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AUTOMATION, THE FUTURE OF WORK AND INCOME INEQUALITY IN THE ASIA–PACIFIC REGION[1]

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Introduction

> Last year, it was still quite humanlike when it played. But this year, it became like a god of Go.
>
> – Ke Jie

Ke Jie, the current world champion of the ancient Chinese board game Go, made the statement above after he was beaten by AlphaGo, an artificial intelligence (AI) software developed by DeepMind, the AI arm of Google's parent, Alphabet.[2] AlphaGo distilled thousands of years of human knowledge of Go into better moves of its own. The latest evolution of AlphaGo, AlphaGo Zero, has been hailed as a major advance because

1 I sincerely thank discussants Robert Scollay, Somkiat Tangkitvanich and participants at the 50th anniversary PAFTAD conference in Tokyo from 31 January to 2 February 2018 for insightful comments and suggestions that helped to improve the paper significantly. All errors are my own.

2 Refer to Paul Mozur, 'Google's AlphaGo defeats Chinese Go master in win for A.I.', *New York Times*, 23 May 2017, www.nytimes.com/2017/05/23/business/google-deepmind-alphago-go-champion-defeat.html.

it mastered the game from scratch, with no human help beyond being told the rules. In games against its 2015 version, which famously beat the South Korean Go grandmaster Lee Se-dol, AlphaGo Zero won 100 to 0.[3]

Such is the speed of the development of AI that its mastery of human intelligence is in prospect. Not only has AI developed rapidly in recent years, other major technological advances including big data analytics, advanced robotics, 3D printing and Industry 4.0, have also progressed at pace.

In this paper, the main question to be addressed is the impact of recent developments in AI and advanced robotics on employment and income distribution in the Asia–Pacific region. The paper explores, firstly, recent trends in technological progress, followed by potential drivers of development, the effect of new technologies on employment and income inequality and finally, the geography of innovation and future markets from a perspective focusing on countries' innovation capabilities.

Recent trends in technological progress and the development of automation technologies

Technological progress as reflected by total factor productivity (TFP) growth

In the early 2000s, prior to the global financial crisis (GFC), the growth of total factor productivity (TFP) experienced a turning point and slowed down in key Organisation for Economic Co-operation and Development (OECD) economies including the United States, the United Kingdom and Australia (Figure 6.1). Performance has been divergent amongst economies in the Asia–Pacific region: between 1970 and 2014, the Republic of Korea, China, Taiwan, India and Thailand achieved greater percentage growth in TFP than the OECD average, whereas Malaysia, Singapore, Indonesia and Japan scored less expansion in TFP than the OECD average. Similar to the situation in OECD economies, TFP growth in countries in the Asia–Pacific region slowed down post-GFC as well, with Indonesia being an exception (Figure 6.2).

3 Refer to 'AlphaGo Zero: learning from scratch', *Deepmind*, deepmind.com/blog/alphago-zero-learning-scratch/.

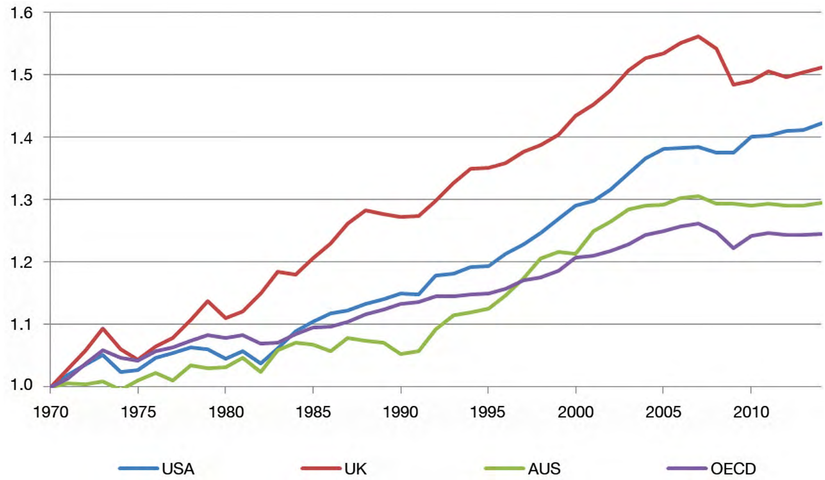

Figure 6.1. Total factor productivity, 1970–2014 (United States, United Kingdom, Australia and the OECD average)

Source. Penn World Tables (Feenstra et al. 2015), international comparisons of production, income and prices, version 9.0. TFP is the portion of output change not explained by the quantities of inputs used in production and is reported at constant national prices (2011=1). Data are normalised to set TFP in 1970 at unity

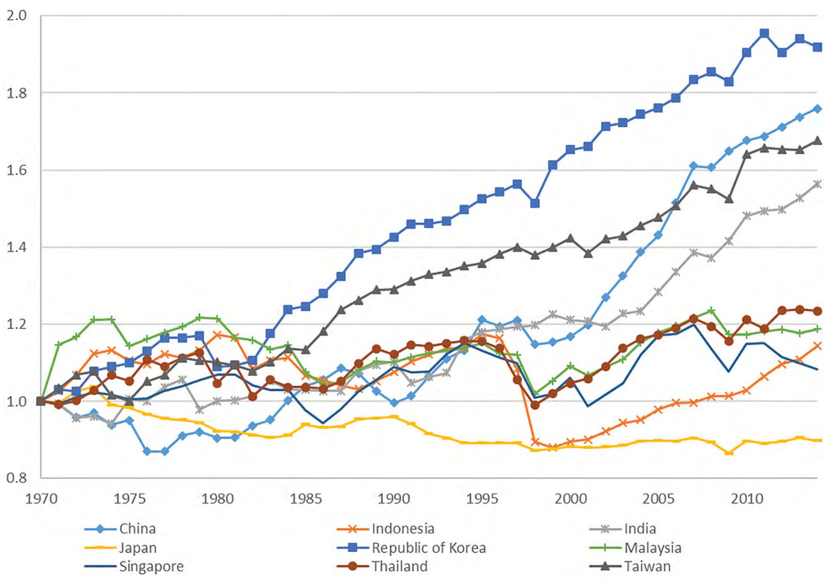

Figure 6.2. Total factor productivity, 1970–2014 (selected economies in the Asia–Pacific region)

Source. Penn World Tables (Feenstra et al. 2015)

What explains the slowdown in TFP growth despite the perceived rapid changes in technologies? Gordon (2014, 2015) argues that the major gains in capital-embodied productivity are in the past and that advances in information and communications technology (ICT) since the 1980s have contributed little thus far. He identifies massive gains accruing from the great discoveries of the nineteenth and twentieth centuries, which include the internal combustion engine, revolutions in materials science, transmitted electricity, sanitation, and health advances such as antibiotics. The more recent ICT advances, he claims, have not revolutionised quality of life and business practices in the way these major innovations did. In response to the claim that the gains from the most recent ICT developments are under-measured (the 'Solow paradox'[4]), Gordon asserts that this is typical of all periods of innovation and is also characteristic of the major gains delivered by older technologies. These views are shared by Clark (2016), Crafts (2016) and Friedman (2016).

In contrast with Gordon and others, the techno-optimists see immense potential for productivity and lifestyle improvements from further expansion of modern ICT, AI and advanced robotics. Mokyr (2013) and Mokyr et al. (2015) argue that, technology anxiety notwithstanding, we are on the cusp of a new era of progress in innovation that will provide an unprecedented boost to productivity. Mokyr et al. (2015) point out what is known as Amara's law, 'We tend to overestimate the effect of a technology in the short run and underestimate the effect in the long run'. Therefore, while TFP growth is often adopted to measure technological progress (Hulten 2001), relatively weak growth in TFP may not necessarily indicate the lack of technological progress, and may arise from implementation lags of new technologies. AI's most impressive capabilities, particularly those based on machine learning, may not have diffused widely. More importantly, like other general-purpose technologies, their full effects won't be realised until waves of complementary innovations are developed and implemented (Brynjolfsson et al. 2017).

Given the unsettled debate on whether weak growth in TFP implies slow technological progress, below I review key aspects of the development in automation and AI specifically in the context of Industry 4.0 that directly impact on firms' production and business models. By doing so, I aim to shed light on recent changes in technology and explore their potential impact on production and jobs in the future.

4 'You can see the computer age everywhere but in the productivity statistics' (Solow 1987).

A new wave of technological progress: Artificial intelligence, advanced robotics, big data analytics, and the rise of Industry 4.0

The new digital economy, such as deep learning and greater collection of data, disrupts all sectors. Data joins traditional production factors such as labour and capital as a new factor of production in various sectors. For example, data generated by sensors or agricultural drones at farms, out on the field or during transportation offer a wealth of information about soil, seeds, livestock, crops, costs, farm equipment, the use of water and fertiliser. Internet of Things (IoT) technologies and advanced analytics help farmers analyse real-time data like weather, temperature, moisture, prices or GPS signals and provide insights into how to optimise and increase yield, improve farm planning, make smarter decisions about the level of resources needed and when and where to distribute them in order to prevent waste (Irima 2016).

The manufacturing sector is also experiencing great changes due to the rise of new technologies. The term 'Industry 4.0' refers to a new developmental stage in the organisation and management of the manufacturing industry's value chain. Industry 4.0 utilises big data analytics to improve the efficiency of firms. According to the Australian Government's Department of Industry, Innovation and Science (2019), Industry 4.0 (the 'fourth industrial revolution') refers to the current trend of improved automation, machine-to-machine and human-to-machine communication, AI, continued technological improvements and digitalisation in manufacturing.

This trend is enabled by four key drivers:

1. rising data volumes, computational power and connectivity
2. the emergence of analytics and business-intelligence capabilities
3. new forms of human–machine interaction, such as touch interfaces and augmented-reality systems
4. improvements in transferring digital instructions to the physical world, such as robotics and 3D printing.

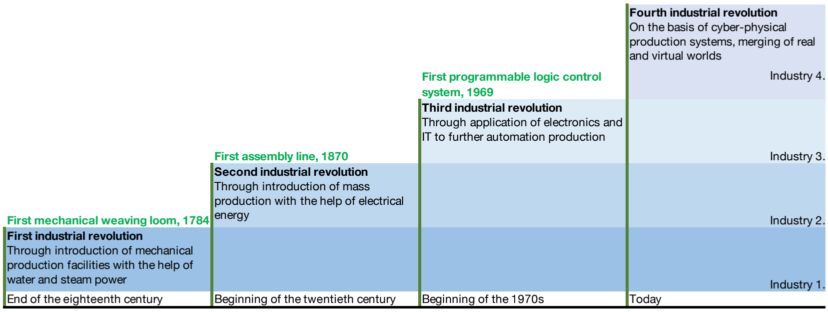

Figure 6.3. Industrial revolutions in history

Source. Deloitte (2014)

The evolution of the four rounds of industrial revolution is presented in Figure 6.3. Traditional manufacturing and production methods are in the throes of a digital transformation, going beyond the automation of production that was driven by developments in electronics and information technology (IT) since the early 1970s. Industry 4.0 features cyber-physical production systems, which are online networks of social machines that are organised in a similar way to social networks. In other words, IT is linked with mechanical and electronic components that communicate with each other via a network. Smart machines continually share real-time data and information about current stock levels, problems or faults, and changes in orders or demand levels, which is collected by sensors attached to robots. Data from one robot is compared to data from other robots in the same or different locations in cloud robotics. Thus, processes and deadlines are coordinated with the aim of boosting efficiency and optimising throughput times, capacity utilisation and quality in development, production, marketing and purchasing (Deloitte 2014). A number of production applications of Industry 4.0 are provided in Baur and Wee (2015), McKinsey Digital (2015), Geissbauer et al. (2016) and UNIDO (2017). The network of cloud robotics allows these connected robots to perform the same activities.

Industry 4.0 and its counterparts are pursued in several major economies including Germany, Japan, the United States, China and Malaysia. In 2015 the Chinese Government introduced its version of Industry 4.0 – 'Made in China 2025', which is an initiative to comprehensively upgrade Chinese industry. The initiative draws inspiration from Germany's Industry 4.0 plan, which was first discussed in 2011 and adopted in 2013. The heart of Industry 4.0 is intelligent manufacturing; i.e. applying the tools of information technology to production.

In the German context, this primarily means using IoT to more efficiently connect small and medium-sized companies in global production and innovation networks so that they not only more efficiently engage in mass production but, just as easily and efficiently, customise products. The Chinese effort is broader, as the efficiency and quality of Chinese producers is uneven, and multiple challenges need to be overcome in a short period of time if Chinese firms are to avoid being squeezed by emerging low-cost producers and more effectively cooperate and compete with advanced industrialised economies. The main objective of the strategy is to ensure that China's manufacturing is innovation-driven and green. It has 10 priority areas of development, including energy saving and new energy vehicles, power equipment, and modern railway equipment (Kennedy 2015; The State Council, The People's Republic of China 2017a, 2017b).

