foster, and Nikolas Jason Zolas. 2023. "AI Adoption in America: Who, What, and Where." CES Working Paper 23-48 (September), Center for Economic Studies, US Census Bureau, Washington, DC.

Noy, Shakked, and Whitney Zhang. 2023. "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence." *Science* 381 (6654): 187–92.

Pizzinelli, Carlo, Augustus J. Panton, Marina Mendes Tavares, Mauro Cazzaniga, and Longji Li. 2023. "Labor Market Exposure to AI: Cross-Country Differences and Distributional Implications." IMF Working Paper WP/23/216 (October), International Monetary Fund, Washington, DC.

Spearman, Charles Edward. 1904. "The Proof and Measurement of Association between Two Things." *American Journal of Psychology* 15 (1): 72–101.

Webb, Michael. 2020. "The Impact of Artificial Intelligence on the Labor Market." Unpublished working paper, Department of Economics, Stanford University, Stanford, CA.

Working with Digital Technologies 5

Introduction

Robots and artificial intelligence (AI) are not the only manifestations of new technologies that affect jobs. This chapter presents evidence on the implications of working with digital technologies and the emergence of digital platforms.

Digital jobs

Digital technologies may increase labor demand by boosting productivity and allowing flexible work arrangements. As the task model suggests, automation and AI may have a negative impact on labor through the displacement effect on tasks that may be automated. However, this may be counterbalanced by the creation of new tasks and jobs that are often associated with new technology, and the increase in labor demand because of the positive productivity effect, as has been the case in China (refer to box 5.1).

In the case of information and communication technology, the productivity effect has typically outweighed the displacement effect at the aggregate level (refer to box 5.2). Furthermore, digital platforms, including e-commerce, have created flexible work arrangements that have proven especially advantageous for demographic groups that previously faced barriers to traditional employment, such as women and youth. To harness the full potential of technological advances and mitigate the associated potential disruptive effects on the labor market, workers should become comfortable working with digital tools.

Box 5.1. The creation of digital jobs in China

The adoption of new technology often creates new tasks and occupations. In China, the increasing adoption of digital technologies induced the government to add new jobs to the National Occupation Classification. Since 2019, the Ministry of Human Resources and Social Security has added 93 new occupations to the classification, which reached a total of 1,658 occupations in 2024. Among the 93 new occupations, nearly half are associated with new technologies. The new jobs range from big data technician and artificial intelligence (AI) technician (added in 2019) to block chain operator (in 2020), integrated circuit technician (2021), cybersecurity evaluator (2024), and generative AI system operator (2024) (refer to table B5.1.1). The trend is closely related to the rapidly evolving technological development in the country. These professions foster technological development, and also respond to the growing need for security, sustainability, and intelligent digital systems across industries.

TABLE B5.1.1 Examples of newly added digital occupations, China

Year	Examples of newly added digital occupations
2019	Internet of Things Engineering Technician Artificial Intelligence Engineering Technician Big Data Engineering Technician Cloud Computing Engineering Technician
2020	Virtual Reality Engineering Technician Intelligent Manufacturing Engineering Technician Artificial Intelligence Trainer Block Chain Application Operator
2021	Integrated Circuit Engineering Technician Cryptography Application Technician Digital Forensics Analyst Industrial Vision System Maintenance Technician
2022	Robotics Engineering Technician Data Security Engineering Technician Agricultural Digitalization Technician Database Operations Administrator
2024	Cybersecurity Protection Evaluator Cloud Network Intelligent O & M Staff Generative Artificial Intelligence System Operator Intelligent Connected Vehicle Tester

Source: World Bank 2024.
Note: O & M = operations and maintenance.

Box 5.2. The literature on employment and the labor impacts of digital connectivity

Impact of internet access

Studies examining the employment effect of digital connectivity have focused on two strands: (a) high-speed broadband and (b) mobile internet connections. In both cases, employment gains through the productivity effect have been shown largely to outweigh the labor displacement effect at the aggregate level.

First, the diffusion of broadband internet connectivity has positively affected employment rates. There has been little labor displacement, while it has increased firm entry, productivity, and exports (Hjort and Poulsen 2019). Studies in developed countries show that broadband internet expansion raises firm labor demand, labor force participation, employment rates, and wage growth.[a] Cariolle, Le Goff, and Santoni (2018) find that fiber optic telecommunication over submarine cable networks improves firm performance in 40 developing countries across Africa, Asia, and Latin America, leading to greater employment among production workers. Hjort and Poulsen (2019) show that high-speed internet access through submarine cables increases firm entry, productivity, and exports in Ghana, Kenya, Mauritania, Nigeria, Senegal, and Tanzania, followed by increases in employee training, worker productivity, wages, and employment rates. In the East Asia and Pacific (EAP) region, broadband infrastructure investment has improved firm and labor productivity and raised worker wages in China (Chen, Liu, and Song 2020; Jin, Ma, and Zhang 2023; Zhang, Tao, and Nie 2022). Broadband adoption is also associated with increases in labor demand, employment growth, and reductions in the unemployment rate in Indonesia, Viet Nam, and other countries of the Association of Southeast Asian Nations (Chun and Tang 2018; Fadzil 2018; Salsabila and Oktora 2022).

The second strand of the literature has focused on the expansion of mobile internet coverage and the associated labor market impact. The expansion of 3G networks and mobile cellular and telephone subscriptions promote labor force participation and higher employment rates (Chiplunkar and Goldberg 2022; Ndubuisi, Otioma, and Tetteh 2021). Evidence on Nigeria, Rwanda, and South Africa suggests that 3G networks and mobile broadband boost wage employment and labor force participation, particularly among women, which may be partially

(continued)

Box 5.2. The literature on employment and the labor impacts of digital connectivity *(continued)*

explained by the enhancements provided by online job searches and by shifts in traditional social norms that may result from the greater reliance on mobile internet and networking.[b] In the EAP region, mobile internet availability is increasing rural household consumption in China, influencing labor force participation in Indonesia, and affecting average household income in Viet Nam (Kusumawardhani et al. 2023; Pham 2023; Wan, Nie, and Zhang 2021).

Studies that do not delineate fixed line and mobile internet but use available survey indicators to proxy for internet access also emphasize the broad effects of internet adoption on labor markets. Access to internet services enhances employment and improve labor productivity and earnings among both salaried and self-employed workers, especially skilled women workers in India and some Latin American countries (Jain 2021; Navarro 2010). In the EAP region, internet access raises firm productivity and employment by reducing information and communication technology (ICT) costs in China and leads to increased household income in rural Indonesia (Ariansyah 2018; Fernandes et al. 2019). In the agriculture sector, internet access increases farm household income in China and boosts agricultural output among younger and more remote households in Viet Nam.[c]

In addition to documenting the overwhelmingly positive effects of internet connectivity, the literature also highlights the heterogeneous employment effects of internet adoption across demographic groups. Several studies focusing on gender disparity suggest that internet adoption may reduce female labor supply by pushing women into unpaid jobs as men shift away from agriculture (Chiplunkar and Goldberg 2022; Klonner and Nolen 2010). Internet availability may also limit the supply of female labor in high-skilled jobs, while sustaining the within-firm gender wage gap (Chun and Tang 2018). In terms of skill differentials, the adoption of skill-biased technology, such as high-speed internet, has favored more well educated workers and shifted labor demand from low-skilled manual tasks to interactive tasks in ICT-driven industries.[d] Such an effect is also more pronounced among younger workers equipped with greater digital literacy (Jin, Ma, and Zhang 2023).

Impact of computer and mobile phone devices

A separate literature discusses the role of computer and mobile phone usage as complementary digital devices that help magnify the positive effect of internet

(continued)

Box 5.2. The literature on employment and the labor impacts of digital connectivity *(continued)*

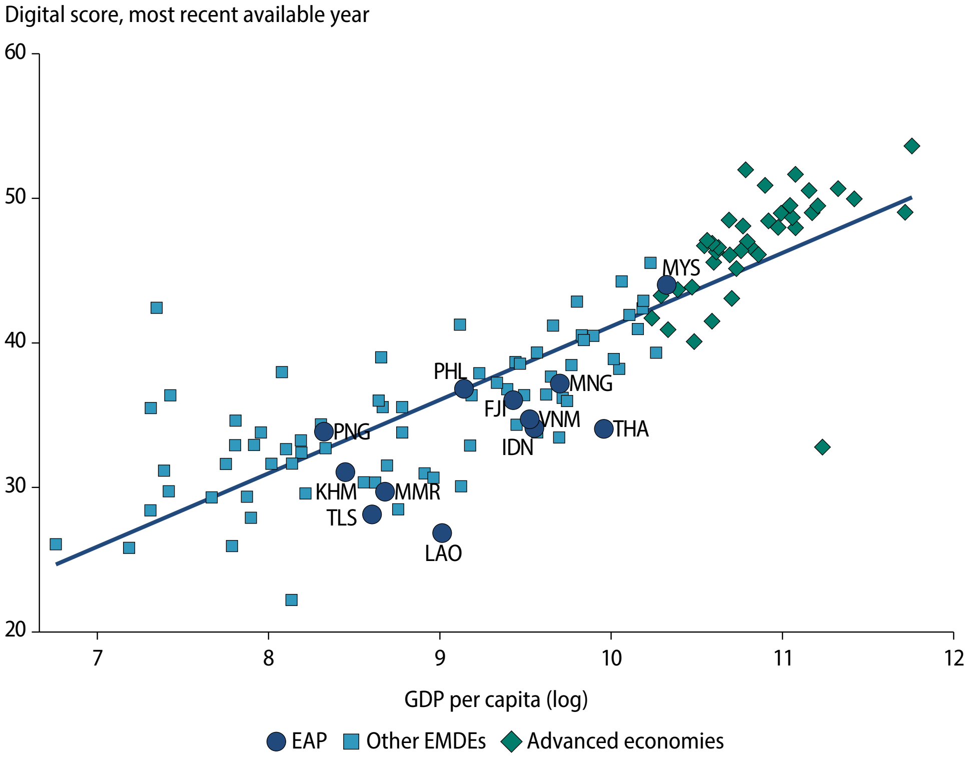
connectivity. Before the internet boom, the availability of computers benefited more well educated workers, potentially increasing wage gaps.[e] In manufacturing production, studies show that computer investment positively affects firm productivity, wage structure changes, and entrepreneurship (Brynjolfsson and Hitt 2003; Fairlie 2006; Krueger 1993). Mobile phone adoption helps reduce price dispersion, improves marketing decisions, and increases market participation, particularly among women, leading to sectoral labor reallocation and fostering nonfarm employment and entrepreneurship.[f] In agriculture, mobile phones provide farm households with information on weather hazards, market conditions, and prices, thereby enhancing decision-making and reducing communication and transaction costs.[g] In the EAP region, mobile phone use has been shown to help reduce energy poverty by increasing household consumption and off-farm income, particularly among poorer and less well educated populations in China (Zang et al. 2023). It has also boosted growth in per capita household consumption in the Philippines (Blumenstock et al. 2020; Labonne and Chase 2009).

a. Refer to Akerman, Gaarder, and Mogstad (2015); Atasoy (2013); Crandall, Lehr, and Litan (2007); Dettling (2017); Fabritz (2013); Forman, Goldfarb, and Greenstein (2012); Ivus and Boland (2015).
b. Refer to Bahia et al. (2021); Caldarola et al. (2023); Donati (2023); Viollaz and Winkler (2022).
c. Refer to Kaila and Tarp (2019); Ma and Wang (2020); Nguyen, Nguyen, and Grote (2023); Nguyen et al. (2023).
d. Refer to Akerman, Gaarder, and Mogstad (2015); Atasoy (2013); Chen, Liu, and Song (2020); Chun and Tang (2018); Forman, Goldfarb, and Greenstein (2012); Hjort and Poulsen (2019); Michaels, Natraj, and Van Reenen (2014).
e. Refer to Autor, Katz, and Kearney (2008); Autor, Katz, and Krueger (1998); Autor, Levy, and Murnane (2003); Goldin and Katz (2008); Katz and Margo (2014).
f. Refer to Andjelkovic and Imaizumi (2012); Emerick (2018); Foster and Rosenzweig (2008); Klonner and Nolen (2010); Muto and Yamano (2009); Shimamoto, Yamada, and Gummert (2015); Tadesse and Bahiigwa (2015).
g. Refer to Aker (2010); Aker and Fafchamps (2015); Aker and Ksoll (2016); Aker and Mbiti (2010); Fafchamps and Minten (2012); Ifeoma and Mthitwa (2015); Jensen (2007); Krell et al. (2021); Lee and Bellemare (2013); Mitra et al. (2018); Mittal and Mehar (2012); Muto and Yamano (2009); Qiang et al. (2012).

One way to measure the digital intensity of jobs is to examine the composition of occupations associated with digital technologies. Intensity may be measured by the level of knowledge and use of digital technologies in each occupation. In general, the digital intensity of jobs is closely associated with country income. East Asia and Pacific (EAP) countries show relatively lower digital intensity compared with advanced economies and other emerging market and developing economies at similar income because of the region's smaller share of high-skilled professionals and employment in digitally intensive and information technology–related occupations (refer to figure 5.1; box 5.3). Within the EAP region, the digital intensity is highest in the Malaysian workforce, reflecting Malaysia's relatively large share of science and engineering professionals and business associates, while the digital intensity of lower-income economies, such as the Lao People's Democratic Republic, Myanmar, and Timor-Leste is lower.

The share of employment in digitally intensive occupations is smaller in EAP countries than in advanced economies and other emerging market and developing economies at similar incomes.

FIGURE 5.1 The share of employment in digitally intensive occupations, EAP and other selected economies



Sources: Original figure for this publication based on data of ILOSTAT (dashboard), International Labour Organization, Geneva, https://ilostat.ilo.org/; Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/.

Note: Countries with more than 1 million population are shown. The digital score is calculated using occupational composition at the ISCO08 2-digit level based on the methodology of Muro et al. (2017) using O*NET data. It ranks the level of digital activities and knowledge required for each occupation in the United States. For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search. EMDEs = emerging market and developing economies; GDP = gross domestic product.

Box 5.3. Measuring the digital intensity of occupations

The digital score measures the degree of digital intensity across hundreds of occupations (Muro et al. 2017). The data are derived from the Occupational Information Network database, which surveys workers in the United States to obtain detailed information on the tasks, skill requirements, and experience associated with the performance of their jobs. Two technology-relevant variables—knowledge: computer and electronics and work activity: interacting with computers—were used (equal weight, scale standardized) to score the digital intensity of occupations. These were converted to ISCO08 2-digit level occupations (40 occupations). The calculated score applies to the US workforce but may be used as a benchmark to measure the relative digital intensity of occupations in other economies.

Table B5.3.1 shows the occupational composition of countries in the East Asia and Pacific (EAP) region ranked by the calculated digital score. Compared with advanced economies, such as Singapore and the United States, the share of information technology–related occupations and high-skilled professionals in the EAP region is smaller, while the share of low-digital occupations, such as jobs in agriculture, manufacturing, construction, and sales is larger, reflecting the cross-country difference in the aggregate digital score.

Although the measure relies on the digital intensity of occupations in the United States, it can be used as a benchmark to evaluate the occupational composition associated with digital technologies. There is also a high correlation between the digital score and the share of workers who use digital technologies on the job (for the example of Viet Nam, refer to figure B5.3.1). This suggests that the rise in the number of digital occupations is closely related to the greater use of digital technologies.

(continued)

Box 5.3. Measuring the digital intensity of occupations *(continued)*

The share of information technology–related occupations and high-skilled professionals is smaller in the EAP region than in advanced economies.

TABLE B5.3.1 Digital intensity score and the share of occupations, by countries

Digital score	Title of occupation	IDN	KHM	MNG	MYS	PHL	THA	VNM	SGP	USA
14	Market-Oriented Skilled Agricultural Workers	18	17	23	4	10	24	9	0	0
18	Cleaners and Helpers	3	1	2	2	4	2	1	3	1
21	Building and Related Trades Workers (excluding Electricians)	2	7	4	2	3	3	5	1	3
24	Subsistence Farmers, Fishers, Hunters, and Gatherers	3	13	1	0	0	3	5	NA	0
27	Drivers and Mobile Plant Operators	4	3	9	5	6	5	4	5	4
28	Food Preparation Assistants	1	0	0	0	1	0	0	2	1
28	Laborers in Mining, Construction, Manufacturing, and Transport	7	4	3	3	10	4	6	1	5
30	Food Processing, Wood, Garment, and Other Trades Workers	6	12	3	2	2	3	4	1	1
31	Agricultural, Forestry, and Fishery Laborers	6	5	0	4	11	3	15	0	1
32	Market-Oriented Skilled Forestry, Fishery, and Hunting Workers	1	2	0	1	2	1	1	0	0
33	Personal Service Workers	5	2	4	5	3	5	4	3	5
34	Stationary Plant and Machine Operators	2	1	1	5	1	3	9	0	1
36	Refuse Workers and Other Elementary Workers	2	0	3	3	2	2	2	1	2
39	Metal, Machinery, and Related Trades Workers	2	2	3	3	1	3	2	1	2
40	Personal Care Workers	0	2	1	1	1	1	0	1	2
40	Street and Related Sales and Service Workers	1	0	0	0	1	1	1	NA	0
41	Assemblers	0	0	0	0	1	2	2	0	1
41	Sales Workers	19	16	8	15	16	14	14	5	6
44	Handicraft and Printing Workers	1	1	0	0	1	1	1	0	0
49	Protective Services Workers	1	0	2	4	2	1	1	2	1
50	Other Clerical Support Workers	0	0	1	1	0	0	1	0	1
50	Legal, Social, Cultural, and Related Associate Professionals	0	0	1	1	0	0	0	2	2

(continued)

Box 5.3. Measuring the digital intensity of occupations *(continued)*

TABLE B5.3.1 Digital intensity score and the share of occupations, by countries *(continued)*

Digital score	Title of occupation	IDN	KHM	MNG	MYS	PHL	THA	VNM	SGP	USA
53	Customer Service Clerks	1	1	1	1	3	1	0	2	4
53	Health Associate Professionals	1	0	1	2	1	0	1	1	5
53	Health Professionals	1	0	3	1	1	1	0	2	4
56	Legal, Social, and Cultural Professionals	0	0	2	1	0	1	0	2	3
57	Chief Executives, Senior Officials, and Legislators	0	0	2	1	1	1	0	3	1
57	Electrical and Electronics Trades Workers	0	1	1	1	1	1	1	0	1
58	Science and Engineering Associate Professionals	1	1	1	5	1	1	1	5	2
59	Numerical and Material Recording Clerks	1	0	1	2	1	1	1	2	1
59	General and Keyboard Clerks	2	2	0	6	2	2	1	4	2
60	Administrative and Commercial Managers	0	0	2	2	1	1	NA	8	2
60	Business and Administration Associate Professionals	1	1	1	5	2	3	1	11	7
61	Business and Administration Professionals	0	1	3	2	1	1	2	10	5
61	Hospitality, Retail, and Other Services Managers	1	0	1	1	2	1	1	2	5
61	Production and Specialized Services Managers	1	0	1	1	1	1	0	5	4
62	Teaching Professionals	4	1	6	5	3	2	2	3	5
69	Science and Engineering Professionals	0	0	5	2	1	1	1	7	3
79	Information and Communications Technicians	0	0	0	1	0	0	1	1	0
86	Information and Communications Technology Professionals	0	0	1	1	0	0	0	3	3

Source: Original figure for this publication based on microdata from national labor force surveys: Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS.

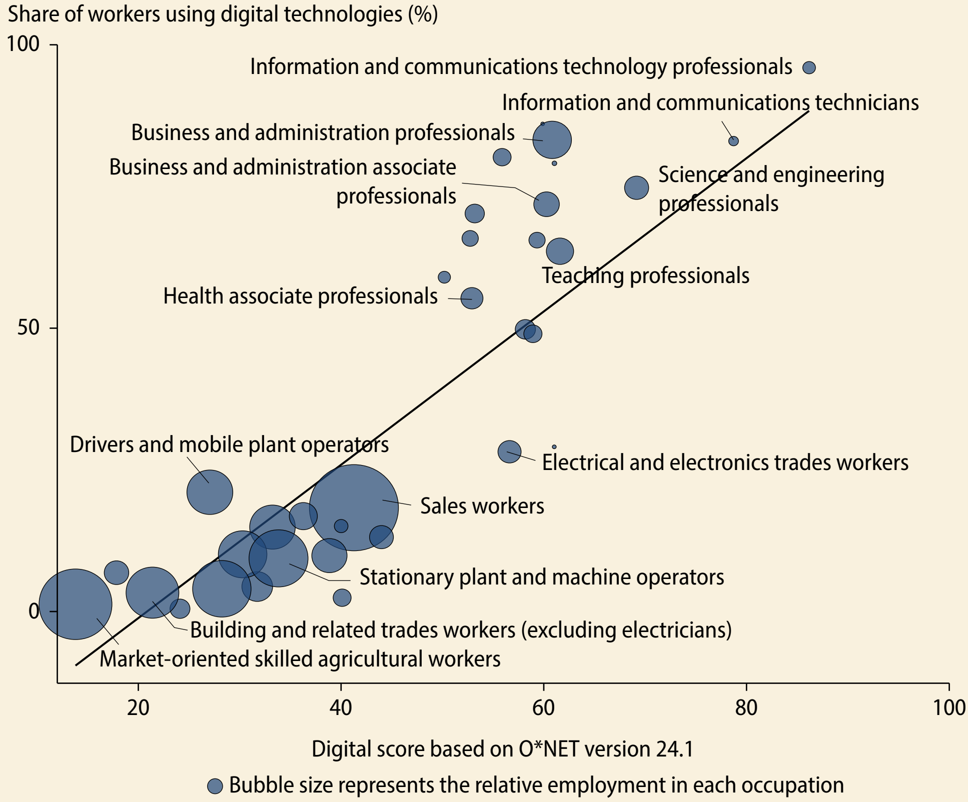
Note: The table shows the share of workforce at ISCO08 2-digit level ordered by digital intensity of occupations. In the table, green indicates a large share (score of 4 or greater), yellow a medium share (scores of 1 to 4), and red a small share (<1). The data refer to the most recent available year. For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search. IT = information technology; NA = not available.

(continued)

Box 5.3. Measuring the digital intensity of occupations *(continued)*

The digital intensity of jobs is correlated with the share of workers who use digital technologies.

FIGURE B5.3.1 The digital intensity score and the share of workers using digital technologies, by occupations, Viet Nam, 2021

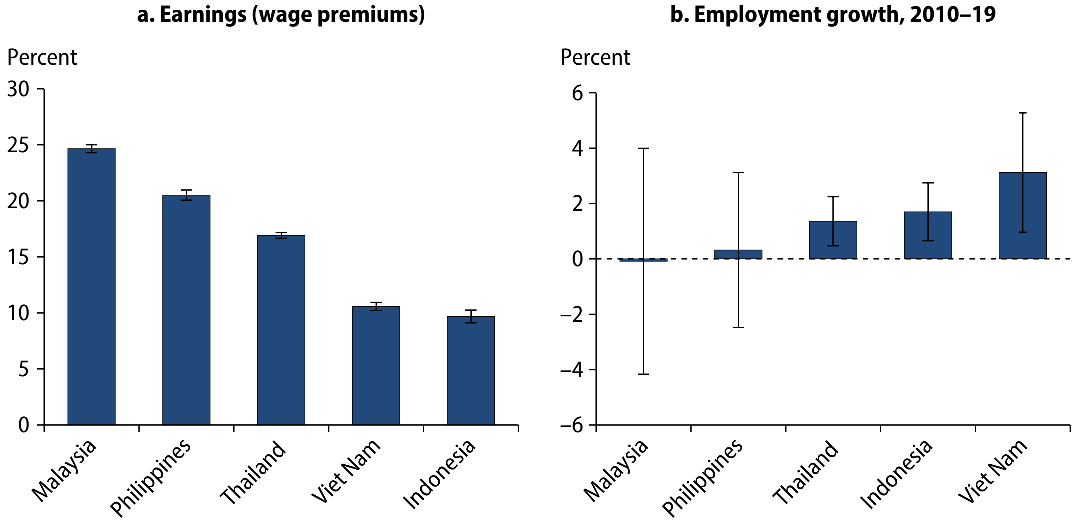


Sources: Original figure for this publication based on GSO 2022; O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/.
Note: The black line illustrates the linear fit.

Working with advanced digital technologies requires more skills and is generally linked with greater earnings. In the EAP region, the digital intensity of jobs is positively correlated with earnings (refer to figure 5.2, panel a). The wage premiums are particularly large in Malaysia, the Philippines, and Thailand (a 25 percent, 20 percent, and 17 percent increase, respectively, corresponding to 1 standard

Digitally intensive occupations are associated with higher wage premiums and higher employment growth in some countries in the EAP region.

FIGURE 5.2 Earnings premiums and employment growth associated with digitally intensive occupations, five EAP countries



Sources: Original figure for this publication based on microdata from national labor force surveys: Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/.
Note: The regressor is the standardized digital intensity score (ISCO08 2-digit level). The whiskers show the 90 percent confidence interval for mean estimates for the wage premium and employment growth. Panel a: The dependent variable is the log of annual earnings in the most recent survey year. Regressions control for age, gender, education, and the 1-digit industry fixed effect. Panel b: The dependent variable is the average annual ratio of earnings to employment growth at the 2-digit occupation level.

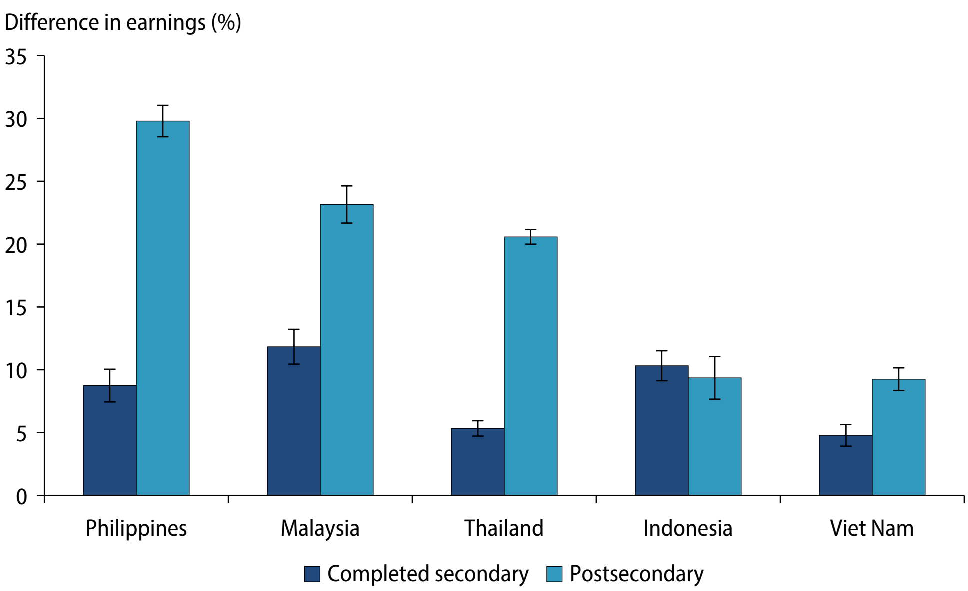
deviation increase in the digital score). The employment change is also positively correlated with the digital intensity of jobs in Indonesia, Thailand, and Viet Nam, suggesting that jobs are being created in digital-intensive occupations (refer to figure 5.2, panel b). However, the association is not significant in Malaysia and the Philippines. Higher wages are likely to attract more workers to digital occupations, but the shortage in demand because of limitations in digital infrastructure and in capable firms and the shortage in supply (a skill shortage) may be inhibiting workers from transitioning to higher-paying digital occupations.

