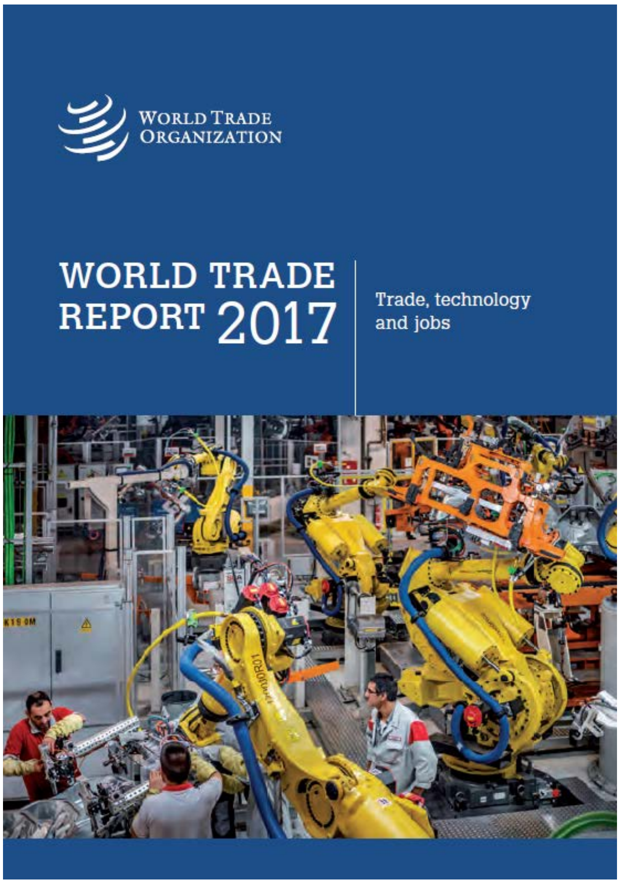
Chapter 3

Impact of technology on labour market outcomes

This section considers the effects of technology on the level and composition of employment and wages. Technological progress, by increasing the productivity of factors of production, expands an economy's production possibility frontier, so that the same amount of output can be produced with fewer resources, or more output can be produced with the same amount of resources.



Contents

Some key facts and findings

- Technological progress can assist workers, through labour-augmenting technology, or replace them, via automation. In both cases, the overall effects on the market's demand for labour are ambiguous.
- Current technological progress has led to a higher relative demand for skilled workers and a lower relative demand for workers performing routine activities.
- The use of computers in the workplace has been the central force driving changes in the wages of skilled workers relative to the wages of unskilled workers.
- Various methodologies have been developed to estimate the share of jobs at risk from automation and computerization. According to these methodologies, the estimated share of jobs at risk tends to be larger in developing countries than in developed countries because of their larger share of employment in routine occupations.
- Automation does not necessarily equate with future unemployment because the development, adoption and widespread use of future technologies will hinge on a number of factors, including feasibility and affordability, as well as the legal and regulatory framework in particular countries and public acceptance of new technology. However, future automation is likely to be disruptive for workers whose skills will become obsolete and who face the risk of job losses and having to switch tasks and jobs.

1. Introduction

Technology can be broadly defined as "the state of knowledge concerning ways of converting resources into outputs" (OECD, 2011a) or as the "machinery and equipment developed from the application of scientific knowledge" (Oxford English Dictionary). There are two types of processes involved in producing a new technology: invention and innovation. Invention involves the formulation of scientific principles or processes. Innovation entails the direct application of this knowledge to a useful purpose in response to presumed profit opportunities. As argued in Section B of this report, innovation can take the form of new products or a new quality of a product (product innovation) or of new production techniques (process innovation). New technologies stemming from innovation have effects on the economy, and on society more generally, that are proportional to how widely they are adopted. General purpose technologies (GPTs) – technologies that transform both household life and the ways in which firms conduct business (Jovanovic and Rousseau, 2005) – have more widespread effects across firms and sectors than technologies destined for particular production processes or purposes.

Technology can complement workers (so-called labour-augmenting technology) or substitute for them (so-called labour-saving technology, or automation). If technology complements workers, this implies that it increases labour productivity. Autopilot technology on planes or statistical software for data analysis are good examples of labour-augmenting technologies. Automation technologies, in turn, complete cognitive or manual tasks without human intervention.[1] Repetitions (such as executing loops in a programme code or corking wine bottles in a winery) are good examples of automation.

Several recent studies show the positive effects of new technology on labour productivity. In the valve-manufacturing industries of the United Kingdom and the United States, the adoption of computer-controlled technology resulted in a substantial increase in productivity by reducing setup time, production time and inspection time (Bartel et al., 2007). Collard-Wexler and De Loecker (2015), who study the US steel industry, show that the (partial) displacement of older technology (vertically integrated producers) with a new production process (the minimill) was responsible for over one-third of the increase in the industry's total factor productivity, or 38 per cent in the period 1963 to 2002. Shifts to energy-efficient technology may increase workers' productivity, such as the move from standard fluorescent lighting to LED lighting in factories, which improves working conditions in hot humid climates in Bangalore (India) due to the lower heat emissions produced by LED lighting (Adhvaryu et al., 2016).[2] In the services sector, a travel agency in China which employs 16,000 workers saw a 13 per cent rise in labour productivity for home-based workers (Bloom et al., 2015). Box C.1 shows how technological change that raises labour productivity can be conceptualized in a production possibility frontier (PPF) framework.

Box C.1: Technological change in a production possibility frontier (PPF) framework

The production possibility frontier (PPF) of an economy describes the amount of output that can be produced for given amount of inputs, measured in efficiency units.

To see how technological change affects an economy's PPF, consider the simplest possible case of a two-sector economy (x and y), with production in both sectors being subject to diminishing returns to a single factor of production: labour. Diminishing returns imply that, in each sector, the marginal productivity of labour diminishes in the amount of labour employed in that sector. With diminishing returns, the PPF is concave (as plotted in Figure C.1). Another characteristic of production functions giving rise to concave PPFs are different factor intensities across the two sectors (even under constant returns) (see Snyder and Nicholson, 2010, pages 416-7).

Production functions for the two goods are $x=\sqrt{\widetilde{L_x}}$ and $y=\sqrt{\widetilde{L_y}}$, where $\widetilde{L_i}, i=x,y$ represent the efficiency units of labour allocated to each sector (physical units of labour multiplied by a sector-specific technology parameter A_i):

$$\widetilde{L_x} = A_x L_x \text{ and } \widetilde{L_y} = A_y L_y$$

Box C.1: Technological change in a production possibility frontier (PPF) framework *(continued)*

The PPF of this economy is represented by the following quarter circle:

$$y^2 = A_y L - \frac{1}{A_x} x^2,$$

where

$$L = L_x + L_y$$

is the total amount of labour in the economy. This is represented by the solid line in panels (a), (b) and (c) of Figure C.1 (the solid line in panels (a)-(c) of Figure C.1 is drawn assuming $A_x = A_y = 1$ and $L = 100$).

