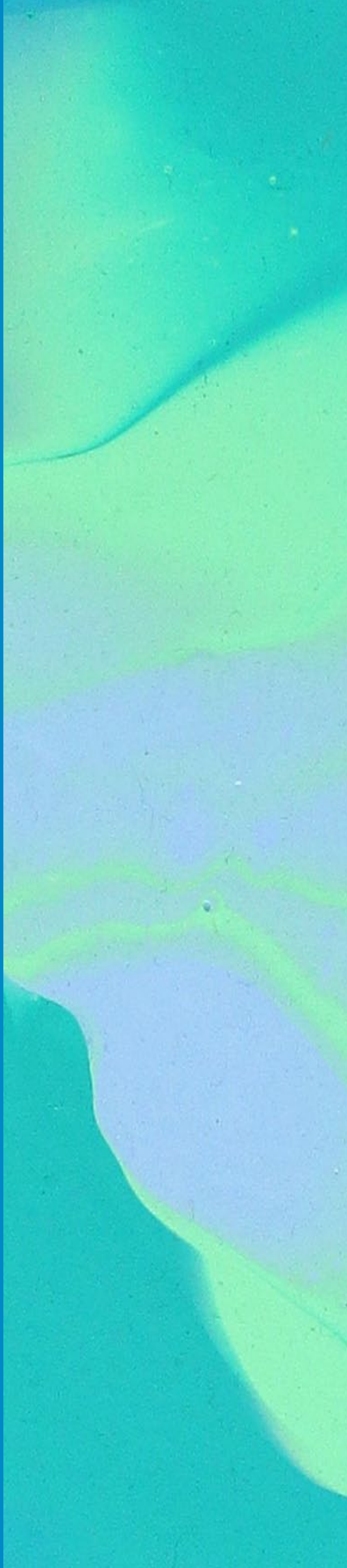
2

HOW TECHNOLOGY AFFECTS JOBS



How technology affects jobs

Developing Asia has created 30 million jobs annually in industry and services over the past 25 years. Job creation has been accompanied by improved productivity, rising earnings for workers, and large reductions in poverty. Contributing to this process are shifts in employment from sectors with low productivity and pay, such as agriculture, to sectors with higher productivity and pay. However, a larger part of the aggregate productivity gains come from sector-specific improvements in productivity, mainly thanks to technological advances such as high-yielding crop varieties in farming, modern machine tools in manufacturing, and information and communication technology in services.[1]

The jobs challenge is far from over. From 2015 to 2030, the labor force in developing Asia is projected to increase by about 11 million per year. So Asia needs more jobs but also better jobs. The broad contours of action and policy needed to meet the jobs challenge are well known: timely and appropriate investments in education, infrastructure, and research and development, as well as a policy framework emphasizing macroeconomic stability, openness to trade and foreign direct investment, and an investment climate conducive to business (ADB 2015a, 2017a). However, concern is growing that some elements of this framework will no longer improve labor market outcomes for many workers. Paradoxically, the concern stems from the fundamental driver of human progress throughout history: technological change.

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While future prosperity is sure to derive from advances in robotics, three-dimensional printing, artificial intelligence (AI), and the internet of things—technologies that enable the often-cited Fourth Industrial Revolution—some of them also pose new challenges for workers. In particular, the growing sophistication of robotics and AI raise the possibility of unprecedented automation and displacement of labor. In apparel and footwear manufacturing, for example, "workerless factories" are being tested using completely automated production. In services, it is becoming technically feasible to automate more complex tasks in occupations such as customer support. How will new technologies affect developing Asia's ability to generate more and better jobs?

This is the central question of this chapter. Considering the many uncertainties that arise in any analysis of a nascent and rapidly evolving phenomenon, the question is addressed through several exercises that together shed light on how the relationship between technology and jobs will likely play out in the region. The exercises are embedded within an analytical framework that clarifies the different channels through which technology affects jobs. Moreover, they focus on different aspects of technology and capture their effects in various ways, some more direct than others. Thus, while some exercises look at the effects of automation through, for example, the adoption of industrial robots in manufacturing, others take a broader view of technology and capture its effects through more efficient production or distribution of goods and services along the global supply chain.

The analysis concludes that several forces will likely work against the pervasive job displacement that some predict. In the first place, the economic feasibility of automating in many parts of Asia today lags technological feasibility, leaving the adoption of the latest laborsaving technologies some ways off. Perhaps most importantly, higher productivity will generate more demand for novel goods and services, providing a powerful countervailing force to automation-driven displacement of labor. Moreover, technological advances and economic growth will generate new occupations and industries, further contributing to job growth.

Clearly, though, new technologies and automation will impose hardships on some workers. Several types of jobs will be lost. While new ones will appear, they will require skills that workers do not yet possess, and they may arise in locations removed from the homes of displaced workers. Low wage growth and higher unemployment among the less-skilled could become, alongside other causes of income inequality, a feature of labor markets if governments fail to take action. Accordingly, this chapter looks at the implications for public policy, especially on education and skills development, and on labor regulations and social protection systems, while touching on other topics.

Rising concern over technology displacing jobs

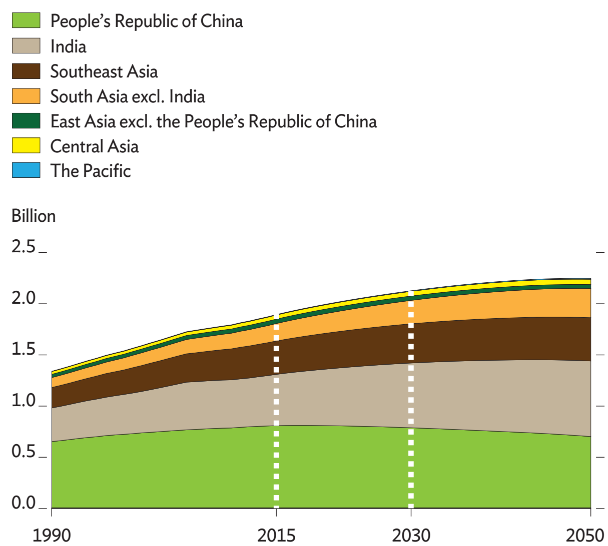
An overview of labor markets in Asia and the Pacific reveals how important higher productivity is to reducing poverty and improving the quality of jobs to make them more remunerative and formal. Technological progress plays a vital role in raising productivity but inevitably raises nagging concerns about job security. Today, robotics and AI promise ever greater improvements to productivity, but will these benefits come with ever worsening job prospects for working people? Assessing this possibility is important but not straightforward. Technology affects job prospects through several channels, calling for an analytical framework that clarifies the various channels and the conditions under which they operate. The first step in constructing such a framework is to consider the shape of the labor market and workplace in developing Asia today.

Asia at work

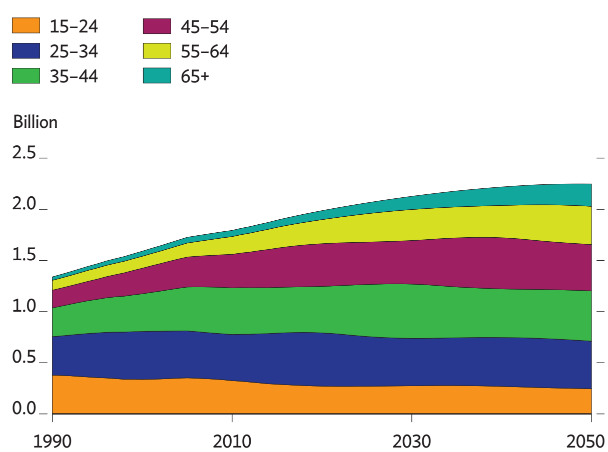
Developing Asia has the largest regional labor force in the world, with nearly 2 billion workers. India and the People's Republic of China (PRC), the region's two giants, account for almost 70% of the total (Figure 2.1.1a). The regional labor force is projected to grow by 0.5% annually from 1.9 billion in 2015 to 2.1 billion in 2030 and 2.2 billion in 2050. India is projected to account for 30% of the regional total labor force by 2030, with the PRC share declining to 37%. One cause of this shift is that the labor force is aging. The decline in the share of the 15–24 age group and an increase in the share of the three oldest age groups are quite evident for the region as a whole (Figure 2.1.1b). Considerable variation in age distribution exists by country, with different implications for growth in the national labor force (Figures 2.1.2 and 2.1.3). Economies with relatively young current populations, such as Nepal and Pakistan, will experience larger increases in their labor force and need policies to ensure an adequate number of

2.1.1 Labor force in developing Asia

a. By subregion (15 years old and above)



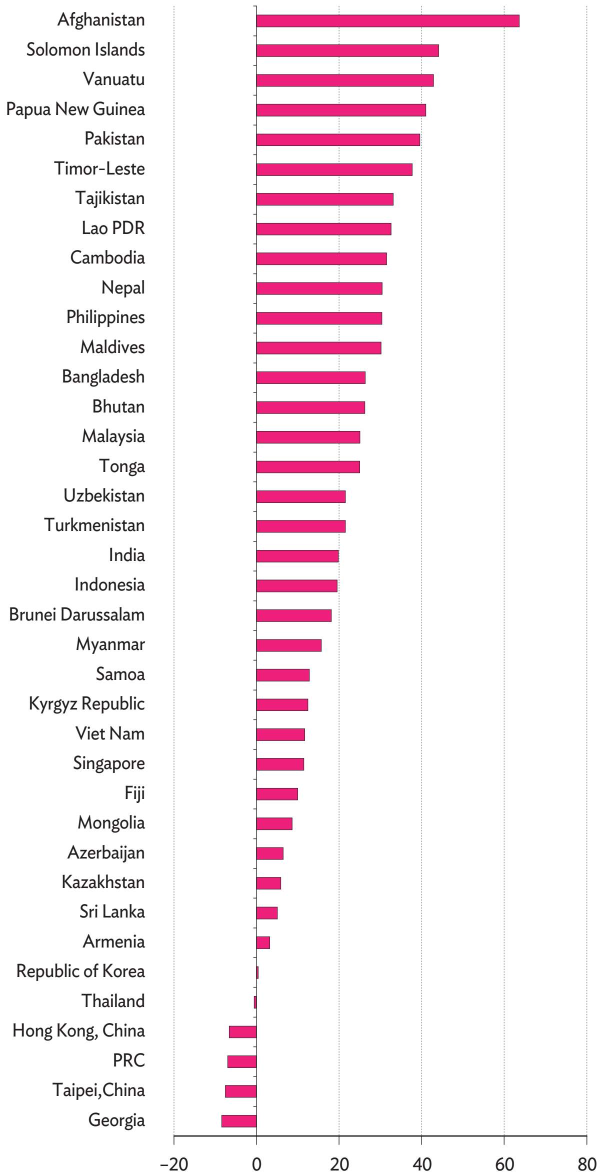
b. By age group



Note: Southeast Asia includes Brunei Darussalam, Cambodia, Indonesia, the Lao People's Democratic Republic, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Viet Nam. South Asia excluding India includes Afghanistan, Bangladesh, Bhutan, Maldives, Nepal, Pakistan, and Sri Lanka. East Asia excluding the People's Republic of China includes Hong Kong, China; Mongolia; the Republic of Korea; and Taipei,China. Central Asia includes Armenia, Azerbaijan, Georgia, Kazakhstan, the Kyrgyz Republic, Tajikistan, Turkmenistan, and Uzbekistan. The Pacific includes Fiji, Papua New Guinea, Samoa, Solomon Islands, Timor-Leste, Tonga, and Vanuatu.

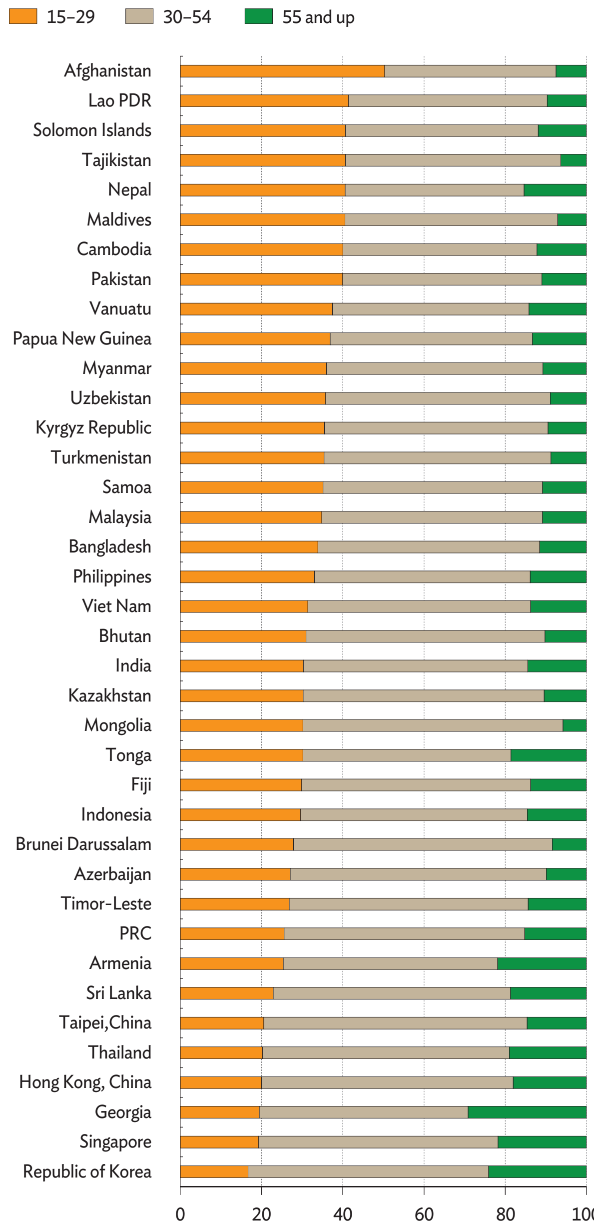
Source: International Labour Organization. ILOSTAT. http://www.ilo.org/ilostat (accessed 10 August 2016).

2.1.2 Percent change in labor force size, 2015 to 2030 (%)



Lao PDR = Lao People's Democratic Republic, PRC = People's Republic of China.
Source: International Labour Organization. ILOSTAT. http://www.ilo.org/ilostat (accessed 22 February 2018).

2.1.3 Distribution of labor force by age group, 2015 (%)

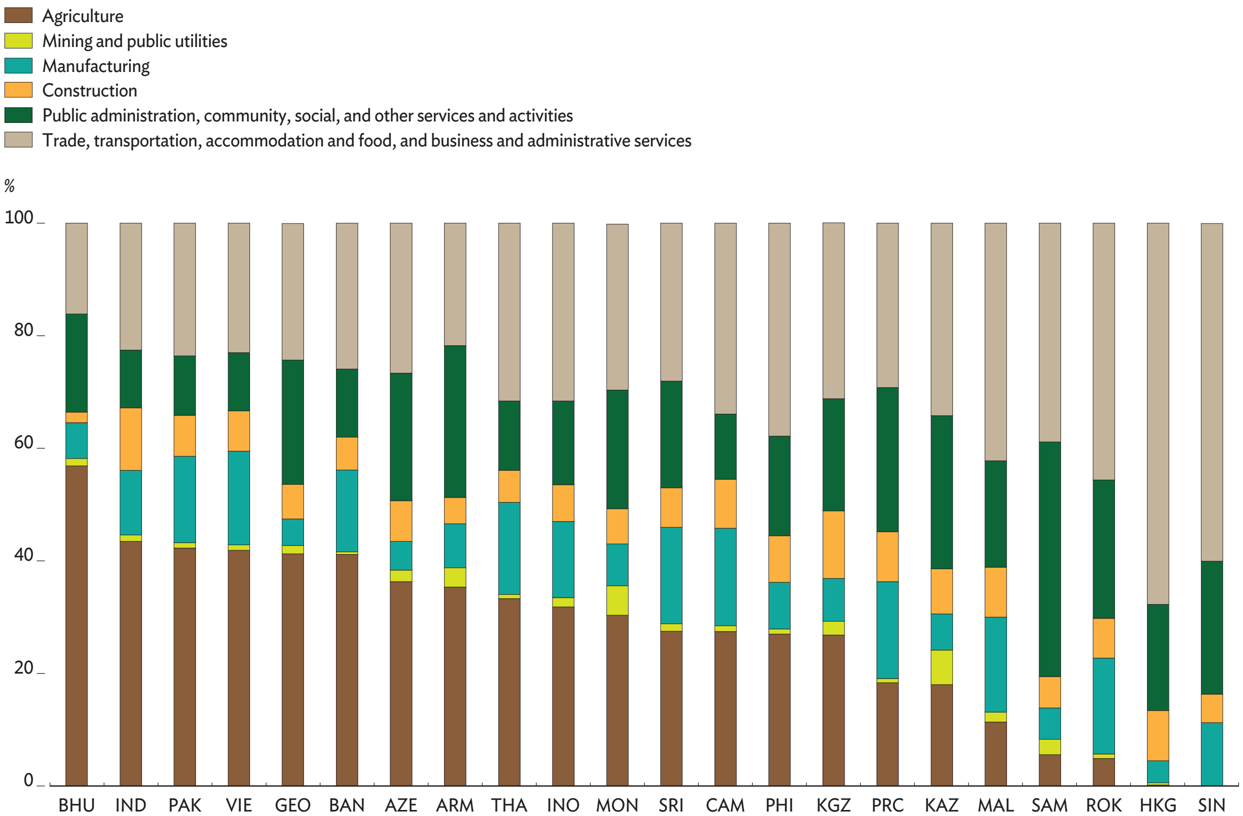


Lao PDR = Lao People's Democratic Republic, PRC = People's Republic of China.
Source: International Labour Organization. ILOSTAT. http://www.ilo.org/ilostat (accessed 22 February 2018).

productive jobs. Meanwhile, economies with aging populations, such as the PRC and the Republic of Korea, must ensure that workers are well looked after when they retire and that productive opportunities exist for those older workers who wish to continue working.

On average, agriculture employs one-third of the workforce in developing Asia, excluding high-income economies, where it employs less than 5% (Figure 2.1.4). In general, the share

2.1.4 Employment by sector, selected developing Asia, 2016



ARM = Armenia, AZE = Azerbaijan, BAN = Bangladesh, BHU = Bhutan, CAM = Cambodia, GEO = Georgia, HKG = Hong Kong, China, IND = India, INO = Indonesia, KAZ = Kazakhstan, KGZ = Kyrgyz Republic, MAL = Malaysia, MON = Mongolia, PAK = Pakistan, PHI = Philippines, PRC = People's Republic of China, ROK = Republic of Korea, SAM = Samoa, SIN = Singapore, SRI = Sri Lanka, THA = Thailand, VIE = Viet Nam.

Source: International Labour Organization. ILOSTAT. http://www.ilo.org/ilostat (accessed 15 March 2018).

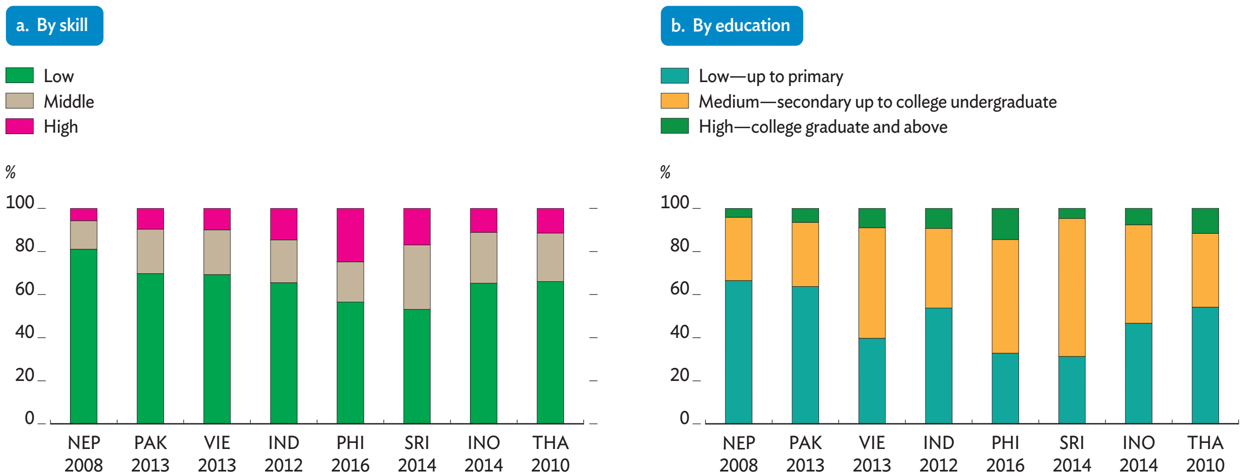
of employment in agriculture (which often entails paid work off the farm) declines as gross domestic product per capita rises. Conversely, as economies grow richer, the share of employment in manufacturing and especially services increases. The structural shift, however, occurs at different speeds across countries.

Another way of characterizing employment is in terms of the types of tasks done. This, too, varies by stage of development. Workers in lower-income economies generally carry out tasks that are often termed lower-skilled (Figure 2.1.5a). Also, low-income economies generally have a larger portion of workers with low educational attainment (Figure 2.1.5b).

How well are Asia's workers doing?

Whether individuals in the labor force are able to find jobs is usually the first metric used to judge labor market performance. On this count, developing Asia does well for adults. The median unemployment rate is relatively low at 3.0%, and the mean

2.1.5 Employment share by skill and education



IND = India, INO = Indonesia, NEP = Nepal, PAK = Pakistan, PHI = Philippines, SRI = Sri Lanka, THA = Thailand, VIE = Viet Nam.
Note: Skills classification is based on World Bank (2016).
Source: ADB estimates using labor force surveys, various countries.

at 3.8% (Table 2.1.1). While unemployment rates are higher for young participants—the median at 10.7% and the mean at 12.6%—the bigger developmental challenge for the region is underemployment. This can mean workers employed for fewer hours than they would like, or involuntary underemployment, but is most apparent as workers employed in low-paying, less-productive jobs—both common features of the informal sector and fundamental determinants of whether a job is good or not.

This raises the question of what determines workers' earnings. Empirically, a key determinant is where a person is employed. Table 2.1.2 shows that, among the three sectors with relatively large shares of total employment, typically 10% or above, average wages are lowest by far in agriculture. In fact, average wages in manufacturing and in the services wholesale and retail trade, hotels, and restaurants—that is, services that typically do not require tertiary education—are often 50% higher in nominal terms. This wage gap is wider than typical urban–rural cost differentials.

A variety of factors determine a worker's earnings: worker supply and demand, regulatory and institutional issues like minimum wage and collective bargaining laws, and even social norms on "fairness" and gender relationships. However, a key determinant of wages is labor productivity, or how much output a worker produces. Table 2.1.2 shows average labor productivity in agriculture considerably lower than in manufacturing and services.

2.1.1 Employment, unemployment, and informal employment in Asia and the Pacific, 2015 or latest

Region	Economy	Working-age population ('000)	Ratio of employment to population	Youth unemployment rate	Adult unemployment rate	Informal employment share of nonfarm employment
East Asia	People's Republic of China	1,132,960	68.4	10.1	3.6	...
	Republic of Korea	43,017	60.3	10.5	3.1	...
	Taipei,China	19,842	56.4	12.0	3.1	...
	Hong Kong, China	6,384	59.2	10.5	2.7	...
	Mongolia	2,023	56.9	13.1	3.9	24.5
South Asia	India	763,132	51.5	10.1	1.2	84.7
	Pakistan	111,515	50.2	6.6	2.5	78.4
	Bangladesh	106,265	54.7	9.9	2.9	...
	Sri Lanka	16,671	51.3	20.7	2.6	62.1
	Nepal	14,878	64.7	2.2	1.0	...
	Bhutan	559	61.6	10.7	1.3	...
Southeast Asia	Indonesia	186,101	61.7	22.6	2.9	72.5
	Viet Nam	69,736	76.1	7.0	1.3	68.2
	Philippines	64,936	59.7	15.0	4.0	70.1
	Thailand	55,238	68.8	1.0	0.3	37.7
	Myanmar	33,935	64.2	1.6	0.5	...
	Malaysia	21,388	65.8	10.7	1.5	...
	Singapore	3,300	65.7	10.3	2.0	...
Central Asia	Kazakhstan	12,831	67.6	3.9	5.4	...
	Azerbaijan	6,678	61.9	13.4	3.8	...
	Kyrgyz Republic	4,079	57.7	15.0	5.9	...
	Georgia	3,010	59.7	30.8	10.2	...
	Armenia	2,107	50.9	32.0	16.4	17.6
The Pacific	Fiji	588	52.0	19.2	5.5	...
	Vanuatu	143	66.0	10.6	3.7	...
	Samoa	117	29.4	19.1	6.4	...

... = data not available.