Other economies also regard Industry 4.0 as an opportunity to access the global value chain. Jeff Connolly, chair of Australia's Prime Minister's Industry 4.0 Taskforce, says 'Australia should see the fourth industrial revolution as an opportunity. If we establish a broad-based capability to use global engineering and manufacturing platforms based on advanced materials, the often spruiked access by our SMEs to global supply chains are more a reality now than they have been at any time in the past' (Department of Industry, Innovation and Science 2019).

Clearly, it will be a costly and disruptive process for society when firms transform to Industry 4.0. However, these costs are unlikely to prevent firms and governments from putting effort into developing and applying these new technologies and ways of production, as all participants realise that, unless they keep up with best-practice science and technology, they will fall hopelessly behind in the global competition (Mokyr et al. 2015). It is expected that competition between firms, nations, and major trading blocs will stimulate continued efforts for technological gains. For example, at the time of the introduction of mechanisation, including water and steam power, eighteenth-century British writers conceded that machinery might 'destroy the necessity of labour', but still recommended its introduction, because other nations would otherwise outcompete Britain (Mokyr 2013). An important driver of this development is that robot adoption is a response to faster business cycles in all manufacturing sectors, and the requirement to produce with greater flexibility tailored to customer demand. A new generation of industrial robots will pave the way for ever more flexible automation. 'Robots offer high levels of precision and their connectivity will play a key role in new digital manufacturing

environments,' says Joe Gemma, president of the International Federation of Robotics (IFR): 'Increasing availability enables more and more manufacturers from companies of all sizes to automate' (IFR 2017).

Some robot manufacturers are also considering leasing models, particularly in order to accelerate adoption by small-to-medium-sized manufacturers. Simplification is a key trend for this market segment. The ongoing need for robots that are easier to program and use, and the increasing need for flexible automation, initiated the development of smarter solutions. This is especially useful for industries that do not employ in-house specialised production engineers. Robots that are simple to use will enable the deployment of industrial robots in many industries to sustain efficient and flexible manufacturing. The simplification of robots and the facilitation of deployment is exemplified by the sale of 3D printers to consumers who are essentially transformed into producers.

New technologies pose challenges and opportunities for firms in developing countries. On the one hand, firms in developed economies such as Germany, Japan and the United States host pools of technical talents that allow them to draw on significant technological knowhow. Their technological lead could be further strengthened in this new round of technological breakthrough, establishing them as superior to firms that lag in terms of productivity and product quality. On the other hand, firms in developing countries may be able to leapfrog to new technologies. Technology leaders may switch to new and more efficient technologies at a slower pace because their capital investment locks them in to vintage technology (Arther 1989; Brezis et al. 1993; Perkins 2003).

The Estonian Government's choice between a digital network and an analogue phone system is a case in point. The Finnish Government offered Estonia its analogue phone system for free following the collapse of the Soviet Union and as the Finns upgraded to a digital network. Estonia declined, choosing to bypass analogue telephony and move straight to a digital network of its own design. As it developed its own government, it skipped the typewriter-and-paper stage and began putting its services online from the outset. Every school in Estonia was online by 1998, just four years after the country was experiencing widespread fuel shortages and breadlines. Today, Estonia is one of the most connected countries in the world, having the world's fastest internet speeds and prosperous online services and businesses (Ross 2016).

Hallward-Driemeier and Nayyar (2017) recognise the possibility of technological leapfrog from a limited manufacturing base in developing economies. If countries can leapfrog into using new technologies, there may be no cost for not developing a manufacturing sector at this point. If, however, countries need to have a manufacturing sector using traditional (Industry 2.0) methods to build the capabilities required to support more sophisticated processes, the dynamic cost of not industrialising now could close off future manufacturing opportunities (Hallward-Driemeier & Nayyar 2017).

The market for robots and automation technologies

The market for robots is growing rapidly.[5] According to IFR, since 2010, the demand for industrial robots has accelerated considerably due to the ongoing trend toward automation, continued innovative technical improvements in industrial robots, and rapidly falling price of computing equipment (Figure 6.4).[6] Between 2011 and 2016, the average increase in industrial robot sales was 12 per cent per year and the average annual supply rose to about 212,000 units, which is an increase of about 84 per cent compared to the average annual supply between 2005 and 2008. This is a clear indication of the tremendous rise in worldwide demand for industrial robots. In terms of units, it is estimated that by 2020 the worldwide stock of operational industrial robots will increase from about 1,828,000 units at the end of 2016 to 3,053,000 units. This represents an average annual growth rate of 14 per cent between 2018 and 2020. Australasia is still the world's strongest growth market for industrial robots, followed by Europe and the Americas (Figure 6.5).

The operational stock of robots is estimated to increase by 16 per cent in 2017 in Australasia, by 9 per cent in the Americas and by 7 per cent in Europe. Since 2016, the largest number of industrial robots in operation are in China. In 2020, this will amount to about 950,300 units, considerably more than in Europe (611,700 units). The Japanese robot

5 Information and data on the international robotics market are from the website of the International Federation of Robotics (ifr.org/).

6 There are two general categories of robots: industrial and service robots. An industrial robot is designed to be used in goods manufacturing. A service robot operates semi- or fully autonomously to perform services useful to the wellbeing of humans and equipment, excluding manufacturing operations (Bekey et al. 2006).

stock will slightly increase in the period between 2018 and 2020. About 1.9 million robots will be in operation across Asia in 2020, which is almost equal to the global stock of robots in 2016.

There are five major markets representing 74 per cent of the total sales volume in 2016: China, the Republic of Korea, Japan, the United States, and Germany (Figure 6.5). China has significantly expanded its leading position as the largest market with a share of 30 per cent of the total supply in 2016. With sales of about 87,000 industrial robots, China came close to the total sales volume of Europe and the Americas combined (97,300 units). Chinese robot suppliers continued to expand their home market share to 31 per cent in 2016. Over the longer term, Chinese robot suppliers aim to grow into major suppliers of robots in the world market. Policymakers in China view robotics as a stepping stone to a broader strategic goal of succeeding in emerging markets for AI, driverless vehicles and digitally connected appliances and homes. The development of the robotics industry contributes to China's transition from a technology imitator to a technology innovator (Bloomberg News 2017).

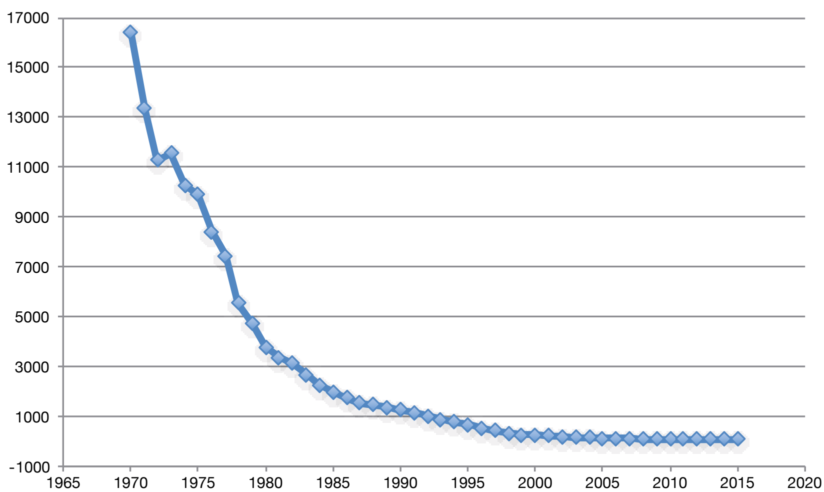

Figure 6.4. Price index of gross fixed capital formation in computing equipment (2010 = 100)

Source. EU KLEMS

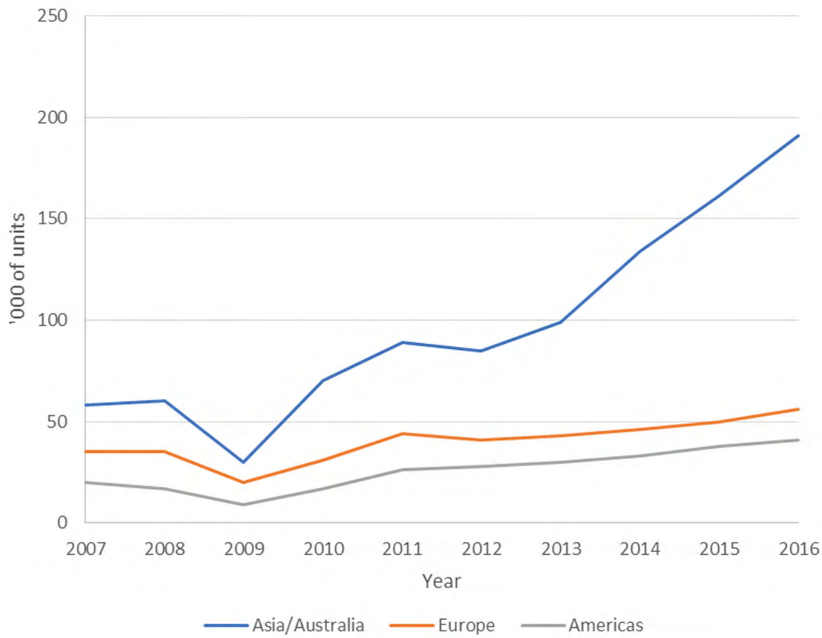

Figure 6.5. Estimated annual shipments of industrial robots by regions

Source. International Federation of Robotics (2017)

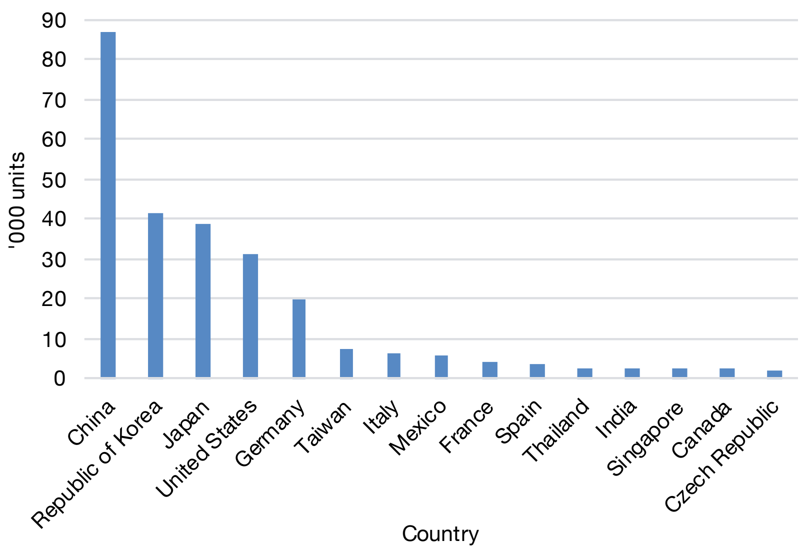

Figure 6.6. Annual supply of industrial robots in the 15 largest markets in 2016

Source. International Federation of Robotics (2017)

The Republic of Korea is the second-biggest market in the world. Due to major investments by the electrical and electronics industry in robots, annual sales have increased considerably. About 41,400 units were sold in 2016, which is a rise of 8 per cent compared to 2015. In Japan, robot sales increased by 10 per cent to about 38,600 units (2016), reaching the highest level since 2006 (37,400 units). Japan is the predominant robot-manufacturing country. Since 2010, the production capacity of Japanese robot suppliers has increased in order to meet the growing demand for industrial robots: production more than doubled from 73,900 units in 2010 to 152,600 units in 2016 (52 per cent of the global supply in 2016). In the United States, robot installations increased by 14 per cent to a peak of 31,400 units in 2016. This continued growth since 2010 is driven by the trend to automate production in order to strengthen the competitiveness of American industries in overseas markets. Germany is the fifth-largest robot market in the world and by far the largest in Europe. In Germany, the annual supply and operational stock of industrial robots in 2016 had a share of 36 per cent and 41 per cent respectively of total robot sales in Europe.

In terms of industry distribution, the automotive industry is the major customer for industrial robots with a share of 35 per cent of the total supply in 2016. The electrical/electronics industry has been catching up, reaching a share of 31 per cent of the total supply in 2016. If a country has a rapidly growing automotive and electrical/electronics industry, it tends to have higher robot density in the manufacturing sector; that is the number of industrial robots per 10,000 persons employed in manufacturing (this measure takes into account differences in the size of the manufacturing industry in various countries). The average global density of robots in the manufacturing industry in 2016 is approximately 74 industrial robots installed per 10,000 employees. The most automated countries in the world measured by this statistic in 2016 were the Republic of Korea (631 units of industrial robots per 10,000 employees), Singapore (488 units of industrial robots per 10,000 employees), Germany (309 units of industrial robots per 10,000 employees), and Japan (303 units of industrial robots per 10,000 employees).