Working with digital technologies yields a higher wage premium among the more educated. Digital occupations exhibit heterogeneous wage premiums across education groups. Compared with workers with primary educational attainment or less, workers who have completed secondary education and especially workers who have received tertiary education have experienced higher wage premiums for more advanced digital occupations (refer to figure 5.3). The literature also suggests that complementary skills, such as socioemotional skills, language proficiency, or critical thinking are important in digital occupations (Cunningham et. al. 2022; Deming and Kahn 2018; Grundke et al. 2018).

Women may benefit more than men by working with digital technologies. A heterogenous effect may be observed in earnings and employment growth by sex. In Indonesia, Thailand, and Viet Nam, women who work with digital technologies experience greater wage and employment growth (refer to figure 5.4). Digital technologies also enable people who were previously out of the labor force, such as women and youth, to benefit from flexible work arrangements by using e-commerce and digital labor platforms. These new informal workers are more well off than traditional informal workers in earnings and earnings prospects (refer to box 5.4).

Working with digital technologies yields a higher wage premium among the more educated.

FIGURE 5.3 The effect of education and digital intensity on earnings, five EAP countries

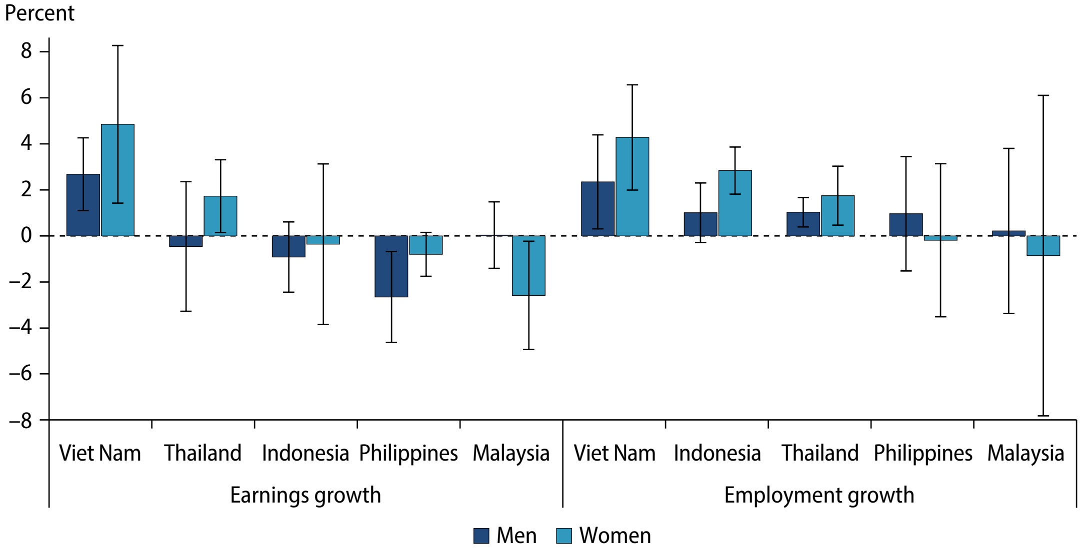


Sources: Original figure for this publication based on microdata from national labor force surveys: Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/.

Note: The bars show the coefficients of the interaction term between educational attainment (base: primary or less education) and the standardized digital intensity score (ISCO08 2-digit level). The whiskers show the 90 percent confidence interval for mean estimates of the earnings premium. The dependent variable is the log of annual earnings in the most recent survey year. Regressions control for age, gender, education, and the 1-digit industry fixed effect.

Women working with digital technologies tend to exhibit greater growth than men in earnings and employment.

FIGURE 5.4 **Growth in earnings and employment, by sex, five EAP countries, 2010–19**



Sources: Original figure for this publication based on microdata from national labor force surveys: Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/.
Note: The regressor is the standardized digital intensity score (ISCO08 2-digit level). The whiskers show the 90 percent confidence interval for mean estimates of the wage premium and employment growth. The dependent variable is the median annual earnings growth/employment growth during 2010–19 at the 2-digit occupation level.

Box 5.4. Digital jobs, informality, and female labor force participation in Indonesia

Digital technologies have become common in the workplace in Indonesia. Statistics show a rapid rise in the share of digital employment in the labor force in Indonesia (refer to figure B5.4.1, panel a). Digital workers accounted for less than 10 percent of the working-age population in 2018 (14 percent among the employed), but the share had increased to almost 30 percent by 2023 (43 percent among the employed). A significant rise is noticeable in digital employment in the informal sector and

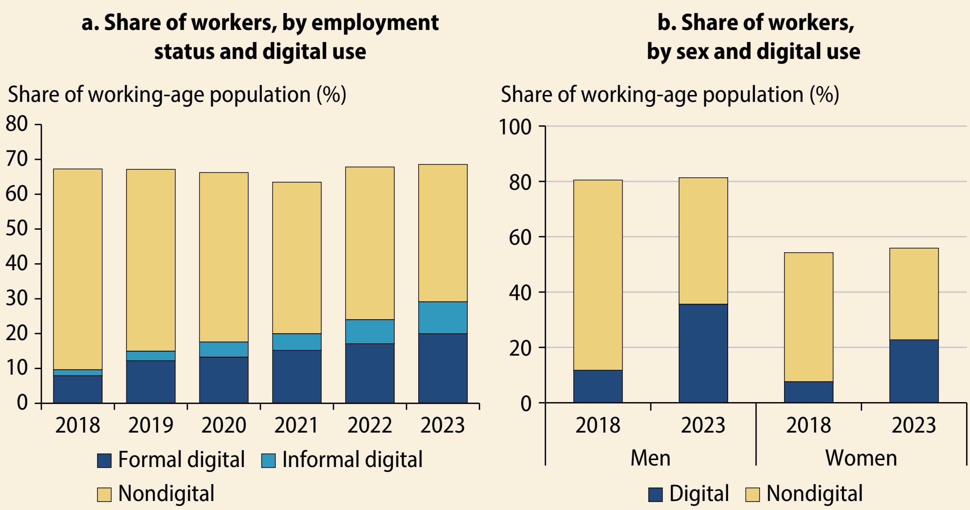
(continued)

Box 5.4. Digital jobs, informality, and female labor force participation in Indonesia *(continued)*

among women, which may be associated with the growth in jobs based on digital platforms (gig work and e-commerce) (refer to figure B5.4.1, panel b). The ratio of female employment to the working-age population rose by 1.7 percentage points in 2018–23 compared with 0.8 percentage points among men. Evidence suggests that, among all women, the incidence of e-commerce engagement (selling) is highest especially among women who are primarily engaged in housework. E-commerce and other platform jobs could help expand the opportunities for women in the labor market (World Bank 2021).

An increasing share of workers, both formal and informal, men and women, use digital technologies.

FIGURE B5.4.1 Share of workers using digital technologies, by sex and formal or informal status, Indonesia, 2018–23



Source: Original figure for this publication based on data of 2018–24 rounds of Sakernas (Survei angkatan kerja nasional, National Labor Force Survey) (dashboard), Badan Pusat Statistik (Statistics Indonesia), Indonesian Statistics, MIT Dataverse, Massachusetts Institute of Technology, Cambridge, MA, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/OU8V2M.

Note: The working-age population covers ages 15–64. Digital workers are defined as workers who use digital technologies and the internet in their primary jobs.

(continued)

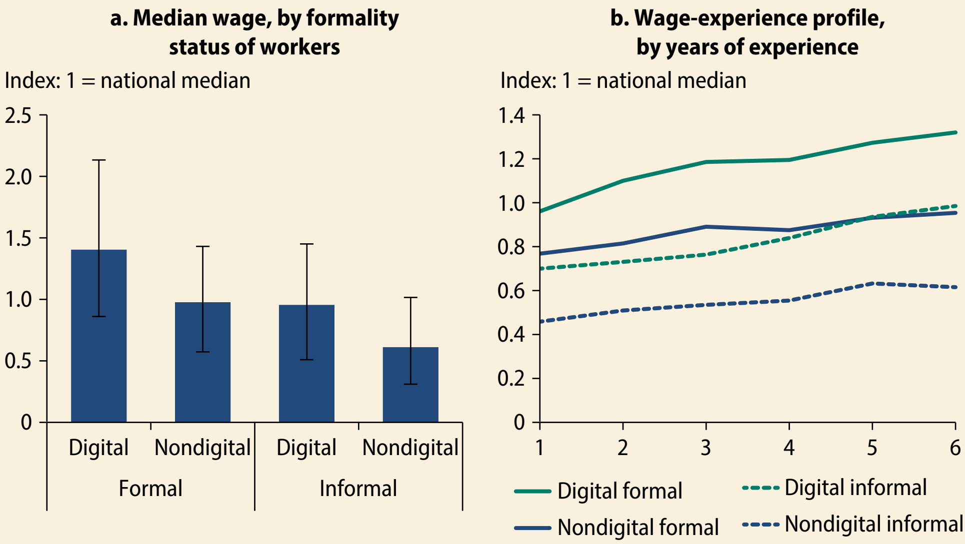
Box 5.4. Digital jobs, informality, and female labor force participation in Indonesia *(continued)*

In both the formal and informal sectors, digital workers earn significantly more than nondigital workers. Digital workers in the informal sector earn almost the same amounts as nondigital workers in the formal sector, indicating that digitalization could shrink the gap between the formal and informal sectors (refer to figure B5.4.2). Positive wage differentials between the digital and nondigital sectors also increase with job tenure.

Despite the expansion and positive wage prospects of informal digital workers, most of these workers do not have insurance or pensions (refer to figure B5.4.3). Furthermore, digital gig work is available primarily among urban men, and these workers put in an average of 10 hours a week more than every other type of worker in Indonesia (World Bank 2021).

Digital workers in both the formal and informal sectors enjoy a wage premium.

FIGURE B5.4.2 The digital premium, by formal and informal status and job tenure, Indonesia



Sources: Original figure for this publication based on data of 2018–24 rounds of Sakernas (Survei angkatan kerja nasional, National Labor Force Survey) (dashboard), Badan Pusat Statistik (Statistics Indonesia), Indonesian Statistics, MIT Dataverse, Massachusetts Institute of Technology, Cambridge, MA, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/OU8V2M.

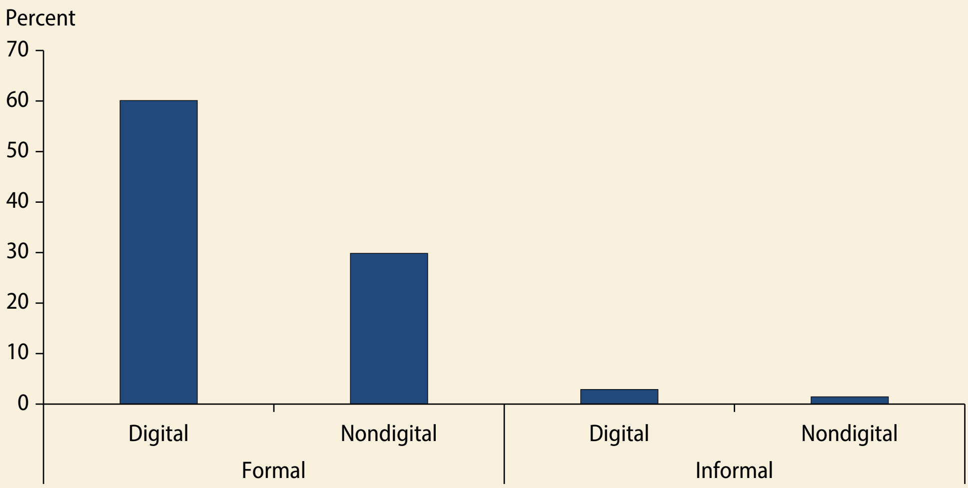
Note: The figure shows real median wages. Panel a: Whiskers show the 25th and 75th wage percentiles.

(continued)

Box 5.4. Digital jobs, informality, and female labor force participation in Indonesia *(continued)*

Most digital workers in the informal sector do not have insurance or pensions.

FIGURE B5.4.3 Share of workers who have insurance or pensions, by digital work and formal or informal status, Indonesia, 2023

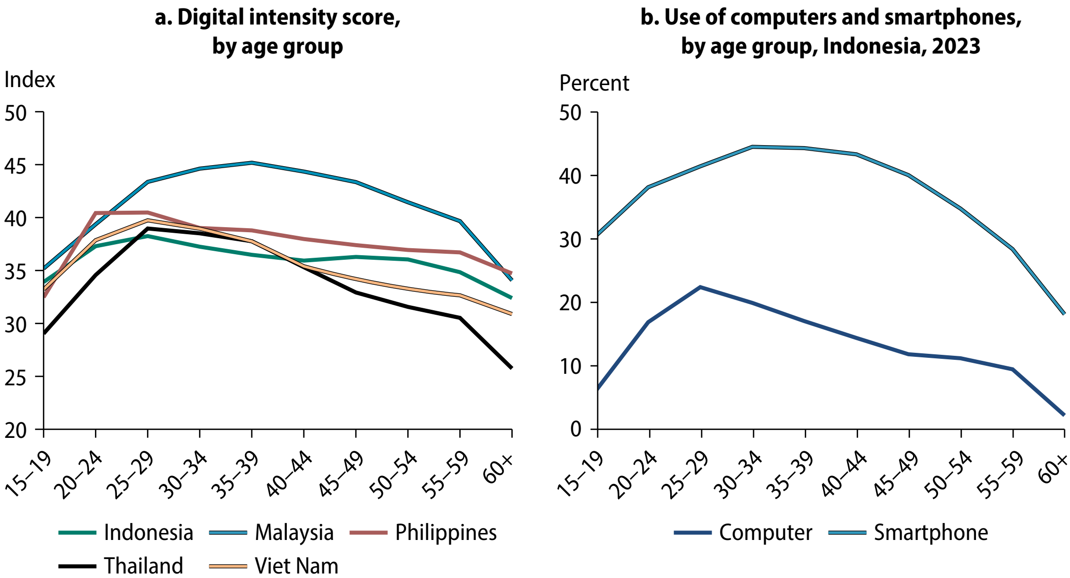


Source: Original figure for this publication based on data of Sakernas (Survei angkatan kerja nasional, National Labor Force Survey) (dashboard), Badan Pusat Statistik (Statistics Indonesia), Indonesian Statistics, MIT Dataverse, Massachusetts Institute of Technology, Cambridge, MA, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/OU8V2M.

Relative to younger workers, older workers in the EAP region are less engaged in digital occupations and less likely to be equipped with digital devices at their jobs and thus are less well positioned to benefit from working with digital technologies. In five countries of the Association of Southeast Asian Nations, the average digital intensity score of workers declines with age (if the youngest workers are excluded), which may be because older workers in the region are less digitally skilled (refer to figure 5.5, panel a). In Indonesia, for example, the use of digital devices, such as computers and smartphones, declines with age (if the youngest workers are excluded) (refer to figure 5.5, panel b). Overall, these patterns suggest that older workers in the EAP region benefit less from digital technologies on the job.

Relative to younger workers, older workers in the EAP region are less highly engaged in digital occupations and less often equipped with digital devices in the workplace.

FIGURE 5.5 Digital intensity and computer use among workers, by age group, five EAP countries



Sources: Original figure for this publication based on microdata from national labor force surveys: Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; O*NET Online, Occupational Information Network, National Center for O*NET Development, Employment and Training Administration, US Department of Labor, Raleigh, NC, https://www.onetonline.org/; August 2019–23 data of Sakernas (Survei angkatan kerja nasional, National Labor Force Survey) (dashboard), Badan Pusat Statistik (Statistics Indonesia), Indonesian Statistics, MIT Dataverse, Massachusetts Institute of Technology, Cambridge, MA, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/OU8V2M.
Note: Panel a: Data refer to the most recent available year. Workers who use computers include workers who use both computers and smartphones.

Digital platforms

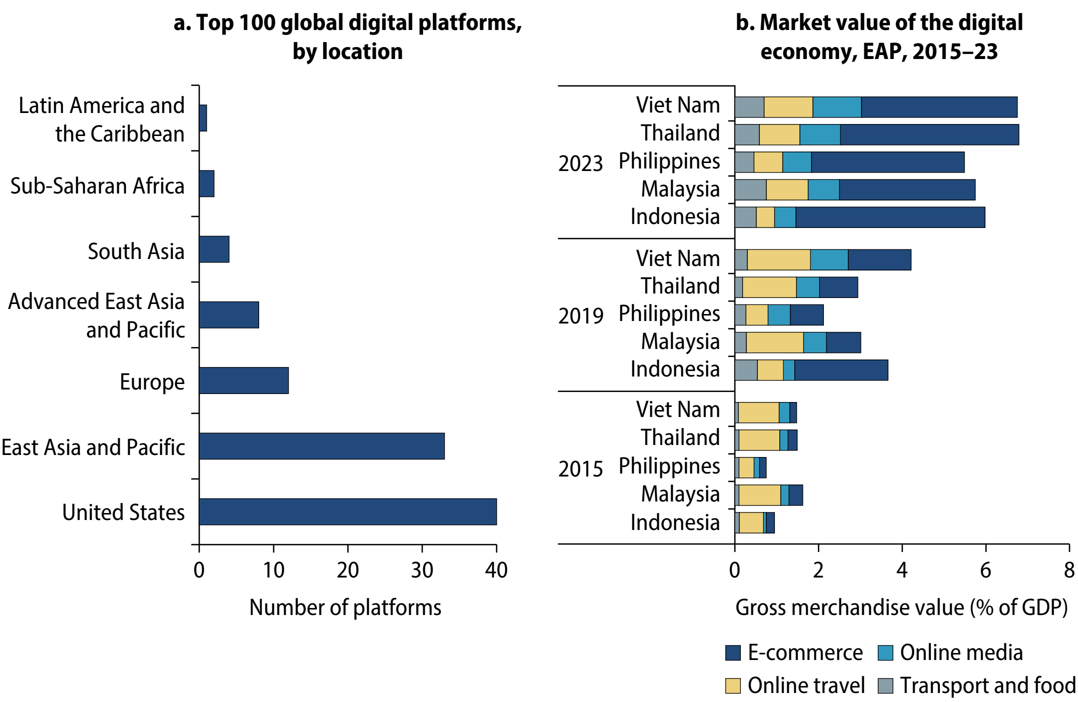
The usefulness of new technologies has encouraged applications involving new business tools, such as digital platforms. These platforms affect labor markets in at least two ways. First, the platforms operate on a large scale and thus may accelerate automation and AI adoption and hence the effect of each on employment. Second, in general, platforms enhance the efficiency of intermediation and may therefore also affect the number and nature of jobs through better matching and the emergence of new tasks.

Some of the most valuable and rapidly growing firms in the EAP region rely on digital platforms. China's Alibaba, Meituan, and Tencent, Indonesia's GoTo, and Singapore's Grab are major players in e-commerce, delivery, and ride hailing, with revenues that rival those of Amazon, eBay, and Uber. However, the dynamism of the sector extends beyond these well-known examples. Indeed, a third of the world's largest digital platform firms (top 100 companies) are headquartered in the EAP region, which is second only to the United States on this indicator (refer to figure 5.6, panel a).

The size of the platform economy has been increasing rapidly across EAP countries. A way to visualize the rapid growth over time of the platform economy in the region involves considering trends in the gross merchandise value of the economy. An estimation of Google, Temasek, and Bain and Company (2023) in their

The size of the digital platform economy has been increasing rapidly and uniformly in EAP countries.

FIGURE 5.6 Top 100 digital platforms worldwide and the market value of the EAP digital economy



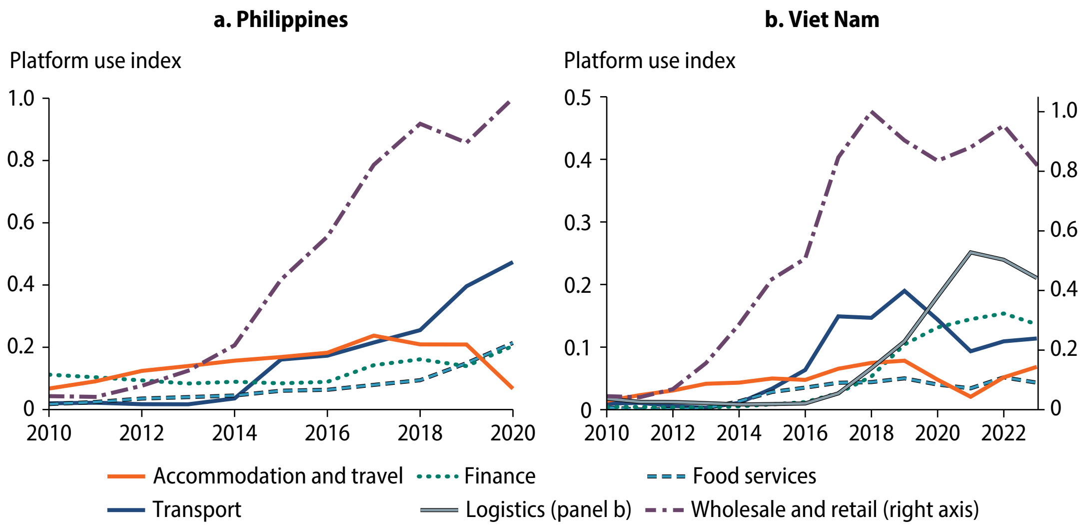
Sources: Original figure for this publication based on Complete List of Unicorn Companies (dashboard), CB Insights Tracker, CB Insights, New York, https://www.cbinsights.com/researchunicorn-companies; FactSet Fundamentals (dashboard), FactSet Research Systems, Norwalk, CT, https://www.factset.com/marketplace/catalog/product/factset-fundamentals; Google, Temasek, and Bain and Company 2023; UNCTAD 2023.
Note: GDP = gross domestic product.

annual report on the digitalization of Southeast Asia shows rapid growth in gross merchandise value among all EAP countries in 2015–22 (refer to figure 5.6, panel b). At current market rates, the size of the digital platform economy is between 5 percent and 7 percent of gross domestic product (GDP) in most EAP countries.

The rapid diffusion of digital platforms in EAP countries may be gauged by observing website traffic in the Philippines and Viet Nam. Platform diffusion may be proxied using data on Google search trends involving major platforms in these countries (refer to figure 5.7). The most explosive growth in website traffic may be observed in the wholesale and retail sectors in both countries. Major e-commerce platforms, such as Grab, Lazada, and Shopee, appeared in 2012–15, and transport and logistics platforms were established in 2015–20. Digital platforms have represented a shock in competition for incumbent firms in the sectors in which the platforms operate. Thus, e-commerce platforms are cutting into the business of traditional wholesalers and retailers by offering customers new ways of connecting with suppliers, such as through online matching, review, and rating systems (Bailin Rivares et al. 2019).

The rapid diffusion of digital platforms in the Philippines and Viet Nam, especially in retail and logistics industries, can be observed from website traffic.

FIGURE 5.7 Growth in user traffic on digital platforms, the Philippines and Viet Nam

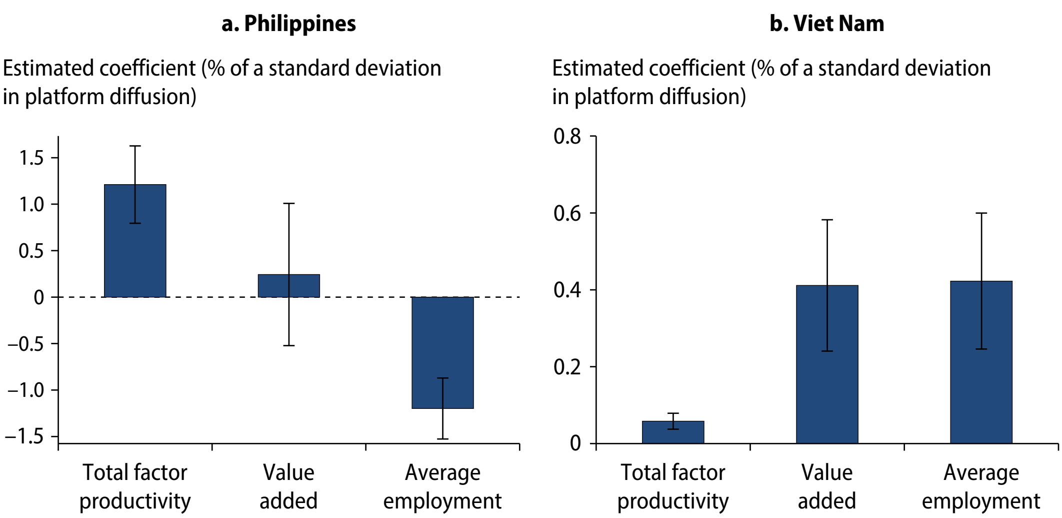


Sources: Original figure for this publication based on data of Baillin Rivares et al. 2019; Google Trends (website), Google, Mountain View, CA, https://trends.google.com/trends; Semrush (software as a service platform), Semrush Holdings, Boston, https://www.semrush.com/.
Note: Information on major online platforms for each sector were collected as web traffic data from Semrush for the Philippines and Viet Nam. The platform use index is normalized relative to retail platform use in 2020 for each country.