Note: Data are for 2015 except working age population in India 2012, Nepal 2008, Bangladesh 2013, Fiji 2010, Vanuatu 2009, and Samoa, 2014; youth unemployment and adult unemployment rate in Fiji, Kazakhstan, the People's Republic of China, and Singapore 2013; informal employment share of nonfarm employment in Thailand 2016, Mongolia 2014, India 2012, Pakistan 2010, Sri Lanka 2009, Indonesia 2009, Viet Nam 2009, and the Philippines 2008.

Source: International Labour Organization. ILOSTAT. http://www.ilo.org/ilostat (accessed 1 September 2017).

The imperative of improving labor productivity

Given the pattern of relative labor productivity and wages across sectors described above, some combination of raising agricultural productivity and shifting agricultural workers into more productive sectors should improve labor market performance considerably. In fact, evidence indicates that economies that are more successful at moving workers from low- to high-productivity sectors—that is, at effecting structural change—have done better on several dimensions of labor market performance, including larger reductions in poverty (Figure 2.1.6a) and self-employment (Figure 2.1.6b).

2.1.2 Wages and relative productivity by sector

Country	Year	Sector	Share in total employment (%)	Share in total wage employment (%)	Share of workers with less than college (%)	Ratio to agriculture sector	
						Wage	Productivity
India	2012	Agriculture	47	36	97.29	1.00	1.00
		Manufacturing	12	14	90.92	1.79	3.01
		Trade, hotels, & restaurants	12	7	87.31	1.79	2.54
Philippines	2016	Agriculture	29	14	97.75	1.00	1.00
		Manufacturing	8	11	88.72	1.75	9.48
		Trade, hotels, & restaurants	24	18	86.71	1.50	2.57
Indonesia	2014	Agriculture	35	14	99.42	1.00	1.00
		Manufacturing	13	20	96.98	2.00	4.28
		Trade, hotels, & restaurants	23	14	95.84	1.75	1.93
Nepal	2008	Agriculture	65	17	98.91	1.00	1.00
		Manufacturing	8	19	95.86	2.21	1.59
		Trade, hotels, & restaurants	11	8	94.47	2.21	2.30
Viet Nam	2013	Agriculture	47	11	98.97	1.00	1.00
		Manufacturing	14	29	93.60	1.15	2.86
		Trade, hotels, & restaurants	17	10	93.45	1.15	2.07
Pakistan	2013	Agriculture	43	15	99.03	1.00	1.00
		Manufacturing	14	22	94.19	1.50	1.86
		Trade, hotels, & restaurants	16	10	94.33	1.33	2.24
Sri Lanka	2014	Agriculture	28	14	99.64	1.00	1.00
		Manufacturing	18	21	98.86	1.36	3.16
		Trade, hotels, & restaurants	16	11	98.96	1.45	2.90

Notes: Trade, hotels, & restaurants includes both wholesale and retail trade. Relative wages are based on median monthly wages of wage workers.
Sources: ADB. The Statistical Database System. https://sdbs.adb.org (accessed 8 January 2018); Labor force surveys, various countries.

Another significant part of making jobs more productive is raising productivity within sectors. In fact, a larger portion of economy-wide or aggregate labor productivity growth in Asia derives more from rapid increases in labor productivity within sectors than from movements of labor from low- to high-productivity sectors (Figure 2.1.7).[2]

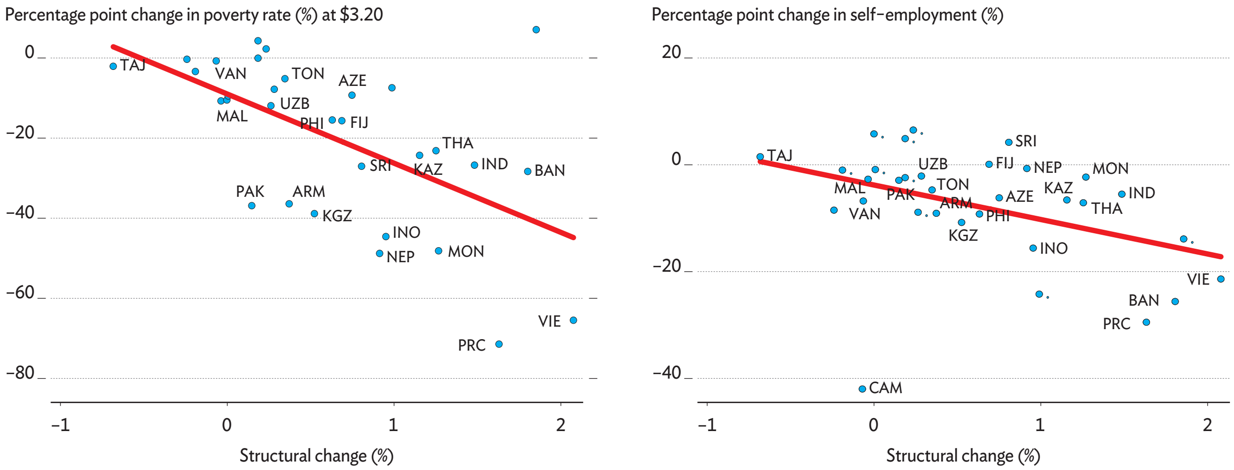
Technology is a key driver of improvement in within-sector productivity growth

While within-sector productivity growth can be achieved by reallocating workers from low- to high-productivity firms and farms, it also occurs by improving the productivity of individual firms and farms. A key driver of this process is the use of new technologies. The adoption of new, high-yielding varieties of grain, fruit, vegetables, and even livestock—used in combination with improved fertilizers, irrigation, and machinery—has boosted agricultural productivity on

2.1.6 Structural change, poverty reduction, and self employment

a. Structural change and reduction of $3.20/day poverty, 1993–2013

b. Structural change and change in self-employment rates, 1993–2013



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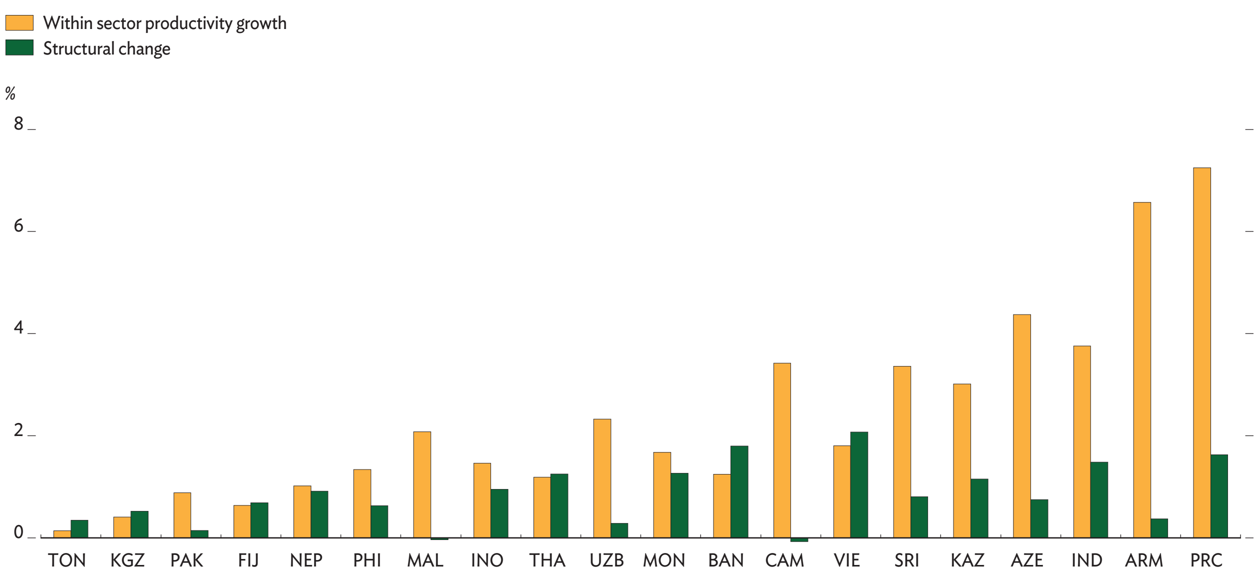
Notes: Panel A contains 31 countries and panel B 32 countries classified as low- and middle-income countries by the World Bank in 1993. Following Mcmillan, Rodrik, and Verduzco-Gallo (2014), changes in economy-wide labor productivity can be broken down into two components: improvements in sector-specific labor productivity and structural change. These computations are based on three sectors: agriculture, industry, and services.

Sources: International Labour Organization. ILOSTAT. http://www.ilo.org/ilostat (accessed 15 March 2018); World Bank. PovcalNet. http://iresearch.worldbank.org/PovcalNet/ (accessed 8 March 2018); World Bank. World Development Indicators. http://databank.worldbank.org/data/home.aspx (accessed 1 March 2018).

2.1.7 Components of labor productivity growth, 1993–2013



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Note: Three sectors—agriculture, industry, and services—were used to calculate these components of labor productivity growth.

Sources: International Labour Organization. ILOSTAT. http://www.ilo.org/ilostat (accessed 15 March 2018); World Bank. World Development Indicators. http://databank.worldbank.org/data/home.aspx (accessed 1 March 2018).

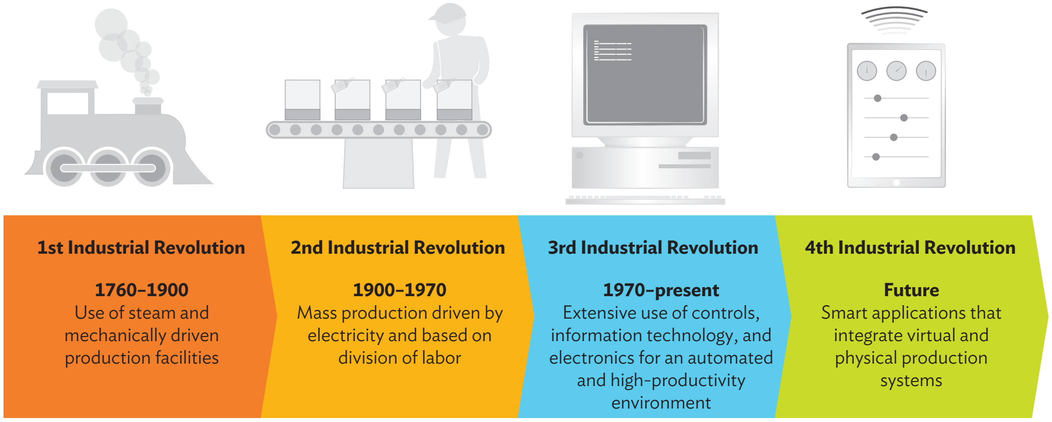
Asian farms and raised rural standards of living. It has enabled workers to move out of subsistence farming while allowing those who remain to produce more food (Estudillo, Sawada, and Otsuka 2006). Similarly, the use of modern machine tools such as numerically controlled lathes in manufacturing, and of information and communication technology in services, has been crucial in raising factory and office productivity, allowing better wages for workers.

However, concern is growing that the very latest technologies could prove to be disruptive for workers, displacing jobs without creating nearly enough new ones. This could be particularly problematic for countries with a lot of young workers. For example, recent research suggests that manufacturing—a sector instrumental to economic success in developing Asia—may have lost its power as an engine of job creation (Felipe, Mehta, and Rhee 2018). One reason behind the lower peak for industrial employment share could be technology. Ever-increasing opportunities for automation can enable more manufactured goods to be produced without a correspondingly large increase in employment. Even in many services, new technologies are raising the specter of labor-displacing automation.

Understanding the relationship between technology and jobs

From knitting machines and power looms to electricity and computers, automating production has been at the heart of economic development. Since the first industrial revolution starting with the steam engine, being able to automate tasks in a production chain has been instrumental to raising labor productivity (Figure 2.1.8). Across history, automation has always displaced workers, generating anxiety about technological change. However, displacement has been accompanied by the emergence of new occupations, and job opportunities have not diminished. Moreover, not all technology displaces human labor. Magnetic resonance imaging and X-ray machines, for example, perform functions humans cannot, thereby complementing, not displacing, human labor in medical care. However, the advent of the Fourth Industrial Revolution has heightened automation anxiety. Underpinned by more sophisticated robots and computing power, automation is taking over more and more tasks once thought to be uniquely human (Box 2.1.1). The key issue is whether the Fourth Industrial Revolution is different from previous ones. Is widespread “technological unemployment”—as warned by notable thinkers such as David Ricardo, Karl Marx, and John Maynard Keynes—more likely this time around?

2.1.8 Industrial revolutions: four episodes of technological breakthrough



Source: ADB based on Schwab (2017).

This section presents an analytical framework that explains the different channels through which technology affects jobs.

A useful framework for analyzing the impact of new technologies on jobs is provided in Autor, Levy, and Murnane (2003), Acemoglu and Autor (2011), Autor (2015), and Acemoglu and Restrepo (2018). This framework recognizes that any given job consists of a bundle of tasks. They can be classified along two dimensions: either manual or cognitive, and routine or not. The technical feasibility of automating tasks

2.1.1 Technological advancements that define the Fourth Industrial Revolution

- **Artificial intelligence** (AI) is the science and engineering of rational, intelligent machines that act, work, and solve problems the way humans do. Machine learning—or "deep learning," a subset of AI—is the science of teaching computers to learn and apply data without being explicitly programmed.
- **Quantum computers** are powerful machines that run new types of algorithms to process information more holistically. They may one day enable revolutionary breakthroughs in the discovery of new materials and drugs, the optimization of complex synthetic systems, and AI.
- **Biotechnology** covers a broad range of technologies that employ living organisms to make products such as drugs and therapeutics, nutritional compounds, biofuels, and materials with novel functions.
- **Blockchain technology** is an incorruptible digital ledger of economic transactions that can be programmed to record not just financial transactions but virtually anything of value. This type of technology powers cryptocurrencies such as Bitcoin and Ethereum.
- **Three-dimensional printing**, a manufacturing process that additively builds three-dimensional objects using computer-aided design, allows the construction of complex objects with less material than traditional manufacturing.
- **New generation robotics** such as sewbots, Baxter, and the *leichtbauroboter* (lightweight robot) intelligent industrial work assistant, better known as LBR iiwa, open new possibilities for automating tasks on factory floors, particularly in light manufacturing such as textiles and apparel.

Sources: Blockchain Research Institute 2018; IBM Q Network webpage; Lee 2016; McCarthy 2007; Winston 2010.

using some combination of machines and computing power tends to be higher for routine and manual tasks, such as repetitive physical operations. Further, a particular task may be automatable but the associated job safe from being displaced because automation may only restructure the job, such that workers are freed up to focus on other tasks. By implication, only jobs consisting mainly of routine and manual tasks, such as machine operator and assembler, will likely be displaced. Jobs that entail some routine and manual tasks, such as clerk and IT assistant, are less likely to be displaced.

To illustrate, Figure 2.1.9 shows that occupations with a larger share of routine tasks are more likely to be automated, while those with a lower share are less likely. Workers in occupations in quadrant 4 (researchers and managers) are safe because the majority of their tasks are difficult to automate and new technology augments the value of their labor. In contrast, workers in quadrants 1 and 2 hold jobs with mostly routine tasks, including cognitive routine jobs (accountants and bank tellers) and manual routine jobs (sewing machine operators and assembly line workers). These jobs are at risk of displacement by laborsaving technology. Manual and nonroutine jobs in quadrant 3 (cook and hairdresser) are not yet heavily affected by laborsaving technology.

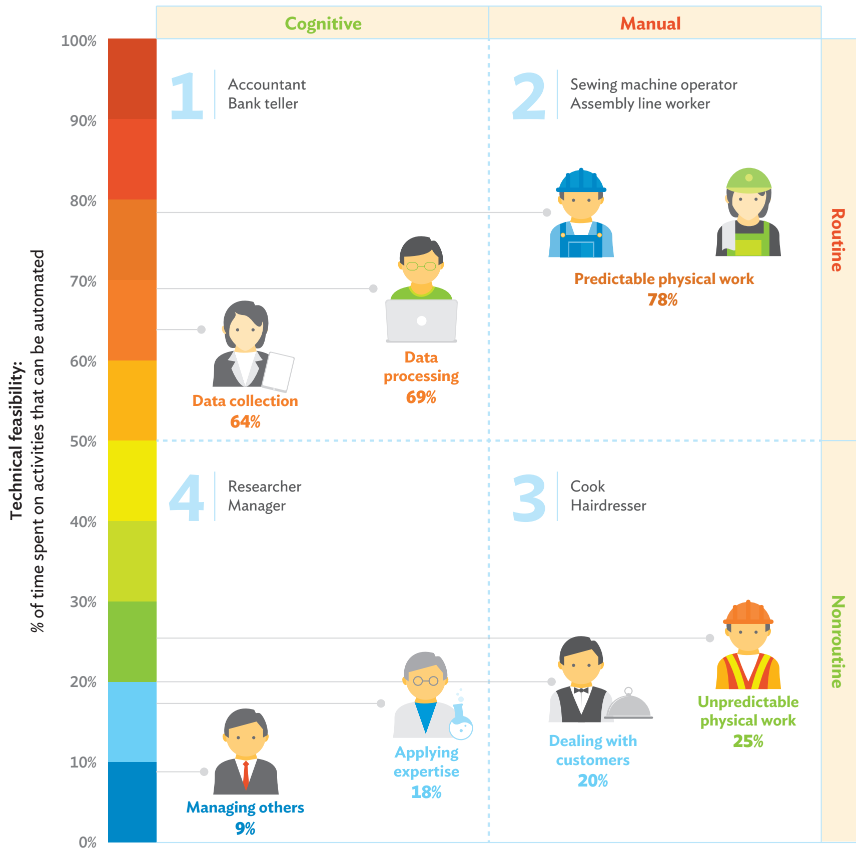
Concern that automation could cause widespread job loss is cited in many recent studies (Table 2.1.3). However, the concern appears to stem from considering only the displacement effect of automation, many of these studies ignore other effects (Figure 2.1.10). Channels through which automation has an impact on jobs can be divided into within-firm or -industry effects and between-industry effects.

Within-firm or -industry effects. There are three main channels through which new technology affects labor demand within a firm or industry:

(i) **Displacement effect.** Because robots and computers are good at routine tasks, demand will fall for jobs comprising mainly routine tasks. A manual worker in an industrial warehouse whose job is to fetch products from shelves, for example, is likely to be displaced, perhaps by Kiva system robots, which can traverse large floor spaces to find products much faster than humans. Interestingly, though, displacement is bounded by tasks that humans accomplish effortlessly but computer programmers struggle to code into routines. Polanyi's Paradox recognizes that we know more than we can tell (Autor 2015, Polanyi 1966).

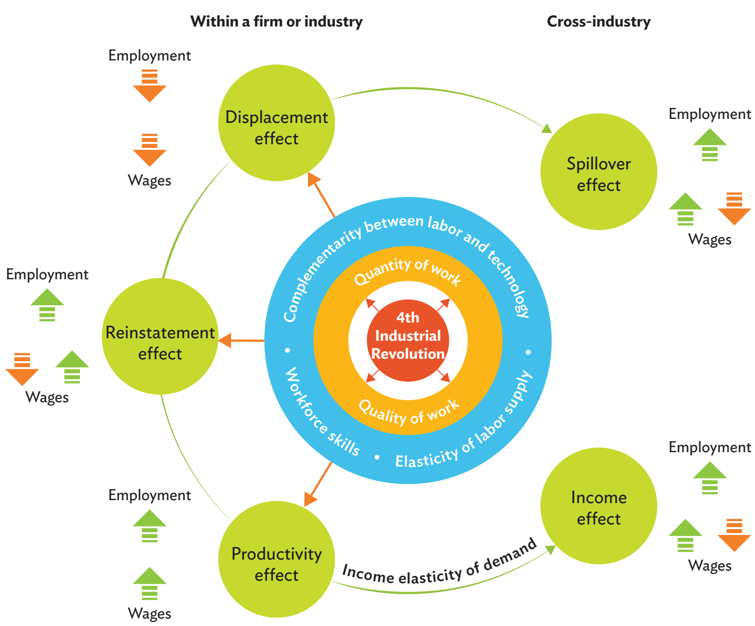
(ii) **Productivity effect.** Sometimes called a scale effect, it is when automation improves productivity and lowers production costs. Under normal conditions, this lowers the price of goods and services, which raises demand for them. As industrial robots become

2.1.9 Impact of automation on jobs



Note: Percentages are from Frey and Osborne (2017) estimates on probability of automation. Framework is based on Acemoglu and Autor (2011).

2.1.10 Analytical framework of countrywide effects



Notes: Arrows indicating a rise or fall in employment or wages reflect empirical findings from existing studies, but they do not necessarily mean the result is obtained each time the effects are studied (Table 2.1.3).

Source: ADB based on Autor (2015) and Acemoglu and Restrepo (2018).

2.1.3 Recent studies on the impact of automation on jobs

Study	Key findings	Impact of technology	Country coverage
Acemoglu and Restrepo 2017a	☐ During 1990–2007, adding industrial robots correlated negatively with employment and wages. ☐ Each robot cut six jobs and reduced wages by 0.5% per 1,000 workers. ☐ In manufacturing, routine manual and blue-collar jobs were most affected.	E↓ W↓	US
Autor and Salomons 2017	☐ During 1970–2007, combined productivity growth was associated with increased employment countrywide. ☐ Each 1.0% rise in total factor productivity predicted a 0.3% rise in employment. ☐ Productivity growth in one industry had positive job spillover elsewhere in the economy.	E↑	19 OECD members
Bessen 2017	☐ During 1984–2007, computer use was associated with 3% average annual job loss in manufacturing and 1% annual job gain elsewhere. ☐ Demand in manufacturing or mature industries was weak, while productivity gains created new demand elsewhere or in newer industries.	E↑ nonmanufacturing E↓ manufacturing	US
Chang, Rynhart, and Huynh 2016	☐ Technology will increase productivity, rendering some occupations obsolete and creating new ones. ☐ ASEAN members relying heavily on labor-intensive jobs are most vulnerable to automation. ☐ Up to 70% of salaried workers—in automotive, electronics, and textile manufacturing and in retail service sectors—face automation.	E↓ W↓	ASEAN members
Frey and Osborne 2017	☐ By 2033, 47% of US jobs could become automated. ☐ Transportation and logistics, office and administrative support, and production labor will be most affected. ☐ Wages and educational attainment relate negatively with an occupation's probability of automation.	E↓ W↓	US
Frey and Rahbari 2016	☐ Automation will likely replace jobs faster in developing countries. ☐ The PRC risks losing 77% of jobs to automation, India 69%, and Ethiopia 85%, against an OECD average 57%. ☐ Technology-using sectors like professional services have expanded rapidly as many jobs became tradable.	E↓	OECD members plus Ethiopia, India, and the PRC
Graetz and Michaels, forthcoming	☐ During 1993–2007, industrial robot use increased labor productivity, total factor productivity, and wages. ☐ Robotics accounted for 10% of GDP growth and 16% of labor productivity and wage growth in industries with high robot density. ☐ Robots replaced low-skilled and some middle-skilled jobs but had little effect on high-skilled jobs.	E↑ W↑	17 developed countries—14 in Europe, plus Australia, the Republic of Korea, and the US
Mann and Püttmann 2017	☐ During 1976–2014, automation was associated with positive effects on total employment. ☐ Every new automation patent per worker brought a 0.2 percentage point increase in the ratio of employment to population. ☐ Automation is associated with jobs lost in manufacturing and in routine work, but with growth in jobs elsewhere.	E↑	US
McKinsey Global Institute 2017a	☐ Automation could raise productivity growth globally by as much as 1.4% annually. ☐ At least 30% of the work done in some 60% of occupations could be automated. ☐ Manufacturing, retail trade, accommodation and food service, and some middle-skill jobs are most susceptible to automation.	E↓ W↓	46 countries, both developing and advanced

continued next page

2.1.3 Recent studies on the impact of automation on jobs

Study	Key findings	Impact of technology	Country coverage
McKinsey Global Institute 2017b	☐ Automation could displace up to 15% of work globally by 2030. ☐ Up to 375 million workers globally, or 14% of the global workforce, will likely need new jobs and new skills if automation is rapid. ☐ Income inequality could grow in the US and other advanced economies as demand rises for high-wage jobs and falls for middle-wage jobs. The PRC and other emerging economies will likely see the highest net middle-wage job growth—in services and construction, among other areas—boosting the middle class.	E↓ W↓	46 countries, both developing and advanced
PricewaterhouseCoopers 2017	☐ By the early 2030s, automation could replace 38% of jobs in the US, 35% in Germany, 30% in the UK, and 21% in Japan. The risk in the UK is 56% in transportation and storage, 46% in manufacturing, 44% in wholesale and retail, and 17% in health care and social work. ☐ New automation technologies will create new jobs and, through productivity gains, generate new income and spending, creating new jobs that are more difficult to automate, primarily in services. ☐ In the UK, the average income should rise with productivity gains, but income inequality could worsen.	E, net long-term impact unclear in the UK W↑ UK	Germany, Japan, the UK, and the US
UNCTAD 2017	☐ During 2005–2014, more robot use is associated with a slight drop in manufacturing employment share and real wage growth across the sample, except in Mexico, Portugal, and Singapore. ☐ Robots displace routine tasks usually done by workers in the middle of the pay scale.	E↓ W↓ manufacturing	64 countries

ASEAN = Association of Southeast Asian Nations, E = employment, EU = European Union, FDI = foreign direct investment, GDP = gross domestic product, OECD = Organisation for Economic Co-operation and Development, PRC = People's Republic of China, UK = United Kingdom, UNCTAD = United Nations Conference on Trade and Development, US = United States, W = wages.