The development of robot density in China was the most dynamic in the world due to the significant growth of robot installations in recent years. Particularly between 2013 and 2016, the rate of robot density accelerated in China, from 25 units to 68 units. Due to the dynamic development of robot installations since 2010, the robot density in China rose from 25 industrial robots per 10,000 employees in the manufacturing industry in 2013 to 68 units in 2016, and that in the United States increased

significantly from 114 installed robots per 10,000 employees in the manufacturing industry in 2009 to 189 robots in 2016. In 2016, the average robot density was: 99 units in Europe, 84 in the Americas and only 63 in Asia. Overall, the potential for robot installations in countries with low robot density is high, and Asia will continue to be a leading growth centre of robotics.

Drivers of automation

What drives the significant growth in robotics investment in the Asia–Pacific region? Striving for lower cost production and higher quality output to stay competitive in international competition is an important motivation. An underlying driver of automation in the Asia–Pacific region could be an ageing population. In general, economies in this region are experiencing a demographic transition toward older populations. Figure 6.7 and Figure 6.8 show the old-age ratio – the ratio of those aged 65 or older to the working-age population (people aged 15–64); and the youth-dependency ratio – the ratio of those aged 0–14 to the working-age population.

The increasing number of elderly has been evident throughout the region and the cohort is projected to grow further in the next two decades. Conversely, the youth cohort has shrunk and will continue to decline in the coming years, except for Hong Kong (Figure 6.7 and Figure 6.8). Due to its rapid economic growth, developing Asia is compressing industrialisation and economic transformation into a much shorter time period than did the advanced economies, and the region is also replicating the demographic transition of the advanced economies within a much shorter time frame. In fact, the unprecedented speed and scale of the ageing of the region's population are largely driven by the region's exceptional economic growth (Park & Shin 2011).

Demographic change can have significant impacts on economic growth. The economic needs and contributions of individuals vary over the course of their economic lives. Firstly, working-age adults tend to work more than the young or elderly. As emphasised by Gordon (2016), demographic change is the first 'headwind' to slow down economic growth in the developed world, for an older population reduces labour-force participation and productivity. A larger labour force, therefore, contributes directly to economic growth. Secondly, working-age adults tend to save more than the young or elderly. A larger labour force indirectly contributes to growth through higher savings rates that boost the investment rate and the accumulation of capital,

especially if newly added capital is embodied with new technologies. Thirdly, building on Hansen (1938), an increasingly popular thesis is that developed economies are afflicted by 'secular stagnation', partly because an ageing population creates an excess of savings relative to investments (Summers 2013; Teulings & Baldwin 2014). Fourthly, to the extent that physical capital can substitute for labour, an economy can accumulate more capital to compensate for the slowdown in the growth of the labour force. For example, older workers may need more capital than younger workers to compensate for their diminished physical strength and, therefore, there is more rapid adoption of automation technologies in countries with a larger ageing population (Acemoglu & Restrepo 2017b). Last but not least, demographic change has a sizable effect on a society's demand for goods and services and may induce structural changes in output and production. For example, in ageing economies, the need for care outstrips the number of available caregivers. Caregiver robots or 'carebots' have been developed to perform care-giving jobs that involve dull, dangerous, heavy and dirty work as well as tasks requiring a high level of knowledge and skill (Gallagher et al. 2016).

Another driver of automation is the rising cost of labour in the Asia–Pacific region. By following the East Asian model, a number of countries in the region achieved stellar performance in economic growth via the agency of moving into the global production chain and accessing the global goods and capital market (Perkins 2013). With the factor-price-equalisation theorem of Stolper and Samuelson (1941), free trade in finished goods leads to equal relative compensation across trading partners for productive input, albeit under a set of highly restrictive assumptions. Subsequent theorising has maintained the focus on the market-integrating impact of trade but without relying on the Stolper–Samuelson framework. For example, a recent contribution by Baldwin and Robert-Nicoud (2014) demonstrates the impact on wage convergence under outsourcing (trade-in-tasks) rather than trade-in-goods. Empirical evidence suggests a convergence across countries in the wage rates of workers of the same skill group within the same industry classification (Zhou & Bloch 2017).

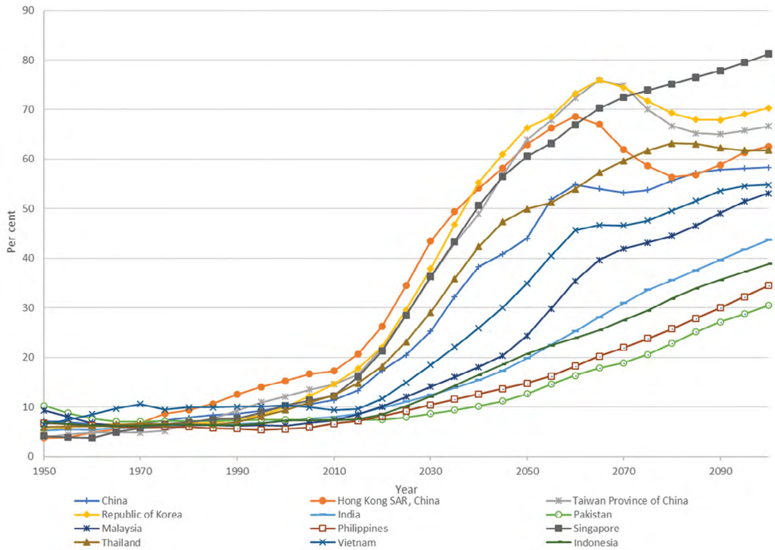

Figure 6.7. Dependency ratios in selected Asian economies, defined as population aged 65 and older as a share of population aged 15 to 64, 1950–2100

Source. United Nations (2017)

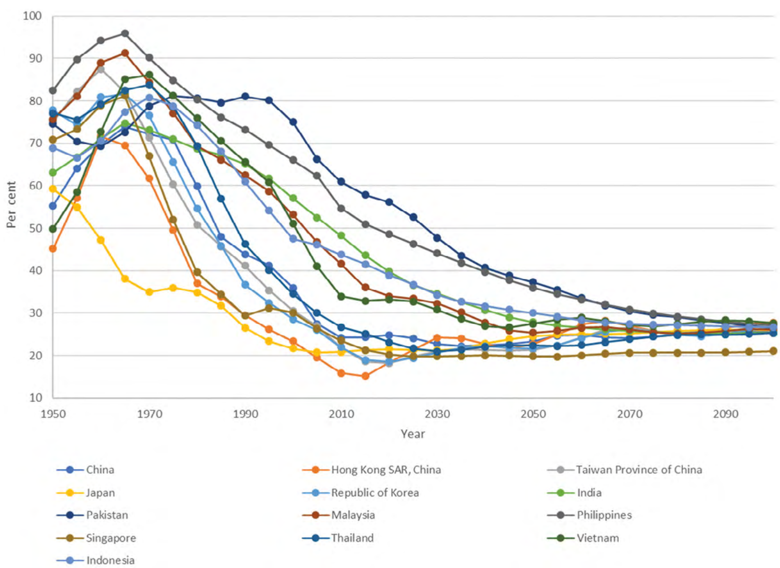

Figure 6.8. Dependency ratios in selected Asian economies, defined as population aged below 14 as a share of population aged 15 to 64, 1950–2100

Source. United Nations (2017)

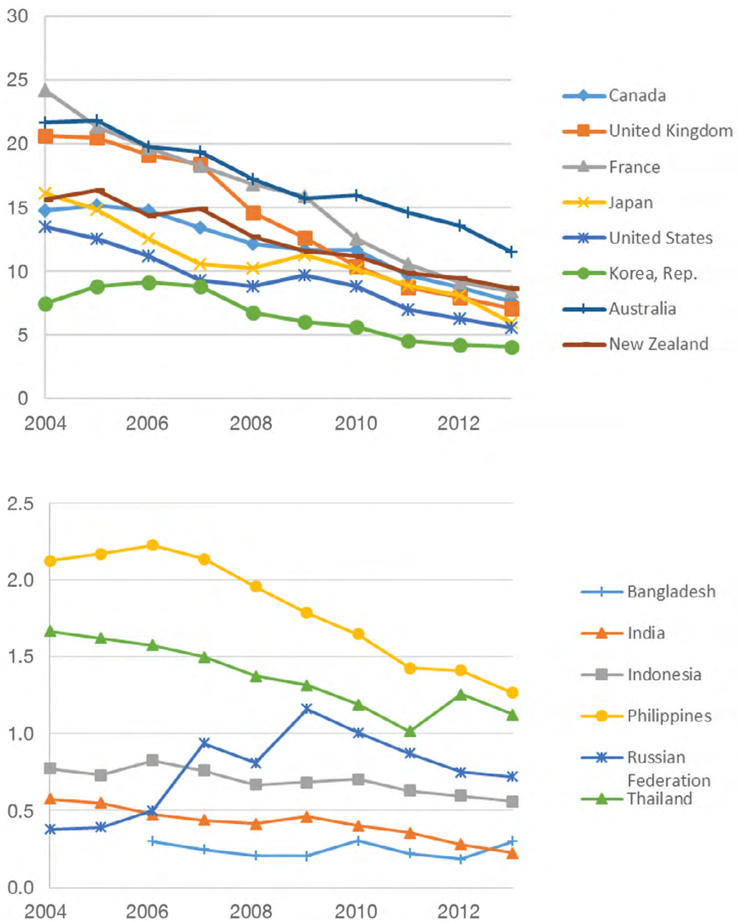

Figure 6.9. Minimum wages in selected countries divided by the minimum wage in China (2004–13)

Note. The calculation uses a harmonised series of statutory nominal gross monthly minimum wages in US dollar terms in various economies.

Source. Author's calculation based on data from the International Labour Organization (ILO) (2017)

Wage rates in developing Asia have converged towards those in advanced countries. Figure 6.9 presents minimum wages in selected countries divided by the minimum wage in China. The minimum wage can be a proxy for the cost of low-skill labour. The results show that the minimum wage in China has caught up rapidly with those in advanced economies but less strongly with minimum wages in other Asian economies. This

cross-country pattern of minimum wages suggests that, overall, minimum wages in the emerging Asian countries as a group are catching up with those in advanced economies.[7]

Unit labour costs (ULC) are often viewed as a broad measure of international price competitiveness. They are defined as the average cost of labour per unit of output produced. They can be expressed as the ratio of labour cost per worker[8] to output per worker (labour productivity) (OECD 2017). To derive a country's international price competitiveness, it is necessary to calculate both labour cost per worker and labour productivity. Figure 6.10 presents ratios of labour productivity (output per worker) of selected countries over that of China. Overall, the extent of China's labour productivity catch-up towards the labour productivity of advanced economies is greater than the extent of the relative rise in China's minimum wage. This suggests that ULC in China have fallen against those in advanced economies and hence its international price competitiveness has risen. The change in China's international competitiveness compared with other developing economies in the sample is more attenuated and, therefore, the emerging Asian countries overall have achieved stronger international price competitiveness compared with advanced economies. The fall of ULC, however, is slowing down as developing Asia's labour productivity has gradually plateaued following the global financial crisis (GFC) of 2007–08, as seen in Figure 6.10. This trend of ULC threatens developing Asia's international price competitiveness in the long run. To maintain competitiveness in international markets, firms are investing in automation to enhance labour productivity and to save labour costs in production. Firms in advanced economies are also ramping up investment in automation and AI to maintain the lead in labour productivity and thus their competitiveness. This mechanism is potentially the key to driving the surge in investment in automation and AI in developing and advanced economies.

7 Because the International Labour Organization database (www.ilo.org/travail/areasofwork/wages-and-income/WCMS_142568/lang--en/index.htm) does not consistently provide wages by skill level for countries of interest, but does provide such data for the minimum wage across time, the minimum wage is adopted as a proxy for the wages of low-skilled workers.

8 In recent years, anecdotal evidence and empirical analysis suggests that the Chinese economy has reached the so-called 'Lewisian turning point' wherein the labour population starts to decline, while the movement of labourers from agricultural communities to the cities comes to an end (Lewis 1954; *The Economist* 2012; Cai & Du 2011; Cai & Wang 2010). And yet, precisely whether China has moved into an integrated national labour market without difference between rural and urban sectors is still debated. Athukorala and Wei (2017), for example, claim that labour shortages and wage increases in booming provinces reflect institutional constraints on labour mobility, rather than the rapid depletion of the economy-wide surplus labour pool. Despite the debate, wage growth is clearly strong.