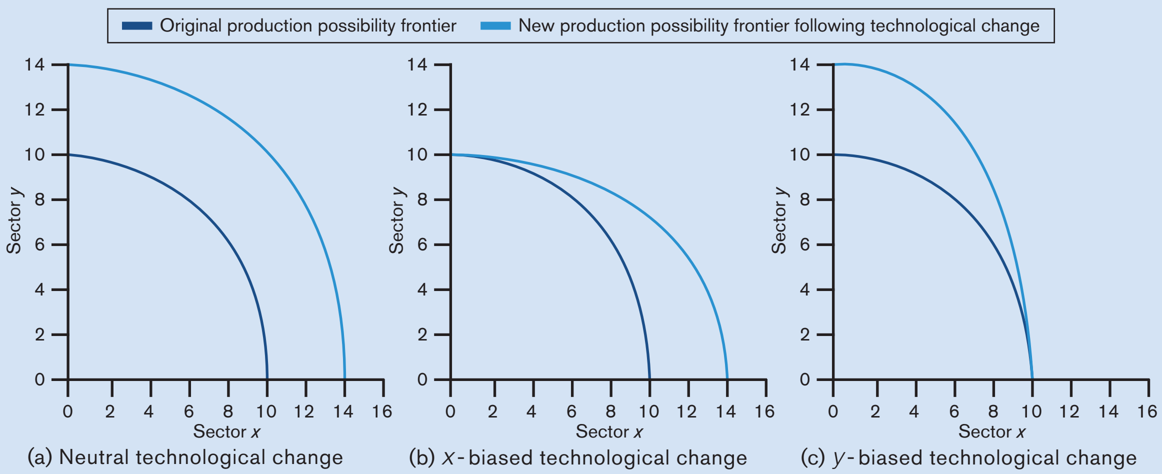
Technological progress – an increase in A – causes an outward shift in the PPF. This is due to the fact that an increase in A increases the marginal productivity of labour in the sector(s) where it occurs, so that the economy can produce more with the same amount of physical units of input (in this case, with the same number of workers). Marginal productivity of labour in sector i, $i = x,y$ is equal to $\frac{1}{2}\left(\frac{A_i}{L_i}\right)^{\frac{1}{2}}$. This increases in A_i and, due to diminishing returns, decreases in L_i.

Panels (a)-(c) of Figure C.1 represent three types of technological progress. In panel (a) such progress is neutral, since it increases labour productivity equally in the two sectors. This is referred to as Hicks-neutral or balanced productivity change. This type of technological progress could, for instance, be due to the introduction of a general-purpose technology (GPT), adopted in all sectors. This is represented by a parallel outward shift in the PPF from the solid to the dashed line – the dashed line is drawn assuming a doubling of productivity in each sector, so that $A_x = A_y = 2$, and keeping $L = 100$. In panel (b), technological progress is biased in favour of sector x: it is assumed that technology improves labour productivity only in x, and not in y. Panel (c) presents the opposite case of technological change biased in favour of sector y.

The dashed line in panel (b) is drawn assuming a doubling of productivity only in sector x, $A_x = 2$, and keeping $A_y = 2$ and $L = 100$. Conversely, the dashed line in panel (c) is drawn assuming a doubling of productivity only in sector y, $A_y = 2$, and keeping $A_x = 2$ and $L = 100$. Clearly, even if technological change occurred in both sectors, it would still be biased in favour of one sector if the increase in labour productivity was larger in that sector than in the other.

In all cases, technological change causes an outward shift in the PPF, allowing the economy to produce (and consume) more for a given amount of inputs. Note that the equilibrium of the economy (not shown in the figures) will be at the point of tangency between the PPF and the highest indifference curve representing consumers' preferences. The new equilibrium could also be reached with international trade. Trade, rather than shifting the PPF, changes relative prices and allows for a separation between production and consumption decisions. In this sense, trade and technology could have the same effects in general equilibrium.

Figure C.1: Technological change in a production possibility frontier framework



Source: WTO Secretariat.

The use of computers, information technology (IT) and the internet has effects that go far beyond labour productivity. Digital trade and international e-commerce reduce transaction costs and boost the transparency of markets (Lippoldt and House, 2017). They allow consumers a more convenient and efficient shopping experience, raising living standards beyond real GDP growth (Hulten and Nakamura, 2017). More generally, the use of information and communications technology (ICT) increases the availability of market information, leading to a better and more stable functioning of markets (consider improved job matches in the labour market due to more readily available information on wages, job vacancies, skill requirements, and labour market conditions).

The effects of labour-augmenting and labour-replacing technologies on labour demand are ambiguous. An example is the introduction of technologies in agriculture. The related increases in agricultural labour productivity can be correlated with a reduction in agricultural employment if, as a result of falling relative prices of agricultural goods, economy-wide prosperity increases and household demand for agricultural produce grows less than demand for other goods. Automation, in turn, is intrinsically labour-saving, as it reduces labour requirements per unit of output produced. However, even labour-saving technology can be associated with rising labour demand due to lower production costs. The first part of this section reviews the mechanisms that give rise to the ambiguous effects of technology on employment, and discusses their empirical relevance.

By making some products or production processes obsolete, and by creating new products or expanding demand for products that are continuously innovated, technological change is necessarily associated with the reallocation of labour across and within sectors and firms. Such technology-induced reallocations affect workers differently, depending on their skills or on the tasks they perform. ICTs tend to be used more intensively and more productively by skilled workers than by unskilled workers. Automation tends to affect routine activities more than non-routine activities, because machines still do not perform as well as humans when it comes to dexterity or communication skills. In Section C.3, evidence is presented in favour of the hypothesis that the labour market effects of technology are relatively more favourable to skilled workers and to workers performing tasks that are harder to automate.

Advances in smart technology, artificial intelligence, robotics and algorithms, often referred to as the fourth industrial revolution, are taking place at unprecedented pace. Graetz and Michaels (2015) report that from 1993 to 2007, mean robot density increased by more than 150 per cent in 17 industrial countries. Boston Consulting Group (2017) reports that the number of industrial robots in operation could increase from the current figure of between 1.5 and 1.75 million to between 4 and 6 million by 2025. These significant increases in automation, and the potentially even wider use of robots in non-industrial sectors, have sparked a debate on the future of work, in particular on whether the demand for human labour might decrease permanently, leading to a "jobless future" characterized by artificial intelligence and robotics at a massive scale. Section C.4 reviews the evidence on the pace of technology adoption and the arguments of technology optimists and pessimists regarding the future of work. The section also discusses the implications for skills development.