Note: Studies listed above were released between 2015 and 2018. This is not an exhaustive list of recent studies.

more sophisticated and widely used in production lines in Asia and the Pacific, for example, the cost of producing cars could go down, pushing down prices and spurring increased demand for cars. To the extent that increased demand requires hiring more workers, it could offset the displacement effect from automation.

(iii) **Reinstatement effect.** Automation can spawn new labor-intensive tasks and jobs, raising demand for labor. New job categories could emerge as AI is introduced into production, for example, or when a more sophisticated industrial robot is introduced on a factory floor and needs programming or tending.

Cross-industry effects. Adopting new technology in one industry has an impact on productivity and jobs in other industries. There are two main channels through which cross-industry effects change labor demand.

(i) **Spillover effect.** As one industry adopts new technology, positive spillover affects other industries in at least three ways. First, firms in downstream industries benefit from cheaper and/or better-quality inputs, while firms in upstream industries benefit if the output of the automating industry expands. Second, other industries learn the benefits of adopting the new technology. Third, workers with new skills and knowledge move between industries, spreading technological know-how.

(ii) **Income effect.** When technology complements labor, workers' higher incomes create positive spillover on other industries through increased demand for goods and services. A software developer whose income has increased thanks to complementarity between automation and human labor, for example, may want to buy a bigger car, a faster computer, better health care, more vacations, or other leisure services.

Aggregate impact on employment. Still other factors influence how technology affects jobs.

(i) **Complementarity between labor and technology.** If workers carry out tasks that are complemented by automation, demand for such workers will likely increase, as will their wages. If workers perform tasks that can be done solely by machines, they are likely to be displaced. That said, the technical feasibility of automating a set of tasks does not necessarily make automation economically viable. The price of new technology relative to labor cost is a crucial determinant of whether automation takes place.

(ii) **Elasticity of labor supply.** An example would be a within-industry effect with technology complementing human labor. Even if demand for tasks supplied by a software developer rises, there can be no significant change in employment unless there is an adequate supply of appropriately skilled workers. Assuming labor supply is not very elastic, wages earned by software developers and researchers tend to rise, which incentivizes more workers to enter those jobs. However, high labor supply elasticity—an abundance of workers with the requisite training as a software developer—could mitigate wage gains.

(iii) **Demand response to income elasticity.** Rising incomes in one industry create demand for goods and services in other parts of the economy, but this depends on how responsive demand is to increased income. Consider again the example of software developers whose labor is complemented by automation. How much of the increase in wages are they willing to spend on goods and services supplied by other sectors? The answer will help determine employment and wages in the other sectors.

(iv) **Workforce skills.** To take advantage of automation and new types of tasks created in the economy, workforce skills need to match technological requirements. New tasks require new skills, and education and training are key. A mismatch between skills and technologies slows the adjustment of employment and wages, hindering productivity growth.

Indeed, careful investigation of time series data spanning many decades shows these forces at play, countering the job displacement effects that arise when new technologies allow a given output to be produced by fewer workers (Box 2.1.2).

2.1.2 Productivity and employment: different forces at play

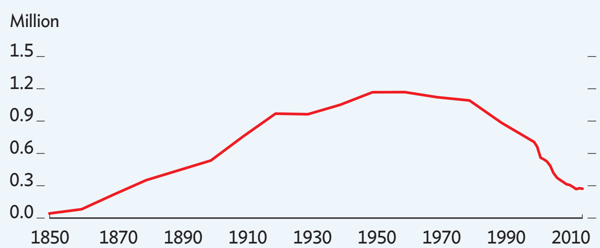
Bessen (2017), an analysis of employment data spanning decades, powerfully illustrates the idea that laborsaving technologies can raise employment in adopting industries. With the introduction in 1814 of textile power looms in the US, productivity soared, reducing prices, raising incomes, and increasing demand for textile products. Similarly, the assembly line Henry Ford introduced in 1913 increased productivity in the automobile industry, reducing prices and increasing demand for cars. Long-term employment trends in the US show that strong employment growth took place in the decades when technological advances improved labor productivity (box figure). Bessen (2017) called this the "inverted U" pattern of employment, wherein employment expands for an extended period before it starts declining. Employment in the US textile industry, for example, grew for about a century before it peaked and began declining.

Similarly, Autor and Salomons (2017) studied 19 high-income countries and shed further light on whether laborsaving technological progress erodes employment. As in Bessen (2017), the relationship between productivity growth and employment growth was positive in aggregate. However, at the industry level, rising labor productivity forces down employment within the industry, and this phenomenon prevails across all industries. The study reconciles these seemingly opposite results by showing that, when one industry improves labor productivity, spillover affects employment in other industries. Spillover stems from the income effect pushing up final demand and interindustry demand linkages.

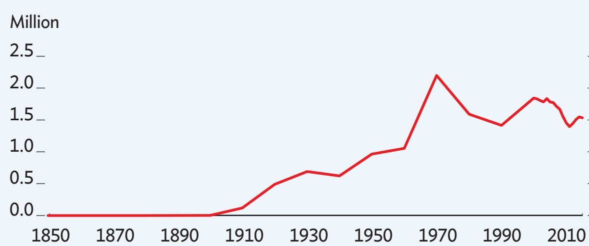
To fully understand the impact of technology on employment, it is important to examine the impact of productivity gains using input–output analysis, as this sheds light on interindustry linkages and final demand effects (Autor and Salomons 2017). Later in this chapter, this method is used with multiregional input–output tables produced by the Asian Development Bank to show that, indeed, countervailing forces are at play thanks to rising demand.

Long-term trends in employment in manufacturing

a. Textile, thread, and fabric jobs in the United States



b. Auto and auto equipment jobs in the United States



Source: Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 6.5. http://doi.org/10.18128/D020.V6.5 (accessed 23 February 2018). Cited in Bessen (2017).

Reasons for optimism on job prospects

Empirical evidence presented in this section shows that the anxiety over automation is overblown, and that predictions are unfounded that a majority of jobs in the developing world may be lost to automation. Three empirical exercises are conducted to back this statement.

First, this section examines trends in Asia's robot usage and shows that robots tend to be concentrated in capital-intensive and high-wage industries. A key point is that, even if it is technically feasible to replace a job with machines, it may not be economically feasible.

Second, analysis of the relationship between technology and employment in global value chains provides further insight into how various forces have affected jobs and will shape their future. Decomposition of employment changes from 2005 to 2015 using a demand-based input–output approach is instructive about how different forces affect job numbers, types, and locations in global value chains. While the technologies needed for extreme automation are only just starting to appear, advances such as computer numerically controlled machines and modern ICT tools were already coming online in factories and firms in Asia over the period covered. Two results stand out: Rising demand, spurred by improved efficiency or labor productivity, more than compensates for technology-induced displacement of jobs. Further, any "reshoring" of production to advanced economies may not be a major threat to employment in developing Asia.

Third, this section examines changes in occupation titles, which show that advances in technology have created new jobs. This is a prominent countervailing force against the displacement effect of technology (Lin 2011). A detailed analysis of occupation titles shows that new types of jobs have emerged in highly skilled occupations. Moreover, a comparison of occupations in the region with those in advanced economies show great scope for job growth.

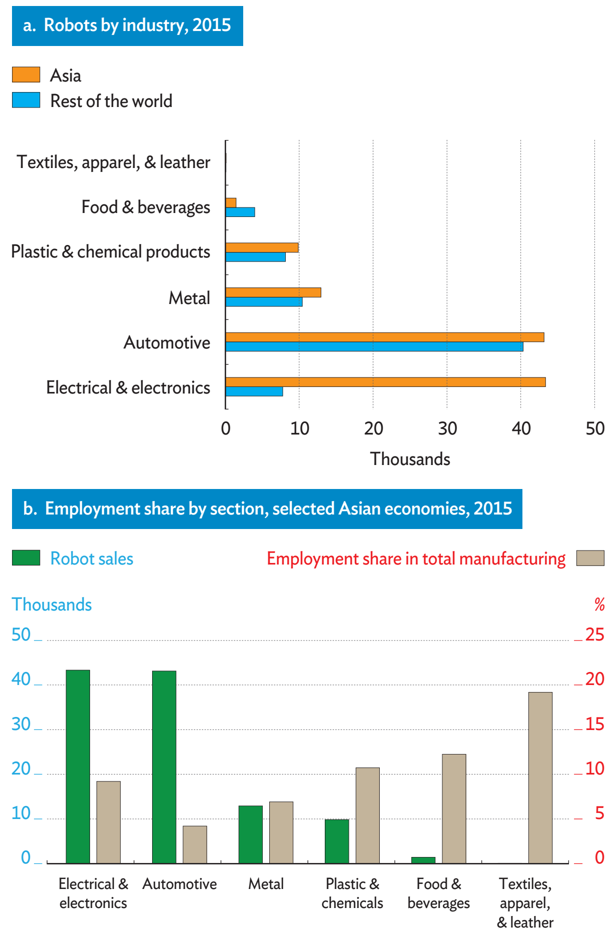
Industrial robots and employment outcomes

Industrial robots are the epitome of new technology and automated systems in production processes. Robots take many forms and shapes and can do many human tasks. The International Federation of Robotics (2016) defines a machine as an industrial robot if it can be programmed to perform physical, production-related tasks without the need of a human controller. The federation database provides information on industrial robot deliveries and robot stock from 1993 to 2015, covering 55 economies including 23 in Asia.

Asia's use of industrial robots is accelerating, its operational stock having risen from 2010 to 2015 by 70% to 887,400 units. The PRC is the world's largest market for industrial robots, annually taking 43% of all sales in Asia and the Pacific, followed by the Republic of Korea with 24% and Japan with 22%. International Federation of Robotics estimates suggest, moreover, that by 2019 almost 40% of the world's industrial robots will be in the PRC. The federation predicts that robot installation will continue to grow in all major Asian robot markets. Robot sales by industry show the largest share of robots in Asian manufacturing going into electrical and electronic goods and the automotive industries. Metal processing comes next, closely followed by plastic and chemical products (Figure 2.2.1a). The robot skillset lends itself to the standardization and fixed nature of automotive and electronics assembly using hard materials, as opposed to soft material such as the fabric used in apparel (United States Government 2016).

The capital-intensive industries that use increasing numbers of industrial robots do not employ many workers (Figure 2.2.1b). The two largest users of industrial robots in Asia, electrical and electronics industries and automotive manufacturers, each accounted in 2015 for 39% of Asia's robot stock but only 9.2% and 4.2%, respectively, of manufacturing employment. In contrast, food and beverages accounted for 1.3% of Asia's industrial robots but 12.3% of Asian manufacturing workers, and textiles, apparel, and leather for 0.1% of robots and 19.2% of workers. The data imply that any adverse employment effects from the use of new technology, particularly robots, will not be widespread. The more labor-intensive manufacturing industries have low rates of robot deployment, largely because automation is not economically viable. The one exception to this trend is the PRC, which employs large numbers of workers in capital-intensive sectors where the potential for robot deployment is high (Box 2.2.1). This means that the PRC is more exposed to automation than other economies in developing Asia.

2.2.1 Annual supply of robots and sectoral employment



Note: Asia includes India; Indonesia; Malaysia; the People's Republic of China; the Republic of Korea; Singapore; Thailand; Taipei,China; and Viet Nam.

Sources: International Federation of Robotics. World Robotics Statistics Database (accessed 23 March 2018); World Input–Output Database–Socioeconomic Accounts (Timmer et al. 2015).

Technical versus economic feasibility

Many recent studies that looked at the impact of automation on jobs focused on the technical feasibility of automating a set of tasks. But technical feasibility is one thing, economic feasibility another. For new technology to significantly

2.2.1 Robots, automation, and jobs in the People's Republic of China

Rapidly rising wages in the PRC have induced firms to embrace automation and robots in a trend that will shift the nature of work and demand for new skills. From 2013 to 2016, annual robot purchases by the PRC increased by 106%, compared with 65% globally. In 2016, the PRC became the world's largest robot market, receiving 30% of global sales. By industry, robots are concentrated in automobiles at 39%; computers, communication, and consumer electronics at 24%; and metal processing at 10%. Because the PRC has a very large workforce, the ratio of robots to workers remains much lower than in advanced countries, but the government announced an ambitious plan to triple the ratio from 49 robots per 10,000 workers in 2015 to 150 by 2020.

According to the China Employer-Employee Survey, which covered over 1,100 manufacturing firms in Hubei and Guangdong provinces in 2016, 49% of workers are in firms with computerized numerically controlled machines, including 9% in firms with robots. The survey found 13% of firms received subsidies for robots purchased in 2013, 20% in 2014, and 18% in 2015. The average subsidy was 20% of the cost.

What kinds of firms automate?

Firms that automate tend to be larger, older, more capital intensive, high-tech, and located in special economic zones—and firms using robots even more so (box table 1). Compared with both unautomated firms and those using numerically controlled equipment, firms using robots are more globalized in that they export a larger share of their production and are more likely foreign owned.

Characteristics of automated firms, by number and type of worker and by wage level

Automated firms generally have twice as many employees as those that are not, and those with robots have 6 times as many. Employees at firms with robots have higher educational attainment and are paid better across all occupations (box table 2). They also have a lower proportion of managers to production and technical workers. The wage premium for technical workers over production workers is 30% in firms with no automated equipment (90% for managers) and 50% in firms with robots (180% for managers). Regression analysis finds the relationship between relative wages and automation persists even after controlling for other company characteristics. Although not necessarily causal, the results are consistent with automation being more complementary to skilled than to unskilled work, suggesting the trend toward automation will likely increase demand for skilled workers in the PRC.

1 Firm characteristics by degree of automation

Feature	No automation	Numerically controlled machines but no robots	Robots
Share of firms (%)	51	40	9
Employees (number)	445	811	2,721
Firm age (years)	11	13	16
Ratio of capital to labor (CNY'000 per employee)	251	296	321
Located in economic zone (%)	56	68	77
Ownership (%)			
State	12	11	15
Domestic private	68	67	43
Foreign	20	22	41
Export share of sales (%)	22	20	29

Source: Jia, Park, and Du 2018.

2 Firm employment and wages by degree of automation

Feature	No automation	Numerically controlled machines but no robots	Robots
Education of employees (%)			
Junior high school and below	50	46	35
Senior high school	33	36	40
College and above	17	18	25
Occupation of employees (%)			
Production workers	73	74	77
Technical workers (Ratio of technical to production workers)	8 (0.11)	10 (0.14)	12 (0.16)
Managers (Ratio of managers to production workers)	13 (0.18)	11 (0.15)	6 (0.08)
Monthly wage by occupation (CNY)			
Production workers	3,887	4,294	4,779
Technical workers (Wage ratio of technical to production workers)	5,062 (1.30)	6,200 (1.44)	7,242 (1.52)
Managers (Wage ratio of managers to production workers)	7,424 (1.91)	9,071 (2.11)	13,372 (2.80)

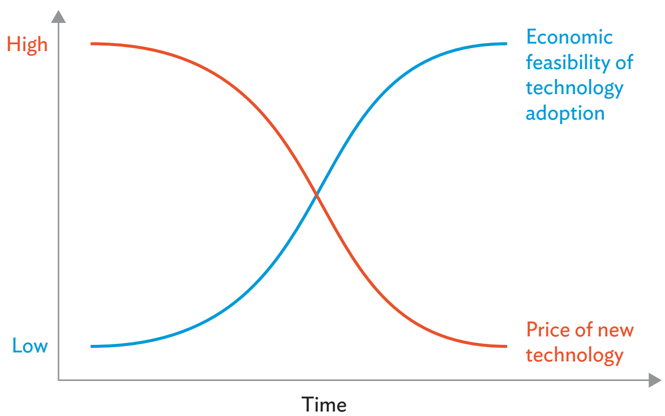
Source: Jia, Park, and Du 2018.

displace human labor, it needs to become economically viable (Figure 2.2.2a). For example, sewing robots—assuming they are sophisticated enough to work with fabric—would have to be sufficiently cheap to displace a Bangladeshi garment worker who earns $68 per month (Box 2.2.2). Hence, even in certain industries where automation is technically feasible, robot deployment is low.

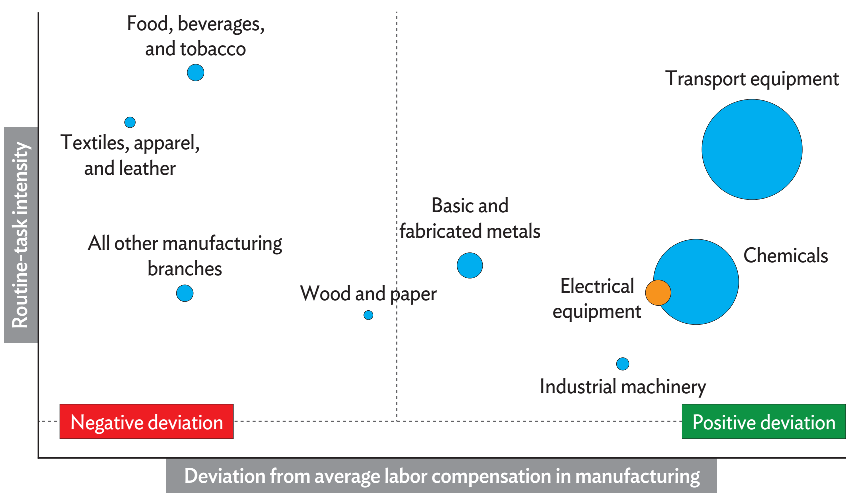
Figure 2.2.2b links the use of robots in manufacturing in selected Asian economies with proxies for the technical and economic feasibility of automation. Bubble size represents robot stock in 2015. The vertical axis of technical feasibility is based on an index of routine task intensity provided by Marcolin, Miroudot, and Squicciarini (2016).

2.2.2 Technical versus economic feasibility of automation

a. Economic feasibility of new technology



b. Evidence from manufacturing, selected Asian economies



Notes: Bubble size represents robot stock in 2015. Wage and robot stock data cover India, Indonesia, Pakistan, the Philippines, Thailand, and Viet Nam.

Sources: Inspired by Mayer (2017) and UNCTAD (2017). Panel A, ADB. Panel B, wage data from labor force surveys in India, Indonesia, Pakistan, the Philippines, Thailand, and Viet Nam; routine intensity index by sector from Marcolin, Miroudot, and Squicciarini (2016); robot stock data from the International Federation of Robotics.

2.2.2 Automation in garment manufacturing in Asia

Garment manufacturing has long been a path out of poverty for low-income economies in developing Asia because it provides steady employment for a workforce with few skills. After agriculture and construction, garments are the third largest employer in the three economies examined here: Bangladesh, Cambodia, and India.

Automation in all three has moved quickly over the past decade, but the main driver differs in each case. Three formerly manual-intensive processes—cutting, spreading, and ironing—are now done more accurately, twice as quickly, and with one-tenth of the workers. A Jacquard weaving machine increases daily output per worker sixfold. Automation reduced labor costs per garment but, more importantly, reduced delivery time for greater flexibility, encouraging factory expansion for exploiting economies of scale. In the three economies, labor equals only 10%–20% of basic garment variable cost. As a result, costs are only marginally affected by wage increases on the one hand and reductions in unit labor cost on the other. Instead, savings from automation derive more from reduced waste and higher volume—and therefore better return on fixed costs. Still, profit margins in recent years have been squeezed by intense competition as suppliers chase sluggish demand growth in consumer markets.

It is difficult to predict how long before full automation occurs. Sewing is a very labor-intensive process. Technological advances in sewing machines have improved accuracy but have not yet replaced jobs. Most executives of large garment exporters say replacing operators with sewing robots is unlikely in the next decade because it is barely feasible, either technically or economically, and the industry would need to adapt. One current estimate says the unit labor cost of producing a cotton shirt in the US is about $7. The approximate cost of producing the same shirt in India is $0.50, in Bangladesh $0.22, and in Cambodia $0.33. Sewing robots should narrow the gap, with some observers saying robotics will reduce basic apparel production costs in the US and Europe to about $0.40. Developing countries would lose their competitive edge, which would encourage reshoring, or reversing the outsourcing of production. However, as discussed below, rising demand from within Asia could be an important offset to job displacement on account of either automation or reshoring.

It shows routine task intensity within manufacturing highest in food, beverages, and tobacco; textiles, apparel, and leather; and transport equipment. The horizontal axis is labor compensation, or wages calculated using labor force surveys. It shows job displacement by robots to be economically more feasible in capital- and skills-intensive manufacturing such as transport equipment, chemicals, and electrical equipment. Bigger bubbles on the right show robot usage more common in sectors where wages are higher.

Robot density and employment

Several new studies examine the impact of industrial robots on employment. The empirical evidence is inconclusive. Acemoglu and Restrepo (2017b) found industrial robot adoption negatively correlated with employment and wages, and this holds across industries. Developments in the US from 1990 to 2017 showed that each additional robot displaced six workers, and raising robot density by one new robot per thousand reduced wages by 0.5%. In manufacturing, the most affected occupations are routine manual—typically blue-collar workers without college degrees. By contrast, Graetz and Michaels (forthcoming) found in 17 developed countries that, from 1993 to 2017, robotics accounted for 10% of GDP growth and, in industries with higher robot density, 16% of labor productivity and wage growth. This study found no evidence of robotics driving down aggregate employment. However, results vary by skills group, with robotics reducing hours worked and wages for low- and middle-skilled workers, but having had no significant effect on high-skilled workers.

So, simple correlation between robot density and employment growth yields a somewhat ambiguous picture. When jobs are divided into routine and not, however, routine employment negatively correlates with robot density, while nonroutine employment positively correlates (Figure 2.2.3). Empirical analysis corroborates these descriptive trends.

Indeed, there is no significant relationship between adopting robots and overall employment (Table 2.2.1a). But when robot adoption is disaggregated by type of employment, the relationship is different: Routine employment decreases with the increased usage of robots, while nonroutine employment increases (Table 2.2.1b). In addition, robot adoption significantly correlates with a decrease in routine manual occupations such as production workers and an increase in nonroutine cognitive occupations such as managers and professionals (Table 2.2.1c). Most important is the difference between developing and developed countries, as the impact of robots on labor demand is larger in developed countries than in developing countries (Table 2.2.1d).

2.2.3 Robot density and employment, routine versus nonroutine

a. Routine employment

b. Nonroutine employment

CAGR = compounded annual growth rate.

Notes: Robot density is the number of robots per 10,000 workers. Routine and nonroutine classification is based on Autor and Dorn (2013).

Sources: International Federation of Robotics. World Robotics Statistics Database (accessed 23 March 2018); International Labour Organization. ILOSTAT. http://www.ilo.org/ilostat (accessed 23 March 2018); results of structural decomposition analysis of jobs using ADB Multiregional Input–Output Tables.

2.2.1 Change in robot inputs and impact on employment, 2005–2015 (ordinary least square estimates)

a. Overall employment

	Change in employment		
	(1)	(2)	(3)
Robot adoption	−0.212 (0.37)	−0.212 (0.73)	−0.663 (0.61)
Country trends	Yes	Yes	Yes
Controls			Yes
Clustered standard errors		Yes	Yes
Observations	758	758	757

b. Routine employment

	Change in routine employment share		
	(1)	(2)	(3)
Robot adoption	-0.048*** (0.01)	-0.048*** (0.01)	-0.048*** (0.01)
Country trends	Yes	Yes	Yes
Controls			Yes
Clustered standard errors		Yes	Yes
Observations	777	777	776

c. Occupational employment shares

	Change in employment share of			
	(1)	(2)	(3)	(4)
	Routine manual	Routine cognitive	Nonroutine manual	Nonroutine cognitive
Robot adoption	−0.055*** (0.02)	−0.002 (0.00)	−0.004 (0.01)	0.061*** (0.01)
Country trends	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Clustered standard errors	Yes	Yes	Yes	Yes
Observations	776	776	776	776

d. Developed versus developing countries

	Change in routine employment share		
	(1)	(2)	(3)
Robot adoption	−0.056*** (0.01)	−0.056*** (0.02)	−0.056*** (0.02)
Developing country x robot adoption (Interaction term)	0.038 (0.03)	0.038** (0.02)	0.036** (0.02)
Country trends	Yes	Yes	Yes
Controls			Yes
Clustered standard errors		Yes	Yes
Observations	777	777	776

* = p<0.1, ** = p<0.05, *** = p<0.01.

Note: Robot adoption is the percentile in the weighted distribution of changes in robot density. Controls include real changes in gross fixed capital formation share in value added and changes in value added. Robust standard errors in parenthesis. Regressions are weighted by 2005 within-country employment shares.