The growth of digital platforms in the Philippines and Viet Nam led to increased firm productivity in dependent sectors, but the firm employment effect was mixed. In both countries, platform diffusion is associated with gains in productivity and in value added among firms that use platform services (refer to figure 5.8, panel a). However, the evidence is mixed across the two countries on the effect on average employment among firms (refer to figure 5.8, panel b). Platform diffusion is correlated with a decline in the average firm's employment in the Philippines, suggesting a labor-saving effect, that is, firms are likely substituting internal employment by external services provided on platforms. In contrast, platform diffusion is associated with an increase in employment among firms in Viet Nam, suggesting there is a positive scale effect whereby the increased productivity among firms is potentially leading to greater firm growth and more labor demand.

Platform diffusion has positive effects on firm productivity and value added, but contrasting effects on employment in the Philippines and Viet Nam.

FIGURE 5.8 The effects of platform diffusion on firm productivity, value added, and employment, the Philippines and Viet Nam



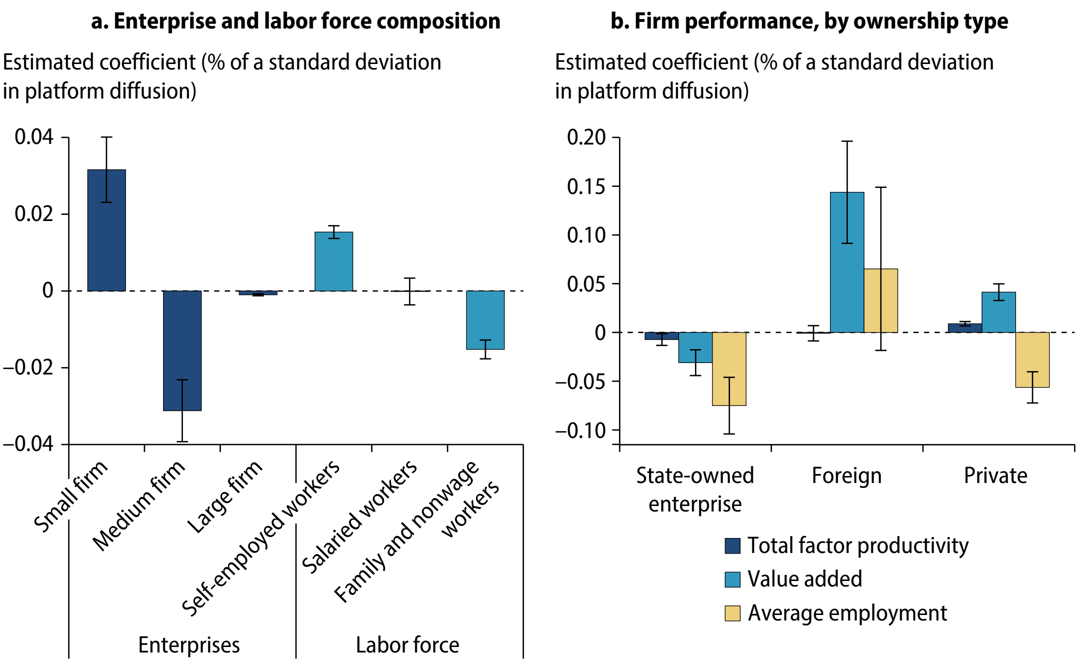
Sources: Original figure for this publication based on data of ASPBI (Annual Survey of Philippine Business and Industry) (portal), Philippine Statistics Authority, Quezon City, the Philippines, https://psa.gov.ph/statistics/survey/business-and-industry/index; CPBI (Census of Philippine Business and Industry) (portal), Philippine Statistics Authority, Quezon City, the Philippines, https://psa.gov.ph/statistics/census/business-and-industry/index; Enterprise Surveys, National Statistics Office, Hanoi, Viet Nam, https://www.gso.gov.vn/en/?s=enterprise+survey&lang=en.

Note: Bars and whiskers present the estimated coefficients and 90 percent confidence intervals from regressions of firm performance metrics on measures of platform diffusion, including firm and year fixed effects. Own-sector results reflect the correlations between firm performance and platform diffusion in accommodation and travel, food services, transport, and wholesale and retail. To aid the comparison of effects, estimates in each country are rescaled and expressed as a percent of the standard deviation in average platform diffusion in that country.

Digital platforms offer new entrepreneurial opportunities for small businesses and self-employed workers within the services in which the platforms operate. The existence of digital platforms has led to more efficient and lower costs in matching between product buyers and sellers (e-commerce) and services (logistics, transportation, finance). Such technological disruption offers new opportunities to individuals who previously could not have afforded entering businesses. Empirical analysis suggests that platform diffusion in Viet Nam has increased the shares of small enterprises and self-employed workers in the economy (refer to figure 5.9, panel a). However, the new competition that platforms have generated against traditional brick-and-mortar business models also implies a negative shock to the

Within the specific service sectors in which digital platforms operate in Viet Nam, platforms generate both business-creation and competition effects.

FIGURE 5.9 Own-sector effects of platforms on enterprise and labor force composition and firm performance, Viet Nam



Source: Original figure for this publication based on 2011–21 Enterprise Surveys, National Statistics Office, Hanoi, Viet Nam, https://www.gso.gov.vn/en/?s=enterprise+survey&lang=en.

Note: Bars and whiskers present the estimated coefficients and 90 percent confidence intervals from regressions of firm and labor force composition (panel a) and firm performance metrics (panel b) on measures of platform diffusion, including firm and year fixed effects. Own-sector results reflect the correlations between firm performance and platform diffusion in accommodation and travel, food services, transport, and wholesale and retail. All variables expressed as shares of total enterprises or the labor force.

performance of less-efficient enterprises, including some state-owned enterprises (refer to figure 5.9, panel b). The empirical evidence presented in figure 5.9, panel b, on the decline in average employment in formal enterprises in both the public (state-owned enterprises) and private sectors also suggests an informalization phenomenon has been fostered by digital platforms: a significant share of salaried workers have left their blue-collar jobs to take up new employment opportunities offered in the informal sector through platforms. This informalization effect may be observed in the passenger-transportation industry following the rapid penetration of digital ride-hailing platforms within the last decade. Box 5.5 offers more nuanced evidence on this effect.

Box 5.5. Income effect of ride-sharing platforms

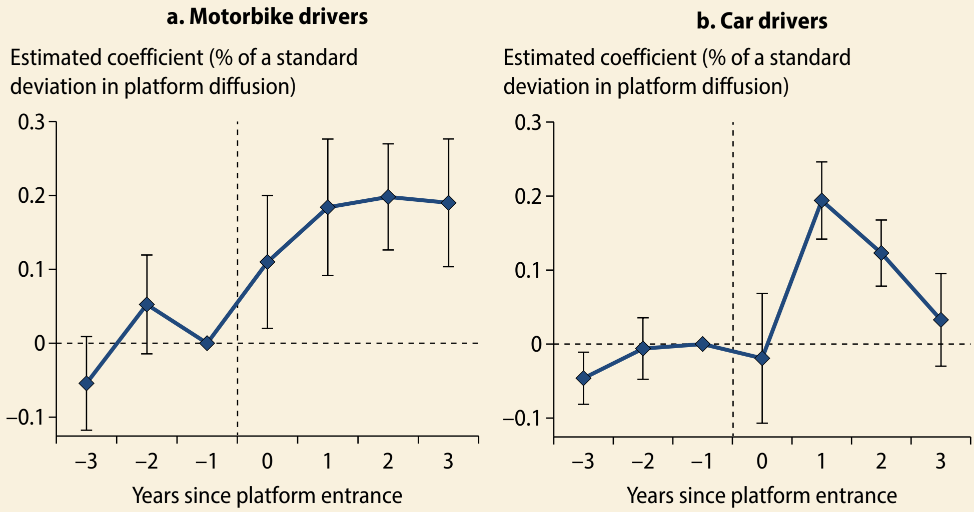
In the last decade, the advent of ride-hailing platforms has helped establish a new business model, offering new job opportunities and labor flexibility globally. Using the staggered introduction of leading ride-hailing platforms in Vietnamese provinces from 2014 to 2021 as a quasi-experimental setting, the analysis investigated the effects of the arrival of digital platforms in a developing country characterized by a significant level of labor informality. Analysis of two separate treatment groups representing distinct segments of Viet Nam's labor market, namely, motorbike and car drivers, revealed substantial positive effects of platforms on worker earnings. The rollout of ride-hailing apps resulted in a more durable impact on motorbike drivers, possibly because of productivity improvements that were introduced to the previously highly informal ride-hailing system (refer to figure B5.5.1, panel a). In contrast, car drivers experienced a notable increase in hourly wages, but only for a short time after the introduction of the platform apps. This positive but short-lived impact is likely explained by the initial platform incentive schemes offered to attract drivers from traditional taxi companies (refer to figure B5.5.1, panel b).

(continued)

Box 5.5. Income effect of ride-sharing platforms *(continued)*

Platform entry had a positive and durable earnings effect on motorbike drivers thanks to technology-driven productivity gains, but the boost in earnings was only transient among car drivers possibly because of a competition effect.

FIGURE B5.5.1 The effects of ride-hailing platform entry on the earnings of motorbike and car drivers, Viet Nam



Source: Original figure for this publication based on 2015–21 Enterprise Surveys, National Statistics Office, Hanoi, Viet Nam, https://www.gso.gov.vn/en/?s=enterprise+survey&lang=en.
Note: Bars and whiskers present the estimated coefficients and 90 percent confidence intervals from a difference in differences regression analysis utilizing staggered ride-sharing platform rollouts across Vietnamese provinces since 2015. The outcome variable is average hourly wages for motorbike drivers (panel a) and car drivers (panel b). The sample is restricted to people ages 16 or more. The regression model controls for year and province fixed effects, age, sex, marital status, educational attainment, province population density, income per capita, and immigration rate. Standard errors are clustered at the province level.

References

Aker, Jenny C. 2010. "Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger." *American Economic Journal: Applied Economics* 2 (3): 46–59.

Aker, Jenny C., and Marcel Fafchamps. 2015. "Mobile Phone Coverage and Producer Markets: Evidence from West Africa." *World Bank Economic Review* 29 (2): 262–92.

Aker, Jenny C., and Christopher Johannes Ksoll. 2016. "Can Mobile Phones Improve Agricultural Outcomes? Evidence from a Randomized Experiment in Niger." *Food Policy* 60 (April): 44–51.

Aker, Jenny C., and Isaac M. Mbiti. 2010. "Mobile Phones and Economic Development in Africa." *Journal of Economic Perspectives* 24 (3): 207–32.

Akerman, Anders, Ingvil Gaarder, and Magne Mogstad. 2015. "The Skill Complementarity of Broadband Internet." *Quarterly Journal of Economics* 130 (4): 1781–824.

Andjelkovic, Maja, and Saori Imaizumi. 2012. "Mobile Entrepreneurship and Employment." *Innovations: Technology, Governance, Globalization* 7 (4): 87–100.

Ariansyah, Kasmad. 2018. "The Importance of the Internet on Improving Economic Welfare: An Empirical Evidence from Indonesian Rural Household." In *Proceedings: The 2018 International Conference on ICT for Rural Development (IC-ICTRuDev)*, edited by Diah Kusumawati, Badar Agung Nugroho, and Emyana Ruth, 118–23. New York: Institute of Electrical and Electronics Engineers.

Atasoy, Hilal. 2013. "The Effects of Broadband Internet Expansion on Labor Market Outcomes." *ILR Review* 66 (2): 315–45.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics* 90 (2): 300–23.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics* 113 (4): 1169–213.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–333.

Bahia, Kalvin, Pau Castells, Genaro Cruz, Takaaki Masaki, Carlos Rodríguez-Castelán, and Viviane Sanfelice. 2021. "Mobile Broadband Internet, Poverty, and Labor Outcomes in Tanzania." IZA Discussion Paper IZA DP 14720 (September), Institute of Labor Economics, Bonn, Germany.

Bailin Rivares, Alberto, Peter N. Gal, Valentine Millot, and Stéphane Sorbe. 2019. "Like It or Not? The Impact of Online Platforms on the Productivity of Incumbent Service Providers." OECD Economics Department Working Paper 1548 (May), Organisation for Economic Co-operation and Development, Paris.

Blumenstock, Joshua Evan, Niall Carrigan Keleher, Arman Rezaee, and Erin Troland. 2020. "The Impact of Mobile Phones: Experimental Evidence from the Random Assignment of New Cell Towers." Background paper, Innovations for Poverty Action, New Haven, CT.

Brynjolfsson, Erik, and Lorin Moultrie Hitt. 2003. "Computing Productivity: Firm-Level Evidence." *Review of Economics and Statistics* 85 (4): 793–808.

Caldarola, Bernardo, Marco Grazzi, Martina Occelli, and Marco Sanfilippo. 2023. "Mobile Internet, Skills, and Structural Transformation in Rwanda." *Research Policy* 52 (10): 104871.

Cariolle, Joël, Maëlan Le Goff, and Olivier Santoni. 2018. "Digital Vulnerability and Performance of Firms in Developing Countries." Working Paper 709 (September), Banque de France, Paris.

Chen, Shiyi, Wanlin Liu, and Hong Song. 2020. "Broadband Internet, Firm Performance, and Worker Welfare: Evidence and Mechanism." *Economic Inquiry* 58 (3): 1146–66.

Chiplunkar, Gaurav, and Pinelopi Koujianou Goldberg. 2022. "The Employment Effects of Mobile Internet in Developing Countries." NBER Working Paper 30741 (December), National Bureau of Economic Research, Cambridge, MA.

Chun, Natalie, and Heiwai Tang. 2018. "Do Information and Communication Technologies Empower Female Workers? Firm-Level Evidence from Viet Nam." ADB Economics Working Paper 545 (May), Asian Development Bank, Manila.

Crandall, Robert W., William Lehr, and Robert E. Litan. 2007. "The Effects of Broadband Deployment on Output and Employment: A Cross-Sectional Analysis of US Data." *Issues in Economic Policy* 6 (July), Brookings Institution, Washington, DC.

Cunningham, Wendy V., Harry Edmund Moroz, Noël Muller, and Aivin Vicquierra Solatorio. 2022. "The Demand for Digital and Complementary Skills in Southeast Asia." Policy Research Working Paper 10070, World Bank, Washington, DC.

Deming, David J., and Lisa B. Kahn. 2018. "Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals." *Journal of Labor Economics* 36 (S1): 337–69.

Dettling, Lisa J. 2017. "Broadband in the Labor Market: The Impact of Residential High-Speed Internet on Married Women's Labor Force Participation." *ILR Review* 70 (2): 451–82.

Donati, Dante. 2023. "Mobile Internet Access and Political Outcomes: Evidence from South Africa." *Journal of Development Economics* 162 (May): 103073.

Emerick, Kyle Jared. 2018. "Agricultural Productivity and the Sectoral Reallocation of Labor in Rural India." *Journal of Development Economics* 135 (November): 488–503.

Fabritz, Nadine. 2013. "The Impact of Broadband on Economic Activity in Rural Areas: Evidence from German Municipalities." Ifo Working Paper 166 (July), Ifo Institute, Leibniz Institute for Economic Research, University of Munich, Munich.

Fadzil, Nurul Asyikin. 2018. "Impact of Digital Economy on the Employment: Evidence from ASEAN Countries." Master's thesis, School of Economics, Finance, and Banking, Universiti Utara Malaysia, Kuala Lumpur, Malaysia. https://etd.uum.edu.my/7816/.

Fafchamps, Marcel, and Bart Minten. 2012. "Impact of SMS-Based Agricultural Information on Indian Farmers." *World Bank Economic Review* 26 (3): 383–414.

Fairlie, Robert W. 2006. "The Personal Computer and Entrepreneurship." *Management Science* 52 (2): 187–203.

Fernandes, Ana Margarida, Aaditya Mattoo, Huy Le Nguyen, and Marc Tobias Schiffbauer. 2019. "The Internet and Chinese Exports in the Pre-Ali Baba Era." *Journal of Development Economics* 138 (May): 57–76.

Forman, Chris, Avi Goldfarb, and Shane Greenstein. 2012. "The Internet and Local Wages: A Puzzle." *American Economic Review* 102 (1): 556–75.

Foster, Andrew D., and Mark R. Rosenzweig. 2008. "Economic Development and the Decline of Agricultural Employment." In *Handbook of Development Economics*, vol. 4, edited by T. Paul Schultz and John A. Strauss, 3051–83. Handbooks in Economics Series 9. Amsterdam: North-Holland.

Goldin, Claudia Dale, and Lawrence F. Katz. 2008. *The Race between Education and Technology*. Cambridge, MA: Belknap Press.

Google, Temasek, and Bain and Company. 2023. *e-Conomy SEA 2023: Reaching New Heights, Navigating the Path to Profitable Growth*. November 1. Singapore: Bain and Company, Google, Temasek International.

Grundke, Robert, Luca Marcolin, The Linh Bao Nguyen, and Mariagrazia Squicciarini. 2018. "Which Skills for the Digital Era? Returns to Skills Analysis." OECD Science, Technology, and Industry Working Paper 2018/09, Organisation for Economic Co-operation and Development, Paris.

GSO (General Statistics Office, Vietnam). 2022. *Report on Labour Force Survey 2021*. Hanoi: Statistical Publishing House. https://www.gso.gov.vn/en/?s=Labour+force+survey&lang=en.

Hjort, Jonas, and Jonas Poulsen. 2019. "The Arrival of Fast Internet and Employment in Africa." *American Economic Review* 109 (3): 1032–79.

Ifeoma, Odunze Daisy, and Hove Tawanda Mthitwa. 2015. "An Analysis of the Impact of the Use of Mobile Communication Technologies by Farmers in Zimbabwe: A Case Study of Esoko and EcoFarmers Platforms." Paper presented at the Association for Information Systems SIG GlobDev 2015 Pre-ECIS Workshop, "Conversations on Development: Can ICTs Make a Difference in Climate, Political, and Health Disturbances?" Munster, Germany, May 26, 2015.

Ivus, Olena, and Matthew Boland. 2015. "The Employment and Wage Impact of Broadband Deployment in Canada." *Canadian Journal of Economics* 48 (5): 1803–30.

Jain, Ritika. 2021. "Information and Communication Technology Adoption and the Demand for Female Labor: The Case of Indian Industry." *BE Journal of Economic Analysis and Policy* 21 (2): 695–722.

Jensen, Robert T. 2007. "The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector." *Quarterly Journal of Economics* 122 (3): 879–924.

Jin, Xin, Baojie Ma, and Haifeng Zhang. 2023. "Impact of Fast Internet Access on Employment: Evidence from a Broadband Expansion in China." *China Economic Review* 81 (October): 102038.

Kaila, Heidi, and Finn Tarp. 2019. "Can the Internet Improve Agricultural Production? Evidence from Viet Nam." *Agricultural Economics* 50 (6): 675–91.

Katz, Lawrence F., and Robert A. Margo. 2014. "Technical Change and the Relative Demand for Skilled Labor: The United States in Historical Perspective." In *Human Capital in History: The American Record*, edited by Leah Platt Boustan, Carola Frydman, and Robert A. Margo, 15–57. Cambridge, MA: National Bureau of Economic Research; Chicago: University of Chicago Press.

Klonner, Stefan, and Patrick James Nolen. 2010. "Cell Phones and Rural Labor Markets: Evidence from South Africa." *Proceedings of the German Development Economics Conference* 56, Ausschuss für Entwicklungsländer, Verein für Socialpolitik, Göttingen, Germany.

Krell, Natasha T., Stacey A. Giroux, Zach Guido, Christian Hannah, Sara C. Lopus, Kelly K. Caylor, and Tyler P. Evans. 2021. "Smallholder Farmers' Use of Mobile Phone Services in Central Kenya." *Climate and Development* 13 (3): 215–27.

Krueger, Alan B. 1993. "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984–1989." *Quarterly Journal of Economics* 108 (1): 33–60.

Kusumawardhani, Niken, Rezanti Pramana, Nurmala Selly Saputri, and Daniel Suryadarma. 2023. "Heterogeneous Impact of Internet Availability on Female Labor Market Outcomes in an Emerging Economy: Evidence from Indonesia." *World Development* 164 (April): 106182.

Labonne, Julien Bernard, and Robert S. Chase. 2009. "The Power of Information: The Impact of Mobile Phones on Farmers' Welfare in the Philippines." Policy Research Working Paper 4996, Impact Evaluation Series 33, World Bank, Washington, DC.

Lee, Kyeong Ho, and Marc F. Bellemare. 2013. "Look Who's Talking: The Impacts of the Intrahousehold Allocation of Mobile Phones on Agricultural Prices." *Journal of Development Studies* 49 (5): 624–40.

Ma, Wanglin, and Xiaobing Wang. 2020. "Internet Use, Sustainable Agricultural Practices, and Rural Incomes: Evidence from China." *Australian Journal of Agricultural and Resource Economics* 64 (4): 1087–112.

Michaels, Guy, Ashwini Natraj, and John Van Reenen. 2014. "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years." *Review of Economics and Statistics* 96 (1): 60–77.

Mitra, Sandip, Dilip Mookherjee, Maximo Torero, and Sujata Visaria. 2018. "Asymmetric Information and Middleman Margins: An Experiment with Indian Potato Farmers." *Review of Economics and Statistics* 100 (1): 1–13.

Mittal, Surabhi, and Mamta Mehar. 2012. "How Mobile Phones Contribute to Growth of Small Farmers? Evidence from India." *Quarterly Journal of International Agriculture* 51 (3): 227–44.

Muro, Mark, Sifan Liu, Jacob Whiton, and Siddharth Kulkarni. 2017. "Digitalization and the American Workforce." November, Metropolitan Policy Program, Brookings Institution, Washington, DC.

Muto, Megumi, and Takashi Yamano. 2009. "The Impact of Mobile Phone Coverage Expansion on Market Participation: Panel Data Evidence from Uganda." *World Development* 37 (12): 1887–96.

Navarro, Lucas. 2010. "The Impact of Internet Use on Individual Earnings in Latin America." Development Research Working Paper 11/2010 (September), Institute for Advanced Development Studies, La Paz, Bolivia.

Ndubuisi, Gideon, Chuks Otioma, and Godsway Korku Tetteh. 2021. "Digital Infrastructure and Employment in Services: Evidence from Sub-Saharan African Countries." *Telecommunications Policy* 45 (8): 102153.

Nguyen, Thanh-Tung, Trung Thanh Nguyen, and Ulrike Grote. 2023. "Internet Use and Agricultural Productivity in Rural Vietnam." *Review of Development Economics* 27 (3): 1309–26.

Nguyen, Trung Thanh, Manh Hung Do, Dil Bahadur Rahut, Viet Hung Nguyen, and Panharoth Chhay. 2023. "Female Leadership, Internet Use, and Performance of Agricultural Cooperatives in Vietnam." *Annals of Public and Cooperative Economics* 94 (3): 877–903.

Pham, Trang Thi. 2023. "Mobile Internet and Income Improvement: Evidence from Viet Nam." WIDER Working Paper 2023/145 (December), United Nations University–World Institute for Development Economics Research, Helsinki.

Qiang, Christine Zhen-Wei, Siou Chew Kuek, Andrew Dymond, and Steve Esselaar. 2012. *Mobile Applications for Agriculture and Rural Development*. Report 96226-GLB (May). Washington, DC: ICT Sector Unit, World Bank.

Salsabila, Roghibah, and Siskarossa Ika Oktora. 2022. "The Impact of Broadband Access on Unemployment Rate in Indonesia 2016–2019." *Asian Journal of Business Environment* 12 (3): 23–30.

Shimamoto, Daichi, Hiroyuki Yamada, and Martin Gummert. 2015. "Mobile Phones and Market Information: Evidence from Rural Cambodia." *Food Policy* 57 (November): 135–41.

Tadesse, Getaw, and Godfrey Bones Bahiigwa. 2015. "Mobile Phones and Farmers' Marketing Decisions in Ethiopia." *World Development* 68 (April): 296–307.

Viollaz, Mariana, and Hernán Jorge Winkler. 2022. "Does the Internet Reduce Gender Gaps? The Case of Jordan." *Journal of Development Studies* 58 (3): 436–53.

UNCTAD (UN Trade and Development). 2023. "E-commerce and Digital Economy Programme, Year in Review 2022; Looking beyond Current Crises: Boosting Digital Readiness in Developing Countries." UNCTAD, Geneva.

Wan, Jianxiang, Changteng Nie, and Fan Zhang. 2021. "Does Broadband Infrastructure Really Affect Consumption of Rural Households? A Quasi-Natural Experiment Evidence from China." *China Agricultural Economic Review* 13 (4): 832–50.

World Bank. 2021. *Beyond Unicorns: Harnessing Digital Technologies for Inclusion in Indonesia*. Washington, DC: World Bank.

World Bank. 2024. *Jobs and Technology: East Asia and the Pacific Economic Update*. October. Washington, DC: World Bank.

Zang, Dungang, Yunqi Yang, Zhijia Hu, Jianfeng He, and Siyu He. 2023. "The Impact of Phone Use on Energy Poverty: Evidence from Tibet, China." Energy for Sustainable Development 72 (February): 11–18.

Zhang, Liangliang, Yunqing Tao, and Cong Nie. 2022. "Does Broadband Infrastructure Boost Firm Productivity? Evidence from a Quasi-Natural Experiment in China." *Finance Research Letters* 48 (August): 102886.

Technology, Jobs, and Structural Transformation: An Integrated View

6

Introduction

This chapter first takes stock of the findings and implications of the analysis so far on the three types of technologies: industrial robots, artificial intelligence (AI), and digitalization, including digital platforms. Although the findings are technology-specific, both the adoption of technology and the impacts on the labor market are interdependent across sectors. The chapter subsequently examines the general equilibrium effects of technology adoption across sectors.

Summary of the empirical evidence

Table 6.1 provides a link between the stylized facts of East Asia and Pacific (EAP) labor markets (chapter 1) and the findings on the impacts of technological change in the region. Automation in manufacturing, brought about by the adoption of industrial robots, is on average associated with positive changes in employment and wages (chapter 3). The productivity effects of industrial robots outweigh the labor-displacing effects in EAP countries. While data limitations preclude analysis of the impacts of digital technologies in agriculture, the previous automation in agriculture was also associated with farm productivity gains and no overall employment displacement effects (refer to spotlight 3.1). It is too early to assess the impacts of AI. Nonetheless, although jobs exposed to AI tend to earn less than jobs that are less exposed, there is no discernible correlation between AI exposure and changes in employment (chapter 4). Digitalization, including digital platforms, are providing new opportunities for the previously unemployed and underemployed by allowing flexible work arrangements; and digital-intensive jobs pay more (chapter 5).