2. Overall net employment and wage effects of technology

Throughout history, technological change has often been a source of anxiety for many workers. In England between 1811 and 1816, a group of workers who called themselves "Luddites" destroyed machinery which they believed was threatening their jobs, especially in cotton and woollen mills. Nineteenth-century economists like Karl Marx and David Ricardo predicted that the mechanization of the economy would worsen conditions for workers, ultimately condemning them to live on a subsistence wage. In the last century, too, prominent economists like John M. Keynes (in the 1930s) and Wassily Leontief (in the 1950s) expressed the fear that more and more workers would be replaced by machines, and that this would lead to technological unemployment.[3] More recently, Brynjolfsson and McAfee (2014) have claimed that such disruptive technologies reduce the demand for labour and put workers at a permanent disadvantage.

This section discusses the mechanisms behind the relationship between technological change and overall employment, and the empirical evidence related to those mechanisms.

(a) Theoretical mechanisms

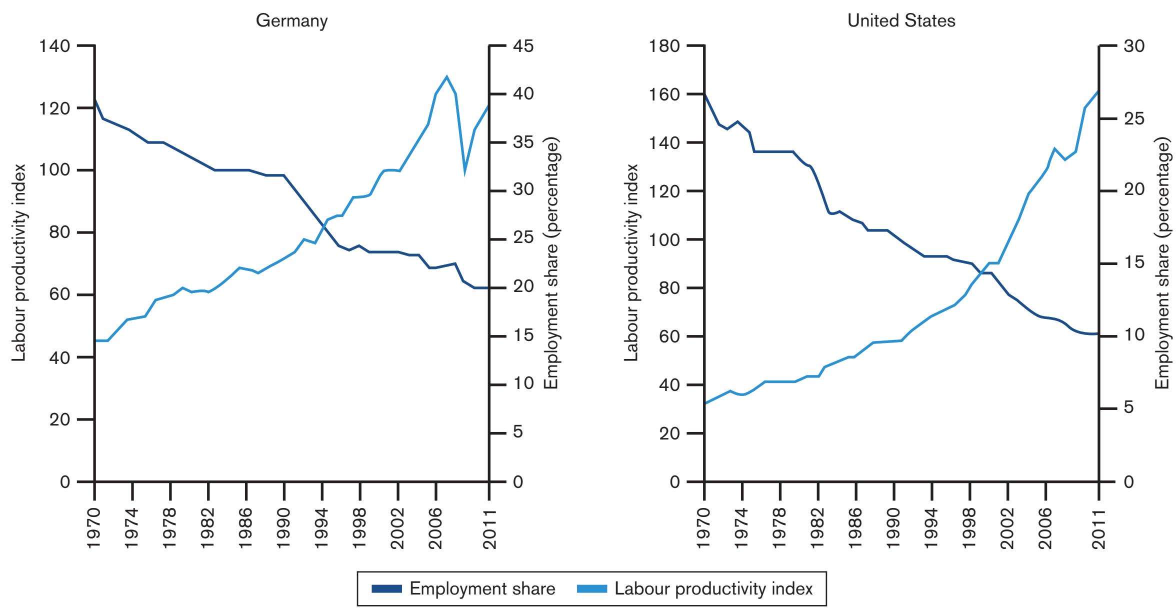
As famously shown by Baumol (1967), technologically advancing sectors – that is, those experiencing more rapid productivity growth – tend to contract as a share of employment, while technologically lagging sectors – that is, those with slow productivity growth – tend to expand. This is because technological progress reduces labour requirements per unit of output produced. Figure C.2 plots indexes of manufacturing employment (as a share of total employment) and labour productivity (output per employed person in manufacturing) between 1970 and 2011 for two major industrial countries (Germany and the United States). During the six decades covered by the data, manufacturing employment as a share of total employment fell substantially, but manufacturing labour productivity increased.[4]

These trends can be correlated with the evolution of one particular type of automation, namely the use of industrial robots, since the mid-1990s.[5] Between 1993 and 1997, robot density (defined as the number of robots per million hours worked) increased by 160 per cent in Germany and by 236 per cent in the United States.[6] Therefore, increasing automation is broadly correlated with lower labour requirements per unit of output in manufacturing adopting such labour-saving technologies. Graetz and Michaels (2015) estimate that, in their sample of 14 industries in 17 countries from 1993-2007, robot densification increased labour productivity by about 0.37 percentage points. According to the authors, this figure is fairly comparable to the estimated total contribution of steam technology to British annual labour productivity growth, which was around 0.35 percentage points, but was sustained over a period that was about four times longer, from 1850 to 1910 (Crafts, 2004, cited in Graetz and Michaels, 2015).

The deployment of labour-saving technologies is not a recent phenomenon. Without going back as far as the Industrial Revolution of the late eighteenth and early nineteenth centuries, one could mention the spectacular decrease in the share of agricultural employment in developed countries during the last century. Autor (2015), for instance, reports that in 1900, 41 per cent of the US workforce was employed in agriculture; by 2000, that share had fallen to 2 per cent, mostly due to a wide range of technologies including automated machinery, such as field machinery and irrigation systems.[7]

Labour-saving technologies, however, are not only deployable in the primary and secondary sectors. The introduction of earth-moving equipment and powered tools displaced manual labour from the construction sector, for instance (Autor, 2015). Occupations such as telegraph or elevator operators, which figured in the 1950 US Census, have been eliminated altogether, due to technological obsolescence in the case of the former and to automation of the latter (Bessen, 2017).[8] Thanks to advances in ICT, the automation of logistics and processing and of self-service (e.g. in document creation and management, which no longer require clerical support, or in retail self-checkout) and digitization (e.g. of data entry and of publishing/printing) are all services sector activities where labour-saving technologies can be deployed and can substitute for workers (see World Bank, 2016).

Figure C.2: Evolution of employment and output per worker in manufacturing of selected industrial countries (1970 to 2011)



Source: US Department of Labor Bureau of Labor Statistics (BLS) International Labor Comparisons (ILC) data.

Notes: Labour productivity measured as output per employed person (index, 2002 = 100 and percentage).