Source: Bertulfo, Gentile, and de Vries, forthcoming.

Technology and employment in global value chains

Driven by revolutionary advances in information technology, production processes have been unbundled across national borders to form global value chains (GVCs).[3] A GVC includes all the interrelated production units that contribute one task or more to the creation and delivery of a final good or service to end consumers. Production units can be nearby or located anywhere on the globe, and labor contributes to virtually every task along the chain. Two additional factors have made this unbundling possible: trade liberalization and lower transport costs through improved logistics, infrastructure, and transport technology. This process redistributed global economic activity, with Asian economies emerging as key players. In 2016, Asia's GVC participation, measured as the share of gross exports of value added used for further processing through cross-border production networks, was 61.1% (ADB 2017b). This was second only to the European Union.

GVCs significantly affect employment in participating economies. Changes in the structure of GVCs, in particular those caused by new technology, have corresponding effects on employment. Developing economies that boost production for the export market often see a significant increase in manufacturing jobs. In Bangladesh, for example, the emergence of GVC-oriented garment exports has created more than 3 million new jobs over the past 2 decades (Farole and Cho 2017). In most low-cost, routine, labor-intensive GVCs such as garments, footwear, and electronics, the largest employment share is occupied by young women, many of them newcomers to the workforce.

GVCs have made it easier for developing economies to adopt new technologies. For example, technologies developed in high-income economies, such as numerically controlled machines and modern ICT tools, are used by factories and firms all along GVCs. Arguably, business use of ICT has been a boon for women in the labor market (Box 2.2.3).

While new technologies improve productivity, they raise two main concerns for developing economies. First, extreme automation can have significant implications for jobs. As Fourth Industrial Revolution technologies such as digital manufacturing become more sophisticated and cost-effective, firms in developing economies could lose many jobs if reshoring production back to advanced economies becomes feasible. In fact, however, if the cost of new technologies lowers significantly, it is conceivable that firms in developing economies may use them too.

Second, to the extent that upgrading technology is skill-biased, it shifts demand from workers with lower skills to those with higher skills, widening inequality. This poses a problem for developing economies competitive in low- to medium-skill activities, as using advanced technology could create a shortage of high-skilled workers and surplus of medium- and low-skilled workers.

Combining multiregional input–output tables developed by the Asian Development Bank with employment data from labor force surveys[4] allows research that examines the relationship between technology and jobs along supply chains in 12 economies in developing Asia, covering 35 sectors from 2005 to 2015.[5] The 12 economies accounted for 90% of employment in developing Asia in 2015.[6] In the tables, a GVC is defined by final products produced by a particular industry in a particular economy. For example, "textiles and textile products finalized in the PRC" is considered a GVC that encompasses a wide range of final products, from garments to awnings and canopies (Timmer et al. 2014).

The analytical framework developed in Reijnders and de Vries (2017) is used to analyze changes in demand for jobs by modeling the input–output structure of the world economy. The focus is on the relative importance of changes in various determinants of demand for jobs in economies and the sectors within them. This analysis is among the first to frame the quantification of these effects in a setting of internationally fragmented GVCs in Asia.

2.2.3 How information technology skills help women find better jobs in Viet Nam

Information and communication technology (ICT) would seem to be gender-neutral, but in fact businesses' increased use of ICT has positive effects for women in the labor market. Chun and Tang (2018) examined this by exploring the interplay between firms' ICT use, demand for tasks, and employment by gender and skill group. Using data from Viet Nam, which has one of the world's most inexpensive broadband networks, recent research found that greater ICT use increases the female share of employment, benefiting in particular college-educated women (though gender disparities in education and training limit the benefit).

Chun and Tang (2018) used data on firms' use of ICT from the Annual Enterprise Census of Viet Nam, 2005–2009. The study measured an industry's task complexity, evaluated by occupation.[a] Complex industries are the most innovative in the economy, heavily relying on highly technical engineering skills, while less complex industries provide basic products and services. The study used the gradual liberalization of broadband internet across provinces from 2006 to 2009 to construct an instrument to measure firms' ICT use, controlled for region, industry, and year fixed effects. The three main findings are as follows.

- **Adopting ICT has a positive effect on a firm's female labor share.** A 10% increase in the number of internet-connected computers per worker increases a firm's female labor share by 3 percentage points. The share increase is 3.5 percentage points when computers are also connected to a local area network (LAN). Compared with firms not using ICT, a firm using a LAN has a higher female labor share by 14 percentage points, one using the internet by 15 percentage points, and one hosting a website by 30 percentage points. These numbers support the observation that ICT use increases relative demand for nonroutine interactive tasks, raising the relative share of women employed.
- **The positive effect is larger for the female share of skilled employment.** ICT raises both the share of skilled college-educated workers and the share of women employed by a firm. A 10% increase in the number of computers connected to the internet per worker increases the female share in college-educated employment in firms by 8 percentage points, and connection to a LAN by 9 percentage points. A firm's use of a LAN correlates with a higher female labor share among the college-educated by 31 percentage points, use of the internet by 46 percentage points, and hosting a website by 69 percentage points.
- **But the effect is weaker in more complex industries.** The interaction terms between ICT variables and the sectoral measure of complexity have negative coefficients, such that women benefit less from ICT in more complex sectors. In these sectors, men may have comparative advantage over women because a higher proportion of men train in highly technical skills. ICT may thus worsen gender inequality in industries more dependent on complex tasks.

These results illustrate the potential that ICT has to generate growth in high-quality employment for women, compared with programs narrowly focused on providing to women capital and training. The results underscore the importance of addressing gender differences in education and training, toward improving gender equality in the workplace. The study highlights ICT as a force for female empowerment in labor markets and the importance of acquiring the ICT skills necessary for the complex computerized and digital tasks essential to innovative industries.

[a] The study constructed an index on occupation complexity, a measure of the need for complex problem-solving skills in each occupation, based on the US Department of Labor's Occupational Information Network.

Source: Chun and Tang 2018.

Decomposition by occupation shows technology, considered alone, reducing labor demand

Three main forces affect employment in economies and industries participating in GVCs. First is the location of a production task and its associated jobs. Second is the use of technology along the GVC, which may affect the number of workers required to meet given demand, the direction of impact on employment depending on whether new technologies replace jobs or complement them. Third, GVC employment is influenced by conditions in the economy and globally, such as total demand for goods and services and changes in consumer preferences.

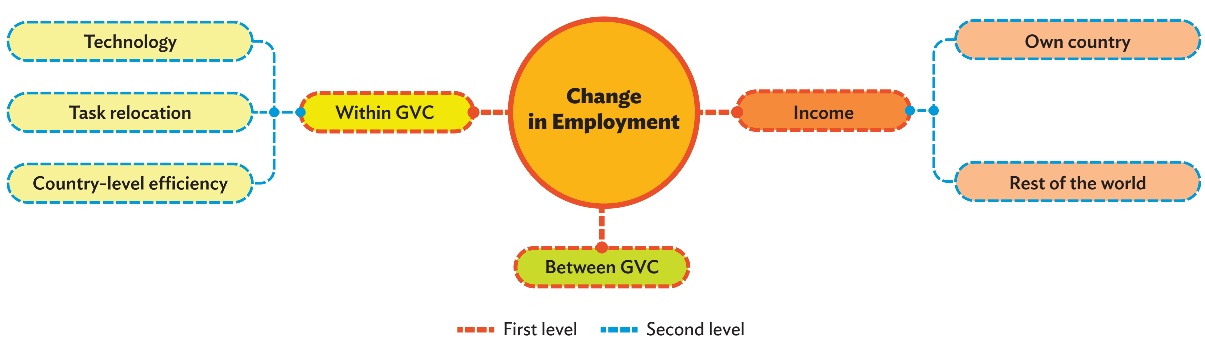
Structural decomposition analysis (SDA) of the multiregional input–output tables achieves two objectives. First, it quantifies changes in labor demand associated with technological change and task relocation. Second, it examines the relative magnitude of these GVC-specific channels with respect to conditions globally and within an economy.

The decomposition of change in an economy's number of jobs from 2005 to 2015 occurs on two levels (Figure 2.2.4). At the first level, the change in employment is decomposed into change *within* the GVC, or changes in employment within the production structure or GVC of a specific final product, and change *between* GVCs, or changes in employment resulting from shifts in consumer demand for different products. If, for example, consumers suddenly spend more on electronics than garments, there will be greater demand for employment in the electronics production chain and less in the garments chain. Finally, income refers to changes in employment caused by changes in global demand for goods and services. In practice, higher income in real terms will increase demand for goods and services, which in turn will increase employment.

The SDA further decomposes the within-GVC channel into (i) technology within the GVC, or changes in employment associated with changes in efficiency within a specific GVC; (ii) task relocation, or changes in employment as the location changes for one production task or more; and (iii) country-level efficiency, or changes in employment from efficiency changes in the economy.[7]

The GVC for garments in the PRC is used to illustrate how to operationalize technology within the GVC and task relocation. If machines replace workers at one or more of the production tasks in the GVC, this will lower the number of jobs in the GVC needed to meet given demand. This channel is labeled "technology within GVCs." If PRC garment manufacturers decide to relocate one or more of the production tasks to Thailand, the jobs for those tasks will be lost in the PRC and gained in Thailand.

2.2.4 Decomposing changes in labor demand



GVC = global value chain.
Source: Based on Reijnders and de Vries (2017).

Assuming other factors are constant—for example, workers in the PRC and Thailand are equally productive—the total number of jobs in the GVC is unchanged, but fewer workers are employed in the PRC and more in Thailand. This is task relocation.

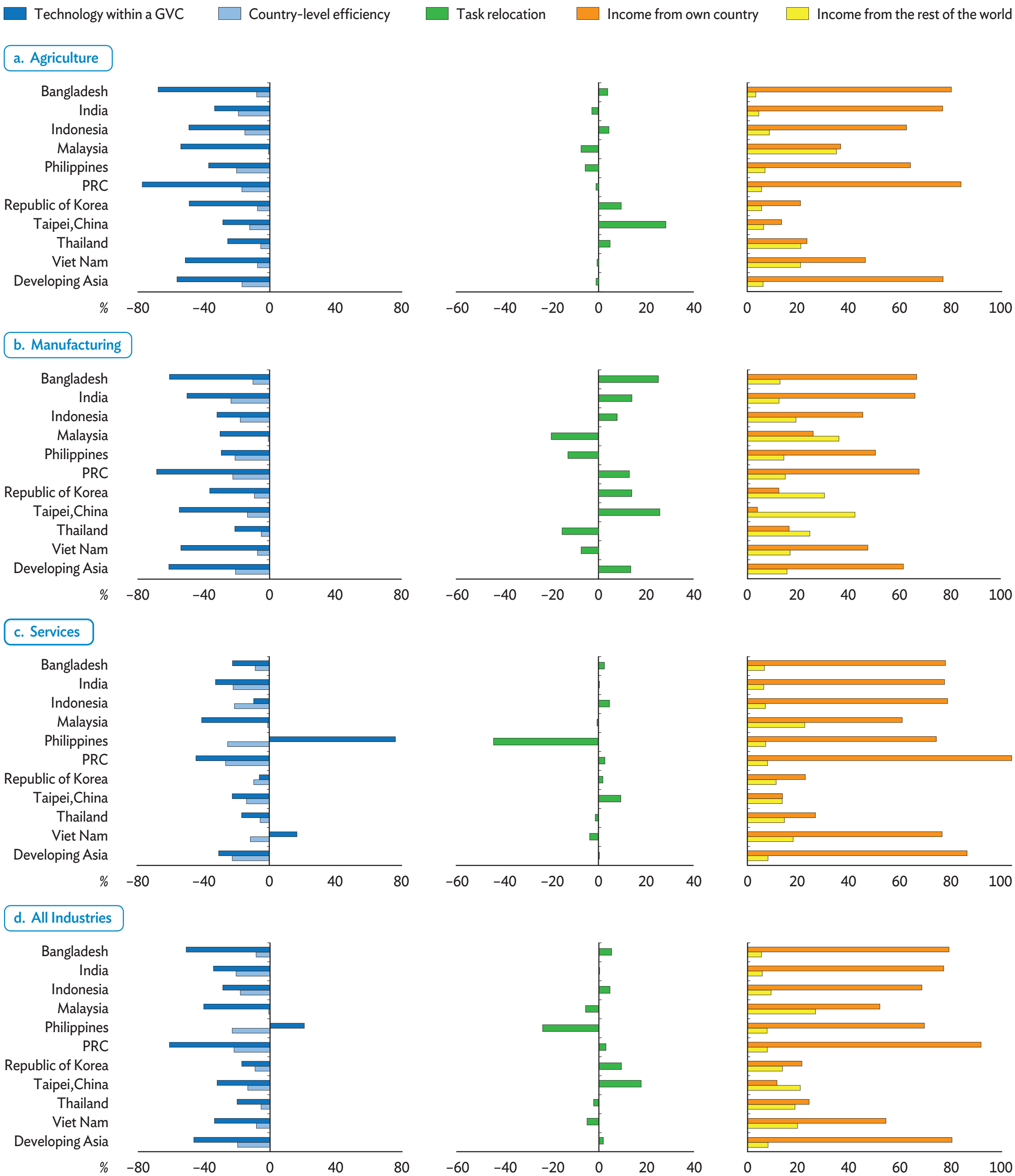
The use of the within-GVC technology channel to capture the effects of industry-specific technological change on jobs operates along the lines of recent research that uses measures of labor productivity growth that vary across industries as an all-encompassing proxy for the effects of technological progress (Autor and Salomons 2017). It bypasses the formidable difficulty of examining the employment implications of specific technological innovations. As noted in Autor and Salomons (2017), the diversity of specific innovations defies both consistent classification and comprehensive measurement. In the model presented here, countrywide economic conditions, which would include the effects of improved economic institutions or rising educational attainment, are captured by country-level efficiency, while technology within the GVC transcends national boundaries and captures technological advances along a specific production chain.

Finally, the second stage of the SDA further decomposes the income channel into "own country," or demand for goods and services originating within a specific country, and "rest of the world," or demand from abroad for goods and services. The purpose is to see what fraction of employment depends on domestic demand and what fraction foreign demand.

This analysis has two outliers. During 2005–2015, the global commodities bust hit hard in Mongolia, an economy heavily reliant on mining, causing a major decline in employment in services. The second outlier is Sri Lanka, where a 30-year civil war ended in 2009, followed by a period of record-breaking economic growth. Particularly affected were the employment numbers for manufacturing. Therefore, they are not always presented in figures (though these may be found in Bertulfo, Gentile, and de Vries, forthcoming[b]).

Figure 2.2.5 presents the results of the SDA for employment in agriculture, manufacturing, and services. The results show that, all other things being equal, technology improvements within GVCs accompany lower employment across all sectors. In the PRC, for example, the decrease in employment associated with technology is 77% in agriculture, 68% in manufacturing, and 44% in services. Notable exceptions are employment in services in the Philippines and Viet Nam, where technological change within GVCs increases demand for certain service occupations: information technology and business process outsourcing in the Philippines, and information technology services in Viet Nam.

2.2.5 Structural decomposition analysis of changes in employment by sector, 2005–2015



GVC = global value chain, PRC = People's Republic of China.

Note: Because manufacturing excludes the industry subsectors electricity, gas, and water supply and construction, "all sectors" is larger than the sum of agriculture, manufacturing, and services. Developing Asia in the decomposition analysis includes Bangladesh, India, Indonesia, Malaysia, Mongolia, the People's Republic of China, the Philippines, the Republic of Korea, Sri Lanka, Taipei,China, Thailand, and Viet Nam.

Source: ADB estimates using the ADB Multiregional Input–Output Database (accessed 20 November 2017); Labor force surveys, various countries; World Input–Output Database—Socioeconomic Accounts (Timmer et al. 2015).

Task relocation is associated with changes in employment that are much smaller and mixed. Bangladesh, India, Indonesia, and the PRC, which are well integrated into GVCs, experience net increases in employment, while others experience net decreases. This suggests that task relocation was not the main driver of changes in employment during 2005–2015.

Rising incomes more than compensate for employment demand suppressed by new technology

The last column of Figure 2.2.5 compares the magnitude of changes in domestic employment associated with changes in income from within the domestic economy and from the rest of the world. It is noteworthy that domestic income effects are generally much larger than those from the rest of the world. In the PRC, for example, the increase in employment associated with own-country income is 83% in agriculture, 68% in manufacturing, and a staggering 105% in services, as opposed to 6%, 15%, and 8% associated with income from the rest of the world. This is an encouraging sign of newly rising consumers in developing Asia, now able to generate domestic demand for products and services. Moreover, the figure shows that increases in employment associated with both sources of income are large enough to offset the combined decrease in employment from changes to technology in the GVC and efficiency in the economy (Box 2.2.4). In fact, in developing Asia, the combined impact of efficiency gains at the country level and technological advances within the GVC, holding all other components constant, is a 66% decrease in labor demand, equal to 101 million jobs per annum. However, concurrently higher demand for goods and services more than offsets this with an 88% increase in labor demand, equal to 134 million jobs per annum.

2.2.4 Rising income offsetting employment losses from technology

The world has witnessed three major technological revolutions, each reducing the labor required to produce a given output. It has not, however, witnessed any increase in structural unemployment. This implies the existence of channels that counterbalance the negative impact technology has on employment. Researchers have in fact identified various such channels, most of which expand aggregate demand, as described by Bessen (2017), for example, in the previous section. Technological innovation generally reduces the prices of goods and raises income per capita. Both effects push up demand, which can outweigh the direct negative impact of technology on employment.

Consider India, which has a large population with income per capita growing at a healthy rate. In 2015, income per capita was about $1,600 annually, and the Indian apparel market was estimated at $59 billion. If the economy grows at 7% annually over the next 16 years, annual income per capita will rise to $2,800 in 2021 and $4,900 in 2031. The apparel market can be expected to expand in response. Using 0.8 for income elasticity, it is expected to reach $93 billion in 2022 and $149 billion in 2032. This increase of output by 2.5 times over the next 16 years can be expected to counter job displacement from future automation in the garment industry.

Routine occupations are more at risk than others

Of major interest is which occupations are more vulnerable to displacement by technology. The taxonomy developed in Autor, Levy, and Murnane (2003), which classifies occupations as routine manual, routine cognitive, nonroutine manual, and nonroutine cognitive, allows for an SDA of changes in employment by occupation type. Unfortunately, this exercise is not possible for agricultural employment because it is difficult to distinguish routine and nonroutine occupations in the sector.

The results of the SDA by occupation type are presented in Figure 2.2.6 for manufacturing and services. The trends are the same as in Figure 2.2.5, but changes in employment are distributed across occupation types. It can be observed on the left that technology change within a GVC correlates with lower employment across countries and occupation types in both manufacturing and services. However, the decrease in nonroutine employment, especially nonroutine cognitive employment, is less pronounced than for routine employment. Bangladesh, the Philippines, and Viet Nam even show an increase in nonroutine employment in services. The findings suggest that technological advances along the supply chain may have been skill-biased in 2005–2015. This should not be surprising, as modern machine tools and ICT have been used in production for some time.

It can be observed on the right that task relocation in manufacturing appears to have a positive effect on nonroutine employment as well. In India, Indonesia, and the PRC, task relocation is associated with increases in nonroutine occupations, both cognitive and manual (Box 2.2.5). Bangladesh and Thailand show increases in nonroutine manual occupations, and Malaysia shows an increase in nonroutine cognitive occupations. In services (excluding outliers in the Philippines and Viet Nam), changes in employment are generally very small and mixed.

New technology pushing up the share of nonroutine jobs

The analysis above quantifies the prevalence of routine and nonroutine employment. In Figure 2.2.7, the focus shifts to employment shares. In general, the magnitude of the change in employment share for manufacturing is smaller and more uniform than for services, which have more diverse dynamics. An increased employment share of nonroutine cognitive occupations accompanies technological advances within the GVC (Figure 2.2.7a). For nonroutine manual occupations, roughly half the economies show increased employment share, the rest decreased. Finally, the change in employment share for both routine cognitive and routine manual occupations associated with new technology is decidedly negative for manufacturing and mainly negative for services. These results follow from Figure 2.2.6, which shows that, although the impact of technological advances is generally a reduction in both routine and nonroutine jobs (conditional on their satisfying the same demand), it is larger for routine jobs. The impact of task relocation is relatively small and mixed.

2.2.6 Structural decomposition analysis of changes in employment by sector and occupation type, 2005–2015

BAN = Bangladesh, DA = developing Asia, GVC = global value chain, IND = India, INO = Indonesia, MAL = Malaysia, PRC = People's Republic of China, PHI = Philippines, ROK = Republic of Korea, TAP = Taipei,China, THA = Thailand, VIE = Viet Nam.

Note: Developing Asia in the decomposition analysis includes Bangladesh, India, Indonesia, Malaysia, Mongolia, the People's Republic of China, the Philippines, the Republic of Korea, Sri Lanka, Taipei,China, Thailand, and Viet Nam.

Source: ADB estimates using the ADB Multiregional Input–Output Database (accessed 20 November 2017); Labor force surveys, various countries; World Input–Output Database—Socioeconomic Accounts (Timmer et al. 2015).

Final demand from advanced economies likely to become less important for employment in developing Asia

The evidence thus far indicates that technological change within a GVC generally accompanies decreased employment across all occupation types, though routine occupations are more affected. As noted above in this section, production technologies such as industrial robots have been used for decades but are now becoming more flexible and affordable.

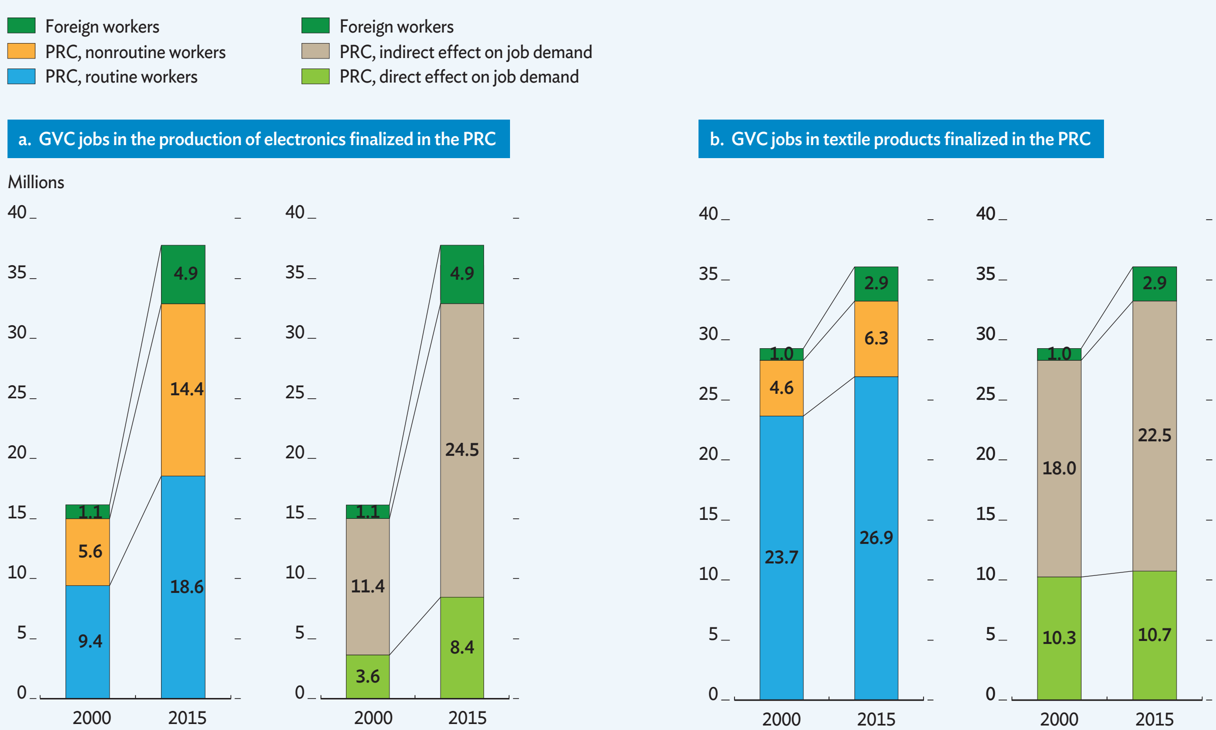
2.2.5 Routine and nonroutine jobs in GVCs: examples from textiles and electronics in the PRC

Box figures 1 and 2 illustrate the GVC concept using final production in the PRC of electronics and textiles. The examples show that producing manufactured products generates substantial indirect labor demand, that labor demand shifts over time toward occupations intensive in nonroutine tasks, and that substantial variation exists across industries in the indirect demand for labor they generate, as well as in relative demand for routine versus nonroutine jobs. Occupation data in each industry and economy are used to characterize occupations by their index of routine task intensity (Autor, Levy, and Murnane 2003). Occupations with scores above average on routine task intensity are considered routine. Other occupations are not considered routine task intensive.