TABLE 6.1 Linking stylized facts about EAP labor markets and the implications of technology adoption

Item	Stylized fact	Industrial robots	AI	Digitalization, platforms
Overall labor market				
Employment	Shrinking working-age population	Net positive changes	No association with employment growth	New opportunities for previously unemployed; new job creation
Wages	Robust growth	Positive changes	AI-exposed jobs are associated with lower earnings	Digital intensive jobs are high-earning
Group heterogeneity				
Age	Youth unemployment; lower LFP of older workers	Younger workers benefit	Younger workers are more exposed	Younger workers benefit, being more familiar with digital tech
Gender	Persistent gender LFP and wage gaps	Both men and women benefit	Women are more exposed	Flexible work arrangements increase female LFP
Education	Gaps in foundational skills; limited advanced skills; large skills wage premium	The more educated benefit	The more educated are more exposed	The more educated workers benefit, but the marginalized can also benefit from digital platforms
Sector and occupation	ICT and tech professions see high wage growth, but not much increase in employment	Routine and physical jobs displaced	Routine and cognitive jobs are more exposed	Digital occupations show high wage premiums; positive employment growth in some countries

Source: Original table for this publication.
Note: AI = artificial intelligence; ICT = information and communication technology; LFP = labor force participation.

However, the benefits of these technological advances are not evenly distributed. For example, younger workers and the more educated tend to benefit more from robotization, while jobs that involve more routine and manual tasks tend to be negatively affected. Exposure to AI is not uniform either. Younger workers, women, and the more educated are more exposed, and, specifically workers in occupations that involve more cognitive or routine tasks are at risk of displacement. Meanwhile, younger workers and women can benefit from the new opportunities created by digitalization and digital platforms.

In sum, new technologies have the potential to help address challenges, such as declining working-age populations in some countries, and can support wage growth through productivity increases. These technologies could also help address labor market inequalities, such as low female labor force participation and youth unemployment. However, because the benefits of new technologies tend to be concentrated among the more educated and nonroutine jobs, they may also exacerbate disparities in job opportunities and earnings. Chapter 7 examines policies that can help ensure that the benefits from new technologies are widely shared. The next section discusses the broader impacts on jobs of the adoption of these technologies across sectors.

Cross-sectoral impacts of technology adoption on jobs

To assess the overall impact of technology on jobs, a consideration of the effects of technology on the whole economy is essential. The empirical evidence examined so far in this report relies on partial equilibrium analysis. A general equilibrium framework is needed to capture the interdependence of technology choices across sectors. The economic viability of adoption in each sector depends on wages and prices, which depend on the choices made in other sectors. For example, the more rapid adoption of labor-saving technologies in one sector could push down economy-wide wages and reduce the incentive to adopt such technologies in other sectors. It is therefore necessary to consider the characteristics of the sectors in which technical change occurs and the ways the various sectors interact, including through the movement of production factors across sectors.

The empirical literature distinguishes three channels that create interdependence among sectors: the job-displacing substitution effect (captured by the elasticity of substitution between labor and capital-embodied technology), the job-creating demand effect (captured by the product demand elasticity), and the cross-sectoral effects through which factors are reallocated among sectors (Acemoglu 2007; Baldwin, Haaland, and Venables 2021). The first channel involves a job displacement effect associated with the adoption of labor-saving technology in any given sector. For example, if labor tasks are more susceptible to automation in agriculture than in manufacturing and services, the agricultural employment share will tend to fall as technology progresses.

The second channel is the job-creating demand effect that arises because technological progress lowers production costs and prices. For instance, if product demand in a sector is more elastic (trade-oriented sectors tend to have more elastic demand, for example), technological change would tend to expand output and employment in that sector.

The third channel results from differences in the relative intensity of capital and labor across sectors. For instance, if technological progress in agriculture displaces labor, then farm wages will fall; labor will relocate to manufacturing and services; and the overall effects on employment will depend on the relative labor intensity of the sectors. (Refer to box 6.1 for details and an illustrative selective summary of recent empirical literature.) If technological progress occurs simultaneously across sectors, the overall impacts on jobs depend on the relative magnitudes of these three effects.

Box 6.1. General equilibrium impacts of technology adoption on jobs

Baldwin, Haaland, and Venables (2021) offer a useful conceptual framework linking technological change and jobs economy-wide. Their analysis distinguishes three channels. The first channel involves a job displacement effect that depends on cross-sectoral differences in the elasticity of substitution between labor and capital-embodied technology. The second channel is the job-creating demand effect that arises because technological progress generates shifts in demand that depend on the product demand elasticity across sectors. The third channel results from differences in the relative intensity and reallocation of capital and labor across sectors. This is captured by Rybczyński elasticity, which measures the change in output of a sector in response to a change in the supply of labor and capital in each sector (Rybczyński 1955). The general equilibrium impacts of technological change depend on the relative magnitude of the three elasticities. The model also illustrates how the presence of a nontradable sector can mitigate the adverse effects of technological change. The demand elasticity in a sector depends on the sector's trade exposure. Thus, export-oriented products that are impacted by technological change exhibit more elastic demand, which tends to mitigate the labor displacement effects.

Herrendorf, Rogerson, and Valentinyi (2014) examine the role of technology adoption in driving relative price changes across sectors. They show that, if the manufacturing sector adopts a technology that significantly boosts productivity, the relative price of manufactured goods will decline. If the elasticity of substitution between capital and labor in manufacturing is high, firms will substitute labor with capital, thereby reducing labor demand in manufacturing. Conversely, if the price elasticity of demand for manufactured goods is high, the lower prices will stimulate demand, potentially increasing labor demand in manufacturing. Their results show

(continued)

Box 6.1. General equilibrium impacts of technology adoption on jobs *(continued)*

that, if relative prices fall most sharply in agriculture, followed by manufacturing and services, the agricultural shares of employment and value added will decline; the services share will rise; and the manufacturing share will decrease less than the agricultural share and increase less than the service share.

Matsuyama (2009) provides insights into the way differences in the patterns of technology adoption across countries may impact jobs. The study shows that, in a two-country model, technological progress in manufacturing tends to reduce the total manufacturing labor share in both countries. If one country experiences stronger technological progress in manufacturing, its manufacturing labor share may initially rise, while the other country's share declines. However, once technological progress in manufacturing deepens, the manufacturing labor share in the leading country will also decline. These results suggest a hump-shaped relationship between technological progress and the manufacturing labor share in the country that experiences more rapid technological advancement.

Álvarez-Cuadrado and Poschke (2011) provide evidence on the role of differences in the elasticity of substitution and product demand elasticities in driving the decline in the agricultural employment share in 12 developed economies. Their evidence suggests that productivity improvements in nonagricultural sectors played a pivotal role before 1960, while agricultural productivity gains became the main driver after 1960. For instance, in the United States, the labor pull channel dominated before World War I, driven by productivity improvements in manufacturing, while, post-World War II, the labor push channel became more significant, as technological advances in agriculture drove workers out of the sector.

Álvarez-Cuadrado and Long (2011) offer complementary evidence on the role of capital-labor substitution in explaining the decline in the agricultural employment share. They find that an elasticity of substitution between capital and labor that is higher in agriculture than in manufacturing and services explains the more rapid growth in the capital-labor ratio in agriculture and the substantial drop in the share of labor in agriculture in the United States between 1960 and 2010.

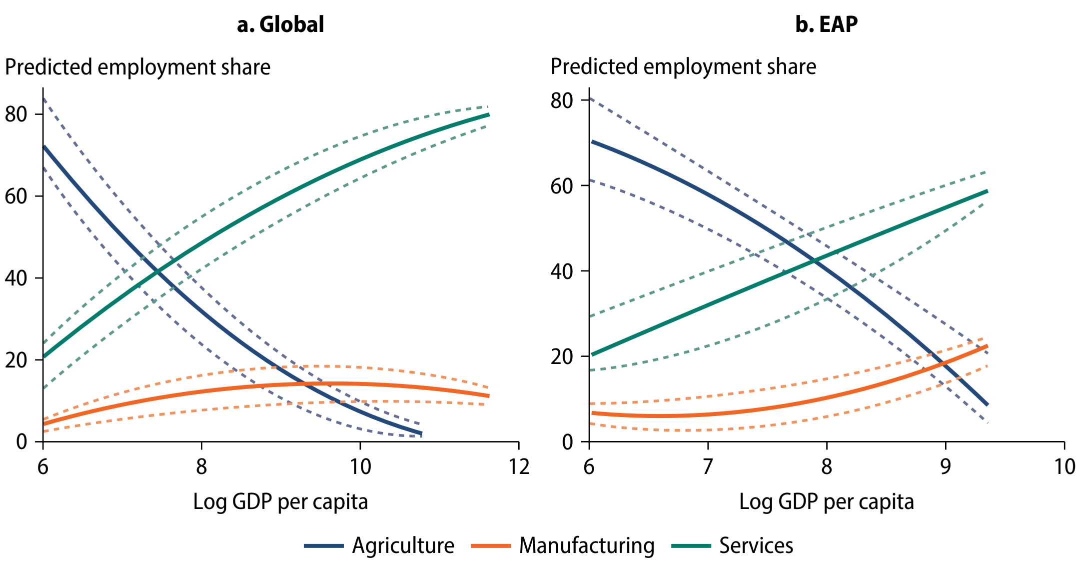
The findings from the general equilibrium literature underscore the importance of relative factor intensities across sectors and the need to account for multiple elasticities in evaluating the labor market consequences of technological progress.

Globally and within the EAP region, as economies grow wealthier and as technology adoption advances, the employment structure is transformed. Employment initially shifts from agriculture to manufacturing and, to a lesser extent, to services (refer to figure 6.1). Employment thereafter shifts more strongly to services. Relative to the early industrialized countries, this shift has taken place at lower levels of income and at lower shares of manufacturing employment in the late industrializing middle-income countries (Rodrik 2016). The EAP region, on average, defies this trend. Whereas, globally, the manufacturing share of employment peaked at around 14 percent at US$15,000 gross domestic product per capita (2021 constant prices at purchasing power parity), manufacturing employment in the EAP region, on average, was still increasing and showing no signs of peaking.

The EAP region resembles the rest of the world in the employment implications of agricultural mechanization, but the implications of industrial robotization in several EAP countries have been different so far. Mechanization in agriculture is

The share of employment in industry has continued to rise in some EAP countries, diverging from the global trend.

FIGURE 6.1 The structure of employment and economic development in EAP and the world, circa 1991–2023



Source: Original figure for this publication based on data of WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.

Note: The lower and upper dashed bands correspond to the predicted employment shares at the 25th and 75th percentiles of the distribution of employment shares at each level of per capita income across countries and over time. GDP = gross domestic product.

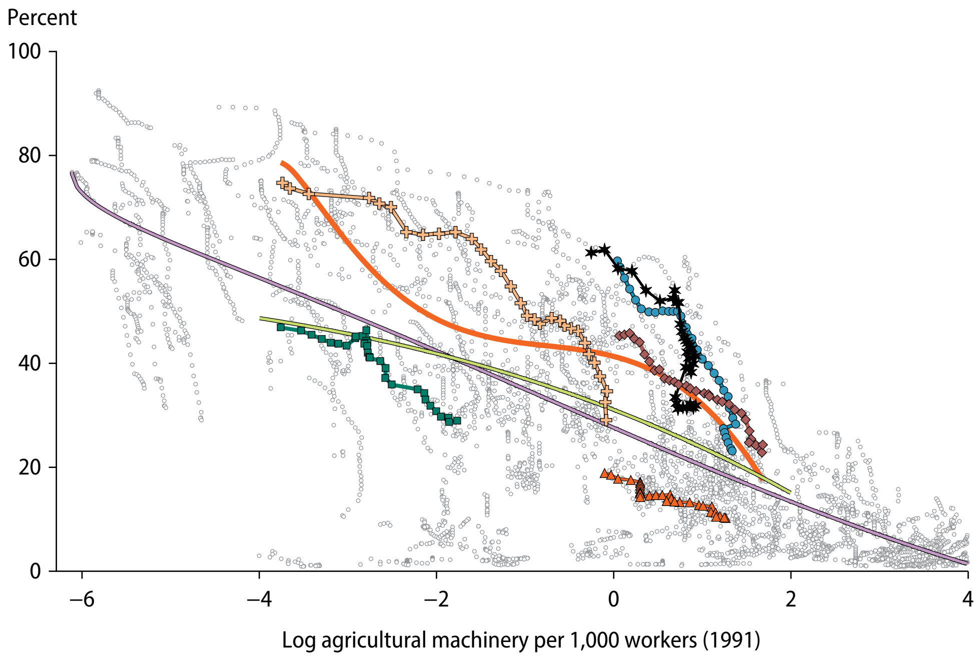
associated with a shrinking share of farm employment globally and in the EAP countries (refer to figure 6.2). Globally, the share of manufacturing employment increases in the early stages of robot adoption and then begins to decline. The fall is sharper in middle-income economies outside the EAP region, which may help explain the phenomenon of premature deindustrialization. Developing countries in EAP have defied this pattern. The share of employment in industry has continued to rise in the region even as countries deepen robot adoption. These macrotrends are consistent with the evidence in chapter 3 showing that localities that experienced more rapid robot adoption also witnessed more rapid employment growth.

EAP's comparative advantage in manufacturing may have been magnified by the productivity boost from the adoption of robots. And the high price elasticity of demand in global markets may have led to a large expansion in the scale of production that was stronger than any negative substitution effects on the demand

The share of employment in industry has continued to rise even in EAP countries with rapid robot adoption, while the share of agricultural employment has shrunk.

FIGURE 6.2 Technology adoption, changes in employment structure, and economic development, EAP and the world, 1991–2021

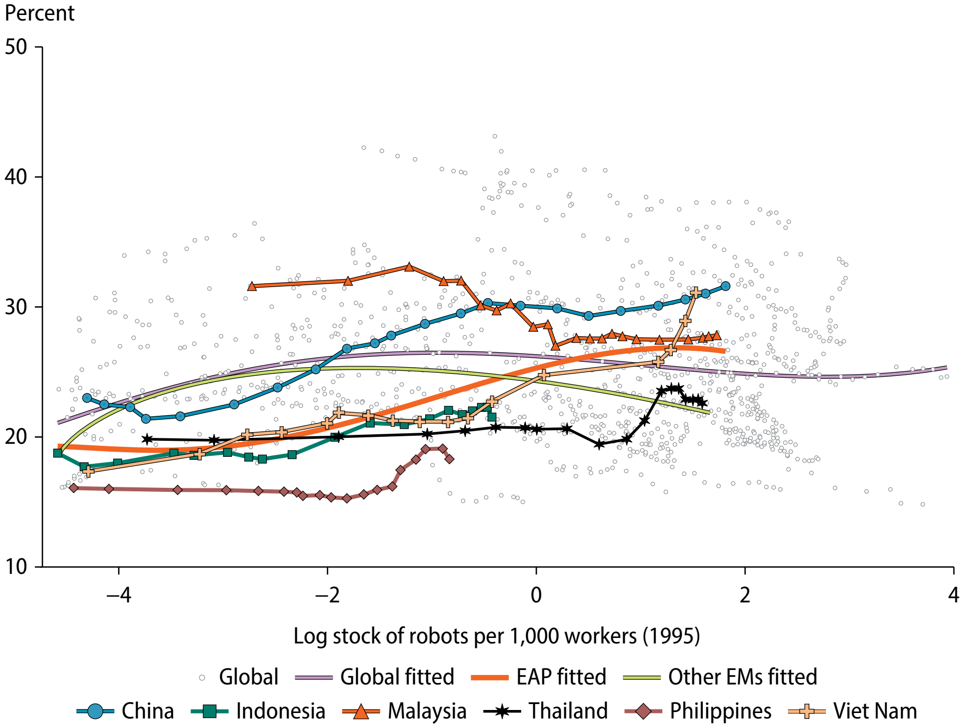
a. Agricultural employment share and mechanization



(continued)

FIGURE 6.2 Technology adoption, changes in employment structure, and economic development, EAP and the world, 1991–2021 *(continued)*

b. Manufacturing employment share and robot adoption



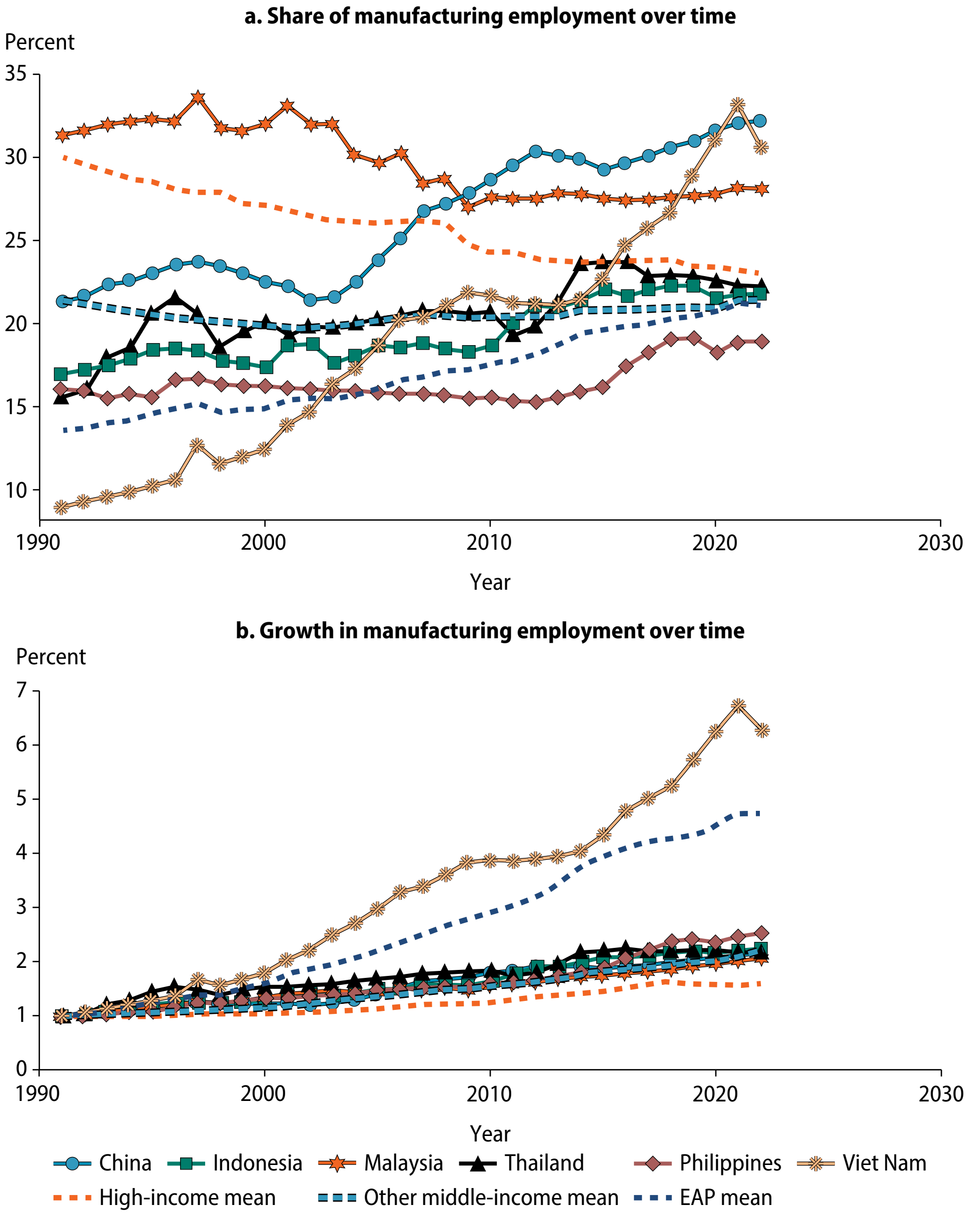
Sources: Original figure for this publication based on data of TiM (Trade in Employment) (database), Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/data/datasets/trade-in-employment.html; USDA 2023; WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.
Note: The fitted lines represent a third-degree polynomial fit. EMs = emerging markets.

for labor. China and Viet Nam, which have seen the most rapid growth in robot penetration, have also seen the fastest growth in the share of industrial employment (refer to figure 6.3). The other two countries with high penetration show mixed outcomes. Malaysia shows a declining share from a high initial share followed by flattening, and Thailand exhibits rising shares of industrial employment followed by flattening.

From a general equilibrium perspective, the agricultural employment share has declined more quickly in the EAP countries in which mechanization has taken place in tandem with a large expansion of employment in export-oriented manufacturing (in China, Malaysia, and Thailand initially and, more recently, in Cambodia and

China and Viet Nam exhibit the fastest rise in the share of industrial employment despite rapid robot penetration.

FIGURE 6.3 Trends in the level and the share of employment in manufacturing, EAP and the world, 1990–2022



Source: Original figure for this publication based on data of WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.
Note: Mean lines show the simple average of countries with population at more than 1 million.

Viet Nam). These developments reflect strong productivity gains from technology adoption in agriculture and manufacturing and differences in the responsiveness of demand. Higher productivity and lower prices have translated into smaller increases in the scale of production in agriculture than in manufacturing.

Having successfully used dynamic export-oriented manufacturing to sustain the transition of employment from agriculture to manufacturing, developing EAP countries need to ensure that, in the future, a dynamic services sector offers productive employment opportunities for people leaving agriculture and manufacturing. In China, Malaysia, Thailand, Viet Nam, and elsewhere, manufacturing dynamism has been driven by openness to trade and foreign direct investment (FDI) in manufacturing and investments in basic and intermediate skills. EAP countries need to harness the potential of AI, especially in the services sector. These opportunities will materialize if reforms are undertaken to open services to trade and FDI and the workforce is equipped with the more advanced skills required by AI-powered technology (World Bank 2024).

References

Acemoglu, Daron. 2007. "Equilibrium Bias of Technology." *Econometrica* 75 (5): 1371–409.

Álvarez-Cuadrado, Francisco, and Ngo Van Long. 2011. "Relative Consumption and Renewable Resource Extraction under Alternative Property-Rights Regimes." *Resource and Energy Economics* 33 (4): 1028–53.

Álvarez-Cuadrado, Francisco, and Markus Poschke. 2011. "Structural Change Out of Agriculture: Labor Push Versus Labor Pull." *American Economic Journal: Macroeconomics* 3 (3): 127–58.

Baldwin, Richard Edward, Jan I. Haaland, and Anthony J. Venables. 2021. "Jobs and Technology in General Equilibrium: A Three Elasticities Approach." Department of Economics Discussion Paper 933 (January), University of Oxford, Oxford, UK.

Herrendorf, Berthold, Richard Rogerson, and Ákos Valentinyi. 2014. "Growth and Structural Transformation." In *Handbook of Economic Growth*, vol. 2B, edited by Philippe Aghion and Steven N. Durlauf, 855–941. Amsterdam: Elsevier.

Matsuyama, Kiminori. 2009. "Structural Change in an Interdependent World: A Global View of Manufacturing Decline." *Journal of the European Economic Association* 7 (2–3): 478–86.

Rodrik, Dani. 2016. "Premature Deindustrialization." *Journal of Economic Growth* 21 (1): 1–33.

Rybczyński, Tadeusz Mieczysław. 1955. "Factor Endowment and Relative Commodity Prices." *Economica* 22 (88): 336–41.

USDA (United States Department of Agriculture). 2023. "International Agricultural Productivity Data Product." September, Economic Research Service, USDA, College Park, MD.

World Bank. 2024. *Services Unbound: Digital Technologies and Policy Reform in East Asia and Pacific*. East Asia and Pacific Development Studies. Washington, DC: World Bank.

Policy Implications 7

Introduction

The countries of the East Asia and Pacific (EAP) region need to harness the productivity potential inherent in new digital technologies while mitigating the risks these technologies pose to workers. Apart from the requirement to build the digital infrastructure to realize this goal, four areas deserve policy attention: equipping the workforce with the digital, socioemotional, and technical skills that complement the new technologies; facilitating labor and capital mobility; removing factor price distortions that could lead to the adoption of inappropriate technologies; and expanding social protection to workers in the new informal digital economy.

Skills

The evidence suggests that workers need skills that are complementary to digital technologies to be shielded from displacement and reap the benefits of the technologies. Predicting future trends in technology is difficult, but three broad types of skills seem relevant. First, digital skills equip individuals to engage with an increasingly digitalized workplace that relies on digital devices, applications, and platforms. Second, social and emotional skills give people a comparative advantage over machines in tasks that involve social interactions, such as in education and health care. Third, advanced technical skills enable individuals to create and work with the new technologies.

As economies grow, the skills they demand expand in variety and complexity, especially as they reach upper-middle-income and high-income status (Bandiera et al. 2022; World Bank 2024c). All countries in the EAP region, from Cambodia to

Viet Nam, require a broad base of foundational skills gained through universal access to quality basic education, which can become the foundation of diversified talent. Yet, even the relatively advanced countries in the region have significant weaknesses in reading and mathematics (Afkar et al. 2023). The notion of foundational skills now encompasses digital and socioemotional skills, which are rarely the focus of schools. To develop the ability to adopt and learn from existing and new technologies, the middle-income countries, such as Indonesia, the Philippines, and Viet Nam, need a workforce with technically skilled workers (from mid-level technicians to engineers and managers) and workers with mid-level and advanced digital skills (ADB and LinkedIn 2022). As countries progress into high-income and innovation-driven economies, such as China, Malaysia, and Thailand, they need a greater emphasis on more advanced skills, ensuring a workforce that includes more scientists and other highly skilled professionals.

The development of workforce skills can be hindered by market and government failures. Governments should seek to ensure equitable access to the development of skills by all members of society, especially the underprivileged. Through financing, regulation, or direct provision, they can remedy some market failures, such as credit constraints and information asymmetries. They should also avoid policy failures by, for example, not allowing political influence to aggravate adverse selection and moral hazard in the choice of teaching staff and to inhibit competition in skills provision. The current rapidly evolving, unpredictable trends in digital technologies call for close cooperation between the public and private sectors.

Digital skills

Japan, the Republic of Korea, and Singapore have implemented comprehensive digital education strategies from which other countries could learn. The strategies include adding digital skills in curricula, the use of digital textbooks, online learning platforms, and coding classes. Schools are equipped with high-speed internet and digital devices. Thus, the GIGA School Program in Japan aims to provide every student with a personal digital device and high-speed internet access. Teachers receive ongoing professional training to enhance their digital and pedagogic competencies. The SkillsFuture for Educators Program in Singapore helps teachers develop their digital competencies and adapt to changes in technology (Fung, Taal, and Sim 2021).