A simple conceptual framework to understand the effects of the deployment of new technologies on overall labour demand is based on the balance between substitution and compensation mechanisms (Vivarelli, 2015). It is argued in Section B that if technological change takes the form of a new product that is substituted for an older one, technological innovation lowers the demand for the old product while it raises the demand for the new product. This translates into an upward shift in the demand for labour used to produce the old product and a downward shift in the demand for the workers who produce the new products. In other words, the substitution mechanism at work operates via product displacement. While the resulting adjustment (with some jobs being destroyed and others being created) may not be without frictions, in this context it is worth noting that higher labour demand in the growing sector can partially or fully offset lower labour demand in the declining sector, a compensation mechanism that can produce ambiguous effects on overall labour demand.[9]

In the case of labour-replacing automation (analysed in Section B as a reduction in the price of capital), technological change induces firms to adopt more capital-intensive technologies and to substitute labour for capital, lowering labour demand at any given wage rate (substitution effect). There are, however, several compensation mechanisms that can counterbalance the initial labour-saving impact of automation, and of process innovation in general (Vivarelli, 2015). First, while workers are displaced in those industries that introduce the technology incorporated in the new machinery, additional workers are needed in the industries that produce the new machinery.

Second, automation (and process innovation more generally) reduces average costs. Acemoglu and Restrepo (2017) show that this leads: i) to a price-productivity effect (as the cost of production goes down, the industry can expand and increase its labour demand); and ii) to a scale-productivity effect (the reduction in costs due to automation results in an expansion of total output, raising the demand for labour in all industries). Similarly, Vivarelli (2015) argues that lower average costs can either translate into lower prices (if the industry market structure is perfectly competitive), stimulating product demand, or into extra profits (if the industry structure is not perfectly competitive). If these extra profits are re-invested in the firm, this investment can create new jobs.

A third compensating effect potentially leading to higher labour demand relates to local demand spillovers. Gregory et al. (2016), who study labour-saving technology in the form of routine-biased technological change (see Section C.3), argue that technological change creates high-tech jobs which generate additional demand in non-tradable sectors.[10] One could cite as an example the ICT sector, which includes manufacturing sectors, e.g. office machinery, and services sectors, e.g. telecommunications.[11] In terms of employment, the ICT sector is small, with ICT occupations accounting for 1 per cent of employment in developing countries, and 2 to 5 per cent in Organisation for Economic Co-operation and Development (OECD) countries (World Bank, 2016).[12] Moreover, the ICT sector only accounts for a minimal proportion of employment creation, because it is by definition capital-intensive.[13] For each job created by the high-tech industry, however, around five additional, complementary jobs are created in the local economy, mostly in the non-tradable services sector (Moretti, 2010; Moretti and Thulin, 2013; Goos et al., 2015).

Fourth, and most importantly, one should consider that technology adoption by firms is a decision affected by various factors, including changes in relative prices of production factors.[14] In the theoretical framework of Acemoglu and Restrepo (2016), as a factor becomes cheaper, the range of tasks allocated to it expands and also generates incentives for direct technologies that utilize this factor more intensively.[15] This implies that by reducing the effective cost of producing with labour, automation discourages further automation and generates a self-correcting force towards stability in the long run. Thus, it is possible that rapid automation need not disrupt labour, but might simply be a transitioning phase towards new technologies benefiting labour.[16]

The extent to which the compensation mechanisms described above can counterbalance the labour-saving impacts of technological change depends on several underlying assumptions and conditions.[17] In this context, it is sufficient to point out that the question of whether technological change increases or decreases overall employment and wages is, ultimately, an empirical one, which will be analysed in the next subsection.

(b) Empirical evidence

So far, the concerns expressed by prominent nineteenth- and twentieth-century economists like Marx, Ricardo, Keyes and Leontief, that the replacement of workers by machines would lead to technological unemployment, have not materialized. Although some individuals may have lost their jobs permanently, the past two centuries of technological progress have not made human labour obsolete.

The employment-to-population ratio rose during the 20th century, and there is no apparent long-run increase in the unemployment rate (Autor, 2015).

Case study evidence focusing on particular sectors and occupations shows that, even after the introduction of labour-replacing technologies, employment increased when those technological changes led to significant scale effects.

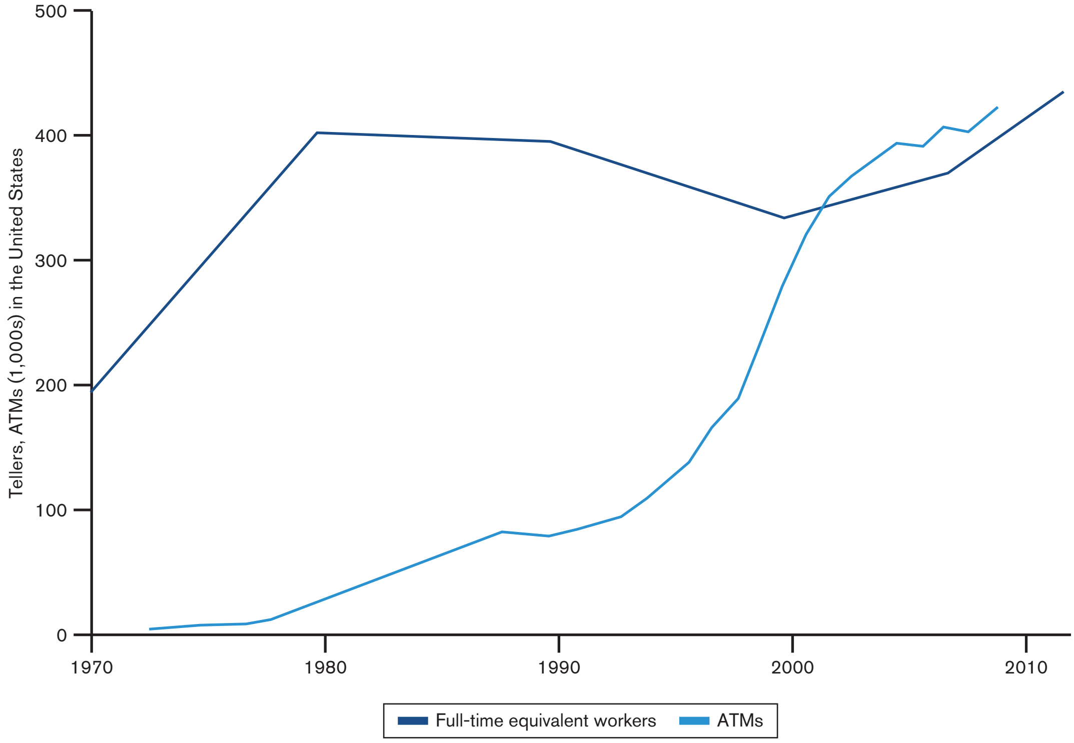
Bessen (2015) reports the telling examples of 19th-century cloth weaving and 20th-century cash-handling. During the 19th century, 98 per cent of the labour required to weave a yard of cloth was automated. However, the number of weaving jobs actually increased. Automation drove the price of cloth down, increasing the (highly elastic) demand for cloth, resulting in net job growth despite the labour-saving technology (Bessen, 2015).