The left panel of box figure 1 shows routine and nonroutine jobs in the PRC involved in the production of electronic products finalized in the PRC. The findings suggest that increased demand for final PRC electronic products increased PRC jobs numbers from 15 million in 2000 to 38 million in 2015. Demand for routine jobs doubled, but demand for nonroutine jobs increased almost threefold. Estimated demand for jobs includes jobs both directly and indirectly involved in the production of electronics finalized in the PRC.

As intermediate inputs needed to produce electronics require their own intermediate inputs (for example, hard disks requiring electric circuits), indirect labor effects can be substantial. The right panel explicitly indicates indirect employment effects.

Box figure 2 shows jobs involved in the production of textiles finalized in the PRC, with several notable similarities to box figure 1 and several differences. First, the number of jobs involved in the production of textiles finalized in the PRC was comparable to electronics in 2015. However, the increase in job numbers was much faster in electronics than in textiles. Second, the share of routine workers involved in the production of textiles is higher than for electronics—in 2015 about 75% in textiles compared with 49% in electronics. Third, indirect employment effects from textiles are substantially smaller than from electronics, the ratio of indirect to direct demand for jobs being about 2 for textiles but almost 3 for electronics in 2015. These differences suggest that industry specialization affects demand for routine versus nonroutine jobs. In addition, the strength and importance of intermediate input linkages differs substantially across products.



GVC = global value chain, PRC = People's Republic of China.

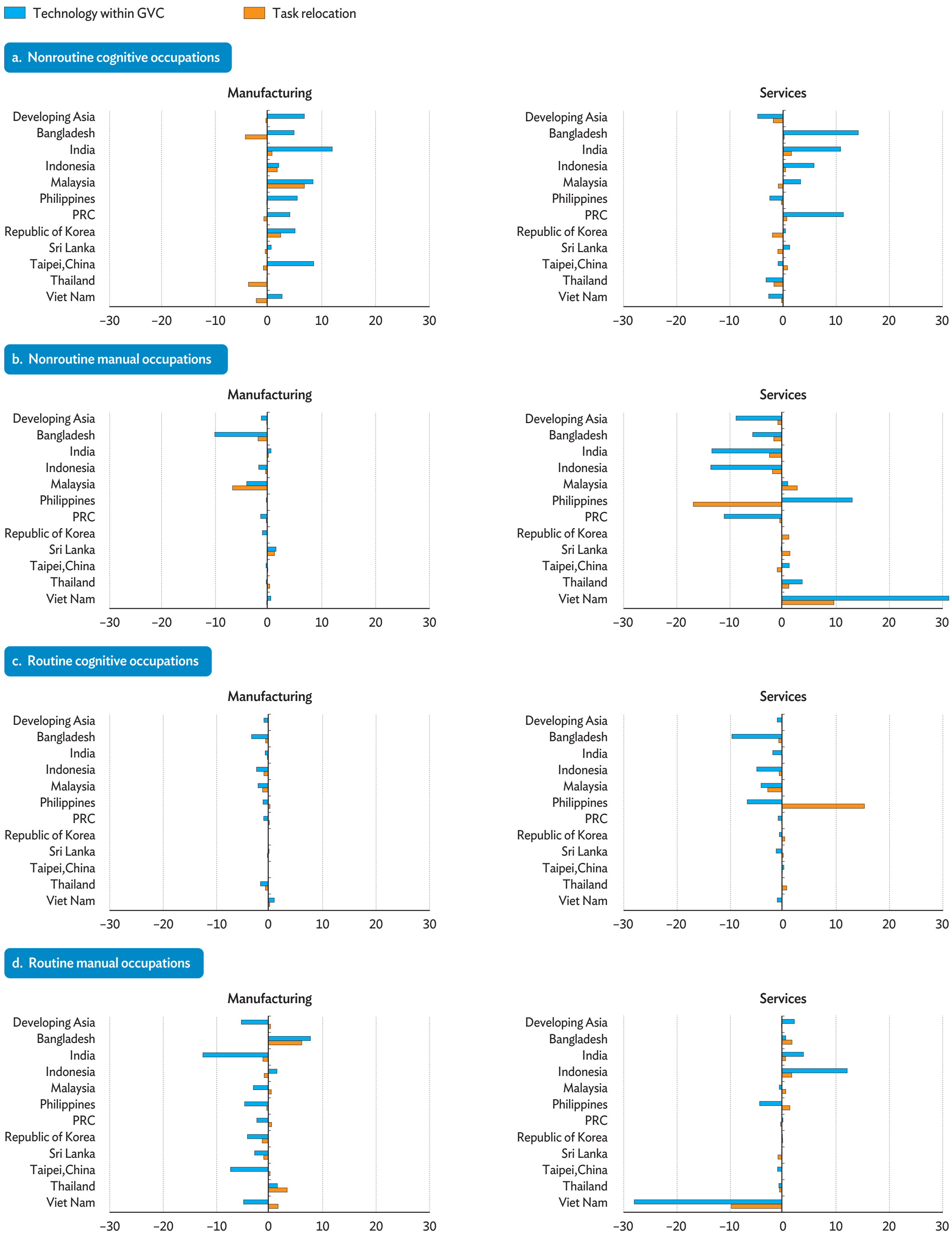
Notes: The right panel shows the number of workers directly and indirectly involved in producing electronic products finalized in the PRC. The left panel decomposes this demand for workers by foreign and domestic and by routine and nonroutine task intensity.

Sources: ADB estimates using data from the ADB Multiregional Input–Output Database (accessed 20 November 2017); Labor force surveys, various countries; World Input–Output Database—Socioeconomic Accounts (Timmer et al. 2015).

Notes: The right panel shows the number of workers directly and indirectly involved in producing textiles finalized in the PRC. The left panel decomposes this demand for workers by foreign and domestic and by routine and nonroutine task intensity.

Source: ADB estimates using data from the ADB Multiregional Input–Output Database (accessed 20 November 2017); Labor force surveys, various countries; World Input–Output Database—Socioeconomic Accounts (Timmer et al. 2015).

2.2.7 Changes in employment share with technological change and task relocation by occupation type, 2005–2015



GVC = global value chain, PRC = People's Republic of China.

Note: Developing Asia in the decomposition analysis includes Bangladesh, India, Indonesia, Malaysia, Mongolia, the People's Republic of China, the Philippines, the Republic of Korea, Sri Lanka, Taipei,China, Thailand, and Viet Nam.

Sources: ADB estimates using the ADB Multiregional Input–Output Database (accessed 20 November 2017); Labor force surveys, various countries; World Input–Output Database—Socioeconomic Accounts (Timmer et al. 2015).

Developing economies that have benefited from production tasks offshored from advanced economies are now concerned about reshoring. They fear, in other words, that it could become economically feasible to move those production tasks back to the home market. In an SDA, reshoring would appear as a sizeable decrease in labor demand from task relocation. Indeed, that reshoring did not happen in 2005–2015 does not mean it will not happen in the near future.

To determine how dependent employment in developing Asia is on final demand from advanced economies, the approach adopted in Los, Timmer, and de Vries (2015) is used. Figure 2.2.8 shows the share as well as the total number of jobs servicing final demand in 2015 decomposed into domestic final demand, final demand from advanced economies, and final demand from the rest of the world.

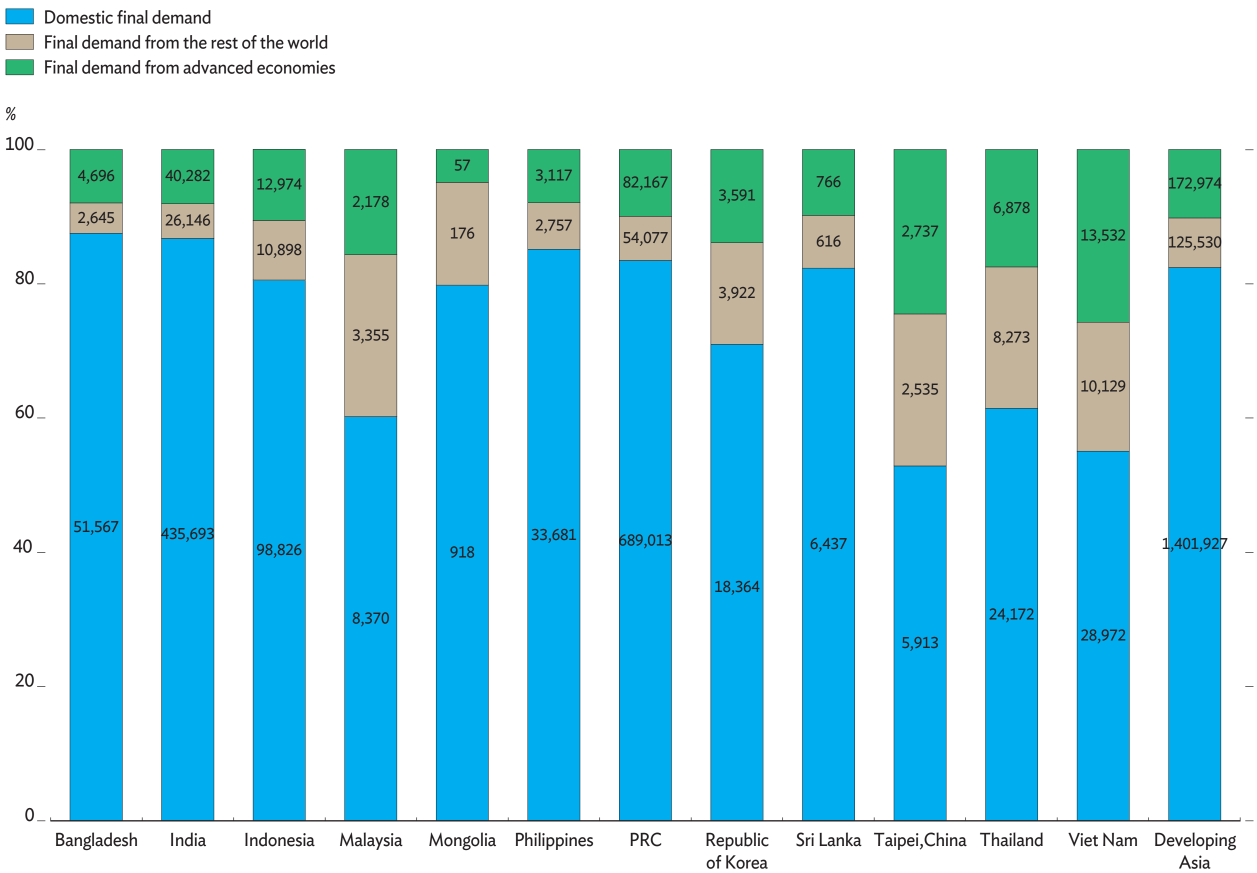
Figure 2.2.8 shows that 82% of employment in the 12 Asian economies depends on domestic final demand, which demonstrates rebalancing away from a growth model led by manufacturing for export to growth led by services and domestic consumption. However, variation across countries has domestic demand in Taipei,China a low 53% and in Viet Nam at 55%, and much higher in Bangladesh at 88% and India at 87%.

About 10% of jobs in the 12 Asian economies service final demand from advanced economies. Taipei,China and Viet Nam are relatively vulnerable to reshoring because they have the highest share of jobs dependent on final demand from advanced economies, at 25% for Taipei,China and 26% for Vietnam. However, bearing in mind that reshoring aims to move production closer to customers and thereby shorten the time required to get a product to market, lower production costs, and improve efficiency, it is noteworthy that consumer markets in advanced economies are increasingly saturated, even as demand from Asia's expanding middle class increases. Figure 2.2.8 shows that, while the share of jobs servicing final demand from the rest of the world is only 7% in the 12 economies as a whole, it is well over 20% in Malaysia; Taipei,China; and Thailand. Markets in the rest of the world have a high potential for growth as well, such that the importance of final demand from advanced countries to employment in developing countries will likely decline over time.

Emergence of new occupations and new industries

One of the less-appreciated channels through which technology affects the labor market is its creation of new occupations and entirely new industries with new jobs. Indeed, from 1980 to 2007, new tasks and job titles and their expansion explained about half of US employment growth (Acemoglu and Restrepo 2017b). Carefully examining growth in occupation titles is one way, however imperfect, to predict which new occupations and industries will emerge in the future.

2.2.8 Job shares servicing foreign and domestic demand, 2015



PRC = People's Republic of China.

Note: The advanced economies are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, the Netherlands, Portugal, Spain, Sweden, the United Kingdom, and the United States. For each of the 12 Asian economies in the figure, the rest of the world includes the other 11 as well as other economies at various stages of development. Developing Asia in the decomposition analysis includes Bangladesh, India, Indonesia, Malaysia, Mongolia, the People's Republic of China, the Philippines, the Republic of Korea, Sri Lanka, Taipei,China, Thailand, and Viet Nam.

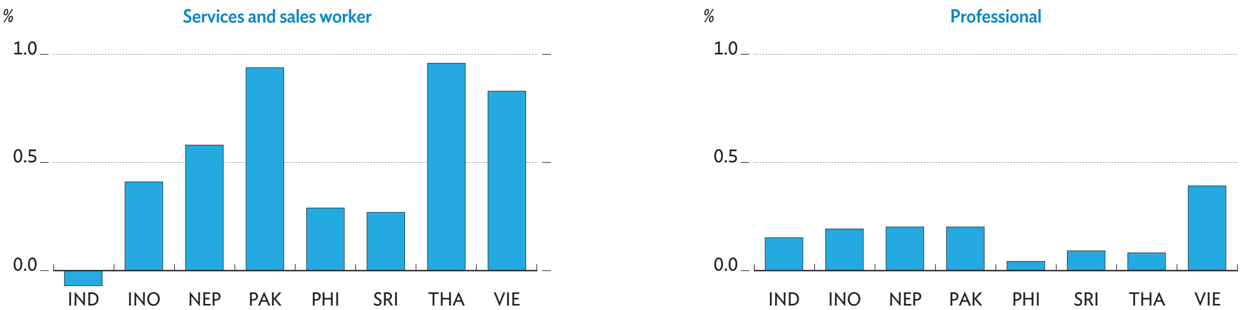
Numbers indicate jobs (in thousand) servicing foreign and domestic demand in 2015.

Sources: ADB estimates using the ADB Multiregional Input–Output Database (accessed 20 November 2017); Labor force surveys, various countries; World Input–Output Database—Socioeconomic Accounts (Timmer et al. 2015).

Where new jobs have been created is evident in changes in employment share by broad occupation category. In nearly all economies considered, occupations categorized as professional or in services and sales increased (Figure 2.2.9). These two types of occupations are both nonroutine. But professional work is classified as cognitive while services and sales are classified as manual. Across developing Asia, then, nonroutine jobs have increased both in manual and cognitive tasks. On the other hand, the importance of skilled workers in agriculture and related sectors has declined.

A more systematic analysis can track the emergence of new occupations by comparing various waves of a country's national classifications of occupations (NCO). Because classifications are periodically updated and revised, changes in the types of jobs and specializations available in different fields indicate

2.2.9 Annual change in employment share by occupation, selected Asian economies



IND = India, INO = Indonesia, NEP = Nepal, PAK = Pakistan, PHI = Philippines, SRI = Sri Lanka, THA = Thailand, VIE = Viet Nam.

Note: India 2000–2012, Indonesia 2000–2014, Nepal 1998–2008, Pakistan 2002–2013, the Philippines 2001–2013, Sri Lanka 2004–2014, Thailand 2000–2010, and Viet Nam 2002–2013.

Source: Labor force surveys, various countries.

structural changes and the emergence of new technologies in the labor market—as when, for example, the proliferation of cable television in India in the 1990s fueled increased demand for cable television installers. Lin (2011), for instance, used "new work," or jobs requiring new combinations of activities (the phrase borrowed from Jacobs [1969]), to observe how US workers and firms adapt to technological change. Successive versions of the US Index of Occupations were compared to identify new job titles and match them with microdata to estimate worker selection into new occupations. Following this approach, the emergence of new occupations can be investigated for several economies in developing Asia that have the necessary data (Box 2.2.6).

Analysis of NCO lists finds the emergence of 60 new job titles out of 2,945 (2.0%) in India in 1968–2004, 120 out of 3,600 (3.3%) in India in 2004–2015, 28 out of 2,338 (1.2%) in Malaysia in 1998–2008, and 42 out of 3,698 (1.14%) in the Philippines in 1990–2012. As in Lin (2011), most new job titles, 43%–57%, are related to ICT. Moreover, as seen from Figure 2.2.10, occupations with the highest proportions of new job titles are mainly nonroutine cognitive. Nearly 40% of job titles under ICT operations and user-support technicians in India were created from 2004 to 2015, and more than 20% in Malaysia from 1998 to 2008.

New job titles are mostly in nonroutine cognitive occupations

In all countries studied, new job titles appear primarily in professional categories (Figure 2.2.11). India presents a particularly interesting case. The 1968–2004 figure shows 93% of all new jobs as professionals, with 36 new job titles, and associate professionals, with 20. A closer look into these two groups reveals that several of the new job titles are mainly engineering and data analyst positions and directly related to the use of personal computers, reflecting

2.2.6 Estimating the emergence of new occupations

As a first step in tracing the emergence of new jobs, an economy's national classification of occupations (NCO) is compared with its preceding version at the most disaggregated level available using an official concordance between the two classifications. Job titles are then identified in the newer NCO that did not exist in the previous one, while controlling for any form of relabeling or reclassification. It is also important to check which International Standard Classification of Occupations the NCO editions are patterned after for two reasons: First, one can identify which technological advances were made during the time studied. Second, one gains insight on what types of new job titles may emerge.

As a second filter and robustness check, the remaining job titles are further compared with the US Index of Occupations. The US Index of Occupations provides occupational titles down to the smallest unit, which means a large number of occupational titles are included. To illustrate, the number of titles listed ranged in 1950–2000 from 25,000 to 31,000 (Lin 2011). The 1950 index lists over 80 titles that contain "engineer" and includes over 10 types of economists with different specializations and functions. The index version used should account for a lag in the emergence of job titles given different stages of development between the country studied and the US. This exercise therefore assumes that job titles in the country at time t is equivalent to the job titles in the US at time $t-n$. For example, the comparison of India's new job titles in NCO 2004 with its previous version in 1968 is cross-checked against the new job titles with the 1950 US Index of Occupations (US at time $t-n$) in the second filtration process. The assumption here is that job titles in India in 1968 are equivalent to job titles in the US in 1950. If the job title in NCO 2004 did not exist in the 1950 US Index of Occupations, it is considered new.

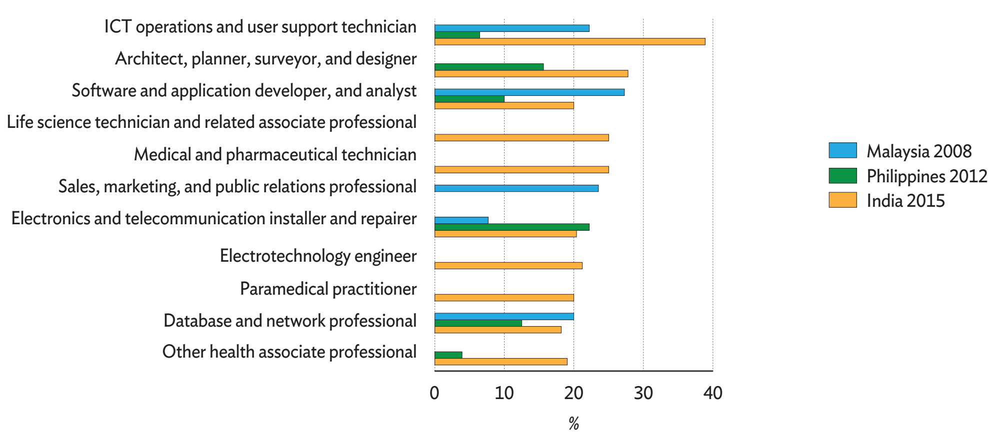
Other indicators of new jobs are used. In some cases, job titles specifying a type of technology not widely used in the previous NCO year are categorized as new. This involves investigating when the technology penetrated the market.[a] For example, managerial positions are generally categorized as old job titles unless the specification entails a new type of technology. Job titles listed as "others," or "not elsewhere classified" but are newly added to the later list are not considered new.

Among the limitations to the technique are measurement error from checking occupation titles manually, the subjective judgment whether a technology was widely used in the previous NCO year, and the use of the US Index of Occupations as proxy for an economy's list of occupations in the previous version. The exercise nevertheless provides insight into the link between the emergence of new types of jobs and new technology in developing Asia. A potential extension of this analysis is to use microdata to check how many individuals in the labor force were actually employed under these new job titles (Lin 2011).

[a] A job title using a technology introduced in 1967 may still be categorized as new if the technology was still not widely used in 1968.

Source: Flaminiano et al., forthcoming.

2.2.10 Occupations with the highest proportion of new job titles, selected Asian economies

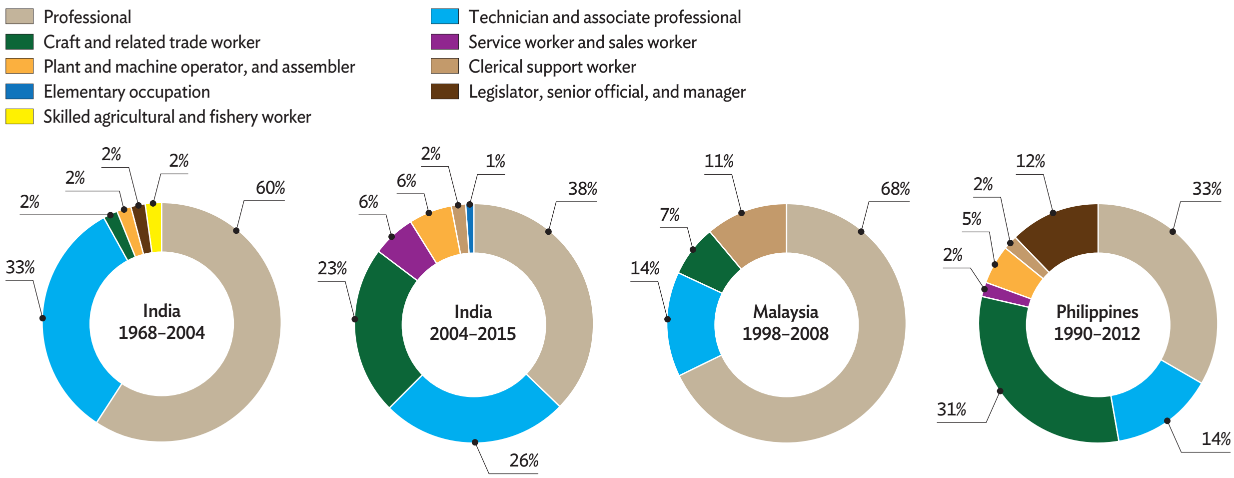


ICT = information and communication technology.

Note: These are occupation groups with the highest proportion of new job titles. Calculations are based on comparisons made between national classification of occupations (NCO) 2004 (based on International Standard Classification of Occupations 1988 [ISCO-88]) and NCO 2015 (ISCO-08) for India, PSOC 1990 (ISCO-88) and PSOC 2012 (ISCO-08) for the Philippines, and MASCO-1998 (ISCO-88) and MASCO-2008 (ISCO-08) for Malaysia. As a robustness check, the 1970 US Index of Occupations was used as proxy for a comprehensive list of occupations in the base year of the economies studied.

Source: Flaminiano et al., forthcoming.

2.2.11 Share of new job titles per broad occupation group



Source: Flaminiano et al., forthcoming.

rapid advances in digital technology in the 1980s: software engineer, system programmer, database design analyst, computer system hardware analyst, computer quality assurance analyst, and computer security specialist, among others. Once again, this resembles findings in Lin (2011) in the US in 1977. By contrast, none of the occupation groups clerks, service and sales workers, and elementary occupations show new job titles, despite employment growing in these occupations. In fact, all three economies show growth in routine cognitive and nonroutine manual employment. For example, in 2004–2015 in India, a third broad occupation group—craft and related trade workers, specifically electrical trade workers, categorized as routine cognitive jobs—hold a significant share of new job titles. Interestingly, the majority of the new job titles in this occupation group are computer numerical control technicians, who are machinists whose jobs entail operating computer-driven machine tools. Examples of job titles are computerized numerical control (CNC) operator machining technician, CNC setter-cum-operator–vertical machining center, CNC programmer, CNC operator–turning. Other new job titles in this occupation group include smartphone repair technician, solar panel installation technician, and optical fiber technician.

Technological progress and economic growth also creating jobs

The growing complexity of life and the modern workplace—the result of technological change and economic growth—will contribute new occupations. A comparison of occupations in the region with those in advanced economies shows great scope for job growth in many sectors. For example, health care and education provide 15% of employment in the US, while finance, insurance, real estate, and other business services provide 19%. In lower- and middle-income economies in developing Asia, health care and education provide only 3.5%–6.0% of jobs, and business services 1.5%–6.0%, suggesting considerable scope for job growth in these services. Similarly, urban parts of developing Asia show much greater variety of occupations than rural parts. As the region urbanizes, many jobs will emerge.