Some countries in the EAP region have undertaken important reforms to address gaps in digital skills. The government of the Philippines has fostered access to digital infrastructure and devices as part of a comprehensive digital strategy. These efforts are being implemented in cooperation with the private sector (refer to box 7.1). A comprehensive digital strategy that includes improvement in digital skills and backbone digital infrastructure, such as internet connection, would also yield greater impacts in the Pacific Islands, where the majority of governments are not yet ready to capitalize on cutting-edge digital technologies such as robots and artificial intelligence (AI). The availability of reliable internet connections will offer the opportunity to provide remote labor-intensive services (for instance, call centers and basic professional services) that make the most of the time zone advantages of the countries as relays between Asia and the United States and of their widespread English fluency.

Box 7.1. Policy responses to the emergence of artificial intelligence in the Philippines

The digital economy is an increasingly important source of income and jobs in the Philippines, accounting for a fifth of total employment in 2023. The impact of artificial intelligence (AI) will depend on how well prepared firms, workers, and public policies are to take advantage. As of 2023, the Philippines ranked 65 in 174 countries on the International Monetary Fund's AI preparedness index, that is, below most of its peers in the Association of Southeast Asian Nations. About 26 percent of jobs in the Philippines are considered highly exposed to displacement by digital technologies and possess low complementarity, indicating they are less able to benefit from these technologies. In business process outsourcing (BPO), a key growth and jobs engine in the Philippines, AI could either augment or undermine the country's competitive edge.

Short-term responses

The government of the Philippines has advanced reforms to develop the digital economy. In 2023, the Digital Workforce Competitiveness Act was passed to address gaps in digital technology and skills (Supreme Court E-Library 2022). In July 2024, the government launched the National Artificial Intelligence Strategy Roadmap 2.0 and the Center for Artificial Intelligence Research (DTI 2024). The roadmap reinforces the 2021 roadmap and upgrades national development strategies following recent technological advances (DOST-PCIEERD 2020). The AI center, meanwhile, aims to position the Philippines as a global leader in AI-driven innovation (ECCP 2022).

The government is preparing a national jobs masterplan with a key focus on skills development and training appropriate for emerging technologies (Cruz 2024; NEDA 2024). The legislature is advancing proposals on the development and responsible

(continued)

Box 7.1. Policy Responses to the Emergence of Artificial Intelligence in the Philippines *(continued)*

use of AI and to address the associated impact on government services, innovation, labor markets, and the future of jobs (Senate of the Philippines 2023).

Addressing longer-term challenges

Poor education quality hinders the ability to harness the potential of new technologies to improve the productivity of Philippine workers. Reading proficiency and mathematics skills are necessary to use AI and automation effectively, but an estimated 91 percent of children of late primary-school age in the Philippines cannot read and understand an age-appropriate text. Teacher working conditions, selection processes, and professional development must be enhanced to improve teaching and learning in the country.

The recent reform to streamline the curriculum can help teachers and students struggling with many subjects. The new curriculum has a stronger focus on foundational literacy and numeracy and on twenty-first century skills. In tertiary education, similar reforms include a curriculum update, faculty training, research and development, and industry partnerships.

The government is also addressing digital infrastructure gaps. It has lifted foreign ownership restrictions in services, including telecommunication, facilitated the construction and sharing of mobile towers, and adopted a national digital connectivity plan that aims to deploy broadband infrastructure in remote and isolated communities across the country.

Private sector initiatives: Spotlight on BPOs

The private sector has acknowledged the potential disruptions associated with AI, particularly among less-skilled workers (CIPD 2017). The BPO industry has updated the industry roadmap and seeks to use AI to enhance the productivity of its workers (IBPAP 2024; Talavera 2024). Around two-thirds of BPO member firms have adopted or piloted AI initiatives, including Agent Assist, aimed at worker augmentation instead of outright automation (IBPAP 2024). Industry associations have developed common standards for skills development, such as the Philippine skills framework, including in analytics and AI, and support the upskilling of academic faculty by partnering with schools and industry partners, such as Google and NVIDIA (DICT 2021; DICT and AAP 2024).

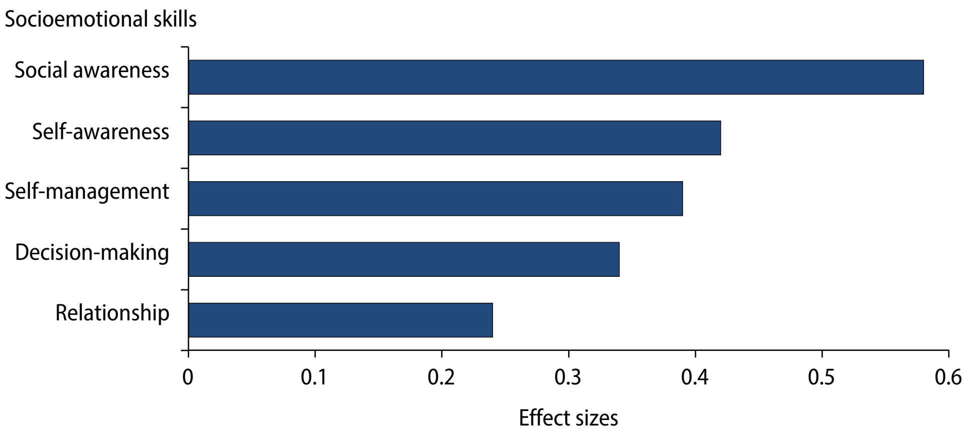
Social and emotional skills

Research supports the notion that social and emotional skills are malleable and teachable through school interventions (Steponavičius, Gress-Wright, and Linzarini 2023). Multiple meta-analyses of rigorous evaluations of socioemotional learning programs show improvement from preschool to secondary school and across national contexts (Cipriano et al. 2023; Grant et al. 2017; Jones et al. 2021). The Organisation for Economic Co-operation and Development (OECD)'s latest review of recent studies finds that not all social and emotional skills are equally teachable and that the effectiveness of socioemotional learning programs varies with the quality of implementation and context (Steponavičius, Gress-Wright, and Linzarini 2023). For instance, empathy, cooperation, self-control, assertiveness, emotional control, social problem-solving, and self-efficacy are the most teachable skills (refer to figure 7.1).

Various countries have implemented programs to integrate socioemotional learning into basic education systems, demonstrating different approaches and impacts

Socioemotional skills can be developed in schools.

FIGURE 7.1 Meta-analysis of socioemotional learning programs: Average impacts



Source: Original figure for this publication based on van de Sande et al. 2019.
Note: Meta-analysis covers 40 randomized controlled trials and quasi-experimental design studies in 12 countries on children, ages 11–19. Decision-making = ability to make caring and constructive choices about personal behavior and social interactions across diverse situations. Relationship = ability to establish and maintain healthy and supportive relationships and navigate settings effectively with diverse individuals and groups. Self-awareness = ability to understand one's own emotions, thoughts, and values and how these influence behavior in and across contexts, including recognizing one's strengths, limitations, and possession of well-grounded confidence and purpose. Self-management = ability to manage one's emotions, thoughts, and behaviors effectively in different situations and to achieve goals and aspirations. Social awareness = ability to understand the perspectives of and empathize with others, including those from diverse backgrounds, cultures, and contexts.

(refer to box 7.2). Social and emotional skills are now included in the curricula of most OECD countries and other developing economies, such as Colombia and India. Other countries have implemented stand-alone programs to develop specific socioemotional skills, which allows for rigorous evaluation of impacts. In the EAP region, efforts in this area are nascent. The government of Malaysia recently started integrating socioemotional learning in schools with a strong focus on providing teachers with training and resources to deliver socioemotional learning lessons effectively.

Box 7.2. Fostering the socioemotional skills of children

The governments of Colombia and the Republic of Korea have implemented comprehensive programs to integrate socioemotional learning into regular curricula and teaching in basic education. In Colombia, socioemotional learning has been integrated into the basic education curriculum, and teachers are trained to deliver structured lessons and activities that encourage students to develop empathy, positive social interactions, and emotional regulation. In Korea, socioemotional learning and creativity have been integrated as cross-curricular themes in all subjects. For instance, socioemotional skills are embedded in the teaching of mathematics and science through activities that encourage initiative-taking, decision-making, and collaboration. This integrated approach aims to develop socioemotional skills alongside cognitive skills.

In Indonesia, a large-scale intervention has been implemented to develop a growth mindset—that is, beliefs that intelligence and other socioemotional qualities are not fixed but develop with effort—across 2,404 public junior secondary schools and 160,000 students. The intervention has included structured lessons delivered in schools by teachers. A rigorous evaluation found positive impacts on growth mindset and test scores on the national standardized mathematics exam, as well as gains in science and English language in schools with a higher quality program implementation (World Bank 2019a). The intervention was cost-effective, at an average of US$0.25 per student.

In North Macedonia and Türkiye, two separate at-scale interventions (in the former case, nationwide) have been shown to be cost-effective in developing socioemotional skills related to grit—the ability to persevere and sustain interests over time—and improve academic achievement among elementary- and

(continued)

Box 7.2. Fostering the socioemotional skills of children *(continued)*

middle-school children, especially the disadvantaged (Alan, Boneva, and Ertac 2019; Santos et al. 2022).

In Türkiye, a pedagogical intervention was implemented in 134 primary schools, covering about 11,000 students and 425 teachers. It was aimed at improving learning among elementary school children by fostering their curiosity. The intervention involved creating a sense of information deprivation and quantifying children's urge to acquire information and their retention ability. A rigorous evaluation found significant positive impacts on curiosity, knowledge retention, and science test scores that persisted into the middle-school years (Alan and Mumcu 2024).

Advanced technical skills

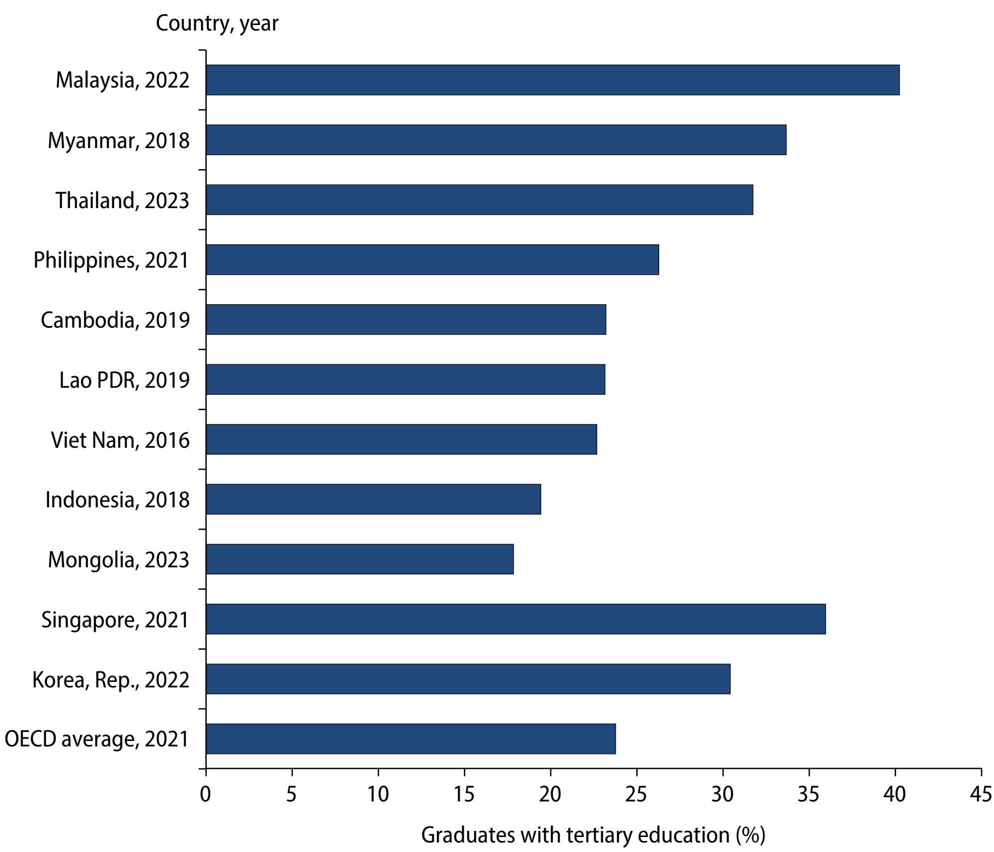
To reap the benefits of new technologies, EAP countries need a larger pool of talent with diversified and more advanced technical skills. Research shows that higher-level technical skills, usually acquired through education in science, technology, engineering, and mathematics (STEM), are critical enablers of technology diffusion and subsequent innovations (World Bank 2024a). These skills are thus essential for invigorating productivity growth that will sustain economic growth, job creation, and gains in labor incomes. Workers need to be equipped with these skills to benefit from working with new technologies.

However, the supply of graduates in STEM fields is limited in many EAP countries. Except in Malaysia, the share of STEM graduates among all tertiary graduates is much smaller in EAP countries than in Korea and Singapore (refer to figure 7.2). Combined with a small share of workers with tertiary educational attainment (under 30 percent of the labor force), this results in a short supply of talent to gain the productivity and labor market advantages deriving from new technologies.

There is evidence that engineers play a crucial role in driving the technology adoption and innovations that spur productivity growth. Countries in which the engineering workforce has been successfully increased have become better equipped to adopt the technologies and achieve the economic and productivity benefits. Maloney and Caicedo (2022) use long-term historical data in the United States to show that countries with a higher relative supply of engineers in 1880 subsequently experienced more rapid technology adoption—including information and communication technology—and skills-based and knowledge-intensive economic activities nearly a century later (refer to figure 7.3). They also show that large differences in engineer densities across Latin American countries at similar income in 1900 predicted the divergent growth trajectories over the next century and therefore the growth of jobs and wages.

The supply of STEM graduates is limited in the EAP region.

FIGURE 7.2 The supply of STEM graduates, EAP region, circa 2020

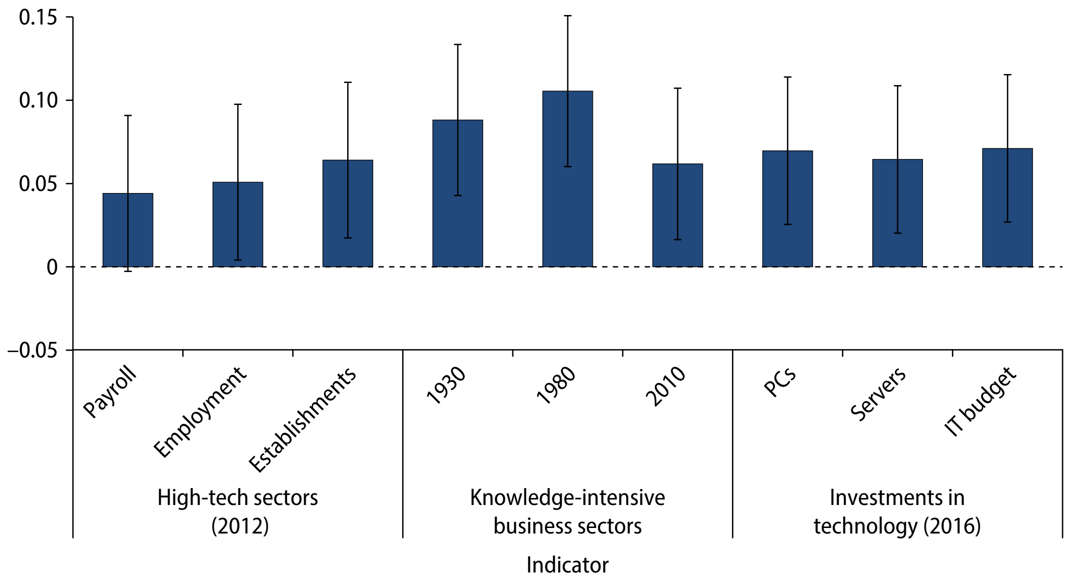


Source: UIS.Stat (dashboard), Institute for Statistics, United Nations Educational, Scientific, and Cultural Organization, Montreal, https://data.uis.unesco.org/.

Note: OECD = Organisation for Economic Co-operation and Development; STEM = science, technology, engineering, and mathematics.

The supply of engineers in the United States is positively correlated with long-term technology adoption and innovation, including in the digital sector.

FIGURE 7.3 Correlation coefficient with engineering density, selected indicators, United States



Source: Original figure for this publication based on Maloney and Caicedo 2022.
Note: The figure shows the coefficients from cross-county regressions of each indicator as dependent variable, including engineers per 100,000 male workers at the county level as independent variable and other controls. Whiskers correspond to 95 percent confidence intervals. IT = information technology. PCs = personal computers.

Countries such as China, India, and Korea offer valuable examples of ways to boost STEM technical education and the size of the engineering workforce (refer to box 7.3). These countries showcase how policy reforms, targeted educational policies, and strong government-industry collaboration can work more effectively. Their success in building the technical skills of the workforce highlights three key principles: (1) building a strong foundation of literacy and numeracy in basic education enables the acquisition of more advanced skills later on, (2) promoting industry participation in curriculum design and providing work-based learning opportunities are important in building skills the market needs, and (3) governments should foster the creation of opportunities and capacities in tandem. In these economies, the ready supply of technical skills in digital areas helped spur the growth of technology-intensive sectors, which led to an expansion of opportunities through skill-based growth.

Box 7.3. Building advanced technical skills to harness digital technologies

Korea has made significant strides in fostering STEM education geared to engineering and digital technologies. The country has promoted industry participation in skills development by involving leading companies in curriculum design and providing work-based learning opportunities. The Meister high schools—specialized vocational high schools that train students in specific industries—address critical skill needs in priority sectors, including information and communication technology, semiconductor manufacturing, and biotechnology. They offer a customized vocational training curriculum developed in collaboration with industry to ensure alignment with technology trends and labor market demand. The Meister schools have partnered successfully with companies such as Hyundai Motor Company and Samsung Electronics to secure the placement of graduates and support curriculum development and mentorship programs. For example, a survey of graduates from the Busan Meister Technical High School found that 72 percent felt adequately prepared to find a job and 78 percent took additional training beyond the regular program (Joo 2016).

China and India have achieved a remarkable expansion in STEM tertiary education—now producing the largest pool of engineers globally—through substantial investments in higher education. In China, the prioritization of STEM education has led to a rapid increase in university enrollments in engineering programs and the establishment of numerous research and development centers by multinational corporations. China's surge in engineering graduates has fueled the country's growth in medium- and high-technology industries, such as electronics, green technologies, and telecommunication. In India, the expansion is driven by government initiatives and close private sector involvement that has supported the boom in software and business process outsourcing services.

It is essential that skills development goes hand in hand with policy reforms that create jobs in order to foster a virtuous cycle between capacities and opportunities (World Bank 2024a). The experiences of countries such as China, India, Korea, and Malaysia illustrate how expanding the supply of technical skills can enable a transition to higher–value added manufacturing and services if countries create an environment that sustains strong demand for skilled workers.

In several EAP countries, the expansion of tertiary enrollment has meant that the supply of college-educated workers is outpacing the demand. Some countries have also seen a decline in college premiums and higher unemployment rates among college graduates, for example in China, Indonesia, and Malaysia. The findings in this report indicate that digital technologies have a pro-youth and pro-skill bias. Thus, the technologies may help narrow the employment gap between youth and older workers, provided the younger cohorts are equipped with skills complementary to the technologies.

New technologies have proven effective in teaching basic skills and show promise in the development of technical and socioemotional skills (Afkar et al. 2023). Computer-assisted learning can address gaps in the numeracy and literacy skills necessary for acquiring technical skills (World Bank 2021). AI-powered virtual reality is increasingly being used in tertiary education and technical training to simulate real-world scenarios and provide immersive, hands-on interactive experiences. Emerging evidence demonstrates its effectiveness in the development of technical competencies and socioemotional skills, such as collaboration and problem-solving in STEM and related technical areas (Angel-Urdinola, Castillo-Castro, and Hoyos 2021). Virtual reality–aided training offers a more cost-effective alternative for delivering hands-on learning experiences in programs that typically require costly laboratory infrastructure. Additionally, online learning platforms expand training and education resources, enabling workers to update their skills continuously to meet the evolving demands of the digital economy.

Facilitating labor and capital mobility

The mobility of labor and capital is crucial for the resource reallocation that accompanies technological advances. Workers, including those displaced by automation, would ideally move to firms, locations, and jobs where their skills can be more productively utilized. At the same time, high labor mobility fosters economic agglomeration, helping firms secure the necessary skills to adopt new technologies and grow to their optimal scale. Capital also needs to relocate to sectors, firms, and locations where it can earn the highest returns. The agglomeration of firms and workers can enhance the quality of labor market matches, boosting productivity and job creation opportunities.

Impediments to capital mobility in EAP countries have been analyzed in other studies (for example, de Nicola, Mattoo, and Timmis 2025; World Bank 2024b). These include restrictions on firm entry and exit because of burdensome licensing requirements and bankruptcy procedures. Also relevant are policies that lock resources into inefficient firms, such as support for loss-making state-owned enterprises and lending directed toward zombie firms. Reforms to enhance the competitiveness of markets and ensure a level-playing field would help allocate capital efficiently and gravitate to the most innovative firms and sectors.

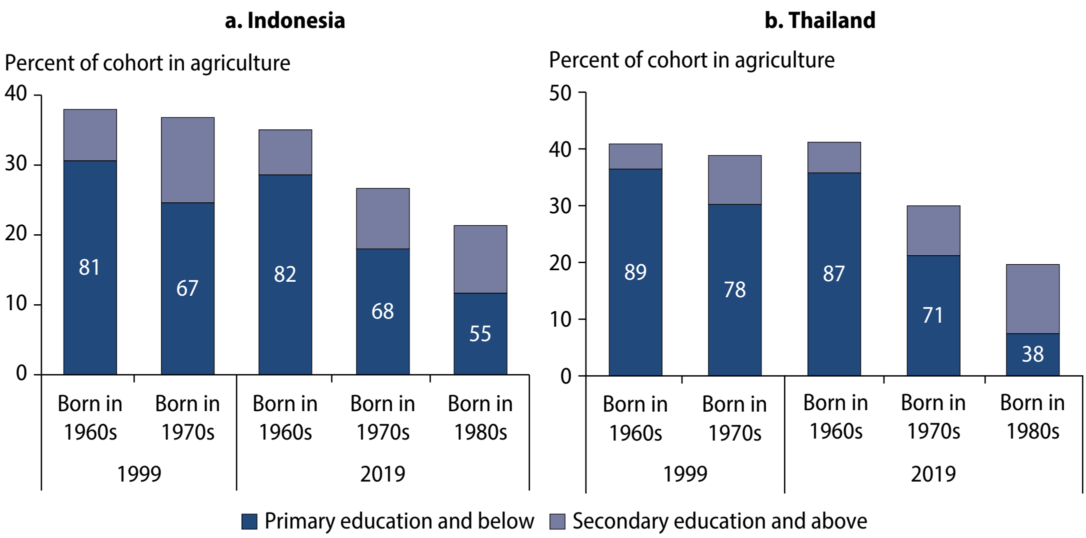
Labor mobility can be impeded by market failures and policy distortions. The former include poor information about job opportunities, underdeveloped housing markets, and inadequate basic services and connectivity in lagging areas; the latter include rigid labor market institutions and the inadequate portability of benefits (Bryan and Morten 2019; Deininger and Goyal 2024; Lagakos et al. 2018; Nayyar and Kim 2018; OECD 2018). These frictions hinder worker reallocation, negatively affecting productivity, employment, and earnings (Donovan and Schoellman 2023).

Evidence suggests that labor market frictions are significant in EAP countries. In China, the hukou system, which restricts spatial movement by regulating the access of migrants to publicly financed services in urban areas, has hindered efficient labor relocation and negatively affected labor market outcomes (Ngai, Pissarides, and Wang 2019; Tombe and Zhu 2019). In Viet Nam, the household registration system (ho khau) that regulates access to housing and public social services has curtailed rural-urban migration, locking many farmers in low-productivity agricultural jobs (Liu and Dang 2019).

These barriers to labor mobility can trap entire cohorts of workers in low-productivity employment. In Indonesia and Thailand, for instance, the share of the population born in the 1960s who work in agriculture barely changed between 1999 and 2019 (and even rose slightly in Thailand) (refer to figure 7.4).

Barriers to labor mobility can trap generations in low-productivity employment.

FIGURE 7.4 Share of workers employed in agriculture in total employment, by birth cohort, 1999 and 2019



Sources: Original figure for this publication based on data of Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; World Bank 2024a.

Note: The sample includes wage employees, self-employed, employers, and unpaid employees. The numbers inside the bars indicate the percentage of the total with primary education or below.

Around 30 percent–35 percent of this cohort still work in agriculture. In contrast, the share of agricultural employment has fallen among the youngest cohorts. Indeed, most of the decline in the share of agricultural employment over the last two decades is associated with cohorts born in the 1980s who are entering employment in manufacturing and services. While an important part of this shift reflects improvements in education, an important share of the more educated in younger cohorts are still employed in agriculture. A recent study in Indonesia shows that, even accounting for improvement in the skills of the population, reducing other barriers to internal mobility could lead to productivity and labor income gains of around 20 percent (Bryan and Morten 2019).

Policy reforms that remove these and other barriers to labor mobility can facilitate better job transitions during technological upgrading (Basso, D'Amuri, and Peri 2019). Recent reforms to the hukou system in China and the ho khau system in Viet Nam have eased residence requirements and improved worker mobility, especially to booming areas with more technology-intensive and export-oriented firms, although migrants still face restricted access to basic services (World Bank 2014, 2019b; World Bank and VASS 2016).

Reforming labor market regulations that increase labor costs and restrict occupational mobility can help harness the benefits of technological change. In Europe, the adoption of automation technologies has been associated with better employment outcomes in countries with low to modest labor costs, mainly because of less labor displacement and, to a narrower extent, higher labor reinstatement (Bachmann et al. 2024). In the United States, high labor mobility, stemming from more flexible labor and occupational regulations, has contributed to productivity gains from automation and facilitated the relocation of displaced workers to other jobs (Dvorkin and Monge-Naranjo 2019a, 2019b).

Targeted active labor market policies can smooth the transition to other jobs among workers displaced by new technologies. Emerging evidence from evaluations of training programs targeting automation-displaced workers suggests such programs can be effective. In Denmark, retraining subsidies mitigated the adverse employment and income effects of automation (Humlum 2020). A training program in Austria was effective in helping workers relocate to new jobs, especially workers who previously held more routine-intensive jobs (Schmidpeter and Winter-Ebmer 2021). These programs can be most effective if they equip displaced workers with the skills that are required in nonroutine work and that are complementary to new technologies, including basic digital skills and socioemotional skills, such as communication and collaboration (Bürgisser 2023).