In the United States, ATMs (i.e. automatic teller machines) were introduced in the 1970s, and their number rose fourfold (from 100,000 to 400,000) between 1995 and 2010. ATMs took over cash-handling tasks, yet since 2000 the number of full-time equivalent bank tellers has increased by 2 per cent per year, substantially faster than the overall US labour force (see Figure C.3). Employment did not fall because ATMs allowed banks to operate branch offices at lower costs. This prompted banks to open many more branches, offsetting the loss in teller jobs (Bessen, 2015).

There is abundant econometric evidence on the overall employment effects of technological change. The studies in this field can be classified according to the type of technological change considered (i.e. product innovation, process innovation, routine-biased technological change,[18] computerization or exposure to industrial robots), the income level of an economy (developed or developing) and the unit of analysis (firm, industry or local labour markets). The general conclusion from this literature is that technology has affected the structure of employment, but has had small (and mostly positive) effects on the overall level of employment (Vivarelli, 2014; Arntz et al., 2016b).

A positive link between technology and employment is especially evident when research and development (R&D) and/or product innovation are adopted as proxies of technological change, as well as when the focus turns to high-tech sectors (Bogliacino et al., 2012). There are, however, a few relevant exceptions, with studies showing negative labour-demand effects of technological change.

Figure C.3: ATMs and full-time equivalent bank tellers in the United States (1970 to 2010)



Source: Bessen (2015).

At the country and industry levels, in a sample of 32 industries in 19 developed economies between 1970 and 2007, Autor and Salomons (2017) find that productivity growth has been employment-augmenting rather than employment-reducing. In particular, the fall in industry-level employment as industry productivity rises (in line with Baumol, 1967) is more than offset by the rise in country-level employment as aggregate productivity rises. This indicates that productivity growth in each sector generates employment growth spillovers elsewhere in the economy. These spillovers are sufficiently large to more than offset employment losses in industries making rapid productivity gains.

In a similar vein, Bessen (2017) finds that between 1984 and 2007, computer use had a significant negative effect on manufacturing employment in the United States, but a mild positive employment effect on other industries. Ebenstein et al. (2015), conversely, argue that greater use of computers and capital equipment is associated with lower employment, higher unemployment and lower labour force participation across all US occupations. Graetz and Michaels (2015), using International Federation of Robotics (2012) data, estimate that across 17 countries over the period 1993-2007, while increased utilization of robots (robot densification) in a range of different industries – particularly in transport equipment, chemicals and metal industries – affected the composition of employment and wages across skill groups (see Section C.3), there were no adverse aggregate employment effects (i.e. no reduction in aggregate hours worked) of robot densification. Moreover, they estimate the positive and statistically significant effects of robot densification on mean wages. This implies that some of the productivity gains from robot densification were shared with workers (Graetz and Michaels, 2015).

Some recent studies consider the effects of technological change on local labour markets. In a study using commuting zones in the United States as units of analysis, Autor et al. (2015) find that exposure to routine task specialization had largely neutral overall employment effects between 1980 and 2007, only affecting the occupational composition within sectors. Acemoglu and Restrepo (2017) consider how exposure to industrial robots affected employment and wages in local labour markets between 1990 and 2007, and they estimate large and robust negative effects of robots on employment and wages across commuting zones. They suggest that an additional robot per thousand workers reduces employment to population ratio by about 0.18-0.34 percentage points (one more robot being associated with a reduction in relative commuting zone employment of 5.6 workers in their favourite specification) and wages by 0.25-0.5.[19]

Conversely, in a study focusing on 238 regions across 27 European countries over the 1999-2010 period, Gregory et al. (2016) find that routine-replacing technological change led to overall positive labour demand effects. In terms of the mechanisms they propose and that were discussed above, this suggests that the labour demand and the local demand spillover effects dominated the substitution effect. The authors argue that the net effect of routine-replacing technological change on labour demand was an increase of between 1.9 and 11.6 million jobs across Europe, depending on whether non-wage income (returns from technology investments) fed back into the local economy in terms of consumption or whether it was spent abroad.[20]

At the firm level, several studies contrast the effects of product innovation and of process innovation, finding negative employment effects of process innovation, which tend to be compensated by positive employment effects of product innovation. Using data on firms in the manufacturing and services sectors in France, Germany, Spain and the United Kingdom, Harrison et al. (2014) find that product innovation has a positive impact on employment, but that process innovation has a displacing effect on employment. However, the positive impact of product innovation generating employment is larger than the displacement effect of process innovation, and therefore the net effect of innovation on employment tends to be positive. Similarly, Hall et al. (2008) find a low but positive effect of product innovation on employment in Italy, and no displacement effect from process innovation.

Concerning developing countries, Ugur and Mitra (2017), who conduct a review of 43 qualitative studies and 12 empirical studies, report that the effect of technology adoption on employment is more likely to be positive when the evidence is related to skilled labour employment and product innovation. The qualitative studies included in the review by Ugur and Mitra (2017) further suggest that the employment effects of technology adoption are more likely to be positive in the presence of strong linkages between innovative firms/farms/industries and the rest of the economy, and in the presence of governance institutions that encourage and facilitate technology adaptation instead of relying on off-the-shelf technology only.

Most recent empirical work on the overall employment effects of technological change in developing countries uses firm-level data. The most comprehensive study is that of Cirera and Sabetti (2016), who use a sample of over 15,000 firms in Africa, Central Asia, Eastern Europe, the Middle East and North Africa (MENA), and South Asia. They show that new sales associated with product innovations tend to be produced with just as much or higher levels of labour intensity. This positive employment effect of product innovation is largest in least-developed countries (LDCs) and in the African region, where firms are less advanced in terms of technological development.

Cirera and Sabetti (2016) also show that process innovations that involve the automation of production do not have a short-term negative impact on firm employment.[21] However, there is some evidence of a negative effect of automation on employment that is manifested in increases in efficiency that reduce the elasticity of new sales to employment (Cirera and Sabetti, 2016).

In developing countries, and especially in LDCs, most technological change occurs because of technology transfer. Trade and foreign direct investment (FDI) are important vectors of technological upgrading because developing countries can import technology embodied in capital goods, in particular machinery (Vivarelli, 2014). The qualitative studies surveyed by Ugur and Mitra (2017) suggest that the employment effects are more likely to be small or negative when technology adoption is dependent on imported technology. Vivarelli (2014) also suggests that technology transfers can reduce the domestic demand for labour in developing countries if they involve labour-saving process innovation.

While the existing empirical literature does not offer conclusive evidence on the overall labour demand effects of technology transfer, there is significant evidence that imports of capital-intensity technologies in developing countries are skill-biased (see the next subsection). Since technology transfer mainly occurs via trade, this is a case in which it is virtually impossible to distinguish between the effects of technology and trade in determining labour market outcomes.