Further, technology will transform some existing occupations. A case in point is informal retail, perhaps the most ubiquitous occupation. In many parts of developing Asia, informal retailers are increasingly using social media platforms to reach many more customers than before (Box 2.2.7).

2.2.7 Informal retail transforming into social commerce

Despite rapid growth in internet use, e-commerce in Southeast Asia remains in its infancy for lack of well-developed digital finance or logistics (Chadha 2016). In Southeast and South Asia, less than a third of companies have their own websites, and only about half use e-mail to communicate with clients and suppliers (ADB 2017b). However, despite small e-commerce markets, developing economies lead the world in social commerce, or unofficial e-commerce using social media.

Social commerce is characterized by online sales and offline payments. It begins on a social media platform, followed by direct communication between buyer and seller, usually using instant messaging apps, and closes using offline payment (Malabuppha 2017). Cash on delivery is widely used (International Trade Center 2017). The popularity of social media turns these venues into cheaper e-commerce platforms than traditional e-commerce. Whereas websites charge commissions, selling on social media is free.

Where online shoppers said they purchased directly through a social media channel

PRC = People's Republic of China.
Source: PricewaterhouseCoopers 2016.

The world's most avid social media shoppers are in Thailand, where 51% of online shoppers report buying on social media, and India at 32% (box figure). Facebook is the preferred platform for selling online in Viet Nam (Asia Pacific Foundation of Canada 2017) and Indonesia (JakPat 2015), and it is widely used in the Philippines (Llamas 2017). Social media sales account for 30% of e-commerce transactions in Southeast Asia (Chadha 2016).

India and Southeast Asia are the largest Facebook and Instagram users globally.[a] Social mobile use is also large and growing. In Southeast Asia, 47% of people are active on social media, with 42% accessing platforms from mobile devices (Klemp 2017).

Social commerce in the region is largely domestic. However, small businesses worldwide are becoming "micro-multinationals" by using digital platforms—including social media—to connect with international customers and suppliers (McKinsey Global Institute 2016). This has created new opportunities for informal retailers. Studies find that small and medium-sized enterprises using e-commerce increase revenues, lower costs, boost profits, add jobs, and are more likely to export and innovate. As digital payment infrastructure and logistics improve, the informal sector will be better able to tap global markets. In an age of digital expansion, the rise of social commerce is making e-commerce a reality for many sellers with few resources or formal skills.

[a] India has the most Facebook users globally at 250 million. Indonesia is fourth with 130 million, the Philippines sixth with 67 million, Viet Nam seventh with 55 million, and Thailand eighth with 51 million. Indonesia ranks third in the world for Instagram users at 53 million, and India fourth with 52 million (Statista 2018).

Some worker concerns remain

So far this chapter has categorized occupations mainly as requiring tasks that are either routine or not, and manual or cognitive. This section considers a more disaggregated classification of tasks. In addition, the degree to which an occupation is intensive in these various tasks is explicitly quantified to further refine the analysis of the impact of new technology on employment and wages. Analysis of India, Indonesia, the Philippines, Thailand, and Viet Nam shows the employment structure in the region shifting toward jobs intensive in nonroutine cognitive, social interaction, and ICT tasks. These tasks generally complement technological progress and may not be readily automated. They tend to require more education and/or relatively advanced training. At the same time, the labor market is moving away from jobs intensive in manual tasks, which tend to require skills that workers with basic education can acquire. Such jobs are more likely to be replaced by machines. The magnitude of these changes in the past decade or so is sizable, and the trend will likely persist. The major challenge for Asian economies is to cope with this structural transformation in the nature of jobs. If Asia's workers are not given the skills in demand—particularly to fill jobs intensive in nonroutine and cognitive tasks—they may be left behind. Incomes for the few with the required skills will rise, exacerbating inequality.

Trends in employment and wages by task intensity in the region

Five indicators here describe the intensity with which workers are required to perform various types of tasks. Four of them pertain to nonroutine cognitive, social interactive, routine cognitive, and manual tasks.[8] A fifth indicator, for ICT tasks, describes computer use at work to capture jobs intensive in tasks that may directly complement new technologies. The methodology used to construct these indicators is presented in Box 2.3.1. Task intensity can be measured, making it possible to examine the task-biased technical change hypothesis: Technological progress and information technology (IT) will likely displace jobs consisting of mainly routine and manual tasks while increasing demand for jobs that involve a lot of abstract and complex cognitive tasks. Occupations and industries in which workers are frequently required to provide advice, teach, or negotiate, among other tasks, score high in social interaction, while high scores in the complex or nonroutine cognitive indicator indicate high intensity in tasks such as writing, using advanced mathematics, or solving complex problems.

2.3.1 Constructing task intensity indicators

Constructing a set of indicators that account for task intensity by occupation and industry requires an appropriate methodology. The indicators are constructed using publicly available country surveys conducted in the 27 OECD member and partner countries (OECD 2013a, 2016a).

Besides background information on education, industry, occupation, sex, and age, the surveys gather information from workers on the requirements of their jobs. Requirements include cognitive skills that encompass reading, writing, mathematics, and the use of information and communication technology (ICT). Questions extend to interaction and social skills, covering collaboration and cooperation, planning, time use for oneself and others, communication, and negotiation. Subjects are asked about physical motor skills, both gross and fine. In addition, they are asked about the frequency and intensity of various tasks their jobs require. There are more than 50 questions on job requirements in the survey. Most questions are coded on a scale from 1 to 5, with greater values indicating greater frequency and/or intensity of the task required at work. Following previous studies on the polarization of employment and given the information provided in Program for the International Assessment of Adult Competencies (PIAAC) surveys, the tasks are grouped into five categories (box table).

Step 1. Assigning survey questions to categories
First, questions in the PIAAC survey providing information pertaining to the five task categories were identified. Principal component analysis determined the extent to which questions from the survey conveyed similar information and was used to compute a summary indicator for each category.

Step 2. Constructing indicators by occupation and industry cell
To account for diverging stages of development in countries in the PIAAC survey, and to ensure robust indicators of country-specific characteristics, the final indicators were obtained from regressions that controlled for country fixed effects. For each of the five task categories, workers' summary indicator of intensity (cat) was regressed on a set of dummy variables accounting for the worker occupation and industry (occ_ind) and a set of country dummies (c) as follows:

$$cat_i = \alpha + \sum_i \gamma_j occ\_ind_{ij} + \sum_k \delta_k c_{ik} + \varepsilon_i, \qquad (1)$$

where i denotes workers, j the occupation-industry combinations, and k countries. The coefficients on the occupation-industry dummies (γ) can be thought of as a rank that measures the task intensity of an occupation-industry combination after controlling for country-specific characteristics. The industries and occupations covered are based on 1-digit ISIC Rev. 4 classification and 2-digit ISCO-08 classification, respectively. To reduce distortion from changes in national classifications in the region over time, as well as those arising from the harmonization with international classification standards, steps 1 and 2 were also conducted using the 2-digit ISCO-88 classification for occupations.

Categories of tasks within occupations and industries

Category	Interpretation	Examples of specific tasks
1. Social interaction and influencing	Frequency of nonroutine interactive tasks	Influencing and advising other people, teaching, giving speeches or presentations, negotiating with people inside and outside of firm, planning the activities of others
2. Cognitive nonroutine	Frequency of nonroutine cognitive tasks	Writing letters, emails, or articles in newspapers, magazines, or newsletters; preparing charts, graphs, or tables; using advanced math or statistics such as complex algebra, trigonometry, or regression analysis; solving complex problems
3. Cognitive routine	Frequency of routine cognitive tasks	Calculating prices, costs, or budgets; using or calculating fractions, decimals, or percentages; using a calculator or spreadsheet software
4. Manual	Frequency of manual tasks	Relying on hand or finger dexterity (methodology and data do not allow manual tasks to be disaggregated into routine and nonroutine)
5. ICT	Use of ICT at work	Ranging from no ICT use to performing complex tasks such as programming

ICT = information and communication technology.

continued next page

2.3.1 Continued

Step 3. Merging task intensity indicators with Asian labor force surveys
Information was gathered on employment and wages in India, Indonesia, the Philippines, Thailand, and Viet Nam using country labor force surveys at two points in time. The time frames vary across countries, with Viet Nam the shortest (2007–2015), followed by Thailand (2000–2010), India (2000–2012), the Philippines (2001–2013), and Indonesia (2000–2014). The indicators obtained in step 2 were merged with country data based on worker occupation and industry.

Step 4. Constructing employment and wage trends for high- and low-intensive tasks
For each country and task category, the employment-weighted mean of the intensity indicator at the beginning of the sample was calculated separately for wage employees and all workers (i.e., wage employees and the self-employed). Occupations and industries whose task intensity fell below the weighted mean were classified as low and those above the mean as high. Changes in employment and wages in high-intensive occupations and industries were compared with low-intensive ones.

Step 5. Comparing the distribution of employment by intensity of tasks across countries
In the previous step, the country's weighted mean was used as a threshold to classify occupations and industries into low- and high-intensive. For illustrating trends over time within countries, this is the preferred threshold because it best describes employment and wage trends representative of the mean worker in each country. However, this country-specific threshold cannot be used when comparing employment distribution by task intensity across countries. As such, for comparison with OECD countries and across Asian economies, the simple average for each type of task was used as a threshold. For example, occupations and industries whose ICT intensity is above the simple mean of the ICT indicator are classified as high and those below as low.

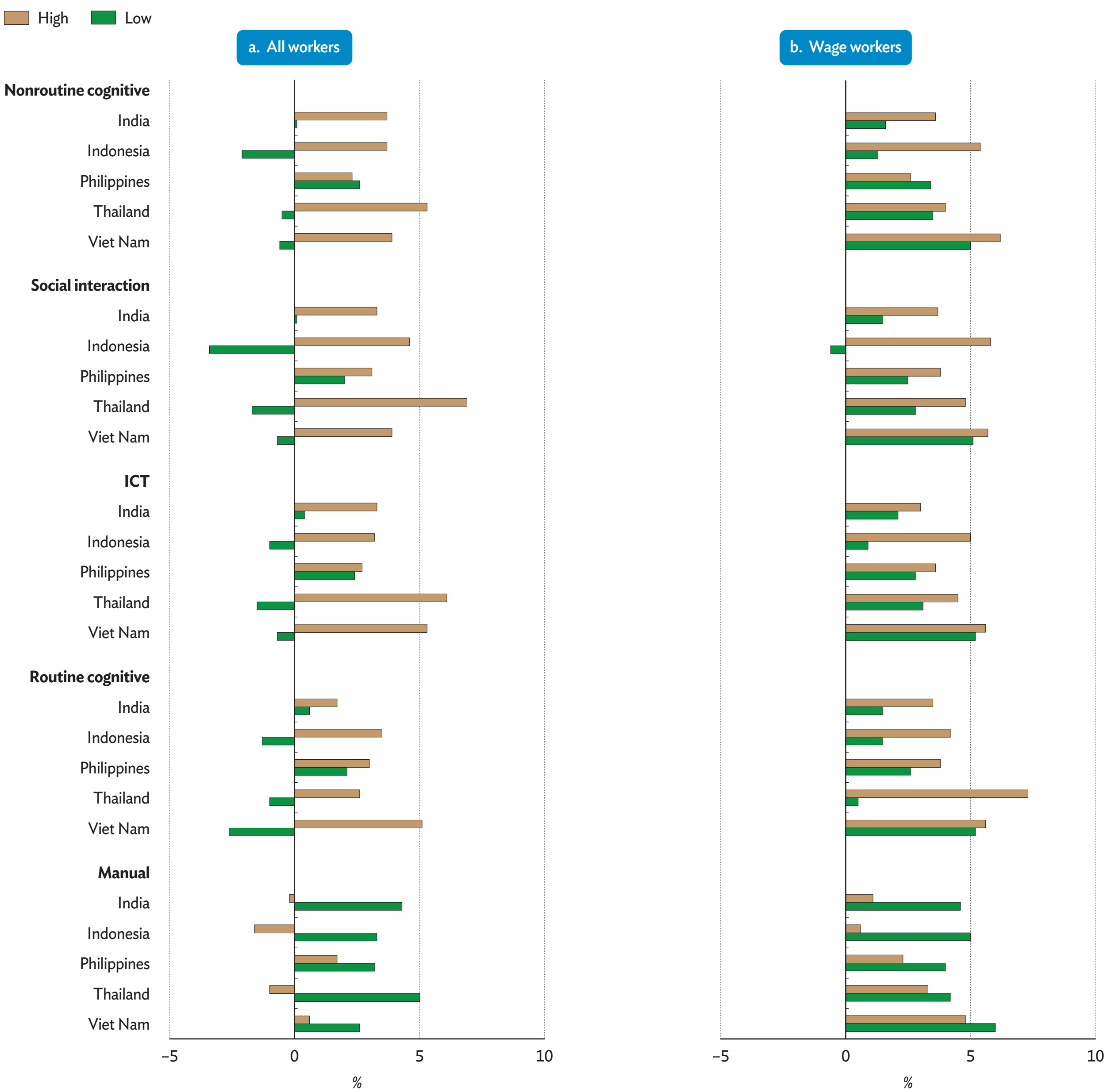
Source: Khatiwada, Lennon, and Zilian, forthcoming.

These two indicators are used to characterize jobs intensive in nonroutine tasks. To describe jobs intensive in routine cognitive tasks, information is obtained on the frequency with which workers are required to use simple arithmetic, for example, in calculating prices and costs. Jobs that require a lot of use of hands or fingers are considered intensive in manual tasks. Finally, information on ICT use provides the basis for determining the intensity of ICT tasks of jobs. With these indicators, jobs in the economies considered can be classified in terms of whether they are high-intensive or low-intensive with respective to the five task categories. These classifications are used to reveal employment and wage trends over time.

For both wage employees and all workers, jobs that are intensive in cognitive, social interaction, and ICT tasks have expanded faster than jobs that are less intensive (Figure 2.3.1a). In fact, in some countries—Indonesia, Thailand, and Viet Nam, for example—jobs less intensive in these categories have contracted. The only exception is the Philippines, where jobs intensive in nonroutine cognitive tasks expanded at a slower pace than their counterparts. This coincided with growth in employment in other categories, including jobs intensive in routine cognitive tasks, a category that includes many types of jobs in IT-business process outsourcing—the call center jobs that provided much of the growth of employment in the sector, which expanded from less than 100,000 jobs in 2004 to almost 1 million in 2013. However, this may change as this large industry shifts toward more nonroutine cognitive tasks (Box 2.3.2).

The opposite occurred for jobs intensive in manual tasks. Low-intensive manual jobs expanded faster than high-intensive ones. Moreover, employment in high-intensive manual jobs has contracted in Indonesia, Thailand, and, to a lesser extent, India.

2.3.1 Annual employment growth by task intensity



ICT = information and communication technology.

Note: Jobs are classified in terms of whether they are high-intensive or low-intensive with respective to the five task categories. These figures use employment estimates for workers aged 15 and above.

Source: Khatiwada, Lennon, and Zilian, forthcoming.

2.3.2 Business process outsourcing in the Philippines

Business process outsourcing (BPO) grew out of increased connectivity as information technology (IT) and other advances created business opportunities for those able to deliver customer service at reduced cost. Estimates give the Philippines 13% of global BPO market share.

In 2013, BPO provided 20% of Philippine exports, 6% of GDP, and 4.2% of wage employment.[a] More recent industry estimates from 2016 put IT-BPO revenue at $22.9 billion, equal to 7.5% of GDP. With formal job creation low in the Philippines, BPO is an attractive option for young graduates. Clerical support dominates BPO jobs, and education and skills requirements vary across the industry. A 2016 labor force survey shows 62% of IT-BPO jobs in clerical support. Nearly 85% of call center workers are either college students or high school graduates, while only 13% have earned college degrees. By contrast, animation BPOs, which require more technical or advanced skills, fill 72% of their entry positions with college graduates. Similarly, college graduates fill 68% of entry positions in medical transcription and 55% in computer-related activities such as software development.

Service delivery automation, in particular robotic process automation, will transform BPO, affecting job creation. Technologies such as artificial intelligence, big data analytics, and cloud computing will alter the type of workers employed, the wages they earn, and the services they deliver to overseas clients. However, even the most pessimistic projections of employment growth show steady increases in IT-BPO job creation in the Philippines. As industry leaders reported at the IT-Business Process Management Summit in Manila in November 2017, demand from North America, Europe, and Australia will continue to fuel employment growth in the industry, as will demand from within Asia and the Pacific as these economies get richer.

The Information Technology and Business Process Association of the Philippines says the share of low-skilled BPO workers will decline from 47% in 2016 to 27% in 2022. Medium-skill occupations will increase from 38% to 46% in 2016, and high-skill occupations from 15% to 46% (box figure).

One of the proposals presented by IT-BPO leaders is a skills-development fund to train IT-BPO workers in new technology and familiarize them with automated service-delivery models. Industry leaders believe the government should contribute to the fund to provide incentives for firms to upskill and reskill. Further, as most BPO workers are university students or graduates, industry leaders believe that educational streams must better align with industry needs. Given growth in computer-related BPO, it is imperative that university education in computer and IT-related majors align with industry needs.

[a] This is from official statistics provided by Bangko Sentral ng Pilipinas and the Philippine Statistics Authority. Reference years for data vary depending on information source. From these two sources, the most recent year is 2013. When data are from labor force surveys, or official sources on labor market data, the latest is 2016. The Information Technology and Business Process Association of the Philippines provides 2016 data based on industry estimates.

Skills composition of the workforce as IT-BPO adjusts to automation

IT-BPO = information technology-business process outsourcing.

Source: ADB using estimates from the Information Technology and Business Process Association of the Philippines.

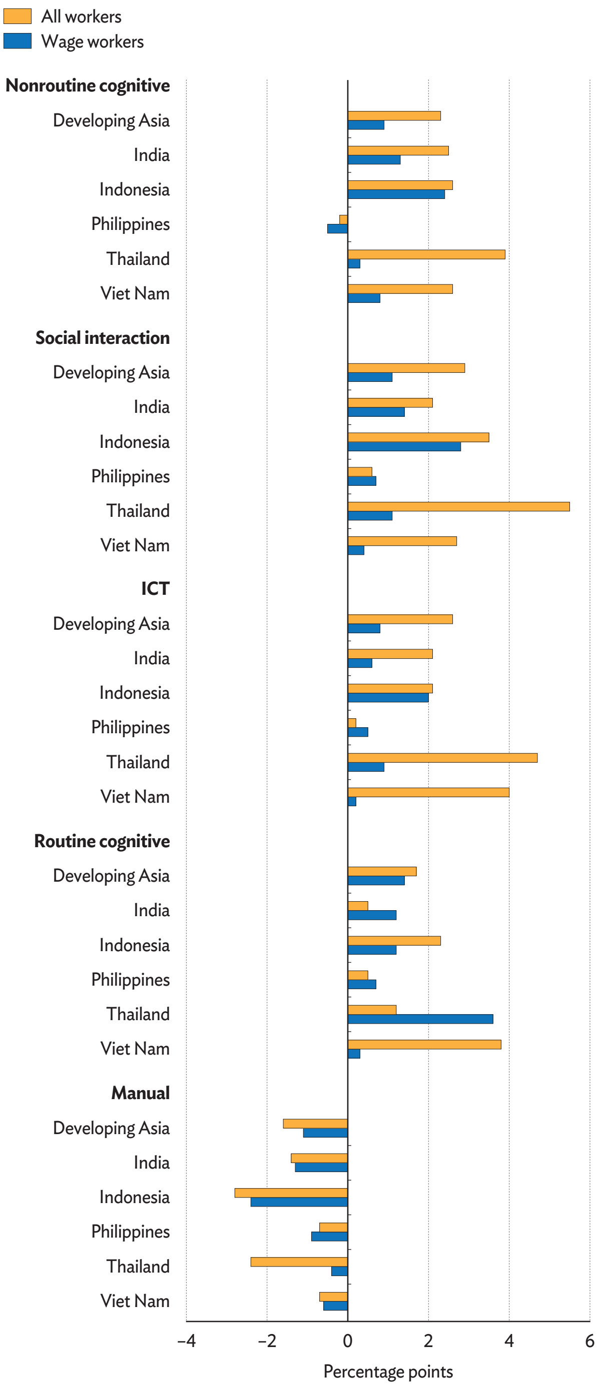
Considering only wage employees, the data show a similar but less pronounced pattern (Figure 2.3.1b). The growth difference between jobs with high and low task intensity means that employment is shifting toward occupations and industries requiring high cognitive, social, and ICT task intensity. This is consistent with relatively slow growth in demand for manual work and for work not intensive in the use of congnitive, social, and ICT skills.

In some countries, the shift in employment across job types has been substantial. From 2000 to 2014, more than 25% of Indonesian workers shifted into jobs intensive in social interaction, 20% migrated to high-intensive jobs in nonroutine cognitive tasks, and 17% moved away from high-intensive manual jobs. Similarly in Thailand, 18% of those employed shifted into high-intensive ICT jobs within just 10 years.

To properly compare the speed of these changes across economies, the growth rate of the share of jobs with high intensity across task types is annualized, which is much like comparing employment growth in these jobs with growth in total employment (Figure 2.3.2). The speed of change varies by the type of task and worker. The categories nonroutine cognitive, social interaction, and ICT show that changes are occurring faster in higher-income Asian economies considered here. Thailand stands out when both wage and self-employed workers are considered, for example, and Indonesia for wage workers alone. In particular, Thai growth in employment in high-intensive jobs in these three categories has outpaced that of total employment by 4.7 percentage points on average. Less dramatic shifts have occurred in the Philippines and Viet Nam. However, the mean speed of change is considerable. Each year, growth in Asian employment in jobs intensive in ICT, social interaction, and nonroutine cognitive tasks is on average 2.6 percentage points faster than overall employment.

How have wages evolved across job types? This information is presented in Figure 2.3.3 using average wages in constant local currency. In most countries, wage gains were larger for jobs intensive in cognitive, social interaction, and ICT tasks than for those less intensive. By contrast, jobs intensive in manual tasks experienced lower increases in wages. This pattern is particularly pronounced in economies with relatively large shifts in employment from low- to high-intensive cognitive, social interaction, and ICT jobs and from high- to low-intensive manual jobs, like Indonesia and Thailand. The Philippines is an outlier, as the trends in average wages are reversed there, except for nonroutine cognitive tasks.

2.3.2 Deviation of high-intensive job growth from all employment growth

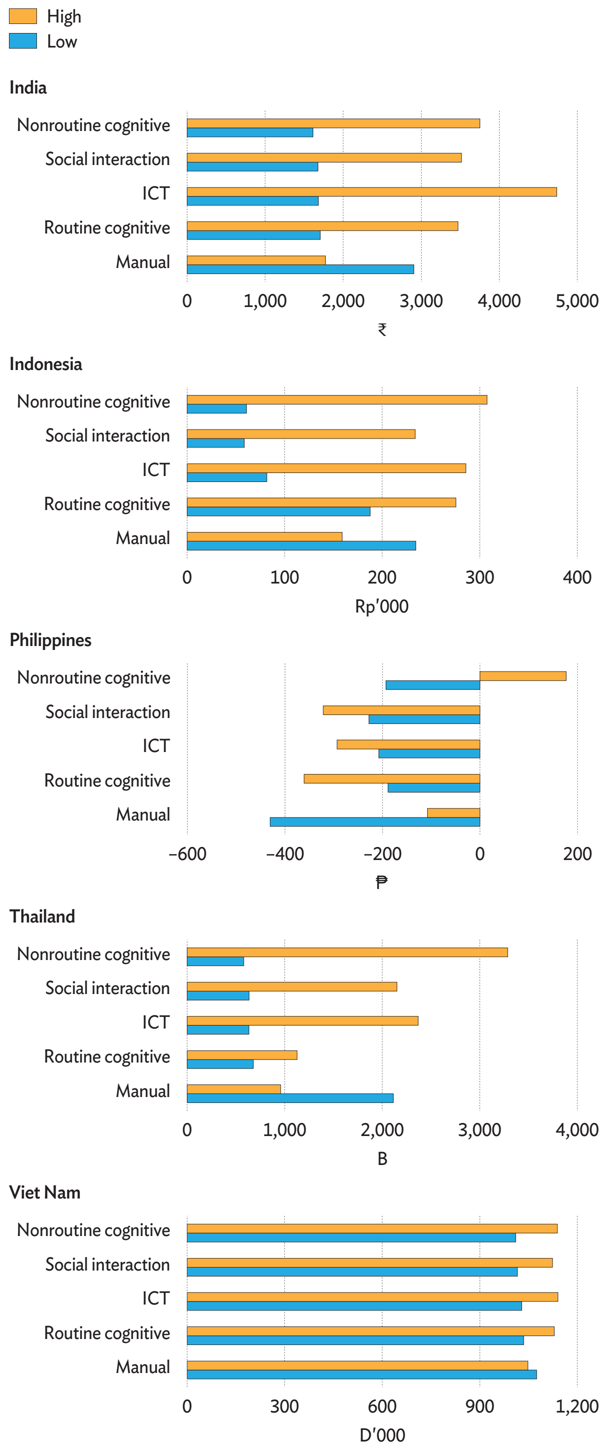


ICT = information and communication technology.