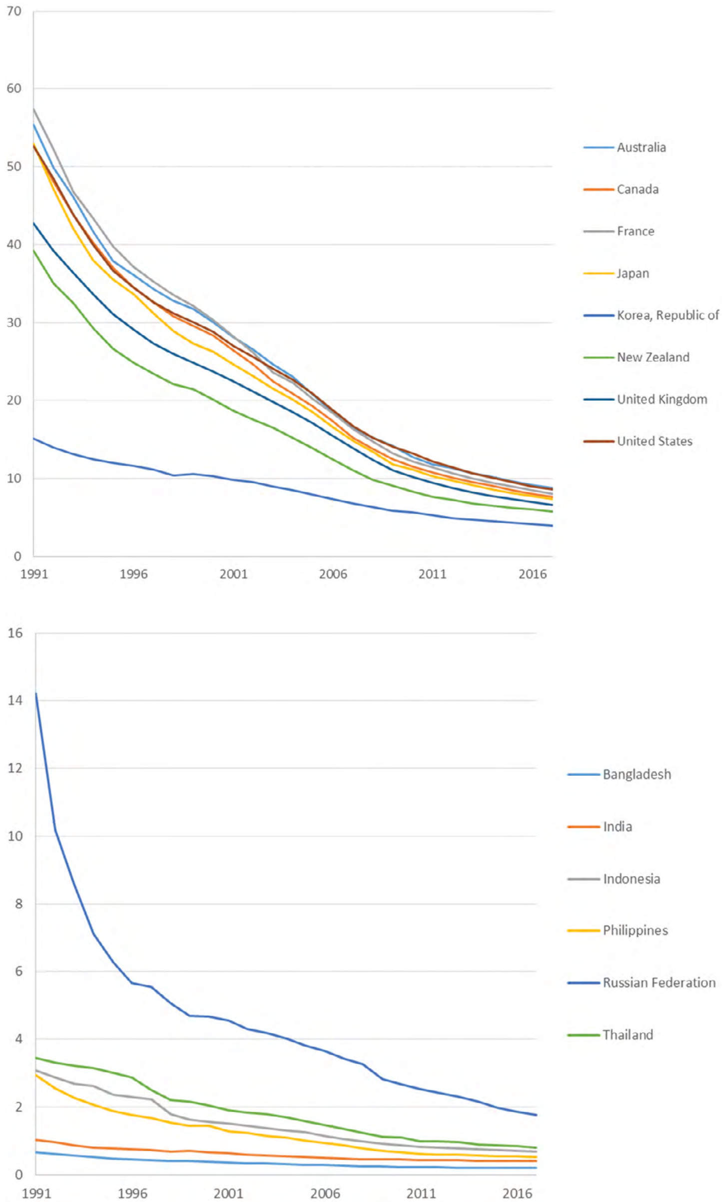

Figure 6.10. Ratios of labour productivity (real output per worker) in selected countries over labour productivity in China

Note: This measure of labour productivity is calculated using data on GDP in constant 2005 US dollars in PPP derived from the World Bank's World Development Indicators database. ILO estimates for total employment are used to compute labour productivity as GDP per worker.

Source. ILO (2017)

Robots and their impact on employment and income inequality

Angst over the rise of robots, job polarisation and income inequality

In the last several decades, substantial changes in wage inequality and job polarisation occurred in most advanced economies, though the United States is a representative case (Acemoglu & Autor 2011). Figure 6.11 shows changes in the US mean real income of males above 25 years old. For males with less than high school or high school and some college education, their mean real incomes fell below the levels in 1991 after the GFC and started to recover only recently. There is a significant divergence in real income earned by males with and without bachelor education and above.[9] In emerging economies such as China, real wages of high-skilled workers have been growing more quickly than those of medium- and low-skilled workers (Figure 6.12). As wage income is a major component in overall income, the distribution of income in these economies has become more unequal, as seen from the rising Gini coefficients. Figure 6.13 shows levels of income inequality, as measured by Gini coefficients, along with the restorative effects of fiscal policies on income distributions. The worsening of labour market conditions for low- and medium-skilled workers is also reflected by their falling share of payment in total value-added in key OECD economies and China (Tyers & Zhou 2017; Zhou & Tyers 2017).

Two main causes of job polarisation in advanced economies are automation and offshoring. Autor et al. (2003) link job polarisation to rapid improvements in the productivity – and declines in the real price – of information and communications technologies. The real cost of performing a standardised set of computational tasks – where cost is measured relative to the labour cost of performing the same calculations – fell by at least 1.7 trillion-fold between 1850 and 2006, with the bulk of this decline occurring in the last three decades (Nordhaus 2007). More recent work also reveals the dramatic fall in real ICT investment prices since 1959 (Byrne & Corrado 2016a, 2016b).

9 For information on wage differentials between skills, please refer to Katz and Autor (1999). This study reports that most industrialised economies experienced a compression of skill differentials and wage inequality during the 1970s, and a modest-to-large rise in differentials in the 1980s, with the greatest increase seen in the United States and United Kingdom.

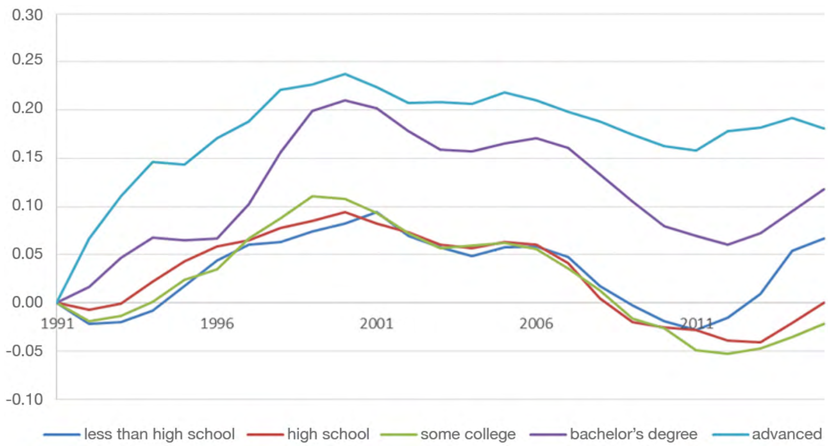

Figure 6.11. Percentage changes in US mean real income from the level in 1991, males above 25 years old (1991–2015)

Source. Reproduced from Figure 4 in Tyers and Zhou (2017)

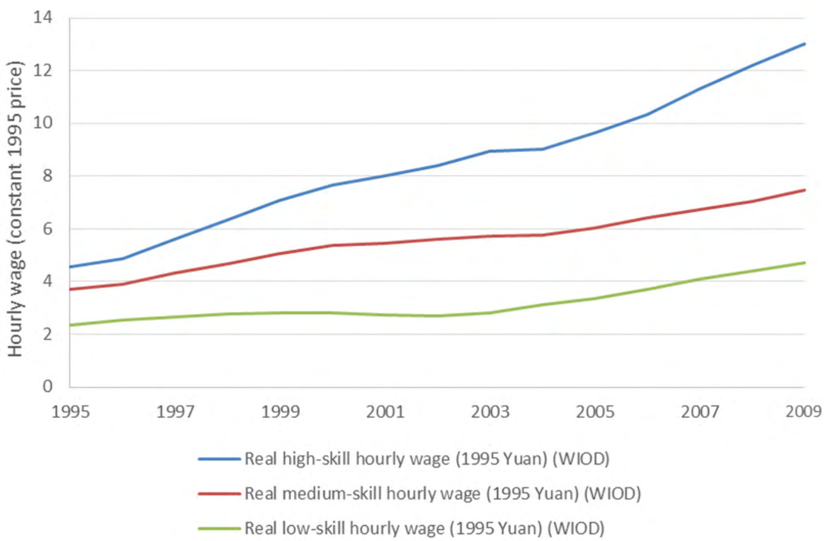

Figure 6.12. Changes in real hourly wages in China by skill level, constant 1995 yuan, 1995–2009

Source. Reproduced from Figure 5 in Zhou and Tyers (2017)

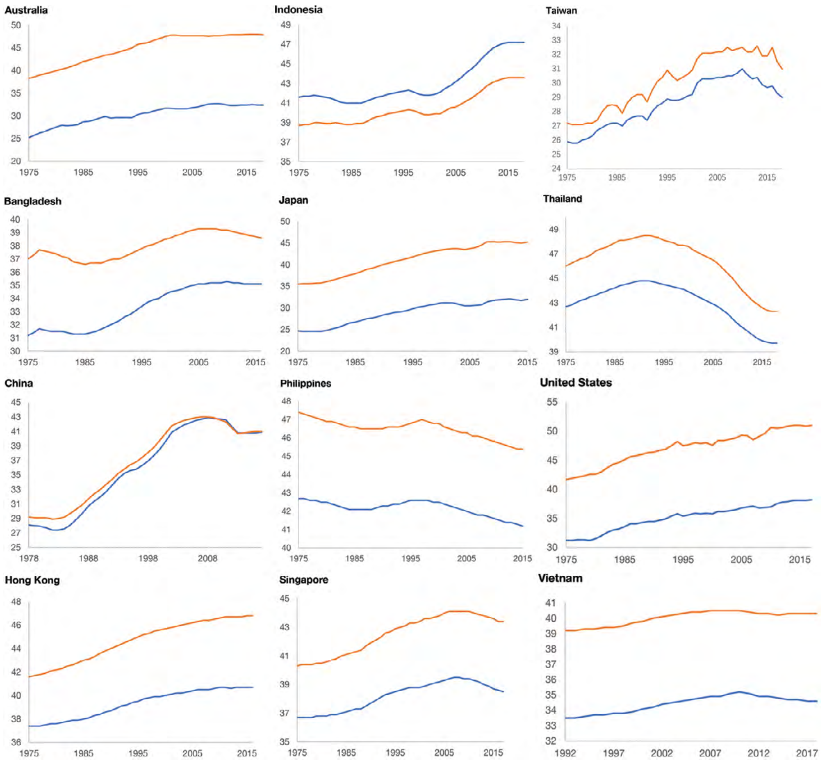

Figure 6.13. Gini coefficient pre-tax and pre-transfer and Gini coefficient post-tax and post-transfer in selected economies in the Asia–Pacific region

Note: The orange line is the Gini index of income inequality in equivalised household (pre-tax and pre-transfer) income. The blue line is the Gini index of inequality in equivalised household disposable (post-tax and post-transfer) income.

Source. The Standardized World Income Inequality Database, Version 8

The rapid, secular price decline in the real cost of symbolic processing creates enormous economic incentives for employers to substitute information technology for expensive labour in performing workplace tasks. Simultaneously, it creates significant advantages for workers whose skills become increasingly productive as the price of computing falls. Computers are increasingly good at replacing human labour in performing routine tasks that are procedural, rule-based, sufficiently well understood and fully specified as a series of instructions to be executed by a machine. Furthermore, these technological advances have dramatically lowered the cost of offshoring. This process of automation and offshoring of routine tasks, in turn, raises relative demand for workers who can

perform complementary non-routine tasks: abstract tasks that require problem-solving, intuition, persuasion; and creative and manual tasks that require situational adaptability, visual and language recognition, and in-person interactions. Since these jobs are found at opposite ends of the occupational skill spectrum – in professional, managerial and technical occupations on the one hand, and in service and labourer occupations on the other – the consequence may be a partial 'hollowing out' or polarisation of employment opportunities (Acemoglu & Autor 2011).

Advanced robotics, artificial intelligence and future work

With the maturing of a new raft of technologies, including Industry 4.0, 3D printing, IoT, AI, automation, augmented reality and virtual reality, the fear of an imminent wave of technological unemployment is again one of the dominant economic themes of our time. Will smart machines replace humans, just as the internal combustion engine replaced horses? The popular narrative often goes as follows: as software and AI advance, production processes become increasingly automated. Workers can be replaced by new and smarter machines – industrial robots, in particular – that are capable of faster and more efficiently performing the tasks formerly carried out by humans. The robots will therefore make millions of workers redundant, especially those with low and medium qualifications, and reshape society in a fundamental way.

There have been dramatic estimates of how many occupations are at risk of being automated, given the type of work they usually conduct (Frey & Osborne 2017). Building on the literature on task content of employment, Frey and Osborne (2017) asked the question: how susceptible are current jobs to these technological developments? To assess this, they implemented a novel methodology to estimate the probability of computerisation for 702 detailed occupations. The data was collected from a survey provided to each worker who answered a set of specific questions relating to activities of their occupation. Frey and Osborne created an algorithm that assigned probabilities of automation to the nine O*NET[10] variables: finger dexterity, manual dexterity, cramped workspace, originality, fine arts,

10 O*NET data is an online service developed for the US Department of Labor. It provides detailed descriptions of the world of work for use by job seekers, workforce development and HR professionals, students and researchers. O*NET data is available at www.onetonline.org/.

social perceptiveness, negotiations, persuasion, assisting and caring for others and, ultimately, the probability of automation of each occupation. According to their estimates, about 47 per cent of total US employment is at risk.

One counterargument to Frey and Osborne (2017) is that, while existing occupations are prone to replacement by robots, there will be new products and industries and hence jobs or tasks created to demand labour. Acemoglu and Restrepo (2015) demonstrate that, although automation tends to reduce employment and the share of labour in national income, the creation of more complex tasks has the opposite effect and, under reasonable conditions, there exists a stable balanced growth path in which the two types of innovations go hand-in-hand. This issue is examined in a task-based framework wherein tasks previously performed by labour are automated, more complex versions of existing tasks can be created and, in performing these new tasks, labour tends to have a comparative advantage. An increase in automation reduces the wage-to-rental-rate ratio, which discourages further automation and encourages greater creation of more labour-intensive tasks, restoring the share of labour in national income and the employment-to-population ratio back towards their initial values.