To sum up the results of this subsection, the empirical literature has overwhelmingly found small and possibly even positive effects of technological change on aggregate labour demand and employment. There are, however, a few relevant exceptions, with some studies showing the negative labour demand effects of technological change. A common theme in the literature is that in developed and developing countries alike, the most relevant effects are found in the composition, rather than in the level of employment. These effects are analysed in the next subsection.

3. The impact of technology on skills and work tasks

The previous subsection considered the overall employment level effects of technology. Due to various mechanisms, including productivity effects and product demand spillovers, it was argued that labour-saving technologies need not reduce overall employment. This subsection considers the heterogeneous effects of technology on workers, depending on their skills and on the tasks they perform at work.

The basic consideration motivating the analysis is that technology can be biased in favour of certain groups of workers depending on their skills or on the tasks they perform. In particular, technology is skill-biased if it tends to complement skilled workers, increasing their productivity when using technology at work, and therefore increasing the relative demand for their labour services for given wages, with little or no direct effect on unskilled workers. Typical examples of skill-biased technical change (SBTC) are information technologies, which are used more intensively by skilled workers than by unskilled workers.[22]

Workers of all skill levels perform a variety of tasks at work. These tasks can be classified along two main dimensions: i) their degree of routinization; ii) whether they are manual or cognitive in nature. An example of a routine manual task is driving an underground train in a city. An example of a routine non-manual task is computing the average of a set of variables. An example of non-routine manual task is babysitting. An example of a non-routine non-manual task is organizing a wedding.[23] The substitution effects of labour-saving technologies discussed in Section C.2 mainly concern routine tasks. Therefore, technological change is routine-biased, in the sense that it decreases the demand for routine tasks (so called "routine biased technical change", RBTC).

The rest of this subsection presents the theoretical mechanisms behind SBTC and RBTC, and discusses their empirical evidence.

(a) Skill-biased technical change

In a set of developed and developing countries, one the most important labour market developments in the 1980s and the 1990s was an increase in the skill premium.[24] Autor et al. (2008) show that, in the United States, the skill premium, while declining during the 1970s, rapidly increased in the 1980s and (less rapidly) in the 1990s. The increase in skill premium since the 1980s also occurred in many other high-income countries, such as Australia, Canada, Germany and Japan, although at substantially slower rates than in the United States (Pavcnik, 2011). Goldberg and Pavcnik (2007) show that increases in skill premium since the 1980s were not confined to developed countries. They also occurred, at different paces, in Argentina, Brazil, Chile, Colombia, Hong Kong (China), India and Mexico during the 1980s and 1990s. In economies such as the United States, in which the increase in the skill premium in the 1980s and 1990s occurred at the same time as an increase in the relative supply of college-educated workers, concurrent with the increase in the supply of skills, there has been an increase in the (relative) demand for skills (Acemoglu and Autor, 2011).

The rapid diffusion of ICTs in the work place is consistent with an increase in the (relative) demand for skills because of complementarity between ICTs and skills. Violante (2008) discusses three alternative formulations of the ICT-skill complementarity hypothesis.

First, a decline in the constant quality relative price of equipment investment, in particular in ICTs, leads to an increased use of equipment capital in production. Since skilled labour is relatively more complementary to equipment capital than is unskilled labour, growth in the equipment stock increases the relative demand for skilled labour and, in turn, the skill premium.[25]

Second, skilled workers are less adversely affected by the turmoil created by major technological transformations, since it is less costly for them to acquire the additional knowledge needed to adopt a new technology. Therefore, rapid technological transitions are skill-biased, as more able workers adapt better to change.

Third, ICTs induce an organizational shift which is skill-biased, because it leads to flatter hierarchical structures where workers perform a wide range of tasks within teams. Adaptable workers who have general skills and who are more versed at multi-tasking activities benefit from this transformation.

Throughout history, technological change has not always been biased towards skilled workers. Goldin and Katz (1998) provide evidence that manufacturing technologies were skill-complementary in the early twentieth century, but may have been skill-substituting prior to that time. Autor et al. (1998) suggest that there was an acceleration in the skill bias of technological change in the 1980s and 1990s in the United States. Acemoglu (1998; 2002) introduced the idea that the development and use of new technology may be directed or endogenous. An increase in the relative supply of skilled workers will make the development and adoption of technologies that complement skilled workers more profitable. In other words, technology will become more skill-biased following an exogenous increase in the supply of high-skilled workers.

According to this framework, technical change has been skill-biased in the twentieth century mainly due to the development of skill-complementary technologies in response to the rapid increase in the supply of skilled workers. In contrast, the early nineteenth century was mostly characterized by skill-replacing technological development because the increased supply of low-skilled workers in the cities made the introduction of technologies that complement unskilled labour profitable. Hence, the accelerating skill-biased technical change in the 1980s in several developed economies is also likely due to the rapid increase in the supply of skilled workers in the late 1960s and early 1970s.

(i) Empirical evidence

There seems to be a consensus that technological change has been skill-biased over the past few decades.[26] In their analysis of 450 US manufacturing sectors during the 1980s, Berman et al. (1994) find a positive relationship between employment shift toward skilled workers and investment in computers and research and development (R&D). Autor et al. (1998) extend the study to include non-manufacturing sectors. They also find that between 1979 and 1993, skill upgrading was larger in US industries with greater computer utilization, with a consequent steady increase in the skill premium.

Firm- or plant-level studies confirm these findings. In a specific plant-level study of the US valve-manufacturing industry, Bartel et al. (2007) show that between 1997 and 2002, the adoption of new computer-based IT equipment increased demand for more skilled workers, particularly those with technical skills. Bresnahan et al. (2002) also provide firm-level evidence that information technology, together with IT-enabled workplace organizational change, is key to skill-biased technological change in the US manufacturing and services industries.

Empirical studies for other OECD countries also produce results that are consistent with the SBTC hypothesis. For instance, Falk and Seim (1999) investigate the link between skill intensity and IT in the service sector of Germany over the period

1994 to 1996. They show that firms with a higher IT investment-output ratio employ a larger fraction of high-skilled workers. In another study, Falk (2001) also shows that ICT penetration in German firms is positively related to the employment share of skilled workers and negatively related to the share of both medium- and unskilled-workers. A study by Spitz-Oener (2006) further confirms that, in Germany, skill demand has increased greatly in occupations adopting technology more intensively. Skill-biased effects of technological change have been assessed in Canada (Gera et al., 2001), France (Greenan et al., 2001), Italy (Piva et al., 2005), Spain (Aguirregabiria and Alonso-Borrego, 2001) and the United Kingdom (Machin, 1995; Gregory et al., 2001). These studies document a positive relationship between employment of skilled labour and various measures of technological innovation, such as the use of computers, R&D intensity, and the number of innovations and patents.