The agglomeration economies resulting from the movement of labor and capital to locations with a higher concentration of technology-intensive industries can generate spillovers that benefit workers in other sectors. The higher wages of more skilled jobs in technology-intensive industries can increase the demand for local goods and services, creating additional demand for workers in services and other sectors. Research in the United States estimates this multiplier effect at five, indicating that each new high-tech job in cities with dense innovation clusters creates five additional jobs in the local service economy in skilled occupations (lawyers, architects, and nurses) and in less-skilled occupations (waiters, hairdressers, and repair persons) (Moretti 2012). Barriers to labor mobility reduce the elasticity of labor supply and lead to smaller job multipliers (Bartik and Sotherland 2019).

Digital technologies can help improve the productivity and earnings of workers who cannot easily move physically to better opportunities. In addition to gig economy apps, digital job intermediation platforms, such as online job boards and freelance marketplaces, have expanded access to job opportunities among workers, including women and youth. Platforms such as Upwork and Freelancer have enabled skilled workers in developing countries to offer their services in a global labor market. These platforms provide flexible work arrangements that allow individuals to balance work with personal and family responsibilities, such as caregiving or education. Evidence shows that workers using these platforms can earn significantly more than they would earn otherwise in local economies, including women who achieve greater financial independence (Kuek et al. 2015; World Bank 2019b). Digital technologies can also help improve the productivity and earnings of small farmers trapped in low-productivity agriculture. Rigorous evaluations show that disseminating information on prices and effective harvesting practices through mobile phones led to a 4 percent increase in yields and a 22 percent increase in the adoption of effective inputs in Sub-Saharan Africa and India (Fabregas, Kremer, and Schilbach 2019; refer to spotlight 3.1).

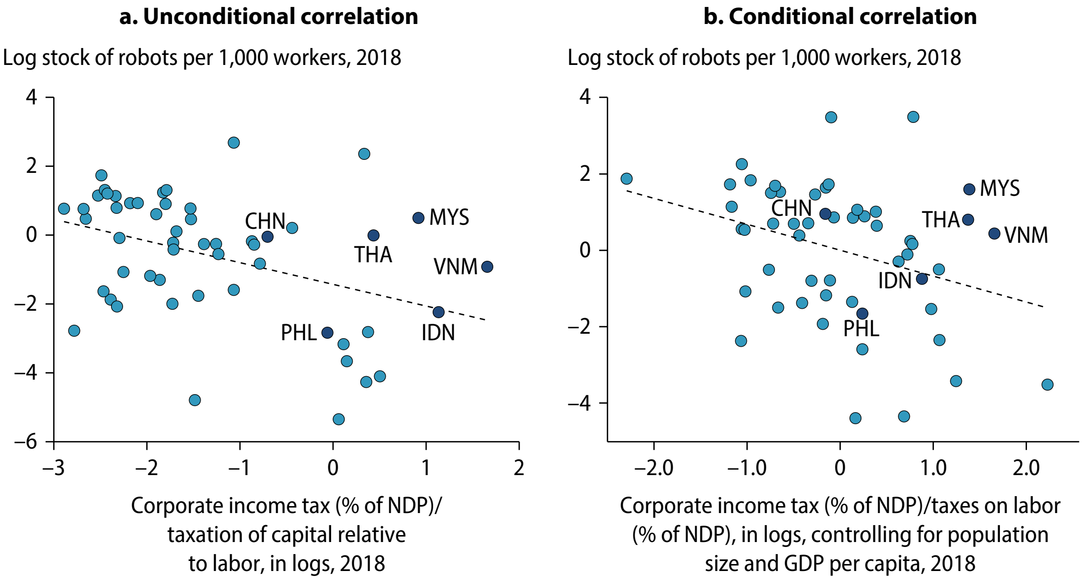
Removing factor price distortions

Taxation policies and subsidies are regularly used to stimulate private investment and innovation. They can alter the effective cost of capital and labor, thereby affecting choices related to factor use, inputs, technology, and capital investments. If capital and labor taxes are set optimally, the decisions of firms on technology adoption are socially optimal, and policies can then focus on transfers or skills training to support those who lose out. However, suboptimal taxes and subsidies lead to distorted firm decisions and potentially suboptimal technology adoption.

Figure 7.5 shows the association between the ratio of taxes collected from capital and labor and the stock of industrial robots (per 1,000 workers) in 2018 for several

Higher taxation of capital relative to labor is associated with lower robot adoption.

FIGURE 7.5 Robot adoption and the relative taxation of capital and labor, 2018



Sources: Original figure for this publication based on Bachas et al. 2022; 2024 data of World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.
Note: The relative taxation on capital relative to labor is computed as the ratio of corporate income taxes and labor taxes collected in each country, based on Bachas et al. (2022). The dashed line corresponds to a regression fit, unconditionally and controlling for total population (proxy for domestic market size) and the share of government expenditures in gross domestic product (GDP) (proxying provision of global public goods). For country abbreviations, refer to International Organization for Standardization (ISO), https://www.iso.org/obp/ui/#search.

developed and developing economies. There is a negative correlation between the two measures, even after controlling for country gross domestic product (GDP) (to proxy for domestic market size) and the share of government expenditures in GDP (to proxy for the provision of global public goods). This negative association suggests that countries in which taxes favor capital relative to labor experience greater rates of adoption of automation technologies. The caveat to this analysis is that taxes on capital—which include corporate income taxes—are not a close proxy for the taxation of robots. Nonetheless, figure 7.5 provides suggestive evidence that tax systems can, in fact, shape the extent of technology adoption. EAP countries ideally need to avoid policy distortions that favor the suboptimal excess adoption of labor-saving technologies. A first step would be to examine current tax and subsidy schemes to remove any provisions favoring technologies that displace labor.

Empirical evidence on advanced economies shows that inadequacies in tax systems can lead firms to adopt automation technologies beyond the socially optimal.

Acemoglu, Manera, and Restrepo (2020) show how the US tax system has evolved to favor excessive automation and suboptimally lower employment. Generous exemptions and allowances (for instance, for depreciation) lead to higher effective tax rates on labor than on capital complementary to automation technologies, such as software and computer equipment. There is evidence that the tax systems of other advanced economies also favor investments in labor-displacing technologies (Brollo et al. 2024). Removing these distortions would bring the adoption of automation technologies closer to what is socially optimal and raise employment levels.

Countries such as China could play a role in steering technological change toward more labor-augmenting technologies. The history of technology development, including recent green technologies, offers examples of how public policy and economic incentives can steer innovation to achieve more socially optimal outcomes (Hémous and Olsen 2021; Mazzucato 2011). Similarly, countries can direct funds into research and development to steer innovation away from pure labor-substituting technologies (Acemoglu, Manera, and Restrepo 2020; Autor 2024; Rodrik and Stantcheva 2021a, 2021b) and encourage development and adoption of other socially beneficial technologies (de Nicola, Mattoo, and Tran 2025).

Expanding social protection to the informal sector

The need to develop schemes to offer social protection for workers outside of regular social insurance systems has become more pressing given the growing prevalence of gig work. Lessons can be drawn from several country experiences on the design of social insurance schemes for gig workers (refer to box 7.4). These schemes range from those run by the public sector (in Colombia and India), public-private partnerships (in Malaysia), and purely private initiatives (in Denmark). The interventions range from remedying informational asymmetries by informing workers about the existence and benefits of schemes (as in India), financial incentives (as in Colombia and Malaysia), and behavioral nudges in each case.

Box 7.4. Innovative approaches to fostering social insurance for gig and self-employed workers

Colombia illustrates the rollout at-scale of voluntary public pension schemes targeted at low-income informal workers and those in the gig economy. Colombia offers a 20 percent subsidy on an individual's accumulated contributions to incentivize workers earning less than the minimum wage to participate. A text-message-based behavioral nudge pilot with affiliates of this scheme increased the savings of both

(continued)

Box 7.4. Innovative approaches to fostering social insurance for gig and self-employed workers *(continued)*

nonsavers and already active savers (Azuara et al. 2021). After 15 months, affiliates who had not been saving before the intervention were saving 14.0 percent or 12.4 percent more than the control group depending on whether they received the SMS for 10 or 15 months.

India illustrates how national platforms can be used to facilitate the take-up of social insurance among informal workers. The government uses the e-Shram portal, comprising a comprehensive national database for self-employed and informal workers, and behavioral nudges to encourage workers to register and participate in social insurance schemes. For example, the platform sends regular reminders and provides easy-to-understand information about the benefits of enrolling in social insurance. By making the process simple and accessible, the e-Shram portal has increased the visibility and participation of informal workers in social insurance programs.

Malaysia illustrates effective government-industry collaboration to extend social insurance to gig workers. The government worked with Grab, a major ride-hailing platform, to provide social insurance to gig workers. The i-Saraan Program allows self-employed individuals, including gig workers, to contribute to a retirement savings scheme. Grab incentivizes its drivers by offering an additional 5 percent matching contribution for those who register with i-Saraan. This partnership has relied on the digital communication channels of the Grab platform to send reminders and nudges to drivers, encouraging them to save for retirement. The approach has increased participation rates among gig workers, demonstrating the potential of behavioral nudges if delivered with digital platforms.

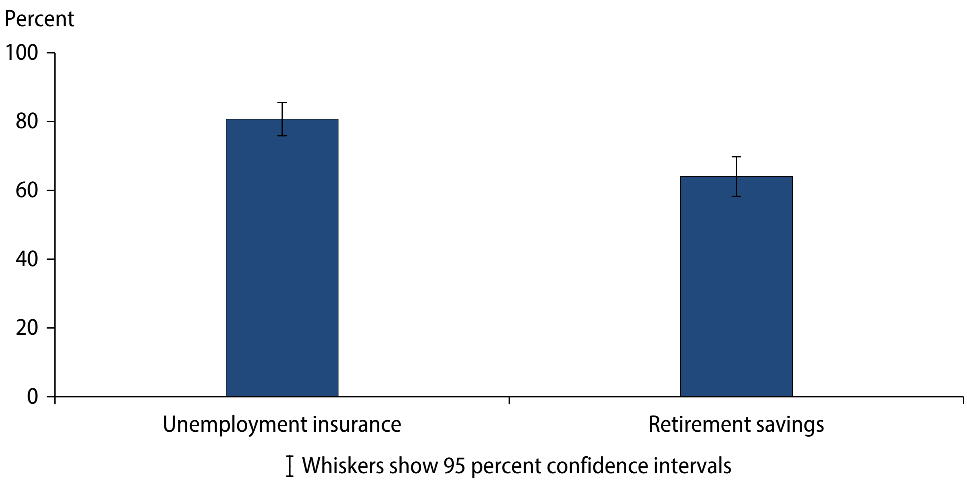
Denmark offers an example of how industry can lead the way in extending social insurance to gig workers. Hilfr, a platform offering house cleaning services, has used its digital platform to create a tiered system for its workers. Those who work long enough on the platform are awarded the status of employees, granting them access to benefits, such as pensions and paid leave. This provides a pathway for gig workers to receive the social protections typically reserved for traditional employees. This approach highlights the potential for private industry to use platforms to incentivize social insurance coverage for gig workers.

Source: Based on Datta and Chen 2023.

A study on Malaysia finds that self-employed workers are willing to accept a slight reduction in income in exchange for regular contributions to social insurance schemes, such as unemployment insurance and pensions (Ghorpade, Rahman, and Jasmin 2024). The findings underscore the importance of designing social insurance programs that align with the financial realities and preferences of self-employed workers (refer to figure 7.6). By incorporating behavioral nudges, such as default enrollment options and regular reminders, countries can enhance the take-up of social insurance schemes among the self-employed.

Gig workers are willing to pay for social insurance.

FIGURE 7.6 **Likelihood of choosing a social insurance package over no insurance, Malaysia**



Source: Original figure for this publication based on Ghorpade, Rahman, and Jasmin 2024.
Note: The figure shows coefficient estimates from a discrete choice experiment in Malaysia, where a choice of interview answers is randomly allocated. Samples include 1,038 gig workers. Unemployment insurance shows the likelihood that workers will choose "Payment of RM 800 per month for six months, 0.5 percent lower income" over "no unemployment insurance and earnings equal to current income." Retirement savings shows the likelihood that workers will choose "Monthly pension upon retirement based on contribution, 5 percent lower income" over "standard/current Employees Provident Fund pension coverage features, and earnings equal to current income."

References

Acemoglu, Daron, Andrea Manera, and Pascual Restrepo. 2020. "Does the US Tax Code Favor Automation?" NBER Working Paper 27052 (April), National Bureau of Economic Research, Cambridge, MA.

ADB (Asian Development Bank) and LinkedIn. 2022. "Digital Jobs and Digital Skills: A Shifting Landscape in Asia and the Pacific." September, ADB, Manila; LinkedIn, Sunnyvale, CA.

Afkar, Rythia, Tara Béteille, Mary E. Breeding, Toby Linden, Andrew D. Mason, Aaditya Mattoo, Tobias Pfutze, Lars M. Sondergaard, and Noah Yarrow. 2023. *Fixing the Foundation: Teachers and Basic Education in East Asia and Pacific*. World Bank East Asia and Pacific Regional Report. Washington, DC: World Bank.

Alan, Sule, Teodora Boneva, and Seda Ertac. 2019. "Ever Failed, Try Again, Succeed Better: Results from a Randomized Educational Intervention on Grit." *Quarterly Journal of Economics* 134 (3): 1121–62.

Alan, Sule, and Ipek Mumcu. 2024. "Nurturing Childhood Curiosity to Enhance Learning: Evidence from a Randomized Pedagogical Intervention." *American Economic Review* 114 (4): 1173–210.

Angel-Urdinola, Diego F., Catalina Castillo-Castro, and Angela Hoyos. 2021. "Meta-Analysis Assessing the Effects of Virtual Reality Training on Student Learning and Skills Development." Policy Research Working Paper 9587, World Bank, Washington, DC.

Autor, David H. 2024. "Applying AI to Rebuild Middle Class Jobs." NBER Working Paper 32140 (February), National Bureau of Economic Research, Cambridge, MA.

Azuara, Oliver, Mariano Bosch, Gustavo Caballero, Fabián Cofré, Stephanie González, Anne Hand, Lukas Keller, Catalina Rodríguez Tapia, María Teresa Silva-Porto, and Fermín Vivanco. 2021. "Saving without Barriers: Lessons from the Retirement Savings Laboratory's Pilot Projects." IDB Monograph 907 (April), Inter-American Development Bank, Washington, DC.

Bachas, Pierre, Matthew H. Fisher-Post, Anders Jensen, and Gabriel Zucman. 2022. "Capital Taxation, Development, and Globalization: Evidence from a Macro-Historical Database." NBER Working Paper 29819 (March), National Bureau of Economic Research, Cambridge, MA.

Bachmann, Ronald, Myrielle Gonschor, Piotr Lewandowski, and Karol Madoń. 2024. "The Impact of Robots on Labour Market Transitions in Europe." *Structural Change and Economic Dynamics* 70 (September): 422–41.

Bandiera, Oriana, Ahmed Elsayed, Anton Heil, and Andrea Smurra. "Presidential Address 2022: Economic Development and the Organisation of Labour: Evidence from the Jobs of the World Project." *Journal of the European Economic Association* 20 (6): 2226–70. https://doi.org/10.1093/jeea/jvac056.

Bartik, Timothy J., and Nathan Sotherland. 2019. "Local Job Multipliers in the United States: Variation with Local Characteristics and with High-Tech Shocks." Upjohn Institute Working Paper 19-301 (April), W. E. Upjohn Institute for Employment Research, Kalamazoo, MI.

Basso, Gaetano, Francesco D'Amuri, and Giovanni Peri. 2019. "Immigrants, Labor Market Dynamics, and Adjustment to Shocks in the Euro Area." *IMF Economic Review* 67 (3): 528–72.

Brollo, Fernanda, Era Dabla-Norris, Ruud de Mooij, Daniel Garcia-Macia, Tibor Paul Hanappi, Li Liu, and Anh D. M. Nguyen. 2024. "Broadening the Gains from Generative AI: The Role of Fiscal Policies." IMF Staff Discussion Note SDN2024/002 (June), International Monetary Fund, Washington, DC.

Bryan, Gharad T., and Melanie Morten. 2019. "The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia." *Journal of Political Economy* 127 (5): 2229–68.

Bürgisser, Reto. 2023. "Policy Responses to Technological Change in the Workplace." JRC Working Paper on Social Classes in the Digital Age 2023/04, Joint Research Center, European Commission, Seville, Spain.

CIPD (Chartered Institute of Personnel and Development). 2017. "AI Is Threat to Low-Skilled BPO Roles in Philippines." News, September 13, 2017. https://www.cipd.org/en/about/news-archive/ai-threat-low-skilled-roles/#:~:text=The%20advance%20of%20artificial%20intelligence,heavily%20on%20the%20BPO%20industry.

Cipriano, Christina, Michael J. Strambler, Lauren H. Naples, Cheyeon Ha, Megan Kirk, Miranda Wood, Kaveri Sehgal, et al. 2023. "The State of Evidence for Social and Emotional Learning: A Contemporary Meta-Analysis of Universal School-Based SEL Interventions." Yale Child Study Center, Yale School of Medicine, New Haven, CT.

Cruz, Beatriz Marie D. 2024. "Gov't 10-Year Jobs Masterplan Must Include AI Courses—NEDA." *BusinessWorld: Economy* (blog), March 13, 2024. https://www.bworldonline.com/economy/2024/03/13/581643/govt-10-year-jobs-masterplan-must-include-ai-courses-neda/.

Datta, Namita, and Rong Chen. 2023. *Working without Borders: The Promise and Peril of Online Gig Work*. With Sunamika Singh, Clara Stinshoff, Nadina Iacob, Natnael Simachew Nigatu, Mpumelelo Nxumalo, Luka Klimaviciute, et al. Washington, DC: World Bank.

Deininger, Klaus W., and Aparajita Goyal. 2024. *Land Policies for Resilient and Equitable Growth in Africa*. Washington, DC: World Bank.

de Nicola, Francesca, Aaditya Mattoo, and Jonathan Timmis. 2025. *Firm Foundations of Growth: Productivity and Technology in East Asia and Pacific*. East Asia and Pacific Development Studies. Washington, DC: World Bank.

de Nicola, Francesca, Aaditya Mattoo, and Trang Thu Tran. 2025. *Green Technologies: Decarbonizing Development in East Asia and Pacific*. East Asia and Pacific Development Studies. Washington, DC: World Bank.

DICT (Department of Information and Communications Technology). 2021. *Philippine Skills Framework for Contact Center and Business Process Management*. Quezon City, the Philippines: DICT.

DICT (Department of Information and Communications Technology) and AAP (Analytics and Artificial Intelligence Association of the Philippines). 2024. *Philippine Skills Framework for Analytics and Artificial Intelligence*. May 7. Quezon City, the Philippines: DICT.

Donovan, Kevin, and Todd Schoellman. 2023. "The Role of Labor Market Frictions in Structural Transformation." *Oxford Development Studies* 51 (4): 362–74.

DOST-PCIEERD (Department of Science and Technology–Philippine Council for Industry, Energy and Emerging Technology Research and Development). 2020. "DOST PCIEERD ETDD, Artificial Intelligence and Information and Communications Technology: Roadmapping Executive Report." August, DOST-PCIEERD, Taguig City, the Philippines.

DTI (Department of Trade and Industry). 2024. "DTI Drives AI Innovation with National Roadmap 2.0 and CAIR Launch." *News* (blog), July 5, 2024. https://www.dti.gov.ph/archives/news-archives/dti-drives-ai-innovation-national-roadmap-2-0-cair-launch/.

Dvorkin, Maximiliano Ariel, and Alexander Monge-Naranjo. 2019a. "Occupation Mobility, Human Capital, and the Aggregate Consequences of Task-Biased Innovations." Economic Research Working Paper 2019-013C (October), Federal Reserve Bank of St. Louis, St. Louis.

Dvorkin, Maximiliano Ariel, and Alexander Monge-Naranjo. 2019b. "On the Dynamics of Occupational Choice, Human Capital, and Inequality." Paper presented at Economics Seminar Series, Terry College of Business, University of Georgia, Athens, GA. September 12, 2019.

ECCP (European Chamber of Commerce of the Philippines). 2022. "PH AI Research Center to Open in September." *Europe-PH News*, August 24, 2022. https://www.eccp.com/articles/2742.

Fabregas, Raissa, Michael R. Kremer, and Frank Schilbach. 2019. "Realizing the Potential of Digital Development: The Case of Agricultural Advice." *Science* 366 (6471): eaay3038.

Fung, Michael, Renzo Taal, and William Sim. 2021. "SkillsFuture: The Roles of Public and Private Sectors in Developing a Learning Society in Singapore." In *Powering a Learning Society during an Age of Disruption*, edited by Sungsup Ra, Shanti Jagannathan, and Rupert Maclean, 195–208. Education in the Asia-Pacific Region: Issues, Concerns, and Prospects Series, vol. 58. Manila: Asian Development Bank; Singapore: Springer Nature.

Ghorpade, Yashodhan, Amanina Abdur Rahman, and Alyssa Jasmin. 2024. "Social Insurance for Gig Workers: Insights from a Discrete Choice Experiment in Malaysia." *International Social Security Review* 77 (3): 3–30.

Grant, Sean, Laura S. Hamilton, Stephani L. Wrabel, Celia J. Gomez, Anamarie Whitaker, Jennifer T. Leschitz, Fatih Unlu, et al. 2017. *Social and Emotional Learning Interventions under the Every Student Succeeds Act: Evidence Review*. Research Report RR-2133-WF. Santa Monica, CA: RAND Corporation.

Hémous, David, and Morten Olsen. 2021. "Directed Technical Change in Labor and Environmental Economics." *Annual Review of Economics* 13 (1): 571–97.

Humlum, Anders. 2020. "Essays on Automation and Labor Markets." PhD dissertation, Princeton University, Princeton, NJ.

IBPAP (IT and Business Process Association Philippines). 2024. *The Big PH IT-BPM Leap: The Philippine IT-BPM Industry Roadmap 2028*. Taguig, the Philippines: IBPAP.

Jones, Stephanie M., Katharine E. Brush, Thelma Ramirez, Zoe Xinyi Mao, Michele Marenus, Samantha Wettje, Kristen Finney, et al. 2021. *Navigating SEL from the Inside Out; Looking Inside and Across 33 Leading SEL Programs: A Practical Resource for Schools and OST Providers*. Preschool and Elementary Focus, 2nd ed. (July). Cambridge, MA: Ecological Approaches to Social Emotional Learning Laboratory, Harvard Graduate School of Education.

Joo, Lan. 2016. "Case Study of an Excellent TVET Institution: Busan Meister Technical High School, Korea." World Bank, Washington, DC.

Kuek, Siou Chew, Cecilia Maria Paradi-Guilford, Toks Fayomi, Saori Imaizumi, Panos Ipeirotis, Patricia Pina, and Manpreet Singh. 2015. "The Global Opportunity in Online Outsourcing." June, World Bank, Washington, DC.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman. 2018. "Life Cycle Wage Growth across Countries." *Journal of Political Economy* 126 (2): 797–849.

Liu, Amy Y. C., and Duc Anh Dang. 2019. "Rural–Urban Migration in Vietnam: Trend and Institutions." In *Rural-Urban Migration in Vietnam*, edited by Amy Y. C. Liu and Xin Meng, 1–30. Population Economics Series. Cham, Switzerland: Springer Nature.

Maloney, William F., and Felipe Valencia Caicedo. 2022. "Engineering Growth." *Journal of the European Economic Association* 20 (4): 1554–94.

Mazzucato, Mariana. 2011. "The Entrepreneurial State." *Soundings* 49: 131–42.

Moretti, Enrico. 2012. *The New Geography of Jobs*. Boston: Houghton Mifflin Harcourt.

Nayyar, Gaurav, and Kyoung Yang Kim. 2018. "India's Internal Labor Migration Paradox: The Statistical and the Real." Policy Research Working Paper 8356, World Bank, Washington, DC.

NEDA (National Economic and Development Authority, the Philippines). 2024. "PH Gov't Unveils Comprehensive Framework for 10-Year Employment Plan." Government News Release, June 29, 2024. https://pco.gov.ph/other_releases/ph-govt-unveils-comprehensive-framework-for-10-year-employment-plan/.

Ngai, L. Rachel, Christopher A Pissarides, and Jin Wang. 2019. "China's Mobility Barriers and Employment Allocations." *Journal of the European Economic Association* 17 (5): 1617–53.

OECD (Organisation for Economic Co-operation and Development). 2018. *OECD Employment Outlook 2018*. Paris: OECD. https://doi.org/10.1787/empl_outlook-2018-en.

Rodrik, Dani, and Stefanie Stantcheva. 2021a. "Fixing Capitalism's Good Jobs Problem." *Oxford Review of Economic Policy* 37 (4): 824–37.

Rodrik, Dani, and Stefanie Stantcheva. 2021b. "A Policy Matrix for Inclusive Prosperity." NBER Working Paper 28736 (April), National Bureau of Economic Research, Cambridge, MA.

Santos, Indhira Vanessa, Violeta Petroska-Beska, Pedro Manuel Carneiro, Lauren Eskreis-Winkler, Ana María Muñoz-Boudet, M. Inés Berniell, Christian Krekel, Omar Arias, and Angela L. Duckworth. 2022. "Can Grit Be Taught? Lessons from a Nationwide Field Experiment with Middle-School Students." IZA Discussion Paper 15588 (September), Institute of Labor Economics, Bonn, Germany.

Schmidpeter, Bernhard, and Rudolf Winter-Ebmer. 2021. "Automation, Unemployment, and the Role of Labor Market Training." *European Economic Review* 137 (August): 103808.

Senate of the Philippines. 2023. "Impact and Effects of Artificial Intelligence (AI) on BPO and OEM Sector." Senate Resolution No. 591 (May 3), Senate of the Philippines, Manila.

Steponavičius, Mykolas, Catharina Gress-Wright, and Adriano Linzarini. 2023. "Social and Emotional Skills: Latest Evidence on Teachability and Impact on Life Outcomes." OECD Education Working Paper 304 (November 15), Organisation for Economic Co-operation and Development, Paris.

Supreme Court E-Library. 2022. "Republic Act No. 11927, July 30, 2022." *Daily Tribune*, Manila Bulletin, August 8, 2022; 118 OG No. 33, 9279 (August 15, 2022), Library Services, Supreme Court of the Philippines, Manila. https://elibrary.judiciary.gov.ph/thebookshelf/showdocs/2/95588.