Until very recently, systematic empirical analyses of the general equilibrium impact of robots and other new technologies on employment were scarce. Acemoglu and Restrepo (2017a) analyse the effect of the increase in industrial robot usage on local US labour markets from 1993 to 2014. Using a model in which robots compete against human labour in the completion of different tasks, it is shown that industrial robots may reduce employment and wages, and that the local labour market effects of industrial robots can be estimated by regressing the change in employment and wages on the exposure to robots in each local labour market – defined from the national penetration of robots into each industry and the local distribution of employment across industries. Using this approach, Acemoglu and Restrepo (2017a) identify large and robust negative effects of industrial robots on employment and wages across commuting zones. The commuting zones most exposed to robots in the post-1990 era do not exhibit any differential trends before 1990. The impact of industrial robots is distinct from the impact of imports from China and Mexico, the decline of routine jobs, offshoring, other types of IT capital, and the total capital stock. According to the estimates, one more industrial robot per thousand workers reduces the employment-

to-population ratio by about 0.18–0.34 percentage points and wages by 0.25–0.5 per cent. The empirical picture that emerges confirms some of the US labour market's darkest concerns about robots.

Whilst the above research shows that industrial robots have caused job and earnings losses in the United States, Dauth et al. (2017) explore the impact of robots on the German labour market. Germany's robot density is higher than the United States, as seen in the discussion above on the market for robots and automation. Despite there being many more robots in operation, Germany is still among the world's major manufacturing powerhouses with an exceptionally large employment share. It ranges from 25 per cent in 2014 (compared to less than 9 per cent in the United States), and has declined less dramatically over the last 25 years. Moreover, Germany is not only a heavy user but also an important producer of industrial robots. The analysis for Germany thus elicits the causal labour market effects of robots in a context with many more manufacturing jobs per capita than could potentially be replaced, but also with many more robots installed in production and robotic producers located close by. Dauth et al. (2017) find that robots have had no *aggregate* effect on German employment. Although robots do not affect total employment, they do have strongly negative impacts on manufacturing employment in Germany. One additional robot replaces two manufacturing jobs on average. This implies that robots performed roughly 275,000 full-time manufacturing jobs in the period 1994–2014. But, those sizable losses are fully offset by additional jobs in the service sector. In other words, robots have strongly changed the composition of employment by driving the decline of manufacturing jobs. Importantly, robot exposure is found to increase the chances of workers staying with their original employer. That is, robot exposure increased job stability for these workers, although some of them went on to perform different tasks to those they were engaged in before robot exposure. This effect seems to be largely down to the efforts of work councils and labour unions, but is also the result of fewer young workers entering manufacturing careers.

The negative equilibrium effect of robots on aggregate manufacturing employment is not, therefore, brought about by direct displacements of incumbent workers and is instead driven by smaller flows of labour market entrants into more robot-exposed industries. In other words, robots do not destroy existing manufacturing jobs, but they do induce firms to create fewer new jobs for young people. Robot exposure causes notable on-the-job gains in earnings for high-skilled workers, especially

in scientific and management positions. Those workers may gain from robots, because they possess complementary skills to this technology and perform tasks that are not easily replaceable. But for low-skilled and especially for medium-skilled manufacturing workers, sizable negative impacts are found. The introduction of robots results in medium-skilled workers, such as machine operators, receiving lower wages and cumulative earnings losses, but even for them no increased displacement risk is found, rather positive employment effects are identified.

These empirical findings reflect a key feature of industrial relations in the German labour market – the manufacturing sector is still highly unionised, and blue-collar wages are typically determined collectively with strong involvement of work councils. It has been frequently argued that German unions prefer maintaining high employment levels, and are willing to accept flexible wage setting arrangements, such as opening clauses, in the presence of negative shocks in order to keep jobs. This flexibility of unions and the resulting wage restraints are seen as one of the leading hypotheses for the strong overall performance of the German labour market (the 'employment miracle') since the mid-2000s.

Another mechanism through which robotics may negatively affect employment and growth is discussed in Benzell et al. (2015). They find that, under the right conditions, more supply produces, over time, less demand as the smart machines undermine their customer base. Highly tailored skill- and generation-specific redistribution policies can keep smart machines from immiserating humanity. But blunt policies, such as mandating open-source technology, can make matters worse.

The above discussion is mainly focused on the impact of automation within an economy. It is also important to examine how trade activities between countries are affected by automation technologies and how these changes influence employment and income inequality across countries. As discussed above, medium- and low-skilled workers in advanced economies experienced decline in employment opportunities over the past several decades. Automation and offshoring are the two causes identified, with the two interrelated. While politicians tend to draw attention to offshoring and the 'hollowing out' of manufacturing activities as the main driver of slack in the low- and medium-skilled labour market, academic research shows that automation exerts greater impact (Acemoglu & Restrepo 2017b; Rotman 2017).

The potential effects of automation on trade activities and employment can be considered in light of the fact that the labour cost differential is a main reason for offshoring (Dachs et al. 2012). A smaller labour cost differential leads, therefore, to more re-shoring. Although the shrinkage of the labour cost differential is favourable for re-shoring, counterforces exist. Firstly, the advantages of production taking place in close proximity to the customer do not favour re-shoring if the customer is not located in the company's home country or region. Offshoring is not only motivated by seeking lower costs, but also as a step towards entering new markets by locating production closer to the customers in foreign countries. So for some firms, closeness to customers works in favour of staying offshore, and was already an essential motive for their previous offshoring decision. According to Sebastien Duchamp, a spokesman for the multinational GE, 'The global environment for manufacturing is changing in a way where we must innovate differently … innovation has to be in the markets you play in, close to your customers; and close to access the best talent wherever it exists in the world' (Khan 2013). GE, like other companies, is responding to the trend of what is called 'mass customisation', or making products to a customer's preferences. As a result, companies are finding it more suitable to have plants closer to their markets and to their research and development units (Khan 2013). Industry 4.0 enhances production for customised products, thereby better serving local customers and preventing offshoring.

Secondly, production in certain industries is difficult to automate as yet. For example, in the sportswear industry, the chief executive of Adidas said 'Asian plants will become more automated, but there were some processes of the roughly 120 steps in creating an Adidas shoe that remain stubbornly resistant to automation … The biggest challenge the shoe industry has is how do you create a robot that puts the lace into the shoe … I'm not kidding. That's a complete manual process today. There is no technology for that' (Hancock 2017). Bottlenecks in automation technologies will slow down re-shoring activities.

Thirdly, being a supplier reduces the likelihood of re-shoring in all specifications of the regression. This can be explained by the fact that many suppliers have offshored production to follow their clients. These customer relations provide an effective 'glue' to keep manufacturing activities at foreign locations, even if external factors like wages or costs of material change (Dachs et al. 2017). If Industry 4.0 strengthens supply linkages between firms, it could act as a force preventing re-shoring.

For systematic reviews of manufacturing re-shoring, refer to Brennan et al. (2015), Stentolft et al. (2016), Dachs et al. (2017) and Delis et al. (2017). How new technologies will affect re-shoring is still under debate.

For advanced economies, the risk to employment is likely to prevail even if re-shoring does occur. This is because new manufacturing plants in advanced economies may translate into more jobs for robots than humans. Lower cost of automation technologies could mean that firms are simply completing the transition that would have taken place earlier without offshoring. Therefore re-shoring may not necessarily boost employment. Chances are that, if there were any positive effect on employment, automated factories would require highly skilled workers, often with training in technology and computers. For developing economies, the concern is firstly that the increased use of robots in developed countries risks eroding the traditional labour-cost advantage of developing countries; secondly, that robot use is working to the advantage of countries with established industrial capacity; and, thirdly, that the share of occupations that could experience significant automation is higher in developing countries than in more advanced ones, where many of these jobs have already disappeared. This could further damage growth prospects in developing countries where manufacturing has stalled or that are already experiencing 'premature deindustrialisation' (UNCTAD 2017). Furthermore, if future international competition hinges on the intensification of the use of robots, the observed effects of automation on employment and wages in advanced economies may also take place in developing economies as these robots are increasingly adopted.

Overall, robots may replace labour in both advanced and developing economies, at least in the short run. Some existing skills will become obsolete and new skills will be in demand. It will be critical to ensure that replaced workers can be retrained to gain skills for new and more complex tasks, and also that all workers develop the mindset of continuous learning to face more rapid technical change and job churning. Clearly public policies, including educational reform and infrastructure investment, will have important roles to play.[11] In the next section, I consider income inequality and the consequences of education and upskilling being insufficient for the smooth transition to new technologies.

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11 Another important headwind of the transition is macro-economic in nature and is not discussed in detail here. The anxiety surrounding robots does not lie in their wider scope, faster speed or greater intrusiveness alone, but in their arrival at a time of subdued global macro-economic dynamism. This has held back the investment needed to create new sectors, where workers displaced by robots could find better jobs (UNCTAD 2017).

Automation and income inequality and the policy response

Alongside the fear that automation will lead to the replacement of labour is concern about the impact of automation on income inequality and the fiscal capacity of nations to redistribute income. Automation may exert upward pressure on income inequality, at least in the short run. Acemoglu and Restrepo (2015) introduce a distinction between low-skilled and high-skilled labour, where the latter has a comparative advantage in producing with newer technologies. This structure implies that both automation, which squeezes out tasks previously performed by low-skilled labour, and the creation of new tasks, which directly benefits high-skilled labour, will increase inequality between the two labour types during the short-run transitions. Nevertheless, the medium-term implications of creation of new tasks could be very different, because these tasks are later standardised and undertaken by low-skilled labour. As a result, there exists a uniquely balanced growth path on which not only the factor distribution of income (between capital and labour) but also inequality between the two skill types is constant.

Technological changes can affect the distribution of income among different factors of production. The introduction of new technology, which usually accelerates growth, may benefit relatively richer segments of the population, and worsen income inequality. If the technological change benefits skilled labour more than unskilled labour, skill premium will go up, which might increase inequality. If the technology is capital-biased, it also could increase income inequality because capital incomes usually accrue to the rich more than to the poor (Yang & Greaney 2017). Based on an elemental three-household general equilibrium model, Zhou and Tyers (2017) quantify the links in China between real income inequality on the one hand and, on the other, changes in factor abundance, total factor productivity, factor bias, the relative cost of capital goods, labour-force participation rates, the fiscal deficit and the unemployment rate. Relative expansion in the stocks of skill and physical capital have, by themselves, mitigated inequality. Yet their effects have been dominated by the combination of structural change and biased technical change, with the latter having the dominant effect. Looking into the future, which is expected to bring a continuation in structural change and a further technical twist away from low-skill labour, this time toward physical capital due to automation, Zhou and Tyers (2017) find that if

the new technology delivers only a shift in technical bias then aggregate performance is impaired by worker displacement that could cause the unemployment rate to rise to anywhere between 20 and 55 per cent so that low-skilled wages are downwardly rigid. If the government protects the welfare of low-skilled households via tax-funded transfers, the transfer burden, either to maintain the welfare of low-skilled households or to constrain income equality, makes capital-owners significant losers. Worker displacement and the capital income tax rate required to contain the rise of income inequality are lessened the more the new technology also delivers increments to total TFP. But the required rates of TFP growth are high relative to what has been achieved by China in recent decades and the potential for continuing this pattern, constrained as it is by the shrinkage of opportunities for 'catch-up' productivity advances, will rely on the productivity effects of AI and robotic advances.

Tyers and Zhou (2017) examine the issue of robotics and income inequality in the US economy using a similar elemental three-household general equilibrium model as in Zhou and Tyers (2017). Applied to the United States, changes in factor bias are shown to have been the primary cause of the observed increase in inequality between 1990 and 2016. The widely anticipated future twist away from low-skilled labour toward capital is examined in combination with expected changes in population and its skill composition. With downward rigidity of low-skilled wages the potential is identified for unemployment to rise to extraordinarily high levels, with possible exacerbation from intensive low-skilled population growth and productivity growth that is no greater than that achieved since 1990. Indeed, the results suggest that productivity growth at twice the pace since 1990 would be needed to constrain unemployment, though even this would not slow the concentration of income. The superior policy response is shown to be a generalisation of the US 'earned income tax credit' system, with financing from taxes on consumption, rather than capital income.

Besides affecting within-county income inequality, the rise of automation may also affect cross-country income inequality. Research has found that after 1985, the growth in absolute global inequality was driven primarily by the accelerated growth of within-country income differences and that, currently, within-country inequality explains 70 per cent of absolute global market inequality (Goda & García 2017). The concern that cross-country income inequality may rise in the future arises from the potential for massive inequality stemming from automation and the 'winner-takes-all'

global economic scenario that pushes low-skilled workers and low-income nations out of competitive positions, thus pushing up inequality levels further. Developed nations may bring back manufacturing and industrial jobs from overseas due to their technological advances in automation, reducing the need for low-skilled labour. Thus, as the World Bank argues, these changes will challenge traditional economic growth models, concluding that the risk of rising inequality in the coming decades is high.