Cross-country studies also confirm the empirical validity of the SBTC hypothesis in advanced economies. Machin and Van Reenen (1998) show that for seven OECD countries (Denmark, France, Germany, Japan, Sweden, the United Kingdom and the United States), the relative demand for skilled workers in the manufacturing sector was positively linked to R&D expenditure between 1973 and 1989. Berman et al. (1998) provide evidence that, for 12 developed countries in the 1980s, three manufacturing industries – machinery and computers, electrical machinery, and printing and publishing – where skill-biased technological changes are most pervasive, together accounted for 40 per cent of the within-industry increase in the relative demand for skills in manufacturing sector.

It is argued above that ICTs induce organizational changes – such as the flattening of hierarchies, the decentralization of authority, and increased multitasking – which are skill-biased. Caroli and Van Reenen (2001) provide evidence for a panel of British and French plants that organizational change and skills are complementary, as they reduce the demand for unskilled workers and lead to greater productivity increases at plants with larger initial skill intensities.

Evidence of skill-biased technological change exists also for developing countries. Using plant-level data for Chile, Pavcnik (2003) finds evidence of capital-skill complementarity. This might contribute to the increased within-industry relative demand for skilled workers during the 1980s, although there might not be a causal relationship. Fuentes and Gilchrist (2005) extend the analysis over an additional nine years (1979-95) to control for unobserved plant-level heterogeneity and find evidence of a robust association between skilled labour demand and technology adoption as measured by patent usage and other technology indicators.

In the case of developing countries, the adoption of new technologies occurs mainly through import flows and FDI inflows, which generate technological spillovers. In a sample of 28 manufacturing sectors for 23 LDCs and middle-income countries over the period 1980–91, Conte and Vivarelli (2011) discuss the occurrence of skill-enhancing technology imports, namely, the relationship between imports of embodied technology and widening skill-based employment differentials. They show evidence of capital–skill complementarity as a possible source of skill bias, and of imported skill-enhancing technology as an additional driver of increasing demand for the skilled workers.

A number of country-level studies provide similar evidence of relative skill bias emerging through embodied technological change in several developing countries, such as Brazil (Fajnzylber and Fernandes, 2009), Costa Rica (Robbins and Gindling, 1999), Ghana (Görg and Strobl, 2002), Mexico (Hanson and Harrison, 1999; Meza, 1999; Fajnzylber and Fernandes, 2009), Turkey (Srour et al., 2013; Meschi et al., 2016) and the Middle East and North Africa region (Mnif, 2016).

Evidence that is common across both industrialized and developing countries is often considered as suggestive of common technological change across the world. Berman et al. (1998) find that in the 1970s and 1980s, across industrialized countries, most industries increased the proportion of the high-skilled (non-production) wage bill to the low-skilled (production) wage bill, despite rising or stable relative wages for high-skilled workers. Berman and Machin (2000) document that relative wage bills of high-skilled workers jointly increased in the manufacturing industries of 37 high-, middle-, and low-income countries during the 1980s. They find that industry-level skill upgrading in all countries was positively correlated with US computer usage and OECD R&D intensity. In summary, changes in skill intensity were similar and widespread across countries at different income levels, and they were closely related to technology usage in industrialized countries. This is consistent with simultaneous global SBTC.

(ii) Quantification of the effects of skill-biased technical change

Some studies quantify the contribution of technology to observed changes in relative employment or relative wages of skilled versus unskilled workers.

These quantification exercises, however, are subject to the important caveats that the results are highly dependent on the definition of technology and vary significantly across different studies.

For the United States, Japan and nine European countries, from 1980 to 2004, Michaels et al. (2014) argue that ICTs can account for up to a quarter of the cross-country variation in demand growth for highly skilled workers. In their study of relative wage and employment outcomes among US workers in the 1980s, Feenstra and Hanson (1999) show that the share of the wage differential paid to non-production workers during the 1980s attributable to technology is equal to around 30 per cent when using high-tech equipment measured with an *ex ante* rental price. When the authors alter their measure of high-tech equipment to place more weight on more recently installed (and thus arguably more advanced) equipment, the contribution of technology to wage outcomes increases substantially, more than tripling. Using US data for the period 1984 to 2003 in a rich structural model, Burstein et al. (2015) find that computerization is the central force driving changes in the skill premium, accounting for 60 per cent of its rise.[27]

(iii) Can technological maturity lead to "de-skilling"?

It has recently been documented that, in about the year 2000, the demand for skills (more specifically, the demand for cognitive tasks that are often associated with high educational skills) underwent a reversal in the United States (Beaudry et al., 2016; Charles et al., 2016). According to Beaudry et al. (2016), in response to this demand reversal, high-skilled workers moved down the occupational ladder and began to perform jobs traditionally performed by lower-skilled workers. This de-skilling process, in turn, resulted in high-skilled workers pushing low-skilled workers even further down the occupational ladder and, to some degree, out of the labour force altogether.

Charles et al. (2016) link these developments to technology. They argue that during the initial adoption phase of a general-purpose technology such as an ICT, demand for cognitive tasks grows fast because the associated machinery and equipment need to be built and installed. However, once the general-purpose technology has been widely adopted, demand for cognitive tasks partially drops because at the maturity of the technology, those activities are still needed for the maintenance and occasional replacement of the technology, but are no longer necessary for its adoption. In absolute levels, demand for cognitive tasks at the technology's maturity still exceeds demand before the introduction of the general-purpose technology, but it is no longer as high as during the initial adoption phase.

The link between de-skilling and automation is even more general. One of the most salient characteristics of automation is the breaking down of complex operations into simple tasks. That was what Ford did in the first car factories at the beginning of the twentieth century. Instead of employing skilled artisanal workers to build cars, as Daimler Benz did in Germany, Ford hired unskilled workers, which were in abundant supply due to large inflows to the United States of immigrants from overseas, to perform simple tasks. In analysing the impact of technology on the future of work, Section C.4 will discuss artificial intelligence (AI). By first recognising patterns in information before the human eye and analytics can, and then breaking complex cognitive tasks into simple tasks that require little or no skills, AI makes the link between automation and de-skilling clear

(b) Routine-biased technical change

While fully consistent with labour market developments in the 1970s and in the 1980s, models of SBTC are less successful in explaining more recent developments. The evolution of the skill premium has been very heterogeneous across countries since the mid-1990s. As detailed in Section B.2, while in some countries there has been a reduction in the skill premium over the last 15 years, in other countries the opposite occurred. An important recent labour market development in many developed countries, such as Germany and the United States, during the last two or three decades has been the hollowing out of middling occupations (employment polarization), as discussed in Section B.2. Several developing countries have also experienced such polarization in the last two decades (World Bank, 2016; de Vries, 2017).