Talavera, Catherine. 2024. "BPO Industry Rides AI Wave." *Philstar: Business* (blog), February 25, 2024. https://www.philstar.com/business/2024/02/25/2335863/bpo-industry-rides-ai-wave.

Tombe, Trevor, and Xiaodong Zhu. 2019. "Trade, Migration, and Productivity: A Quantitative Analysis of China." *American Economic Review* 109 (5): 1843–72.

van de Sande, Marion C. E., Minne Fekkes, Paul L. Kocken, René F. W. Diekstra, Ria Reis, and Carolien Gravesteijn. 2019. "Do Universal Social and Emotional Learning Programs for Secondary School Students Enhance the Competencies They Address? A Systematic Review." *Psychology in the Schools* 56 (10): 1545–67.

World Bank. 2014. *East Asia Pacific at Work: Employment, Enterprise, and Well-Being*. World Bank East Asia and Pacific Regional Report. Washington, DC: World Bank.

World Bank. 2019a. "The Project: Instilling a Growth Mindset in Indonesia." December 13, Mind, Behavior, and Development Unit, Poverty and Equity Global Practice, World Bank, Washington, DC.

World Bank. 2019b. *World Development Report 2019: The Changing Nature of Work*. Washington, DC: World Bank.

World Bank. 2021. *Beyond Unicorns: Harnessing Digital Technologies for Inclusion in Indonesia*. Washington, DC: World Bank.

World Bank. 2024a. *Jobs and Technology: East Asia and the Pacific Economic Update*. October. Washington, DC: World Bank.

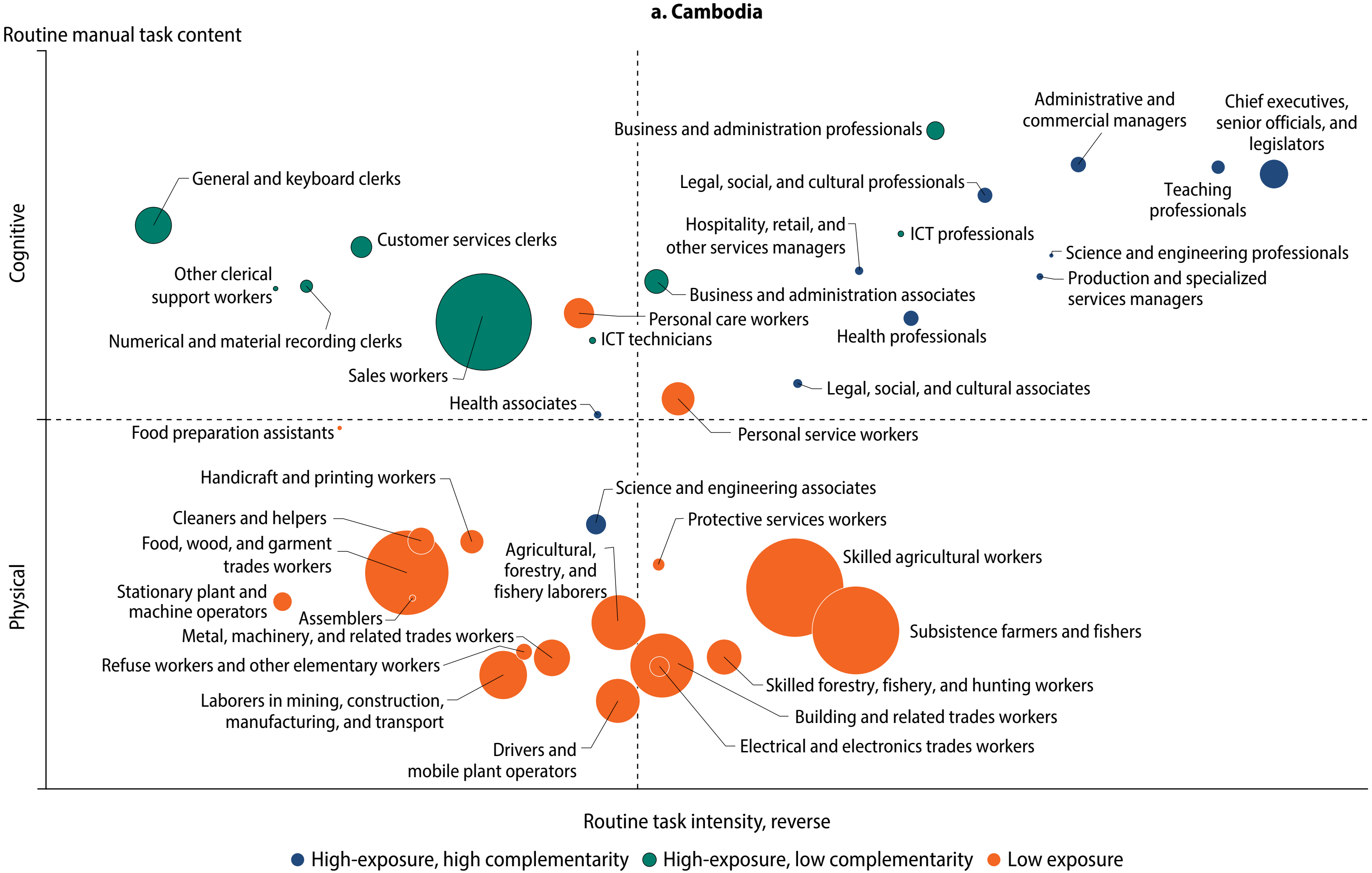
World Bank. 2024b. *Services Unbound: Digital Technologies and Policy Reform in East Asia and Pacific*. East Asia and Pacific Development Studies. Washington, DC: World Bank.

World Bank. 2024c. *World Development Report 2024: The Middle-Income Trap*. Washington, DC: World Bank.

World Bank and VASS (Vietnam Academy of Social Sciences). 2016. *Vietnam's Household Registration System*. June. Hanoi, Viet Nam: Hong Duc Publishing House.

APPENDIX
Supplementary Data

FIGURE A.1 Task intensity and artificial intelligence exposure, EAP



(continued)

FIGURE A.1 Task intensity and artificial intelligence exposure, EAP *(continued)*

b. Indonesia

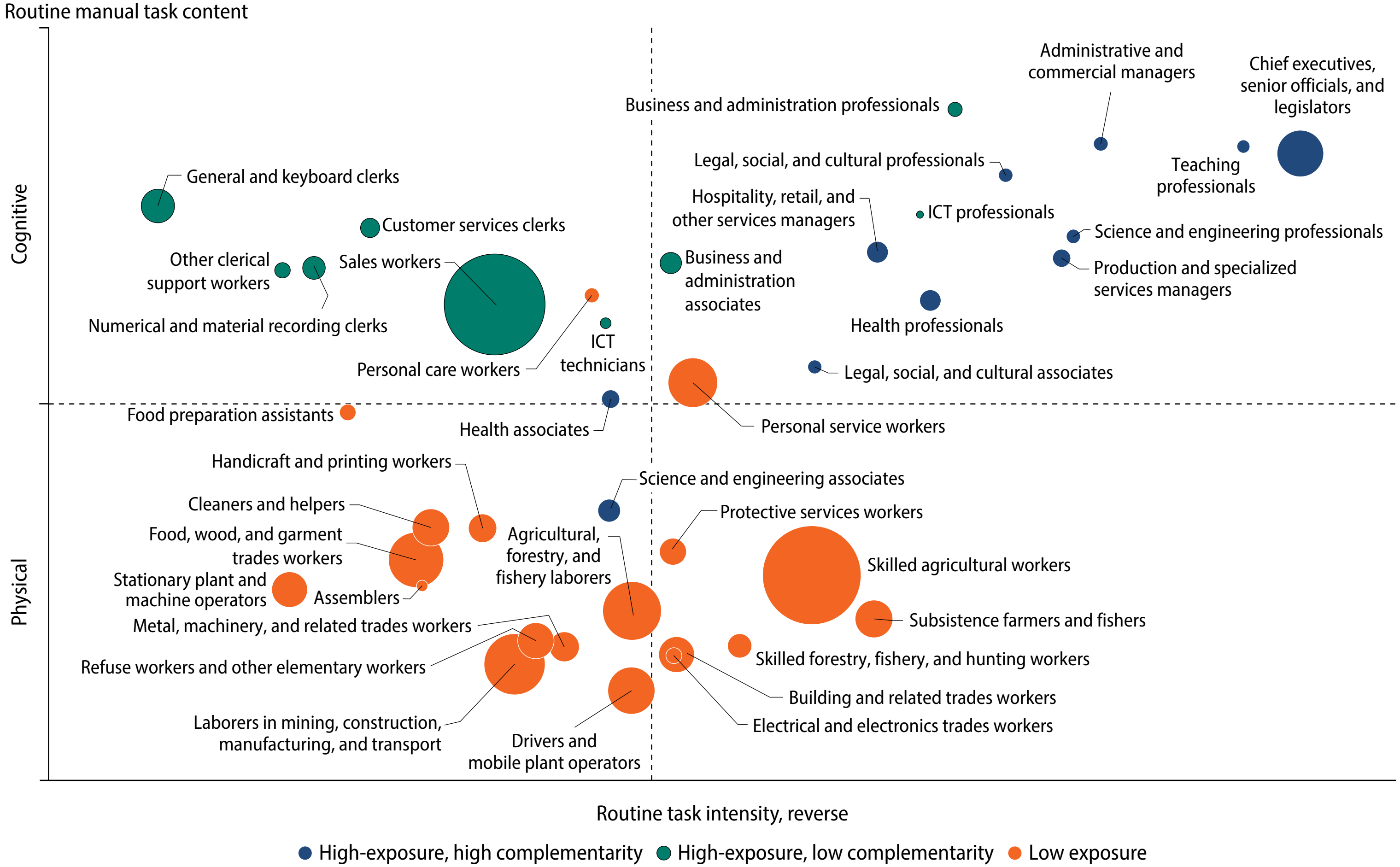


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FIGURE A.1 Task intensity and artificial intelligence exposure, EAP *(continued)*

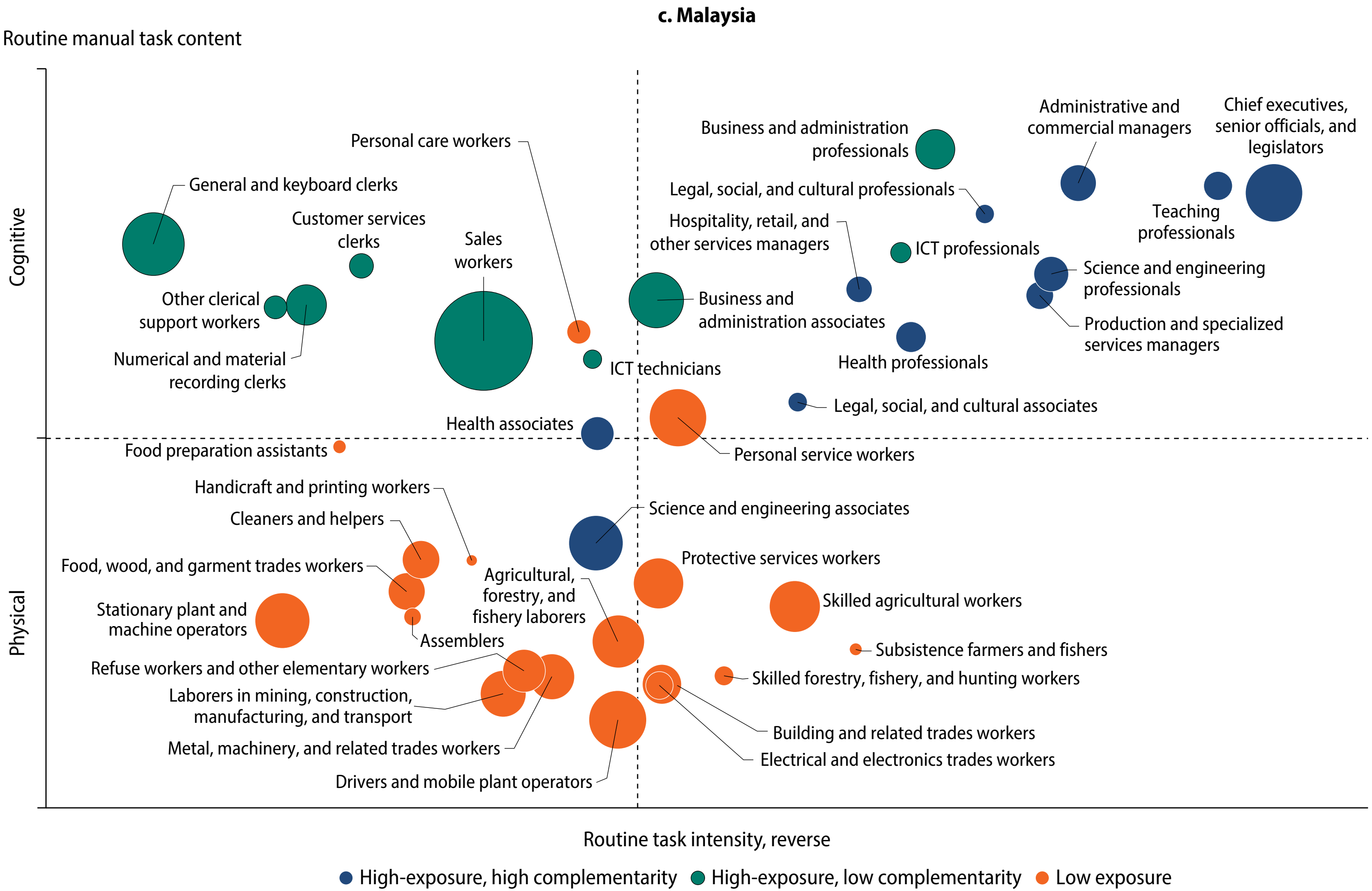

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FIGURE A.1 Task intensity and artificial intelligence exposure, EAP *(continued)*

d. Mongolia

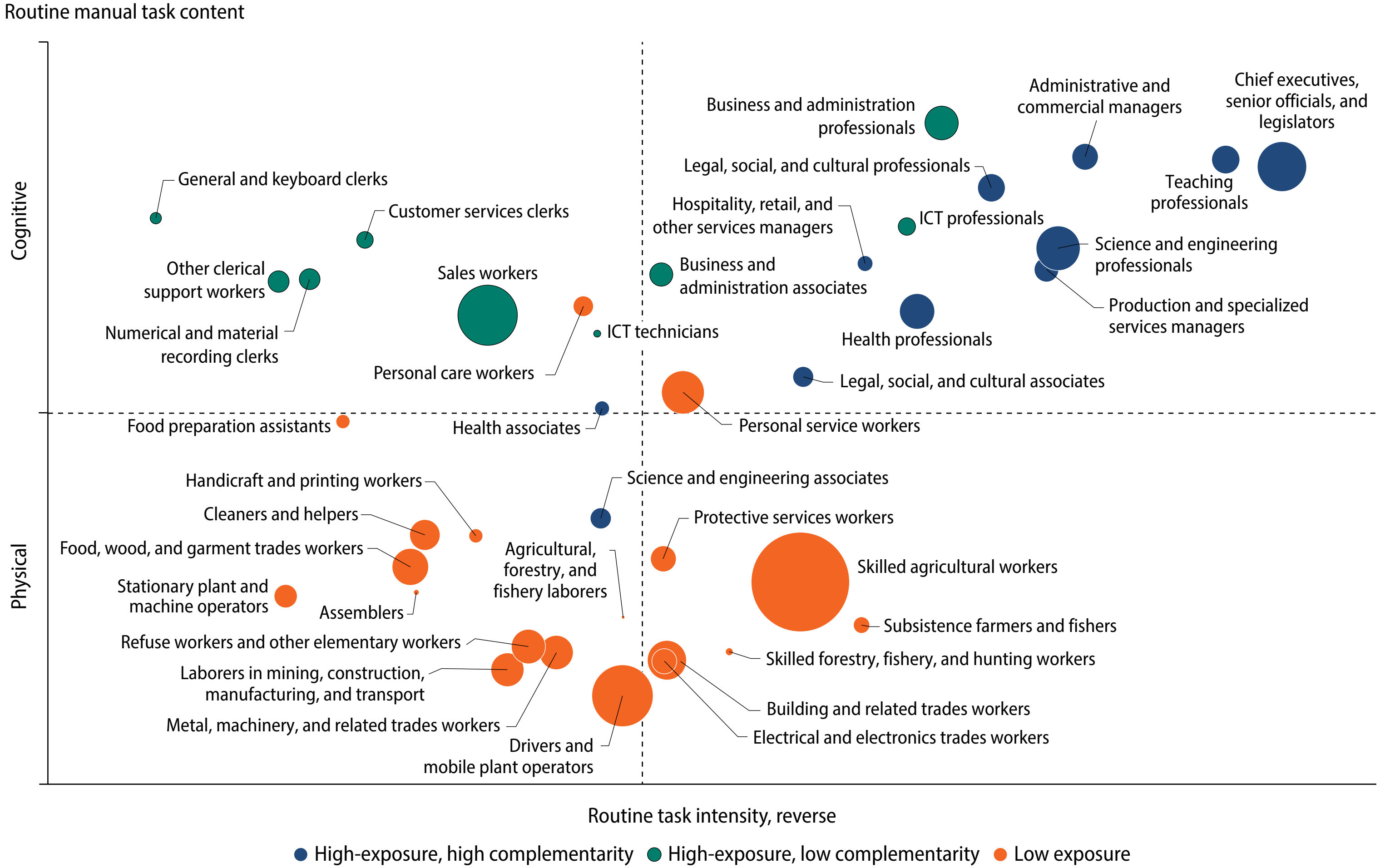

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FIGURE A.1 Task intensity and artificial intelligence exposure, EAP *(continued)*

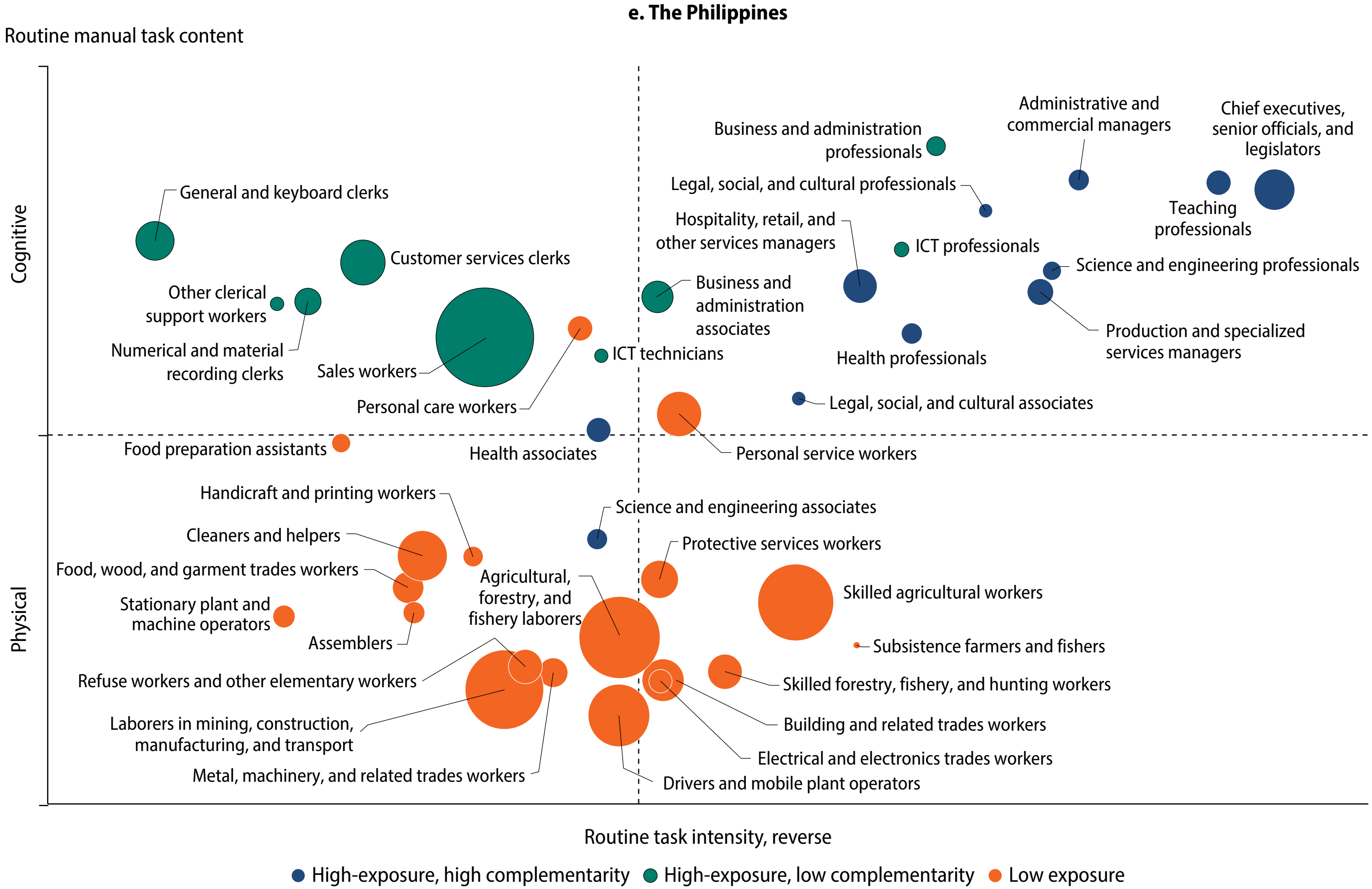

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FIGURE A.1 Task intensity and artificial intelligence exposure, EAP *(continued)*