With the rise of automation and AI, how can individuals adapt to these rapid technological changes? On the one hand, automation and AI may demand more workers who have skills in programming and mathematics. On the other hand, the new technologies may reach a stage of maturity that people no longer need advanced maths or programming skills to utilise the technology, that is 'singularity' in which machines surpass humans and produce more machines (Korinek & Stiglitz 2017). At that stage, skills in liberal arts will become more important and the most important skills are likely to be emotional and communication skills. Before singularity is reached, however, problem-solving and analytical skills and mathematics and programming skills are likely to be increasingly in demand in the future.

It is clear that as automation replaces low-skilled labour and increases demand for workers of higher skill levels, access to high-quality education becomes more important. Relatively well-off households will be able to provide their children with an education to give them the skills and capacity to compete in the labour market in the future. If there is strong inequality of opportunity, income inequality could deteriorate over generations (Golley et al. 2019; UN ESCAP 2017). Policies that aim at reducing inequality of opportunity will help alleviate income inequality and its negative impact when societies are increasingly faced with the rise of robotics and AI. Whether policies such as universal basic income or earned income credit could be adopted to help support the welfare of individuals experiencing job loss due to technical change and to help constrain income inequality is the subject of heated debate (Jessen et al. 2017; Stiglitz 2017).

The geography of innovation and future markets: A capability perspective

The development of automation and AI will have significant impact on the geography of innovation and future markets. Comparative advantages of countries are likely to be reshaped, which will affect export performance. Furthermore, the geography of future innovation is uncertain. It is not yet known whether several leading technology companies will dominate automation and AI and, hence, innovation will be clustered around places such as California's Silicon Valley, or these new technologies will be utilised by local markets and be developed into specialised frontier technologies in locations that suit markets and conditions in local economies. This will have significant impact on future income inequality between nations, as a geographically clustered model of innovation is likely to lead to higher income inequality between nations and a geographically distributed model of innovation will stimulate growth in lagging countries and thus reduce income inequality between nations. It is possible that lagging countries will leapfrog existing technologies and move straight into more advanced ones, thus gaining momentum in technological progress and growth. Firms in developing countries in the Asia–Pacific region could potentially develop niche technologies for domestic markets by leveraging and integrating into the existing platforms of Industry 4.0 of leading countries including China, Japan, Germany and the Republic of Korea (ILO 2016). Whether to stave off the loss of competitiveness relative to advanced economies or to leapfrog to new technologies, a country's key capabilities for technology absorption and innovation will be critical for the success of these efforts.

Future global comparative advantage will be reshaped, as inputs used in production will include not only labour, capital and land but also, and more importantly, information. For example, analytics based on big data require information as key input. Therefore, it is important that an economy maintains strong openness to ideas, international trade, international flow of capital and international migration to stay connected and competitive. To stay connected for information flows requires infrastructure such as broadband and mobile networks. Figure 6.14 and Figure 6.15 present the fixed broadband subscriptions per 100 people, and mobile cellular subscriptions per 100 people in selected economies as indicators of the development of ICT infrastructures. While mobile use shows convergence across these countries, the gap in the use of fixed broadband is significant.

Figure 6.16 shows the 2017 Global Connectivity Index and, again, there is significant opportunity for several economies in the Asia–Pacific region to catch up. Figure 6.17 presents the Networked Readiness Index, which assesses the factors, policies and institutions that enable a country to fully leverage ICT for increased competitiveness and well-being (Baller et al. 2016), and shows similar ranking as that in Figure 6.16.

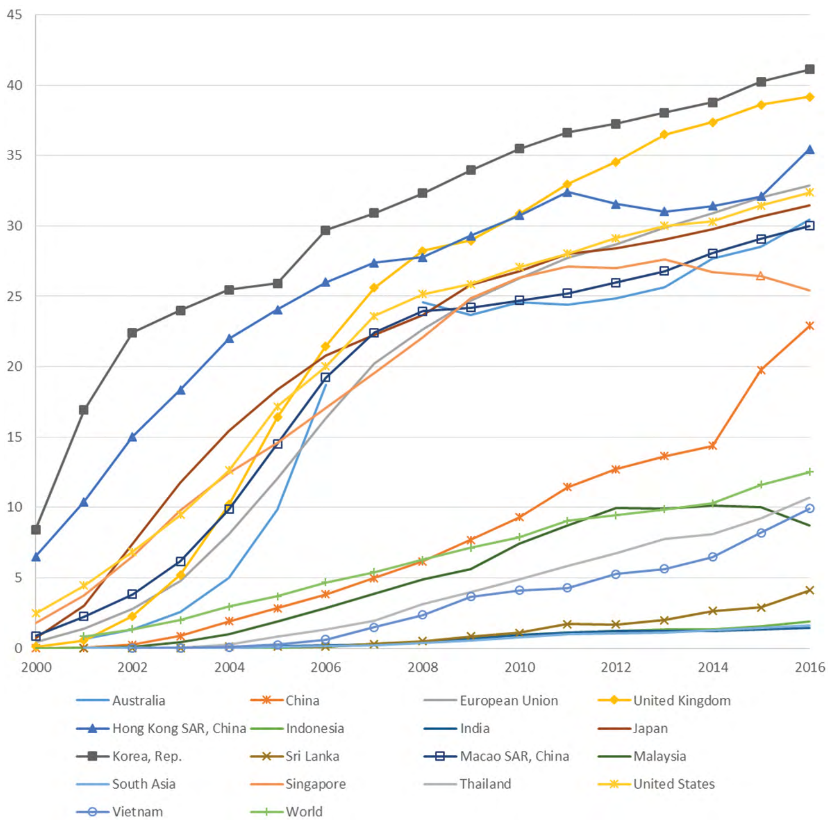

Figure 6.14. Fixed broadband subscriptions (per 100 people)

Source. World Development Indicators

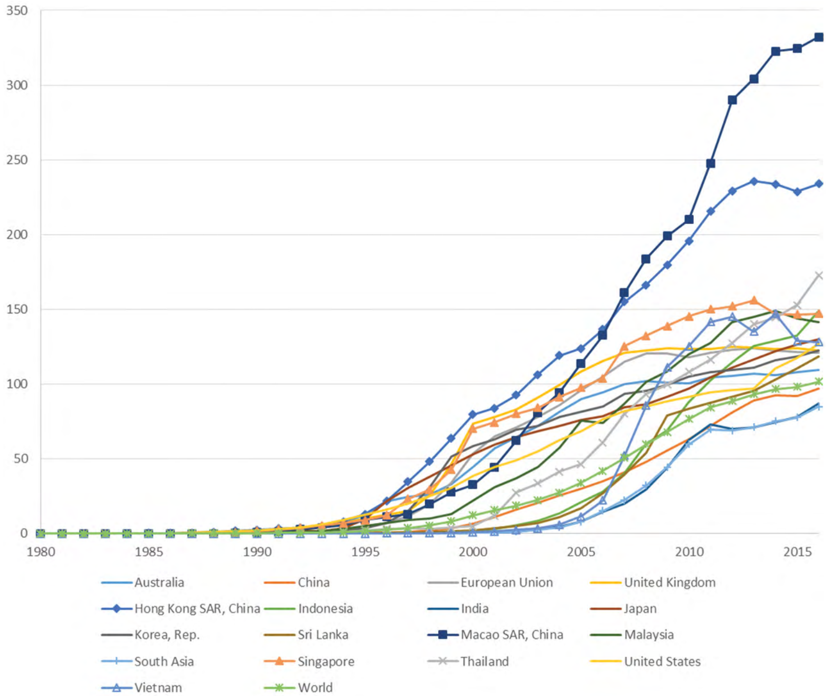

Figure 6.15. Mobile cellular subscriptions (per 100 people)

Source. World Development Indicators

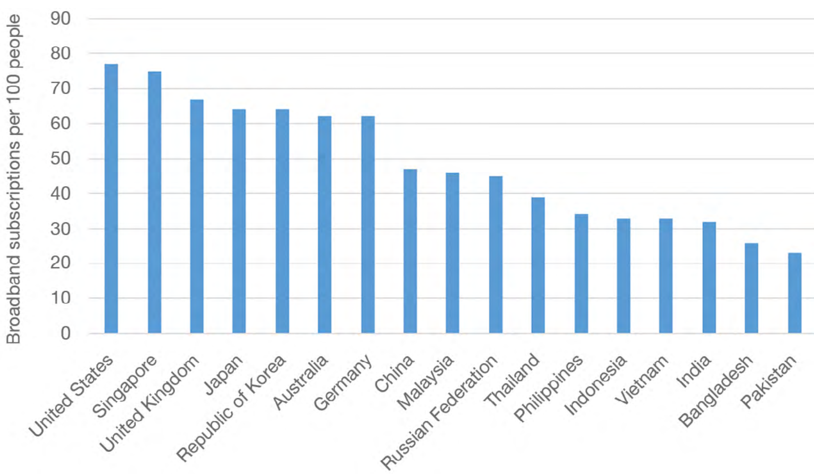

Figure 6.16. 2017 Global Connectivity Index

Source. Global Connectivity Index (2017)

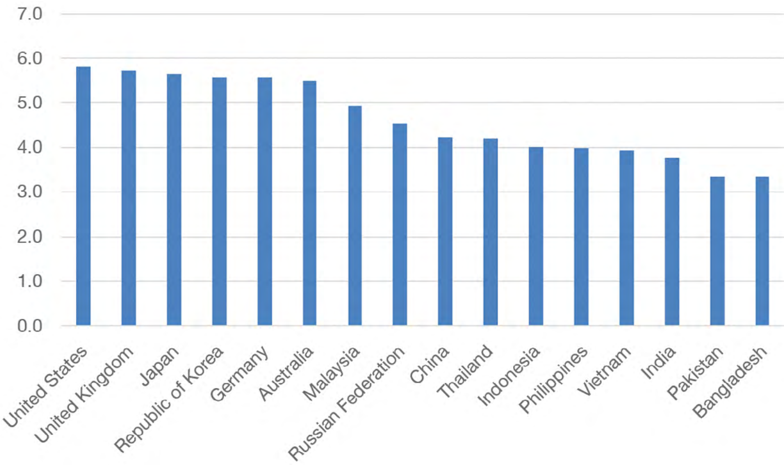

Figure 6.17. Networked Readiness Index

Source. Baller et al. (2016)

Human capital and institutional quality are another two factors that could shape the competitiveness of countries in riding this new wave of technological progress. As human capital and institutional quality complement each other in enabling an economy's technological progress and industrial upgrading, countries with better-educated workforces and better-developed institutions are more likely to lead the round of technological change (Zhou 2016). Table 6.1 shows the share of tertiary-educated people aged 25 and over in selected countries. The variation is wide, ranging from 2.3 per cent in Nepal to 34.8 per cent in the Republic of Korea. As demand for high-skilled workers to invent, improve and implement automation technologies continues in the future, countries with an abundant, well-educated labour force are likely to enjoy higher competitiveness. Firms that aim to be integrated in the Industry 4.0 platform will increasingly demand high-skilled labour, whether in programming and analytics or in liberal arts and creative thinking. A highly educated and well-trained labour force will allow the economy to specialise in niche and advanced technologies, and to better adapt to the servicification of manufacturing under Industry 4.0; that is the development whereby manufacturing firms not only buy and produce more services than before but also sell and export more services as integrated activities (World Bank 2017). Table 6.2 presents measures of ease of doing business and export, logistics performance, and legal protection in selected countries in the Asia–Pacific region. It is evident that, in this region, existing human capital and institutional quality varies significantly, which will potentially affect a nation's technological capability in the era of robotics and AI.

The competitiveness of firms to embrace new technologies and new ways of production also depends on investment in intangible capital and research and development (R&D). Figure 6.18 presents the share of ICT capital of the total capital of selected economies. An economy's total capital consists of structures, transport equipment, machinery, and ICT capital – which includes computers, communication equipment, and software. The share of ICT capital in total capital reflects the importance of information technologies in an economy. Countries in the Asia–Pacific region vary significantly in their share of ICT capital. In 2015, the share is around 25 per cent in the United States; 20 per cent in the Republic of Korea, Taiwan and Germany; 15 per cent in Singapore; 10 per cent in Japan and Australia; 5 per cent in Hong Kong and India; and 1.8 per cent in China. Countries with high ICT share are equipped with strong capability in ICT technologies and are better positioned for competition in automation and AI. There is great potential for countries with low ICT share to catch up in ICT investment in the future. Figure 6.19 shows the share of research and development expenditure in gross domestic product (GDP) in selected countries in the Asia–Pacific region from 1996 to 2015. The Republic of Korea takes the lead in 2015 with R&D intensity of 4.1 per cent, far surpassing East Asia's average of 2.5 per cent. China's R&D intensity is catching up the most rapidly, reaching 2 per cent in 2015 and outpacing Malaysia, Hong Kong, Thailand and Macao SAR.