Note: Developing Asia here comprises five economies: India, Indonesia, the Philippines, Thailand, and Viet Nam. Employment estimates are for workers aged 15 and above.

Source: Khatiwada, Lennon, and Zilian, forthcoming.

2.3.3 Change in average wages by task intensity



Note: Wage estimates by task intensity for wage workers aged 15 and above. Data on monthly wages in local currency are drawn from each country's labor force survey, deflated using national GDP deflators from World Development Indicators. Changes in average wages are over the entire period of analysis: India 2000–2012, Indonesia 2000–2014, Philippines 2001–2013, Thailand 2000–2010, and Viet Nam 2007–2015.

Source: Khatiwada, Lennon, and Zilian, forthcoming.

Analysis thus far has shown substantial differences in employment and wage trends by task intensity indicator.

Employment in the region is shifting toward jobs intensive in nonroutine tasks and toward jobs that complement new technologies. Further, jobs intensive in nonroutine and ICT tasks see faster growth in wages than do jobs intensive in manual tasks. Interesting differences surface between wages in newly created occupations and existing ones (Box 2.3.3). Employment and wage trends strongly suggest that demand is rising for jobs intensive in nonroutine cognitive, social interaction, and ICT tasks relative to demand for manual intensive jobs.

Findings for routine cognitive jobs are perhaps the most surprising in view of the task-biased technical change hypothesis. Rather than contracting as predicted by the hypothesis, demand for routine cognitive jobs is still expanding in the region. One of the reasons behind this continuing expansion may be that these jobs occupy a smaller share of employment in developing Asia than in the developed world. Further, new technology has opened opportunities for workers that are outside of formal employment. Indeed, even among the low-paid and low-skill workers in the informal economy, there are examples where digital technology in particular has allowed productivity and wages to rise in Asia (Box 2.3.4).

2.3.3 Wage differentials between new and old occupations

Studies have shown that new occupations, particularly in new technology industries, tend to pay better than existing ones. Matching identified new job titles with microdata to estimate worker selection into new occupations in the US, Lin (2011) found that better-educated workers are likely to be found in newly created jobs and that these workers earn higher wages than similar workers in older jobs. Wage data by occupation title in Asia was used to study the difference in wages between new and old work.

A survey of business process outsourcing conducted in the Philippines in 2013 found a wage differential in favor of software developers (Bangko Sentral ng Pilipinas 2013). Software developers were the highest-paid employees, with an average annual wage of $18,453, or 6.2% above their average wage in the previous year. Computer programmers were the fifth-highest paid occupation in the Philippines, according to a survey in 2016 (Philippine Statistics Authority 2017). The survey also found that middle- and low-skilled workers in ICT and professional, scientific, and technical activities (PSTA) received wages above average. The average monthly wage of low-skilled workers was highest in these two industries, at ₱13,010 for ICT and ₱12,923 for PSTA, which compared with a low-skilled average monthly wage of ₱10,162 across all industries.

Meanwhile, software developers and programmers in Sri Lanka and Viet Nam earn higher average wages than other ICT professionals. In Sri Lanka, software developers and application programmers earn an average monthly wage of SLRs56,536, more than twice the average monthly wage of SLRs23,333 for database and network professionals or SLRs25,000 for web and multimedia developers. Likewise in Viet Nam, software developers are the highest-paid professionals in ICT, earning average monthly wages of D8,520,000, compared with, for example, D6,297,000 for web and multimedia developers.

2.3.4 Informal jobs, the promise of new technology, and Indonesia's Go-Jek

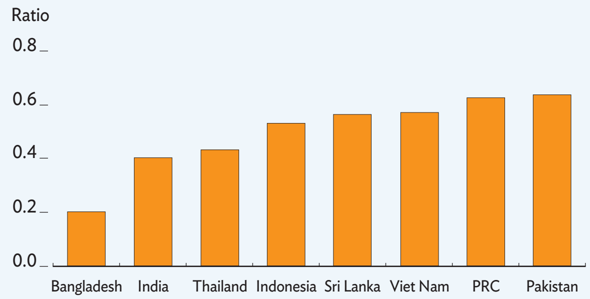
Informal work remains a prominent fixture across developing Asia, ranging from 33% of nonfarm employment in the PRC to 87% in Bangladesh. The median is over 70% in the 10 economies in developing Asia with data. Informal workers earn less than formal workers, their income only 20% of what formal workers make in Bangladesh and 64% in Pakistan (box figure 1). In eight countries with available data, the median informal worker wage is half that of formal workers.

Informal work is often a fallback when formal job opportunities are lacking. Registered firms tend to be larger and more productive, pay higher wages, and serve larger and wealthier markets. Either the formal economy needs to expand to absorb informal workers, or informal productivity needs to rise. The rise of the digital economy seems to be contributing on both fronts and is beginning to affect GDP. In Southeast Asia, for example, the internet economy provided 2% of regional GDP and is growing rapidly (Anandan et al. 2017). Since 2015, ride-hailing has had a compounded annual growth rate of 43%, e-commerce 41%, and online media 36%. Ride-hailing in Indonesia is fiercely contested between international companies like Uber, regionals like Grab, and locals like Go-Jek, Indonesia's informal motorbike service. Go-Jek revolutionized Jakarta's informal transport sector after its January 2015 launch.

Go-Jek is a play on English "go" and Indonesian "*ojek*," or motorcycle taxi, a popular option in notoriously gridlocked Jakarta. With *ojek* drivers spending much of their time waiting for customers, they were not very productive (Ford and Honan 2017). Enter Go-Jek, which supplied *ojek* drivers with a ride-hailing app instantly connecting them to customers. Go-Jek uses global positioning to instantly match passengers to the nearest driver. This allows drivers to serve more customers and waste less time. Passengers are far more satisfied, and drivers get better daily pay, even though Go-Jek drivers' fares can be less than a third of what others charge.

Go-Jek drivers have expanded services to package and food delivery, further boosting earnings (box figure 2). Go-Jek links its drivers increasingly to middle-class customers, whose preference for ride-hailing apps gives them a distinct advantage. But greater connectivity and, hence, productivity require some capital investment. Go-Jek drivers receive credit to purchase smartphones and training in how to use them. The investment pays off for many Go-Jek drivers, who can earn 3 times or more than conventional *ojek* drivers and several times above their old income, either as offline *ojek* drivers or in other informal jobs, or even in some formal employment (Fanggidae, Sagala, and Ningrum 2016).[a] Go-Jek (2017) said its drivers' monthly income increased by 15% since August 2016.

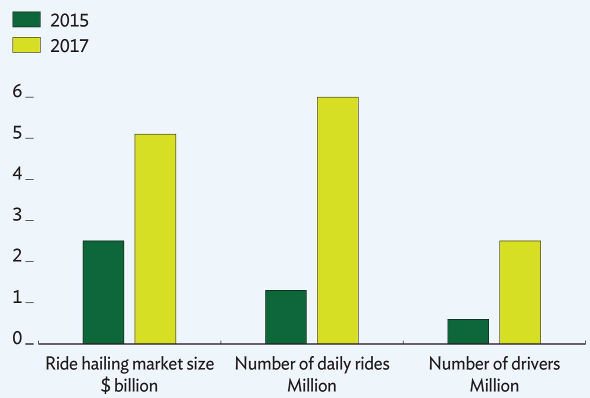
1 Informal–formal wage ratio, various years



Notes: Indonesian figures use wages in Yogyakarta and Banten.

Sources: ADB and BPS (2011); Chen and Hamori (2011); Dasgupta, Bhula-or, and Fakthong (2015); Gunatilaka (2008); Irfan (2008); Maligalig, Cuevas, and Rosario (2009); Nguyen (2013); Unni (2005).

2 Ride hailing in Southeast Asia



Source: Anandan et al. 2017.

[a] Go-Jek drivers make at least Rp150,000 per day, while regular drivers earn Rp50,000–Rp100,000 per day (Ford and Honan 2017). A certain female Go-Jek driver earns 12 times her pay in a previous job as department store sales promoter. A GrabBike driver earns 10 times more than in his former construction job (Yap 2016).

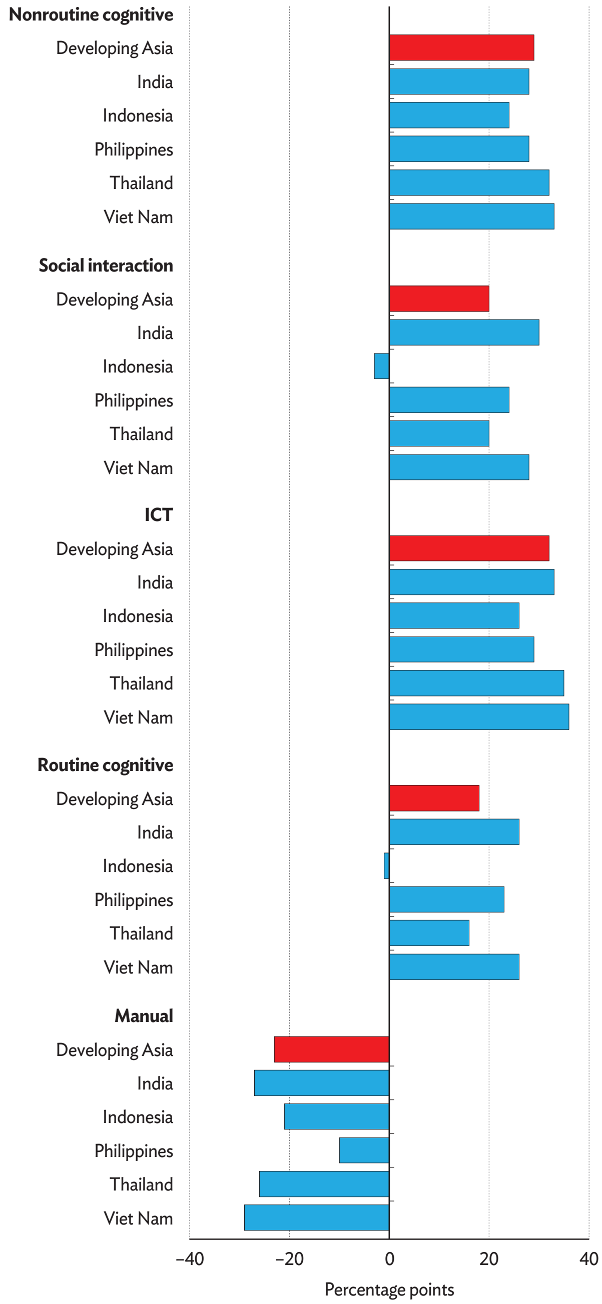
Comparing employment distribution in the region with developed economies

The distribution of employment by task intensity in the region can be compared with the distribution in developed countries. The latter is generated using data from the Program for the International Assessment of Adult Competencies Surveys (OECD 2013a, 2016a) that cover mainly of OECD economies (Figure 2.3.4). As may be expected, economies in Asia and the Pacific have far greater employment shares in manual-intensive jobs and much lower shares in ICT-intensive jobs. If Asia and the Pacific were to have an employment distribution similar to that in OECD countries in nonroutine cognitive, ICT, and manual jobs, some 160 million jobs would have to be transformed in terms of their task structure. To make Indonesian employment structure, for example, look like that of a developed economy, as many as 25% of Indonesian workers would need to migrate to high-intensive jobs in ICT and nonroutine cognitive tasks, and about 20% of workers would need to migrate away from manual-intensive jobs.

While the evolution of Asia's employment structure is unlikely to mirror exactly that of the advanced economies, the broad trends will surely increase employment requiring proficiency in nonroutine cognitive and ICT tasks and remove opportunities in intensive manual work. Indeed, in Indonesia, Thailand, and Viet Nam, jobs less intensive in ICT and nonroutine cognitive tasks, and jobs intensive in manual tasks, are already disappearing.

This has important implications for policy. Not surprisingly, workers in jobs intensive in nonroutine and ICT tasks in particular have high educational attainment. For instance, the average wage worker in high-intensity nonroutine cognitive jobs has completed either secondary school or a short tertiary program, while the average wage worker in a job with low intensity for these tasks will likely have completed only primary education. In addition, wages for jobs intensive in cognitive, social interaction, and ICT tasks are more than twice as high as wages for corresponding low-intensity jobs. Further, wages for jobs with low intensity for manual tasks are 1.8 times higher than those with high intensity for manual tasks.

2.3.4 Difference from OECD in employment distribution by task intensity



ICT = information and communication technology, OECD = Organisation for Economic Co-operation and Development.

Note: Differences in employment distribution are calculated by task category as the share of high-intensive jobs in the OECD minus the share of high-intensive jobs in developing Asia, here comprising five economies: India, Indonesia, the Philippines, Thailand, and Viet Nam. This figure describes how distant the region's employment distribution by task intensity is with respect to the OECD average. Employment shares for Asian economies are from the last year available: 2010 for Thailand, 2012 for India, 2013 for the Philippines, 2014 for Indonesia, and 2015 for Viet Nam. Employment shares for the OECD are from 2011/2012.

Source: Khatiwada, Lennon, and Zilian, forthcoming.

Thus, even as new technology creates jobs, workers engaged in manual work without the skills to carry out nonroutine cognitive tasks or work with emerging technologies are unlikely to be able to seize opportunities as they arise. In other words, new jobs will appear, but they will require skills that many workers do not possess. Workers who carry out mainly routine and manual tasks will likely experience lower wage growth and worsening income inequality. Further, as firms and industries adjust to new ways of producing and distributing goods and services, the resulting disruptions along supply chains may cause unemployment. As discussed in the next section, tackling this downside of new technology will require coordinated action on skills development, labor regulation, social protection, and income redistribution.

The role of government in harnessing technology for workers

While new technology remains central to creating productive jobs, there are some concerns from a worker's perspective. The previous section showed that job prospects for occupations intensive in cognitive, social interaction, and ICT tasks will likely expand, while those intensive in manual tasks will likely shrink. Given the smaller supply of workers proficient in cognitive, social interaction, and ICT tasks, it is not surprising that wage increases have been higher in these occupations. If the trend persists, inequality in the region will continue to deepen (ADB 2012). The worst case would see the wages of less-skilled workers hardly increase at all, which is what happened in the developed economies of today during the first industrial revolution. Then, the average wage of workers barely increased over several decades despite a dramatic increase in labor productivity in manufacturing (Bessen 2015).[9]

The other major issue is labor displacement. Disruption affecting particular types of occupations, industries, and firms will render some of their workers unemployed, unless and until they acquire the skills needed for emerging occupations and industries. The process is neither easy nor cheap.

This section presents various options on how policy makers can deal with these issues. First, education and skills development systems will need to equip Asian workers with the skills required to fill the jobs generated by new technologies. Second, labor regulations and social protection systems must be designed to protect worker incomes, even as firms retain flexibility to adjust workplace practices and job numbers as economic conditions change. Finally, policy on taxes and expenditure will need to ensure sufficient resources for education and skills development and for social protection, and they should bring about more equitable income distribution.

Education and skills development

Despite tremendous progress in expanding access to education, skills gaps remain a concern across developing Asia. More than 100 million children of primary and secondary school age are not in school, and many more leave school without basic literacy and numeracy. This has ripple effects on their employment prospects and widens skills gaps in the labor market. In 2016, 46% of employers in Asia and the Pacific reported difficulty in filling vacancies for skilled positions (ManpowerGroup 2016).

Asymmetric information aggravates skills gaps and mismatches. Educational curricula often misalign with labor market needs, while education and training programs are typically slow to adapt to changes in skills demand. Although workers may want to acquire new skills, they often do not know what skills employers want or their own employment or earnings prospects. Employers, for their part, consider training a risky investment because newly trained employees may leave the company, perhaps leveraging their newly acquired skills. This creates a vicious cycle of employers looking to hire those already with the needed skills while jobseekers do not know the skills they need and have no opportunity to learn them on the job.

Even when individuals have the right skillsets for certain types of jobs, they may struggle to connect with the right employer. Progress is being made in matching jobseekers with potential employers thanks to the diffusion of recruitment portals. No longer relying solely on personal networks, jobseekers can now learn about hundreds of vacancies and their skills requirements. So far, these portals benefit mainly urban mid- to high-skilled workers, but they are expanding rapidly. In Indonesia, for example, the networking platform LinkedIn doubled its users from 4 million to 8 million between 2015 and 2017, with 70% of new users in the 25–44 age group.

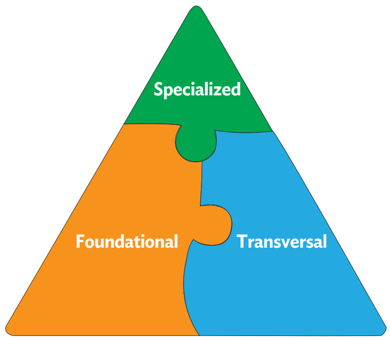
The big challenge facing Asia and the Pacific today is to improve learning outcomes and to prepare for a structural transformation of the economy and the workplace. The good news is that technology, having contributed to the problem, can offer solutions.

Foundational skills in a technology-driven economy

A technology-driven economy makes it more important than ever to learn how to relearn. Solid foundational skills continue to be a crucial prerequisite to further learning. Traditionally, foundational skills included basic reading, writing, and numeracy, but they have grown to encompass two more categories: social and emotional skills, and digital literacy (Figure 2.4.1). These skills build on each other to promote further learning (Acosta et al. 2017, Durlak et al. 2011, OECD 2013b). High social and emotional skills are associated with better reading, writing, and numeracy skills, for example, and solid reading, writing, and numeracy skills are prerequisite for digital literacy.

Digital literacy is fast becoming indispensable for such everyday functions as digital finance and e-government, as well as further education and lifelong learning. It includes not only the ability to use digital devices and platforms, but also knowing how to use them appropriately. The importance of using digital tools intelligently is often overlooked, as many

2.4.1 Skills in a technology-driven economy



Specialized

- Acquired through TVET, higher education, and lifelong learning
- Relate to a specific job, task, academic discipline, or knowledge area
- Can depreciate with technological change and/or lack of practice, so need regular upgrading

Transversal

- Acquired through education and life experience
- Include a range of skills, from critical thinking to creativity and interpersonal skills such as communication skills
- Are transferable across occupations and sectors

Foundational

- Acquired through basic education
- Include reading, writing, numeracy, socio-emotional skills, and digital literacy
- Are a stepping stone to further education and full participation in society

TVET = technical and vocational education and training.
Source: Adapted from UNESCO (2014).

training courses focus exclusively on the mechanics of using a device or specific software. However, learning how to do research—to make sense of and analyze digital content—is now as essential as basic reading and writing skills (OECD 2016b).

Beyond hardware, two elements are fundamental to successful digital literacy programs (World Bank 2016). First, such programs are more effective when embedded in mainstream learning. Standalone programs are less effective because they do not contextualize the use of technology. This requires adapting curricula and learning materials for traditional subjects to integrate digital technologies. Second, teachers must train to adapt pedagogical practices and understand how to use digital technologies to support learning. Many programs have failed because they focused on hardware use, with inadequate attention to teacher training.

Social and emotional skills affect a range of individual outcomes, including learning, employment trajectories, health, and overall life satisfaction. Definitions and terminology vary, but social and emotional skills are generally understood as skills "involved in achieving goals, working with others, and managing emotions" (OECD 2015). They include behavioral traits such as perseverance, self-control, and resilience, as well as such social skills as interacting effectively with others. These skills are malleable, particularly from early childhood to adolescence, and therefore can best be taught and strengthened through childhood education.

Recognizing that different types of foundational skills build on one another, pedagogical approaches are now evolving to develop these skills in tandem. For example, many schools are now encouraging students to adopt a "growth mindset." The concept is based on the idea that one's skills are not inherent but can be developed through effort, commitment, good learning strategies, and support from others (Dweck 2007). Failure and errors provide opportunities to grow and thus become part of the learning process. A similar principle is often used in educational software, especially through the gamification of learning, which relies on trial and error and on learning by doing.

Leveraging new technologies to build foundational skills

Educational technology and e-learning are rapidly growing globally, not least in Asia. With some 600 million young students increasingly connected and eager to use game- and social-based learning, new services and products are flooding the region. Interest in mobile learning is growing as smartphone usage increases.

These initiatives, driven by global and Asian information technology startups, are changing the education landscape. Some are developing initiatives removed from traditional educational arenas, while others are developing tools and services for educators and learners to use in school or at home. One challenge for educators is to determine how best to work with these technology-led businesses to improve learning outcomes cost-efficiently and effectively.

Technology can contribute to foundational skills in several ways. It provides new content to users, thus improving access to learning and teaching resources. Importantly, it contributes to changing pedagogical practices, ushering in an era of learning that is more student-centered.

Software that enables self-paced learning and that tailors teaching to individual students is an important new trend. In its simplest form, self-paced learning occurs when students progress at their own speed through a learning program, some moving faster than others toward more complex material. Adaptive software takes this a step further, directing students through individualized learning pathways. For example, students having more difficulty than others with a particular concept are given more detailed explanations and more exercises for practice. Further, the software forwards individualized data to teachers so they can target specific students for additional tutoring or more advanced teaching. This promotes more inclusive learning cost-effectively. Progress in machine learning and artificial intelligence will make this type of software more sophisticated. As it disseminates, it will change the role of educators from teacher to mentor.

Job-relevant skills in a technology-driven economy

Job-relevant skills are of two types. Transversal skills, which are transferable across occupations and sectors, include interpersonal skills, the ability to think critically, and the ability to solve problems. They are acquired throughout one’s education and life experience. Specialized skills, by contrast, relate to a particular occupation (such as teaching), task (coding), or knowledge area (anthropology). They are typically acquired through technical and vocational education and training (TVET), higher education, and work experience. Specialized skills are likely to depreciate quickly, particularly in a time of fast-evolving technology, and thus require regular updating and upgrading. With more automation and machine learning, higher-order specialized skills applicable to nonroutine tasks will be particularly valuable.

TVET and higher education systems alike face a complex set of challenges. They must expand to accommodate the rising number of graduates, as well as adults seeking to upgrade their skills or retrain. At the same time, they need to improve the relevance of the training and education they provide to respond to fast-changing labor market demand.

Stronger links between TVET and higher education can bring progress toward this goal. To better respond to labor market demand, the People's Republic of China, for example, is transforming many of its universities into polytechnics, and Indonesia is expanding its network of polytechnics. Credit transfer systems are developing to enable TVET graduates to pursue higher education—allowing, for example, a technician to become an engineer—and a university student to choose a more vocationally oriented track. This is an important step toward expanding skillsets in the whole workforce. However, these efforts must be embedded in a comprehensive approach that provides opportunities for experienced workers to upgrade their skills. It involves, for instance, a framework for recognizing prior learning and developing programs for working adults.

Strengthening linkages between firms, universities, and vocational schools is essential to make higher education and TVET systems more responsive to technological change. Traditional approaches remain relevant, such as involving industry partners in the design and delivery of TVET programs and promoting workplace learning. New technologies provide opportunities for deeper and broader partnerships. Online collaborative platforms, for example, can facilitate development of joint projects, including applied research, between schools and enterprises.

Leveraging new technologies for job-relevant skills and learning to relearn

Machine learning and big data analysis can help assess and more closely monitor in real time the evolution of occupations and their task content and required skillsets. However, it requires copious data and works only for sectors and occupations well represented on professional networking and job search platforms. JobKred in Singapore has developed this kind of tool. By mining data and using other sources of information, it assesses the types of skills in demand at any given time for specific occupations. It also provides individualized career guidance to users based on their current skillsets and recommends education or training programs to match them to job requirements. As Asia and the Pacific become better connected, these services can improve labor market intermediation and address the problem of asymmetric information.

With fast-evolving technology rapidly depleting skills, learning to relearn is becoming the new normal. A major implication of lifelong learning is that education and training have to be interwoven with full-time work, so content must be provided in a format that is short, convenient, and mobile. Shorter online education and training programs are emerging in response to this growing demand. So-called "nanodegrees" were developed following the mixed results of massive open online courses. These nanodegrees develop skillsets for targeted professions, incorporating user experience and acknowledging the need to transform content to make it as easy as possible to assimilate. New initiatives—such as the Gnowbe in the US and Singapore, and Funzi in Finland—expand on the concept of short, convenient, and mobile learning with their "mobile microlearning" model, which relies on gamification, short videos tailored to modern attention spans, quizzes interspersed in learning materials, and learners' social interaction.

Fast-changing labor market demand will increasingly require individuals to learn, unlearn, and relearn. Digital technologies, if adapted to local needs, can be powerful tools for individualized and therefore more inclusive learning at different stages of life.