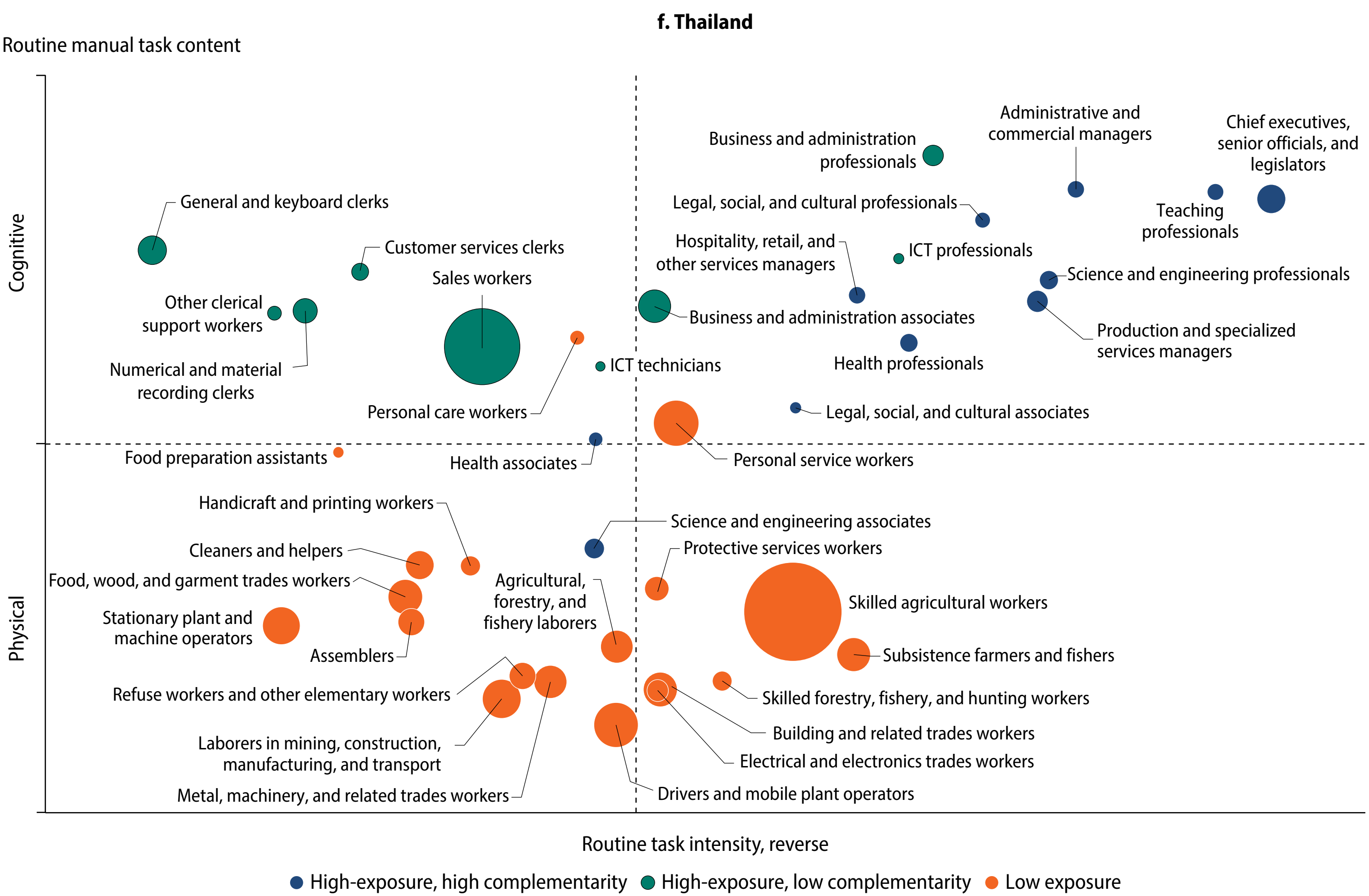

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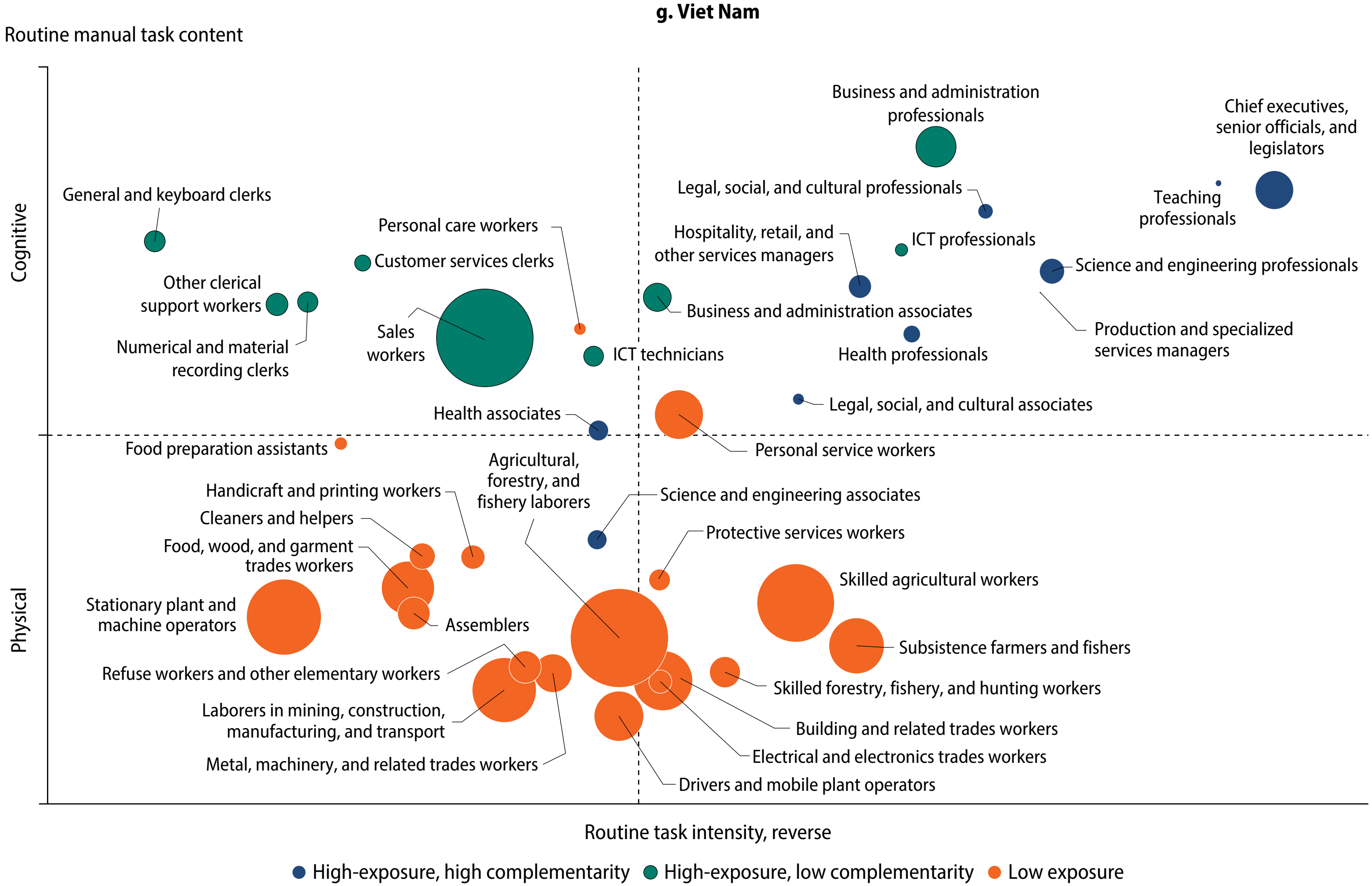
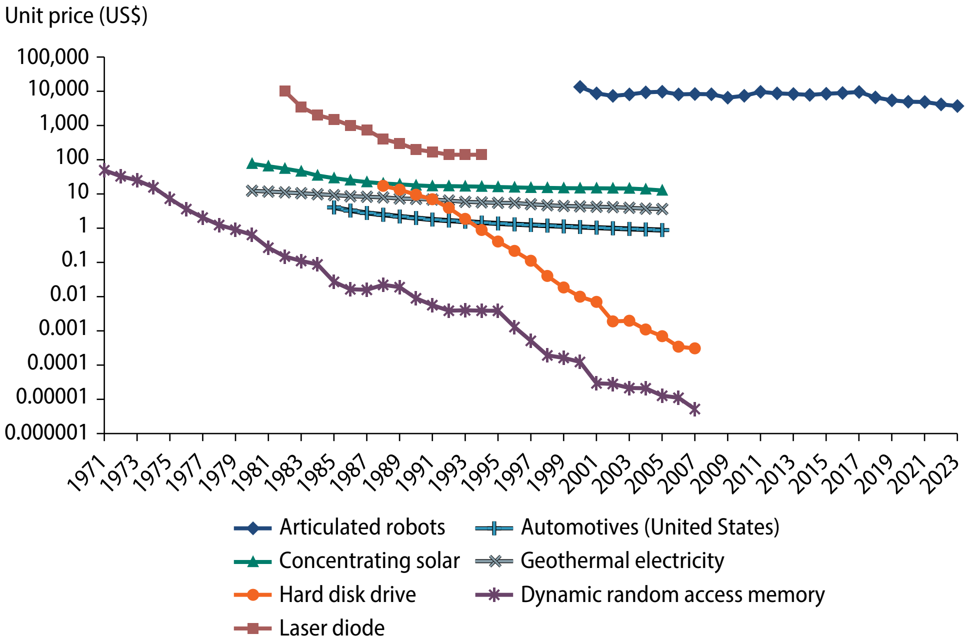
FIGURE A.1 Task intensity and artificial intelligence exposure, EAP *(continued)*



Sources: Original figure for this publication based on data of Autor and Dorn 2013; Felten, Raj, and Seamans 2021; microdata from Labour Force Surveys (dashboard), ILOSTAT, International Labour Organization, Geneva, https://webapps.ilo.org/surveyLib/index.php/catalog/LFS/?page=1&ps=15&repo=LFS; Pizzinelli et al. 2023.

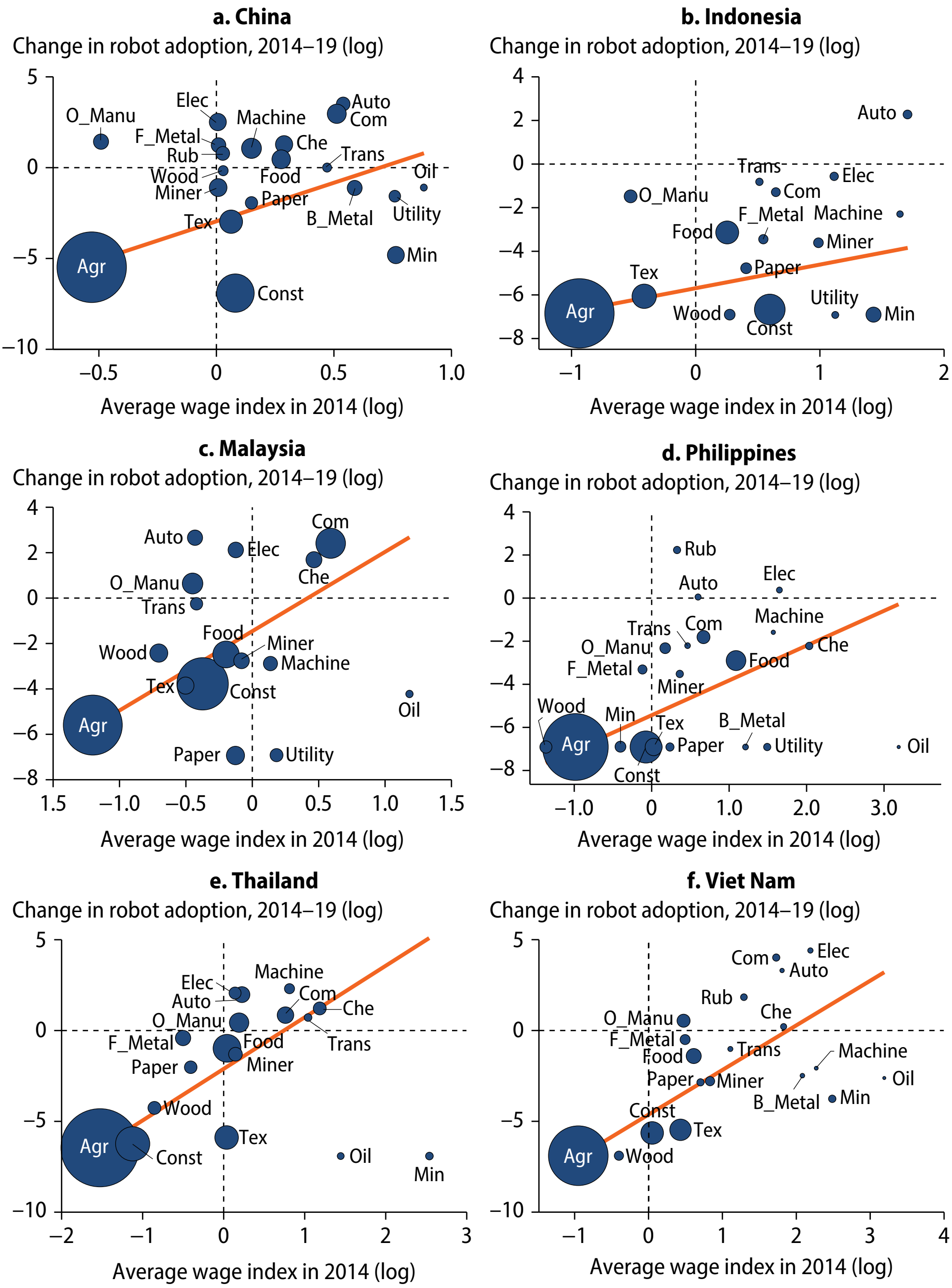
Note: Bubble size refers to the worker share for the most recent available year. Vertical axis measures routine manual content of tasks; horizontal axis measures routine task intensity following Autor and Dorn (2013). Color code is based on the median threshold of the AI exposure measure (Felten, Raj, and Seamans 2021) and the AI complementarity measure (Pizzinelli et al. 2023). ICT = information and communication technology.

FIGURE A.2 Unit price of technology, 1971–2023



Sources: Original figure for this publication based on data of Farmer and Lafond 2016; Our World in Data (dashboard), Global Change Data Lab and Oxford Martin Program on Global Development, University of Oxford, Oxford, UK, https://ourworldindata.org/; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

FIGURE A.3 **Change in robot adoption and wages, 2014–19**



Sources: Original figure for this publication based on data of TiM (Trade in Employment) (database), Organisation for Economic Co-operation and Development, Paris, https://www.oecd.org/en/data/datasets/trade-in-employment.html; World Robotics database, International Federation of Robotics, Frankfurt, https://ifr.org/about-world-robotics/.

Note: The x-axis shows the log of the annual wage index; 0 = national average wage. The y-axis shows the log of the change in the robot stock per 1,000 workers in 2013. To include 0 changes, 0.001 is added to the change in the robot stock. Refer to the TiM database for the full sector names.

Box A.1. Exposure to artificial intelligence and complementarity

Recent advances in artificial intelligence (AI) have generated excitement about the potential of AI to boost productivity, but there are concerns over the potential adverse impact on labor markets through the displacement of workers or transformations in the scope of specific occupations. One measure of the extent of the exposure of each occupation to AI has been constructed by Felten, Raj, and Seamans (2021). They define exposure to AI as the degree of overlap between what AI applications can do and the tasks human workers perform in each occupation. Building on this exposure measure, Pizzinelli et al. (2023) attempt to measure the complementarity between what AI and humans do in each occupation. They construct an index combining complementarity with exposure to determine the extent to which workers in an occupation are shielded from displacement by AI.

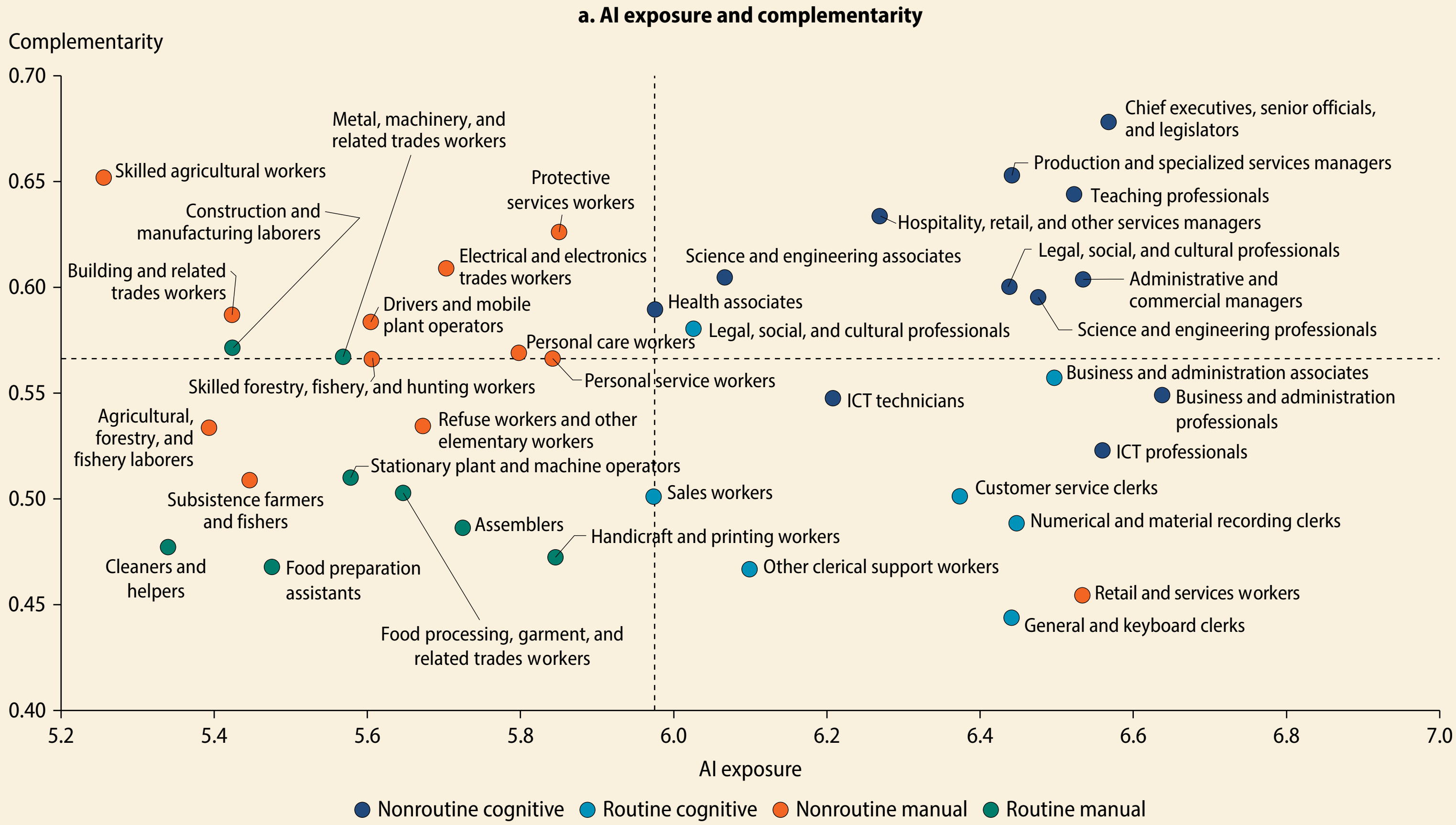
According to the Felten, Raj, and Seamans (2021) measure, AI exposure tends to be greater in jobs characterized by cognitive tasks rather than manual tasks. Occupations that primarily involve nonroutine tasks (whether cognitive or manual) show higher complementarity with AI relative to occupations that involve routine tasks (refer to figure A1.1, panel a). Following Pizzinelli et al. (2023), the AI exposure index can be adjusted to reflect complementarity. Complementarity-adjusted AI exposure, in which a higher index implies a higher risk of displacement, is highly correlated with the routineness of the tasks in a job (refer to figure A1.1, panel b). There is, however, significant heterogeneity across nonroutine tasks in occupations. For example, information and communication technology (ICT) professionals and health professionals share similar intensity in the routineness of tasks, but the former exhibit much greater exposure to displacement by AI. This difference arises because the nature of tasks performed by health professionals are more social and less-codifiable than those performed by ICT professionals.

(continued)

Box A.1. Exposure to artificial intelligence and complementarity *(continued)*

Jobs involving routine and nonroutine cognitive tasks may be replaced by AI, and some jobs involving nonroutine cognitive tasks are likely to be complemented by AI.

FIGURE A1.1 AI exposure and complementarity among routine and nonroutine cognitive tasks, by occupation

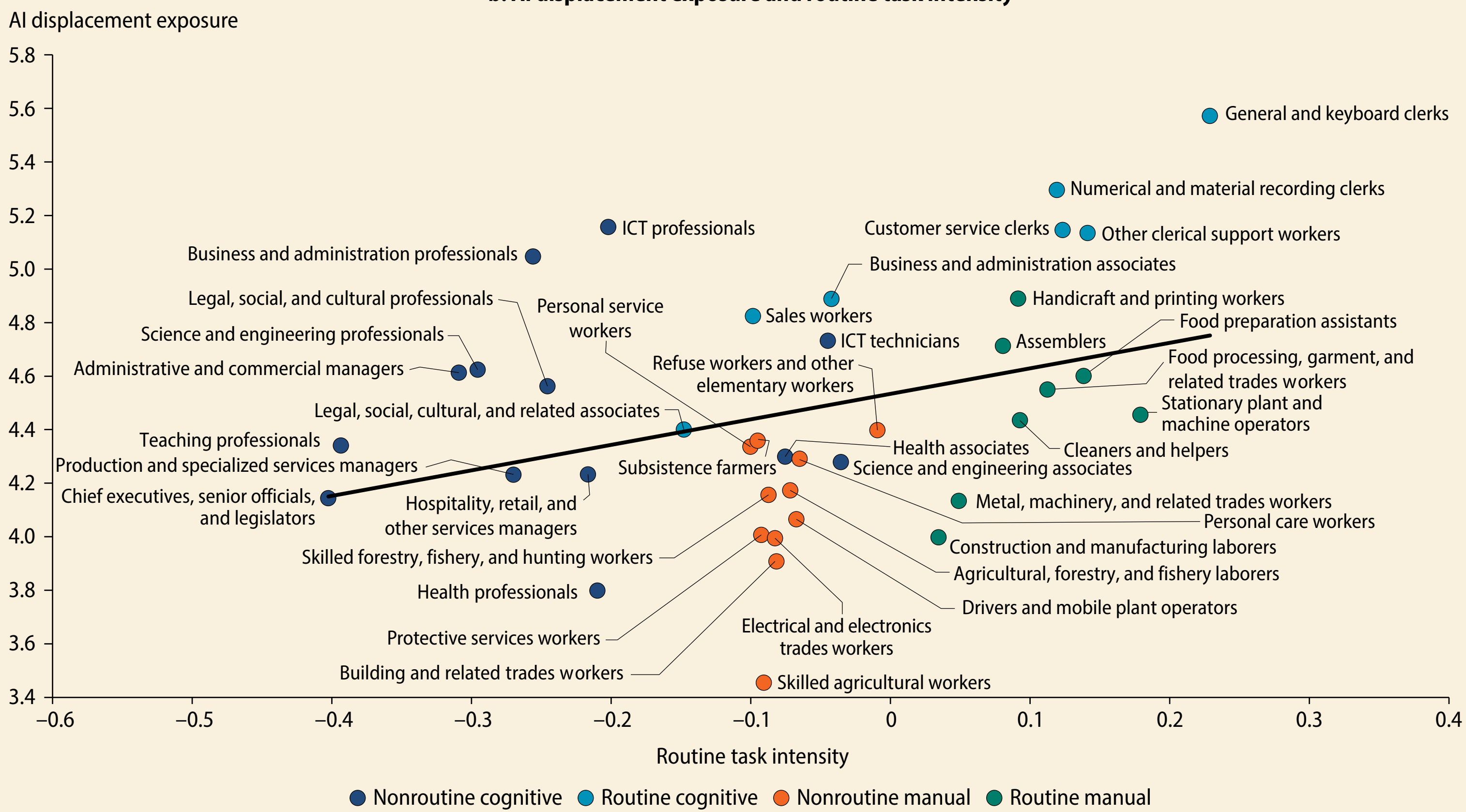


(continued)

Box A.1. Exposure to artificial intelligence and complementarity *(continued)*

FIGURE A1.1 AI exposure and complementarity among routine and nonroutine cognitive tasks, by occupation *(continued)*

b. AI displacement exposure and routine task intensity



Sources: Original figure for this publication based on data of Felten, Raj, and Seamans 2021; Pizzinelli et al. 2023.

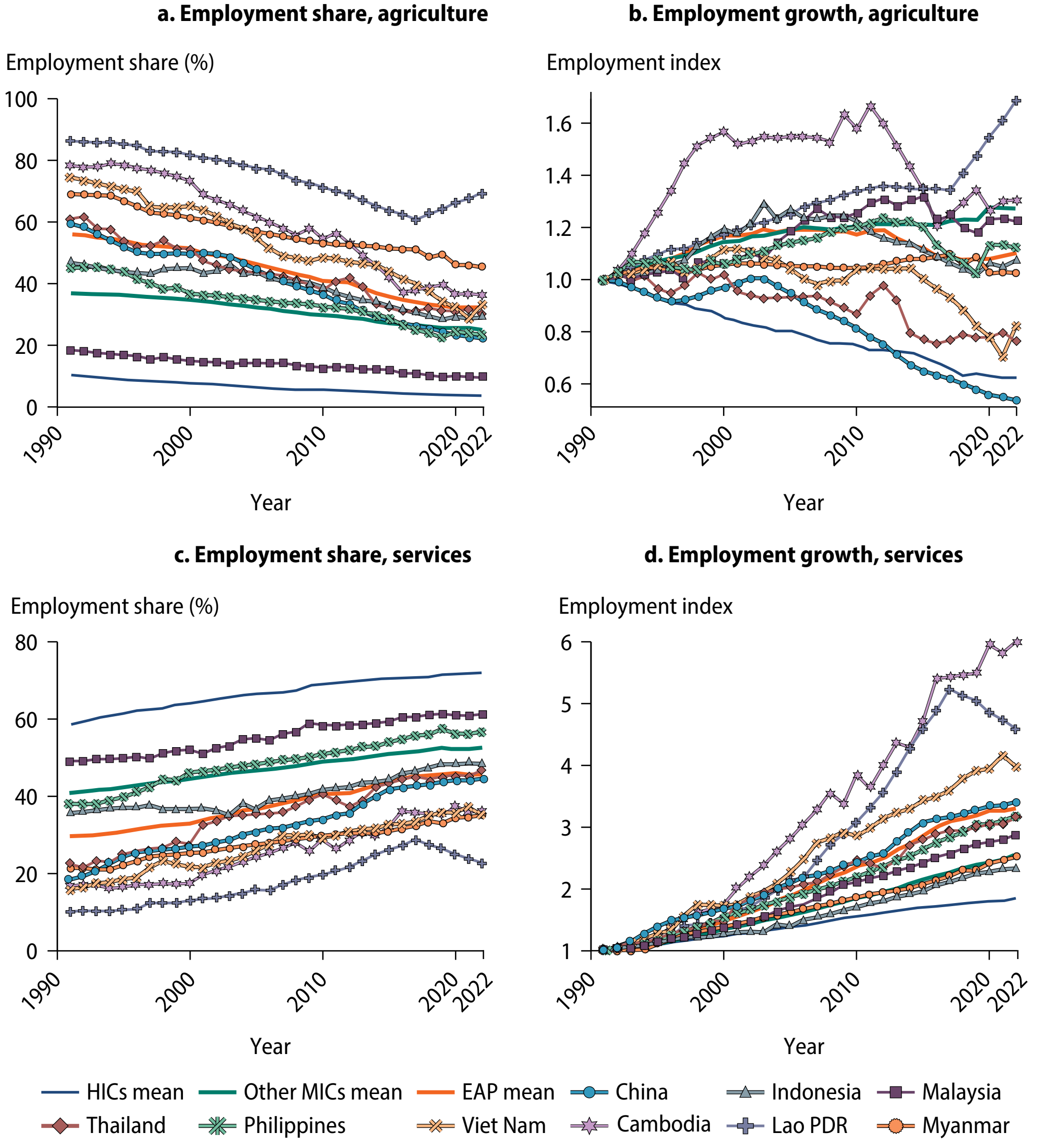
Note: Panel a: The crossed lines show the median. Panel b: The solid black line depicts the linear fit. AI = artificial intelligence; ICT = information and communication technology.

TABLE A.1 Regression results: Agricultural mechanization, employment, and productivity

Explanatory variables	(1) Log agriculture value added per hectare	(2) Log agriculture value added per hectare	(3) Log total agriculture employment	(4) Log total agriculture employment	(5) Agriculture employment share (%)	(6) Agriculture employment share (%)
Log machinery per 1,000 AG workers	0.0461*** (0.0108)	0.0746*** (0.0149)	0.122*** (0.00937)	0.0493*** (0.0113)	−0.0188*** (0.00219)	−0.00129 (0.00243)
Log cropped area	−0.779*** (0.0126)	−0.878*** (0.0128)	0.0816*** (0.0109)	−0.0232** (0.00941)	−0.0171*** (0.00254)	−0.00997*** (0.00201)
Share of cereals in total cropped area	0.0764*** (0.0182)	0.0957*** (0.0158)	−0.0234 (0.0148)	0.0228** (0.0115)	−0.0229*** (0.00346)	−0.00239 (0.00246)
GDP per capita (2015 US$)	0.126*** (0.00697)	0.125*** (0.0125)	−0.0623*** (0.00591)	−0.0700*** (0.00944)	−0.0280*** (0.00138)	−0.0255*** (0.00202)
Log total population	0.718*** (0.0313)	0.577*** (0.0792)	1.040*** (0.0252)	0.882*** (0.0590)	−0.0649*** (0.00588)	−0.0760*** (0.0126)
Constant	7.256*** (0.0245)	7.297*** (0.0324)	13.47*** (0.0202)	13.45*** (0.0241)	0.386*** (0.00471)	0.373*** (0.00516)
Sample (# observations)	3,679	3,679	3,937	3,937	3,937	3,937
R-squared	0.979	0.991	0.996	0.999	0.982	0.995
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trend	No	Yes	No	Yes	No	Yes

Source: Original table for this publication.
Note: AG = agriculture; GDP = gross domestic product.
Significance level: ** = 5 percent, *** = 1 percent.

FIGURE A.4 Trends in employment in agriculture and services, 1990–2022



Source: Original figure for this publication based on data of WDI (World Development Indicators) (dashboard), World Bank, Washington, DC, https://datatopics.worldbank.org/world-development-indicators/.

Note: HICs = high-income countries; MICs = middle-income countries.

References

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.

Farmer, J. Doyne, and François Lafond. 2016. "How Predictable Is Technological Progress?' *Research Policy* 45 (3): 647–65.

Felten, Edward, Manav Raj, and Robert Seamans. 2021. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses." *Strategic Management Journal* 42 (12): 2195–217.

Pizzinelli, Carlo, Augustus J. Panton, Marina Mendes Tavares, Mauro Cazzaniga, and Longji Li. 2023. "Labor Market Exposure to AI: Cross-Country Differences and Distributional Implications." IMF Working Paper WP/23/216 (October), International Monetary Fund, Washington, DC.

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