Establishing a business environment that is friendly to entrepreneurship will stimulate the growth of new firms based on cutting-edge technologies and generate employment opportunities. Unlike traditional routes to industrialisation, when factories employ mass workers and combine workers with machines to produce output under relatively stable technologies, the new model of industrialisation is likely to see more frequent disruptive technological changes and continuous creative destruction aka Schumpeterian growth. Hence, for firms in developing Asia to stay competitive under such a technological paradigm, entrepreneurship plays an important role as the competitive behaviour that drives the market process, alternatively phrased as the introduction of new economic activity that leads to change in the marketplace (Davidsson 2016). Demographics may also have a role to play. Countries with relatively young populations having the opportunity to move into senior management positions will nurture more entrepreneurs and innovation and higher TFP and economic growth (Liang et al. 2014). This mechanism is important when firms adopt and develop a new wave of technologies.

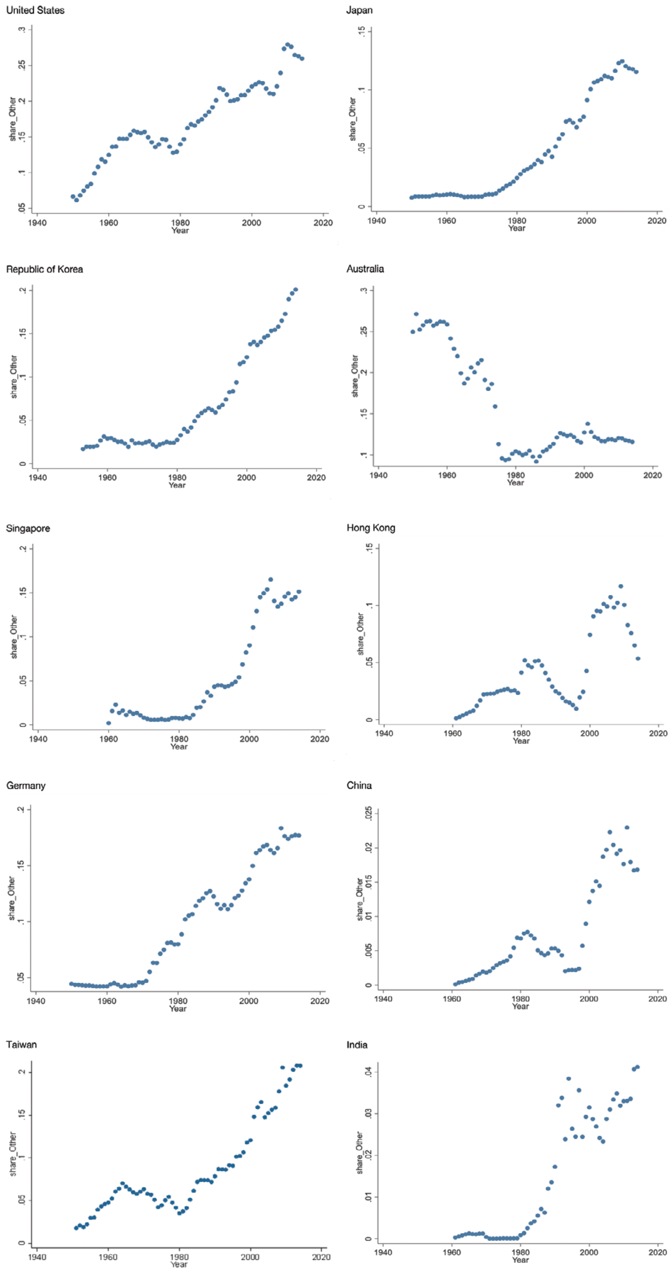

Figure 6.18. Share of real investment in ICT capital in the total capital in selected economies

Note: 'share_other' is the share of real investment in ICT capital in the total capital.

Source. Author's calculation based on capital data in Penn World Table 9.0

Another important determinant of an economy's capability to nurture new technologies is whether government policymakers and regulators are prepared and able to effectively and quickly regulate these new technologies. One policy approach in response to the opportunity and risk associated with emerging new technologies is the regulatory sandbox. A regulatory sandbox creates a 'safe space' in which businesses can test innovative products, services, business models and delivery mechanisms in the context of regulation, with regulators. The sandbox framework enables firms to manage regulatory risks during the testing stage (Zilgalvis 2018). Countries like China, Japan, Singapore, the United Kingdom and Thailand have 'regulatory sandboxes' in which to experiment with regulations for new digital technologies; for example, areas that permit self-driving cars and financial technology.[12] Different countries have different regulatory approaches, which will in turn impact on the uptake and development of new technologies in these countries.

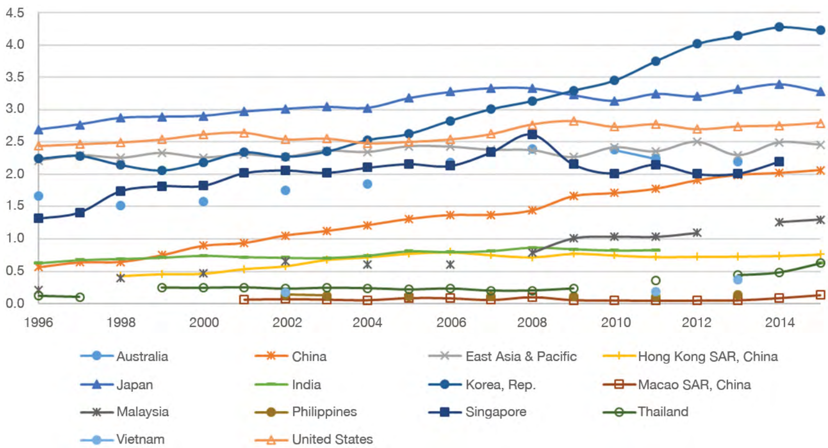

Figure 6.19. Research and development expenditure (% of GDP) in selected countries from 1996 to 2015

Source. World Development Indicators (2017)

12 Overview of regulatory sandbox, Monetary Authority of Singapore, www.mas.gov.sg/Singapore-Financial-Centre/Smart-Financial-Centre/FinTech-Regulatory-Sandbox.aspx; Regulatory sandbox, Financial Conduct Authority, www.fca.org.uk/firms/regulatory-sandbox; *The Westside Story*, From autonomous vehicles to blockchain: regulatory sandboxes are taking off (2018). 5 March, thewestside story.net/autonomous-vehicles-blockchain-regulatory-sandboxes-taking-off/

Table 6.1. People with completed tertiary education as percentage of population aged 25 and over

Country	Completed tertiary education, % of population aged 25 and over
Republic of Korea	34.8
USA	30.9
Singapore	30.6
Australia	25.2
Mongolia	22.5
Japan	19.9
United Kingdom	18.8
Germany	16.1
Hong Kong SAR China	14.8
Macao SAR China	12.3
Thailand	10.0
Sri Lanka	9.5
Taiwan	8.6
Philippines	7.2
India	6.1
Malaysia	5.9
Pakistan	5.5
Myanmar	4.9
Vietnam	4.6
Bangladesh	3.1
China	2.4
Nepal	2.3

Source. Barro and Lee (2013)

Table 6.2. Ease of doing business, infrastructure, legal protection and ease of exporting in selected countries in the Asia–Pacific region

Country	2016 logistics performance index: Overall (1 = low to 5 = high)	2016 strength of legal rights index (0 = weak to 12 = strong)	2014 time to export (days)	2017 ease of doing business index (1 = most business-friendly regulations)
Singapore	4.1	8	6	2
Korea, Rep.	3.7	5	8	4
Hong Kong SAR, China	4.1	8	6	5
United States	4.0	11	6	6

Country	2016 logistics performance index: Overall (1 = low to 5 = high)	2016 strength of legal rights index (0 = weak to 12 = strong)	2014 time to export (days)	2017 ease of doing business index (1 = most business-friendly regulations)
Australia	3.8	11	9	14
Malaysia	3.4	7	11	24
Thailand	3.3	3	14	26
Japan	4.0	5	11	34
Vietnam	3.0	7	21	68
Indonesia	3.0	6	17	72
China	3.7	4	21	78
India	3.4	6	17.1	100
Nepal	2.4	6	40	105
Sri Lanka	N.A.	2	16	111
Philippines	2.9	1	15	113
Bangladesh	2.7	5	28.3	177

Source. World Development Indicators

Conclusion

Despite sluggishness in the growth of total factor productivity in major economies since the GFC, a new round of technological revolution characterised by automation, robotics, AI, big data analytics and Industry 4.0 is rapidly approaching and the full impact of these new technologies is yet to be realised. Industrial robots have been growing quickly in Asia, surpassing the speed of development in Europe and the Americas. This growth in robotics is driven by firms' need to maintain competitiveness in international markets given the ageing population and rising labour costs in the Asia–Pacific region.

The dark side of the rise of robotics is to potentially cause unemployment and aggravate income inequality as future technological progress is skill-biased. Two mechanisms with opposite effects on employment are identified: the labour-replacing effect and the productivity-enhancing effect, with the former reducing employment and the latter creating new jobs and tasks. Income inequality is likely to rise in the short run if the labour-replacing effect dominates before new industries, tasks and jobs are generated.

The rise of automation in major economies including China, the Republic of Korea, Japan, Germany and the United States will have significant impact on the growth trajectory of emerging economies in Asia. If capital deepening continues in China on a large scale, there is less hope that emerging economies can continue to follow the East Asian growth model to prosperity. Instead, firms in these countries could develop technological capability to integrate into the Industry 4.0 platforms of major economies and leverage these new technologies to leapfrog and be successful in niche markets. Staying open and connected, investing in human capital, improving the business environment and stimulating entrepreneurship are strategies that will help firms in the Asia–Pacific region to prosper in the new wave of technological progress.

References

Acemoglu, D & Autor, D (2011). 'Skills, tasks and technologies: Implications for employment and earnings', *Handbook of Labor Economics*, 4, 1043–171. doi.org/10.1016/S0169-7218(11)02410-5.

Acemoglu, D & Restrepo, P (2015). *The race between man and machine: Implications of technology for growth, factor shares and employment*, NBER Working Paper, No. 22252.

—— (2017a). *Robots and jobs: Evidence from US labour markets*, NBER Working Paper, No. 23285.

—— (2017b). *Secular stagnation? The effect of aging on economic growth in the age of automation*, NBER Working Paper, No. 23077, www.nber.org/papers/w23077.

Arther, WB (1989). 'Competing technologies, increasing returns, and lock-in by historical events', *The Economic Journal*, 99, 116–31. doi.org/10.2307/2234208.

Athukorala, P & Wei, Z (2017). 'Economic transition and labour markets in China: An interpretive survey of the "turning point" debate', *Journal of Economic Surveys*. doi.org/10.1111/joes.12206.

Autor, DH, Dorn, D & Hanson, GH (2013). *Untangling trade and technology: Evidence from local labour markets*, NBER Working Paper, No. 18938. doi.org/10.3386/w18938.

—— (2016). 'The China shock: Learning from labor-market adjustment to large changes in trade', *Annual Review of Economics*, 8, 205–40. doi.org/10.1146/annurev-economics-080315-015041.

Autor, DH, Levy, F & Murnane, RJ (2003). 'The skill content of recent technological change: An empirical exploration', *Quarterly Journal of Economics*, 116(4), 1279–333. doi.org/10.1162/003355303322552801.

Baldwin, R & Robert-Nicoud, F (2014). 'Trade-in-goods and trade-in-tasks: An integrating framework', *Journal of International Economics*, 92(1), 51–62. doi.org/10.1016/j.jinteco.2013.10.002.

Baller, S, Dutta, S & Lanvin, B (2016). *Global information technology report 2016: Innovating in the digital economy*. World Economic Forum and INSEAD.

Barro, R & Lee, JW (2013). 'A new data set of educational attainment in the world, 1950–2010', *Journal of Development Economics*, 104, 184–98. doi.org/10.1016/j.jdeveco.2012.10.001.

Baur, C & Wee, D (2015). 'Manufacturing's next act', *McKinsey & Company*, www.mckinsey.com/business-functions/operations/our-insights/manufacturings-next-act.

Bekey, G, Ambrose, R, Kumar, V, Sanderson, V, Wilcox, B & Zheng, Y (2006). *International assessment of research and development in robotics*, WTEC Panel Report, wtec.org/robotics/report/screen-robotics-final-report.pdf.

Benzell, SG, Kotlikoff, LJ, LaGarda, G & Sachs, JD (2015). *Robots are us: Some economics of human replacement*, NBER Working Paper, No. 20941. doi.org/10.3386/w20941.

Bloomberg News (2017). 'Inside China's plans for world robot domination'. 25 April, www.bloomberg.com/news/articles/2017-04-24/resistance-is-futile-china-s-conquest-plan-for-robot-industry.

Brennan, L, Ferdows, K, Godsell, J, Golini, R, Keegan, R, Kinkel, S, Srai, JS & Taylor, M (2015). 'Manufacturing in the world: Where next?', *International Journal of Operations & Production Management*, 36(9), 1253–74. doi.org/10.1108/IJOPM-03-2015-0135.

Brezis, ES, Krugman, P & Tsiddon, D (1993). 'Leapfrogging in international competition: A theory of cycles in national technological leadership', *The American Economic Review*, 83(5), 1211–19.