Labor regulations and social protection

New technologies are transforming the ways work is organized. Because digital technologies in particular allow some types of work to be done remotely, they have great potential to accelerate the rise of part-time, on-call, or temporary employment—arrangements the International Labour Organization calls nonstandard forms of employment. While such forms grant employers flexibility and allow workers to pursue new opportunities in the labor market, perhaps while reconciling work with the demands of home life, they often offer little job security. For some workers it can mean cycling between short-term jobs and unemployment beset by worries over when they will next find work and be paid. Such workers may also have meager social security coverage and face greater occupational safety and health risks. Finally, they are less likely to join a union.

Well-designed labor regulation that takes into account associated aspects of social protection systems is an important element of the policy response to spread the benefits of new technologies. Labor regulation includes legislation to protect employees by establishing rules for hiring and firing; setting some wages, in particular minimum wages; regulating work hours and conditions, not least to protect health and safety; and promoting equal opportunity. By extension, labor regulation includes the social protection elements most often tied to work such as health care, income replacement when a job is lost, and help in finding a new job through information and other support from public and private sources.

The key policy challenge today is that labor regulations and social protection systems now current globally were designed for an era when the expected norm was full-time employment with a single company over the long term. This assumption never described most labor markets in developing Asia, however, and, where it is a reasonably accurate description, new technologies will likely bring widespread changes to the world of work. The prospect of a worker remaining in one job with a single employer over the long term looks less and less likely for large groups of workers.

While a detailed examination of current labor regulations and social protection systems—and how they need to evolve—is beyond the scope of this chapter, the concept of "protected mobility" seems an appropriate guiding principle (Auer 2005). A central aspect of this is to ensure that a highly mobile labor market—and one dealing out more frequent spells of unemployment—has mechanisms that protect worker incomes.

First, labor regulations must avoid two extremes: one that leaves workers with too little protection, and the other that imposes high labor costs that only encourage firms to automate. Using cross-country panel data on manufacturing industries, Hasan, Mitra, and Sundaram (2013) found more restrictive labor regulations associated with higher capital intensity in manufacturing, especially in developing economies and in sectors that either require more frequent labor adjustment or, like garments and footwear, are labor intensive and employ more unskilled workers.

Second, at a time when job security will likely erode, any temptation to restrict job dismissals through blunt means must be avoided. The Centre for Business Research Labour Index database at the University of Cambridge, which covers 22 economies in developing Asia, reports that employers must obtain prior permission from the state to dismiss an individual in India, Indonesia, and, since 2008, the People's Republic of China. Such requirements can make layoffs very cumbersome and costly for firms, effectively raising the cost of hiring labor in the first place. In general, policy makers should be guided by the principle of protecting workers rather than protecting jobs.

In developing countries, transitioning workers to more productive sectors and firms, especially from informal to formal employment, is essential to creating good jobs. Theory and evidence both support the conclusion that restricting dismissals undermines workers' welfare when a better alternative is severance pay or unemployment insurance (Ranjan, Hasan, and Eleazar, 2018).

Third, even severance pay has its drawbacks as workers enter periods of unemployment.[10] Policy makers, especially in middle-income countries, should consider unemployment insurance tailored to developing country circumstances. Such systems can function alongside more traditional public works programs, such as India's Mahatma Gandhi National Rural Employment Guarantee Act, which provides to the needy 100 days of wage employment annually on public works. Worldwide, and especially in advanced economies, unemployment insurance systems more effectively provide adequate income protection without imposing large efficiency costs (Vodopivec 2013). The catch is that such unemployment insurance systems are demanding, both financially and administratively. They therefore need to be tailored to the developing economy capacities (Box 2.4.1). Fortunately, digital technologies allow biometric identification, as in India's Aadhaar system, initiated in 2008 and now covering 1.2 billion people. As they also allow digitized administrative records that can be shared securely and accurately, they hold great promise for building the administrative capacity required to manage a modern system of unemployment benefits. Other large-scale digital ID initiatives in Asia include Indonesia's e-KTP card, Malaysia's MyKad, and Pakistan's NADRA.

Fourth, minimum wages are an important way for policy makers to ensure that less-skilled workers enjoy a decent standard of living and to counter inequality. Good design principles are crucial in setting minimum wages. They need to avoid being either too generous or too meager, and they should rise in line with productivity gains. A rule of thumb is for minimum wages to be 30%–40% of the median wage, or 25%–35% of the mean wage (IMF 2016). Different minimum wages for different locations should accurately reflect differences in the cost of living. At the same time, governments must resist pressure to introduce different minimum wages for different sectors or categories of workers. The more types of minimum wage there are, the more likely lobbyists and special interest groups will interfere and keep the market from playing its vital role in allocating resources.

Fifth, rather than create regulatory barriers to nonstandard forms of employment such as part-time contract labor, it may be better to regulate more neutrally. These workers need social protection too, requiring that social security systems be adapted to increase coverage. Advisable adaptations include lowering thresholds required for minimum hours, earnings, or duration

2.4.1 Adapting unemployment insurance to developing economy realities

In developed countries, unemployment insurance provides income support to workers who have lost their jobs. Systems require both workers and employers to contribute. Once a worker has met certain minimum requirements for length of employment and amount contributed, they qualify for job-loss benefits. Benefits are typically 40%–75% of average earnings and can be collected for a prescribed period, typically 6 months in the US, on the condition that the recipient actively seeks new employment. Studies show that such systems allow job-seekers to smooth consumption while looking for new work. While unemployment insurance may hinder economic efficiency if recipients slow their job search, it has the positive effect of giving workers time to find more suitable reemployment. Moreover, unemployment insurance acts as an automatic macroeconomic stabilizer by contributing to aggregate demand during recessions.

In developing countries, however, unemployment insurance systems are rare. Where they exist, they typically cover only a small fraction of the formal workforce, excluding agricultural and informal workers entirely. The systems are most common in Latin America, though the PRC has one for urban workers. Obstacles for developing countries are large informal sectors and little of the administrative capacity needed to ensure that contributions come as required from both workers and enterprises, and to accurately track workers and confirm their eligibility.

To successfully adapt unemployment insurance systems to developing country realities, governments should do several things: Relax eligibility criteria by permitting informal work without terminating benefits. Rely initially only on worker and employer contributions to finance the system through unemployment insurance savings accounts, as tried in several Latin American countries, in which unused savings merge with retirement accounts. Transition to more sophisticated systems by moving on from simple unemployment insurance savings accounts to a hybrid version, such as the one Chile introduced in 2002. These hybrids are initially funded from worker contributions and subsequently through a "solidarity" fund, partly financed through employer contributions in lieu of paying into existing severance pay systems, and through general taxes, especially as economically vulnerable workers are brought into the system.

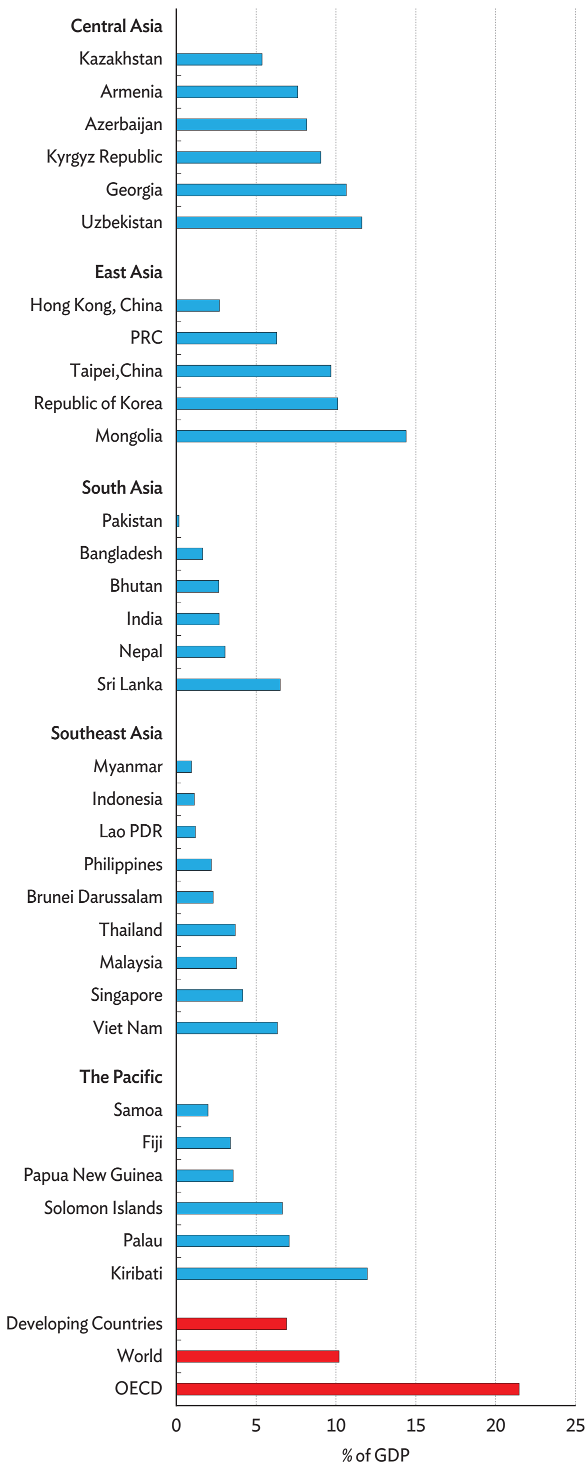
Source: ADB based on Robalino and Weber (2013) and Vodopivec (2013).

of employment; making systems more flexible regarding the contributions required to qualify for benefits; allowing interrupted contribution; and making benefits more portable.

Tax and expenditure policies

Public finance must be the main source for investments in education and training, especially to benefit the economically disadvantaged and those displaced by new technology, and for funding social protection systems. Figure 2.4.2 shows many regional economies spending much less on social protection than do advanced economies. Augmenting social protection expenditure will require governments to raise more revenue. The share of government revenue in GDP is low in many Asian countries—in 2016 about 10 percentage points below the OECD average of 25%. Most government revenue is tax revenue, which can be increased by broadening the tax base, improving tax administration, and making taxes more progressive, which also addresses income inequality.

2.4.2 Public social protection expenditure, 2015 or latest available year

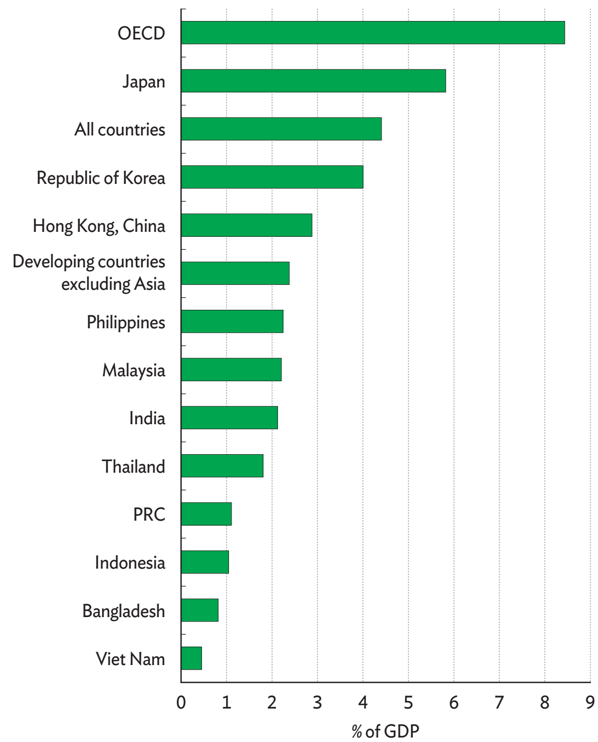


GDP = gross domestic product, Lao PDR = Lao People's Democratic Republic, OECD = Organisation for Economic Co-operation and Development, PRC = People's Republic of China.

Note: Data are from 2015, except 2014 for Bangladesh, Bhutan, India, the Kyrgyz Republic, Pakistan, and Uzbekistan; 2012 for the Lao PDR; 2012 for Malaysia; 2011 for Myanmar; and 2010 for Taipei,China.

Source: International Labour Organization. World Social Protection Report Data. http://www.social-protection.org/gimi/gess/Wspr.action (accessed 2 March 2018).

2.4.3 Personal income tax, 2014 or latest available year



GDP = gross domestic product, OECD = Organisation for Economic Co-operation and Development, PRC = People's Republic of China.

Notes: Simple averages are given for all countries, OECD, and developing countries excluding Asia. Personal tax revenue uses 2014 figures, except 2015 for OECD; 2013 for Bangladesh, India, and the PRC; and 2004 for Viet Nam.

Sources: International Monetary Fund. World Revenue Longitudinal Dataset. https://data.world/imf/world-revenue-longitudinal-dat; Organisation for Economic Co-operation and Development. Revenue Statistics. https://stats.oecd.org/Index.aspx?DataSetCode=REV (both accessed 2 March 2018).

Broadening the tax base

The tax base can be broadened by reining in various exemptions, deductions, and incentives. And, despite tax rates comparable with the world average (though below the OECD average), personal income tax collection is low in Asia (Figure 2.4.3). One reason is relatively high exemption thresholds, and another is slow graduation to the top personal income tax rates (ADB 2012). Tax concessions also keep collection low.

Improving tax administration

Government revenue can be increased by improving tax administration. In the Philippines, for example, weak tax administration is a constraint on government revenue (ADB 2009). Complicated tax systems with many rates, exemptions, deductions, and concessions increase the cost of tax administration and of monitoring compliance, while creating opportunities for tax avoidance and tax planning, which are seen to favor higher-income taxpayers because they generally have more scope for shifting income to avoid higher rates. Unfair tax systems can inhibit willingness to pay taxes. Strengthening governance and institutions is key to improving tax collection, and digital technologies can help (Box 2.4.2).

2.4.2 Goods and services tax in India facilitated using technology

Governments are increasingly using digital technologies to improve tax compliance and enforcement. Digitization can broaden the tax base, reduce administrative costs, improve transparency, ease the compliance burden, and incentivize tax compliance.

On 1 July 2017, India rolled out its goods and services tax (GST), a landmark tax reform that replaced its numerous central government and state taxes with a simplified and unified tax system designed to create a single Indian market. The GST is expected to cut red tape, curb corruption, lubricate domestic trade, broaden the tax base, and increase tax revenue.

All GST filings are handled electronically. GST is implemented through the GST Network, a web-based “one-stop solution” for all India’s indirect tax requirements. The GST Network is the information technology backbone for the GST, providing a common portal where taxpayers can file tax returns and tax authorities can match input credits with the liability declared by suppliers and issue notices. India’s Income Tax Act, as amended on 1 July 2017, likewise requires taxpayers to be registered with the 2008 Aadhaar program, India’s biometric identification system, to file income tax returns. Aadhaar, in turn, is mandated by law to be linked to individual bank accounts. Banks will eventually be required to freeze unlinked accounts as part of the wider government effort to trace tax evasion and formalize the underground economy.

Under this new digital tax regime, the government can put India on a path toward a system with more transparency and greater participation in the formal economy. Mandatory electronic tax filing can better ensure administration at arm’s length by minimizing taxpayers’ personal interaction with tax officials. Increased digitization is further expected to broaden the tax base and lessen tax evasion. A survey using GST data helped the government add 3.4 million new indirect taxpayers as of December 2017 (Government of India 2018).

Making taxes more progressive

The progressive orientation of fiscal revenue systems can be enhanced through taxes on property, inheritance, and capital gains. They can make resource mobilization more equitable at a relatively low economic cost. Taxes levied on immovable property are widely viewed as a fiscal source tailored for local government. Because such taxes are underused in most parts of the world, including in developing Asia, they offer scope for strengthening fiscal resources, particularly for local governments.

Taxes on property include annual taxes on land and property, stamp duties or property transfer taxes, development fees, betterment levies, estate duties or inheritance taxes, and capital gains taxes on property transfers. An attractive feature of property tax is that, among broadly collected taxes, it has the least adverse effect on growth. In addition, property tax is progressive because it is proportional to property value.

Another inherently progressive tax is inheritance tax, which currently exists in only four economies in the region (ADB 2015b). This levy taxes the transmission of wealth (and hence inequality) across generations but has little effect on work incentive. The capital gains tax similarly targets the rich, who tend to own more capital, and does not adversely affect incentives, as the tax is usually levied on gains realized from investments.

Corporate income taxes are similarly low in some Asian economies, partly because of tax incentives to attract investment and to spare activities seen as having social or economic merit. However, income taxes are less progressive if tax incentives go to the high-income special interests who often lobby for concessions. Moreover, such incentives are often inefficient because they simply subsidize activities firms would have undertaken anyway. Thus, tax collection can be increased by broadening the corporate tax base. On a related issue, there have been many articles in the press about taxing robots. Many people worry that extreme automation will destroy countless jobs without replacing them with comparable jobs, causing unprecedented labor displacement. As that proposal is controversial, a more practical option to consider might be to reform policies that subsidize capital, such as tax deductions for interest paid on loans, to raise the cost of capital and thereby buoy demand for labor.

The full agenda is broader

As noted above, governments are tasked with responding to technology and its effects on the labor market. At the same time, they stand to benefit by embracing new technology. From tax compliance and enforcement to smart cities, health care, and education, there is tremendous potential for more efficient and effective delivery of public services. However, governments need to create an environment that enables technology adoption through a two-pronged strategy. As they complete the necessary support infrastructure, they should support research and development and also innovation. In both cases, government involvement is both direct and indirect.

The public sector is directly responsible for providing basic infrastructure such as energy supply and transport. Similarly, given the central role the internet plays in new technologies, developing a nationwide broadband backbone and other ICT infrastructure is essential. Even when parts of the infrastructure are provided by the private sector, the government still has a role to play, whether in allocating space on the spectrum, ensuring competition among providers, or enforcing minimum standards and interoperability. Particularly important, to address inclusion and poverty reduction, is to ensure that service providers cover the "last mile" to the homes, farms, and businesses of the poorest customers. The technological infrastructure that receives the fewest headlines but is the most critical for inclusion and poverty reduction is in remote and lagging regions, where there is little financial incentive for private provision. Technological innovations cannot help areas that lack connectivity. This is especially true for rural areas, where new technologies have considerable potential for raising productivity and earnings in agriculture (Box 2.4.3).

The general view among economists is that the private sector tends to leave a lot of necessary research and development to the public sector, considering it a public good. Government can directly fund research or create an environment that is conducive to private sector innovation. Government-supported research can be conducted in universities or in publicly funded research centers, or by private entities that receive grants or fiscal incentives to undertake research and development. Private sector innovation, meanwhile, requires regulation to protect personal data and privacy, an effective system of intellectual property protection, and the means to ensure that large technology firms abide by the norms of fair competition. Finally, technology startups need adequate capital to get their business off the ground.

Developing Asia has historically relied on abundant labor to support export-led growth. Now it is poised to leverage its expanding middle class to usher in a new era of consumption-driven growth. With the right policies, new technologies can play a key role in this transition.

2.4.3 Technology for agriculture, Asia's biggest employer

Agriculture will remain a top employer in Asia for some time to come. Even if workers continue to leave agriculture at the same rate as in 2000–2015, in 2030 the sector will still employ 21% of the workforce in Bangladesh, 43% in the Lao People's Democratic Republic, and 28% in Myanmar. It is therefore vital that productivity and earnings in the sector be raised to tackle the challenge of worsening inequality in the region.

Productivity can be enhanced, and food security safeguarded, by further extending the use of proven technologies such as mechanization, high-yielding crop varieties, and improved irrigation, fertilizer, and pesticide.

Fourth Industrial Revolution technologies can improve productivity even further. Bioinformatics—combining computer science, biology, math, and engineering to analyze biological data—allows the development of even better crop varieties using modern agricultural biotechnology and genomics (Xue et al. 2008). Dramatic productivity gains can be achieved through precision agriculture, which prescribes exact quantities of seed, fertilizer, pesticide, water, and tillage for individually managed plots as small as 1 square meter using field or remote sensors (Mulla and Miao 2016). Pesticides can be administered by drone, and manual control of drip irrigation can be automated.

Fourth Industrial Revolution technologies may initially benefit mainly larger and better-off farmers, taking time to spread. Precision agriculture is only gradually becoming the norm even in developed economies, with 60% of farmers in Europe and North America expecting current trends in adoption to continue until most farmers use the practice by 2030 (Corsini et al. 2015).

However, some new technologies have potential to benefit smallholder farmers in developing Asia today. Relatively accessible and cheap ICT technologies can cost-effectively help farmers improve production practices, better connect with markets, and narrow the gap between farm gate prices and retail prices—a gap that, for rice in the Philippines, can equal the farm gate price. Branding and marketing can be enhanced. Hazelnut producers in Bhutan use digital data collection to trace produce and verify plant health and best practices, as well as to improve supply chains. Similarly, the Digital India campaign brings villages online to promote knowledge-intensive agriculture, financial inclusion, and rural entrepreneurship (Lele 2017). In the PRC, the Hunan Agri-Telecom Platform uses text messages to send farmers market and other information, and the E-Price App uses the internet, cloud computing, and smartphones to disseminate prices (Singh et al. 2011).

Any technology that provides to farmers an otherwise scarce or expensive resource helps to spur rural growth from the bottom up. Sharing tractors Uber style can help, as can electronic payment of fertilizer subsidies and e-extension to reach remote areas veterinarians and agronomists rarely visit.

Of course, such ICT-based interventions are no silver bullet. They require affordable access to mobile phones and the internet. Meanwhile, internet penetration in Pakistan, for example, is estimated at 15.5%, less than half of the PRC rate of 53.2% (ADB 2017d). Such digital divides pose significant barriers to smallholder farmers. And, in the end, farm gate prices can never be generous where basic transportation and storage infrastructure is weak.

Endnotes

1 Most references to productivity in this chapter are to labor productivity. Growth in output per worker has three main sources: capital accumulation, which provides to workers more equipment to work with; technological change, which usually introduces new types of equipment and machines but includes better ways of managing the shop floor and the firm more generally; and better skills, which are acquired not only through education and training but also from experience. It is widely accepted that technological change is the main driver of increases in productivity.

2 Similar results emerge from a 10-sector decomposition of changes in average labor productivity into structural change and within-sector productivity components.

3 GVCs are also known by various terms, such as global supply chains, international production networks, and production fragmentation. GVCs give rise to offshoring, vertical specialization, trade in value added, second unbundling, and trade in tasks.

4 When labor force surveys or population censuses are unavailable for any given year, total employment as well as occupation-industry shares are interpolated or extrapolated.

5 Employment changes over the decade between 2005 and 2015 are studied to abstract from cyclical factors.

6 Based on ILOSTAT data on employment in developing Asia, which includes 38 economies with employment estimates from the International Labour Organization: Afghanistan; Armenia; Azerbaijan; Bangladesh; Bhutan; Brunei Darussalam; Cambodia; the People's Republic of China; Fiji; Georgia; Hong Kong, China; India; Indonesia; Kazakhstan; the Republic of Korea; the Kyrgyz Republic; the Lao People's Democratic Republic; Malaysia; Maldives; Mongolia; Myanmar; Nepal; Pakistan; Papua New Guinea; the Philippines; Samoa; Singapore; Solomon Islands; Sri Lanka; Taipei,China; Tajikistan; Thailand; Timor-Leste; Tonga; Turkmenistan; Uzbekistan; Vanuatu; and Viet Nam.

7 An efficiency correction is used by constructing a measure of total factor productivity for each country and each year in the dataset using the Penn World Tables, release 9.0 (Feenstra, Inklaar, and Timmer 2015). A concern is that the contribution of trade and technology to changes in jobs is sensitive to the choice of the efficiency correction. Alternative estimates of total factor productivity, including those developed by Inklaar and Diewert (2016), suggest that the results do not qualitatively change.

8 Methodology and data used in this section do not allow manual tasks to be disaggregated into routine and nonroutine.

9 Why were wages stagnant for so long, even as new technology improved labor productivity? Wage growth depends not only on how much output expands per worker, but also on how workers' share in output evolves. This is partly determined by the nature of the technology, but there are other factors: the extent of competition in product markets, workers' bargaining power, the relative mobility of capital versus labor, and even social norms. While unions are one source of worker bargaining power, Bessen (2015) highlighted another: the skills workers possess and their experience. In US cotton mills in the early 19th century, technology was constantly improving, continually changing the skills needed to operate machinery. Because of this, experience did not boost workers' bargaining power. Only when the technology standardized and skill certification became possible did experience translate into bargaining power. If their wages did not improve, workers could move to other firms happy to pay them more.

10 There are several reasons. First, many workers entitled to severance pay fail to receive it. Second, payouts are unrelated to the time unemployed. Third, unless severance pay is very generous, which can impose serious efficiency costs, it is rarely sufficient. Data from World Bank *Doing Business* surveys show that some countries in developing Asia, notably Indonesia and Sri Lanka, require very generous severance pay. By contrast, the few developed countries that rely on mandatory severance pay do not require it to be very generous. These economies do, however, provide unemployment insurance.

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