Brynjolfsson, E, Rock, D & Syverson, C (2017). *Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics*, NBER Working Paper, No. 24001. doi.org/10.3386/w24001.

Byrne, D & Corrado, C (2016a). *ICT prices and ICT services: What do they tell us about productivity and technology?*, Economics Program Working Paper Series, #16-05. The Conference Board.

—— (2016b). *ICT asset prices: Marshaling evidence into new measures*, Economics Program Working Paper Series, #16-06. The Conference Board.

Cai, F & Du, Y (2011). 'Wage increases, wage convergence and the Lewis turning point in China', *China Economic Review*, 22(4), 601–10. doi.org/10.1016/j.chieco.2011.07.004.

Cai, F & Wang, M (2010). 'Growth and structural changes in employment in transition China', *Journal of Comparative Economics*, 38(1), 71–81. doi.org/10.1016/j.jce.2009.10.006.

Clark, G (2016). 'Winter is coming: Robert Gordon and the future of economic growth', *American Economic Review*, 106(5), 68–71. doi.org/10.1257/aer.p20161072.

Crafts, N (2016). 'The rise and fall of American growth: exploring the numbers', *American Economic Review*, 106(5), 57–60. doi.org/10.1257/aer.p20161070.

Dachs, B, Borowiecki, M, Kinkel, S & Schmall, TC (2012). *The offshoring of production activities in European manufacturing*, MPRA Working Paper.

Dachs, B, Kinkel, S & Jager, A (2017). *Bringing it all back home? Backshoring of manufacturing activities and the adoption of Industry 4.0 technologies*, MPRA Working Paper.

Dauth, W, Findeisen, S & Suedekum, J (2017). *German robots – The impact of industrial robots on workers*, CEPR Discussion Paper, No. 12306.

Davidsson, P (2016). 'What is entrepreneurship?' In *Researching entrepreneurship: conceptualisation and design* (pp 1–19). Switzerland: Springer. doi.org/10.1007/978-3-319-26692-3.

Delis, A, Driffield, N & Temouri, Y (2017). 'The global recession and the shift to re-shoring: Myth or reality?', *Journal of Business Research*, 1–12. doi.org/10.1016/j.jbusres.2017.09.054.

Deloitte (2014). *Industry 4.0: Challenges and solutions for the digital transformation and use of exponential technologies*, www2.deloitte.com/content/dam/Deloitte/ch/Documents/manufacturing/ch-en-manufacturing-industry-4-0-24102014.pdf.

Department of Industry, Innovation and Science (2019). 'Industry 4.0', www.industry.gov.au/funding-and-incentives/industry-40.

EU KLEMS Growth and Productivity Accounts: Statistical Module (EU KLEMS), www.euklems.net/.

Feenstra, RC, Inklaar, R & Timmer, MP (2015). 'The next generation of the Penn World Table', *American Economic Review*, 105(10), 3150–82, www.ggdc.net/pwt.

Frey, CB & Osborne, MA (2017). 'The future of employment: How susceptible are jobs to computerisation?', *Technological Forecasting and Social Change*, 114, 254–80. doi.org/10.1016/j.techfore.2016.08.019.

Friedman, B (2016). 'A century of growth and improvement', *American Economic Review*, 106(5), 52–56. doi.org/10.1257/aer.p20161069.

Gallagher, A, Naden, D & Karterud, D (2016). 'Robots in elder care: Some ethical questions', *Nursing Ethics*, 23(4), 369–71. doi.org/10.1177/0969733016647297.

Geissbauer, R, Vedso, J & Schrauf, S (2016). *Industry 4.0: Building the digital enterprise*, PwC, www.pwc.com/gx/en/industries/industries-4.0/landing-page/industry-4.0-building-your-digital-enterprise-april-2016.pdf.

Global Connectivity Index. Huawei, www.huawei.com/minisite/gci/en/.

Goda, T & García, AT (2017). 'The rising tide of absolute global income inequality during 1850–2010: Is it driven by inequality within or between countries?', *Social Indicators Research*, 130, 1051–72. doi.org/10.1007/s11205-015-1222-0.

Golley, J, Zhou, Y & Wang, M (2019). 'Inequality of opportunity in China's labor earnings: the gender dimension'. *China & World Economy*, 27(1), 28–50. doi.org/10.1111/cwe.12266.

Gordon, RJ (2014). 'The turtle's progress: Secular stagnation meets the headwinds'. In C Teulings & R Baldwin (2014). *Secular stagnation: Facts, causes and cures* (pp 131–42) voxeu.org/content/secular-stagnation-facts-causes-and-cures. London: Centre for Economic Policy Research (CEPR), scholar.harvard.edu/files/farhi/files/book_chapter_secular_stagnation_nov_2014_0.pdf.

—— (2015). *The rise and fall of American growth: The US standard of living since the Civil War*. Princeton University Press.

—— (2016). *The rise and fall of American growth*. Princeton University Press.

Hallward-Driemeier, M & Nayyar, G (2017). *Trouble in the making? The future of manufacturing-led development*. Washington, DC: World Bank. doi.org/10.1596/978-1-4648-1174-6.

Hancock, T (2017). 'Adidas boss says large-scale reshoring is "an illusion"', *Financial Times*, 24 April.

Hansen, A (1938). 'Economic progress and the declining population growth', *American Economic Review*, 29(1), 1–15.

Hulten, CR (2001). *Total factor productivity: a short biography*, NBER Working Paper, No. 7471.

International Federation of Robotics (2017). ifr.org/.

International Labour Organization (ILO) (2016). *Regional Reports: ASEAN in transformation*, www.ilo.org/actemp/publications/WCMS_579558/lang--en/index.htm.

Irima, M (2016). 'Five ways agriculture could benefit from artificial intelligence', *AI for the Enterprise*. IBM, www.ibm.com/blogs/watson/2016/12/five-ways-agriculture-benefit-artificial-intelligence/.

Jessen, R, Rostam-Afschar, D & Viktor, S (2017). 'Getting the poor to work: Three welfare-increasing reforms for a busy Germany', *Public Finance Analysis*, 73(1), 1–41. doi.org/10.1628/001522117X14864674910065.

Katz L & Autor, DH (1999). 'Changes in the wage structure and earnings inequality'. In O Ashenfelter & D Card (eds), *Handbook of Labor Economics*, 3A, pp 1463–555.

Katz, L & Murphy, K (1992). 'Changes in relative wages: Supply and demand factors', *Quarterly Journal of Economics*, 107, 35–78. doi.org/10.2307/2118323.

Kennedy, S (2015). 'Made in China 2025', *Center for Strategic and International Studies* (CSIS), www.csis.org/analysis/made-china-2025.

Khan, MS (2013). 'US manufacturing and the troubled promise of reshoring', *Guardian*, 25 July, www.theguardian.com/business/2013/jul/24/us-manufacturing-troubled-promise-reshoring.

Korinek, A & Stiglitz, JE (2017). *Artificial intelligence, worker-replacing technological progress and income distribution*, NBER Working Paper, No. 24174.

Lewis, WA (1954). 'Economic development with unlimited supplies of labour', *The Manchester School*, 22(2), 139–91. doi.org/10.1111/j.1467-9957.1954.tb00021.x.

Liang, J, Wang, H & Lazear, EP (2014). *Demographics and entrepreneurship*, NBER Working Paper, No. 20506. doi.org/10.3386/w20506.

McKinsey Digital (2015). *Industry 4.0: How to navigate digitization of the manufacturing sector*. McKinsey & Company, www.mckinsey.com/business-functions/operations/our-insights/industry-four-point-o-how-to-navigae-the-digitization-of-the-manufacturing-sector.

Mokyr, J (2013). *Is technological progress a thing of the past?*, 8 September. London: Centre for Economic Policy Research (CEPR), voxeu.org/article/technological-progress-thing-past.

Mokyr, J, Vickers, C & Ziebarth, NL (2015). 'The history of technological anxiety and the future of economic growth: Is this time different?', *Journal of Economic Perspectives*, 29(3), 31–50. doi.org/10.1257/jep.29.3.31.

Nordhaus, WD (2007). 'Two centuries of productivity growth in computing', *Journal of Economic History*, 67(1), 128–59. doi.org/10.1017/S0022050707000058.

Observatory of Economic Complexity. (2017). 'Economic complexity index (ECI)', atlas.media.mit.edu/en/rankings/country/eci/?year_range=2011-2016.

Organisation for Economic Co-operation and Development (OECD) (2017). 'Unit labour costs', *Data*, data.oecd.org/lprdty/unit-labour-costs.htm.

Park, D & Shin, K (2011). *Impact of population aging on Asia's future growth*, ADB Economics Working Paper Series, No. 281. doi.org/10.2139/ssrn.1956869.

Perkins, D (2013). *East Asian development: Foundations and strategies*. Cambridge, MA: Harvard University Press. doi.org/10.4159/harvard.9780674726130.

Perkins, R (2003). 'Technological "lock-in". In E Neumayer (ed.), *Internet encyclopaedia of ecological economics*. The International Society for Ecological Economics, isecoeco.org/pdf/techlkin.pdf.

Ross, A (2016). *The industries of the future*. Simon and Schuster.

Rotman, D (2017). 'Artificial intelligence could dramatically improve the economy and aspects of everyday life, but we need to invent ways to make sure everyone benefits', *MIT Technology Review*, www.technologyreview.com/s/603465/the-relentless-pace-of-automation/.

Solow, R (1987). 'We'd better watch out', *New York Times Book Review*, 12 July, p 36.

Stentolft, J, Olharger, J, Heikkila, J & Thomas, L (2016). 'Manufacturing backshoring: A systematic literature review', *Operations Management Research*, 9(3–4), 53–61. doi.org/10.1007/s12063-016-0111-2.

Stiglitz, JE (2017). *The welfare state in the twenty-first century*. Roosevelt Institute, policydialogue.org/files/publications/The_Welfare_State_in_the_Twenty-First_Century.pdf.

Stolper, W & Samuelson, PA (1941). 'Protection and real wages', *Review of Economic Studies*, 9(1), 58–73. doi.org/10.2307/2967638.

Summers, L (2013). 'Why stagnation might prove to be the new normal', *Financial Times*, 16 December, www.ft.com/content/87cb15ea-5d1a-11e3-a558-00144feabdc0.

Teulings, C & Baldwin, R (2014). *Secular stagnation: Facts, causes and cures*. London: Centre for Economic Policy Research (CEPR), scholar.harvard.edu/files/farhi/files/book_chapter_secular_stagnation_nov_2014_0.pdf.

The Economist (2012). 'China's Achilles heel', 21 April, www.economist.com/node/21553056.

The Standardized World Income Inequality Database (SWIID), fsolt.org/swiid/.

The State Council, The People's Republic of China (2017a). english.gov.cn/2016special/madeinchina2025/.

—— (2017b). www.gov.cn/xinwen/2015-05/20/content_2865061.htm.

Tyers, R & Zhou, Y (2017). *Automation and inequality in China*, CAMA Working Paper, 59, papers.ssrn.com/sol3/papers.cfm?abstract_id=3036735.

United Nations (UN) (2017). World population prospects 2017, esa.un.org/unpd/wpp/Download/Standard/Population/.

United Nations Conference on Trade and Development (UNCTAD) (2017). *Trade and development report 2017 – Beyond austerity: Towards a new global deal*, unctad.org/en/PublicationsLibrary/tdr2017_en.pdf.

United Nations Economic and Social Commission for Asia and the Pacific (UN ESCAP) (2017). *Inequality of opportunity in Asia and the Pacific: Education*, www.unescap.org/resources/inequality-opportunity-asia-and-pacific-education.

United Nations Industrial Development Organization (UNIDO) (2017). *Industry 4.0: Opportunities behind the challenge*, Background Paper, www.unido.org/sites/default/files/files/2017-11/UNIDO%20Background%20Paper%20on%20Industry%204.0_27112017.pdf.

Yang, Y & Greaney, TM (2017). 'Economic growth and income inequality in the Asia-Pacific region: A comparative study of China, Japan, South Korea, and the United States', *Journal of Asia Economics*, 48, 6–22.

Zhou, Y (2016). 'Human capital, institutional quality and industrial upgrading: global insights from industrial data', *Economic Change and Restructuring*, 51(1), 1–27. doi.org/10.1007/s10644-016-9194-x.

Zhou, Y & Bloch, H (2017). 'Wage convergence and trade', working paper.

Zhou, Y & Tyers, R (2017). *Automation and inequality with taxes and transfers*, CAMA Working Paper, 70, cama.crawford.anu.edu.au/sites/default/files/publication/cama_crawford_anu_edu_au/2017-11/70_2017_tyers_zhou_0.pdf.

Zilgalvis, P (2018). 'Regulatory sandboxes: An innovation in policymaking', *Startup Nations Summit Surabaya 2018*, www.genglobal.org/startup-nations-estonia-gen-europe/regulatory-sandboxes-innovation-policymaking.

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