Drawing on the seminal contribution by Simon (1960), Autor et al. (2003) present a theoretical framework linking employment polarization to technology. In this framework, technology affects specific tasks, rather than specific skills.[28] Autor et al. (2003) classify work tasks along two main dimensions: i) their degree of routinization; ii) whether they are manual or cognitive in nature. Technological progress tends to replace routine tasks and to complement cognitive skills. This is represented in Table C.1. The ease of automation is determined by the routine versus non-routine nature of work tasks. The skill complementarity is determined by the cognitive versus manual nature of work tasks. Technology is predicted to improve relative employment prospects for workers in the

Table C.1: How technology and skills at work interact

		Skill complementarity	
		High	**Low**
Ease of automation	**High**	Routine cognitive	Routine manual
	Low	Non-routine cognitive	Non-routine manual

Source: World Bank (2016).

Table C.2: Expected effects of technology on employment and earnings by types of occupation

Type of occupation (by skill intensity)	Expected impact on employment	Expected impact on earnings
Non-routine cognitive	Positive	Positive
Routine cognitive and manual	Negative	Negative
Non-routine manual	Positive	Negative

Source: World Bank (2016).

bottom left quadrant, because they perform non-routine tasks (which are not easily automated)[29] and involving cognitive skills, where ICT technologies make them more productive. Workers in the upper quadrants perform tasks subject to automation, and their relative employment prospects are reduced by labour-saving automation technologies. Finally, workers in the bottom right quadrant are the least affected by technology, because they perform non-routine manual tasks, which are neither easily automated nor subject to ICT-skill complementarity.

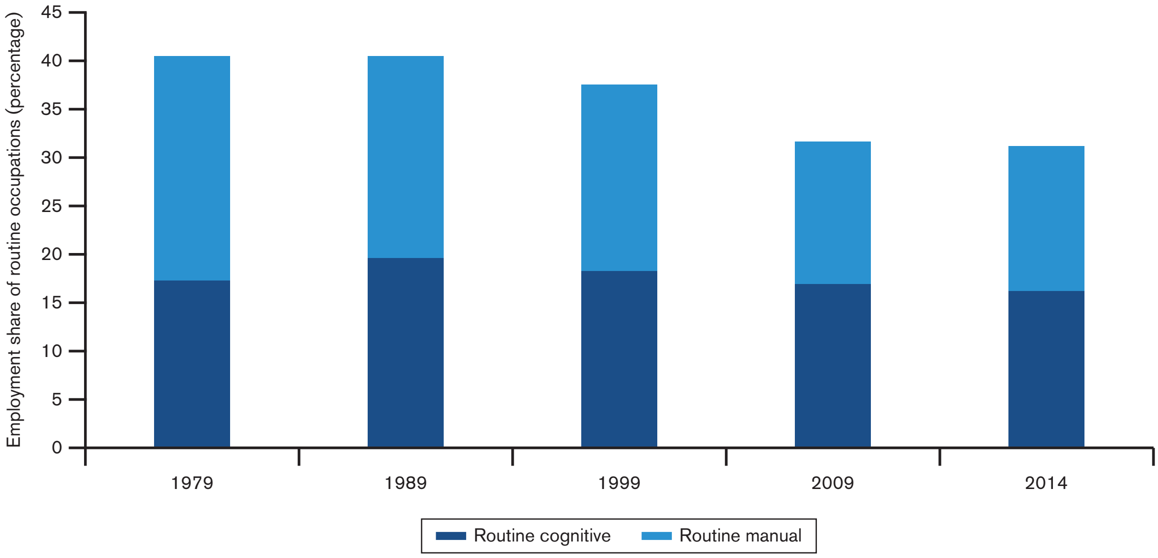
The framework proposed in Table C.1 helps to explain why technology can lead to employment polarization (Autor et al., 2003; 2006; 2008). Non-routine cognitive tasks which – given current technological feasibilities – are difficult to automate and are complementary to ICTs, are typical of skilled professional and managerial jobs, which tend to be assigned to skilled workers. The non-routine manual tasks which are not directly affected by technology are typically unskilled jobs such as housecleaning and tend to be assigned to unskilled workers; routine cognitive or manual tasks, in which technology has the potential to substitute for human labour, are typical of jobs performed by middle-skilled workers.

The discussion so far has focused on relative demand for workers depending on their skills, or on the nature of their work tasks. How changes in relative demand translate into changes in relative earnings crucially depends on labour supply. In particular, the extent to which workers in the lower quadrants of Table C.1 (those performing tasks less susceptible to automation) see their relative earnings increase or decrease depends on the elasticity of labour supply (Autor, 2015).[30] If the elasticity of labour supply is high enough, new entry of labour can partially or fully offset average wage gains that would have occurred. As argued by the World Bank (2016), workers in non-routine cognitive occupations are likely to see their higher productivity rewarded as higher earnings because entry barriers are high (therefore the elasticity of labour supply is low). Conversely, low-skilled workers in non-routine manual occupations are likely to see their earnings fall over time, as middle-skilled workers in routine occupations are displaced by automation and start competing for the available jobs in low-paying occupations, where entry costs are low and the elasticity of the labour supply is high.[31] These insights are summarized in Table C.2.

(i) Empirical evidence

Recent shifts in the nature of work include a strong decline of occupations that are intensive in routine work steps. For the United States, Cortes et al. (2016) document a decrease in routine employment from 40 per cent of the population aged 20-64 in 1979 to 31 per cent of the population aged 20-64 in 2014 (see Figure C.4).[32] At the same time, non-routine manual employment expanded by 3.9 percentage points and non-routine cognitive employment expanded by 6.7 percentage points (Cortes et al., 2016, Table 2).

Figure C.4: Evolution of employment shares of routine occupations in the United States (1979 to 2014)



Source: Cortes et al. (2016).

Notes: Employment shares based on individuals aged 20-64 from the monthly Current Population Survey (US Bureau of Labor Statistics), excluding those employed in agriculture and resource occupations.

With few exceptions, the empirical literature confirms the idea that technological change in developed economies is a major driver in the decline in routine occupations, and in the consequent employment polarization. Conversely, for developing economies, there is limited empirical evidence consistent with the RBTC hypothesis. As already emphasized above when discussing the overall employment effects of technology, comparisons across studies are only meaningful for studies that use the same definition of technological change.

At the level of local labour markets in the United States, Autor and Dorn (2013) show that between 1980 and 2005, local labour markets that specialized in routine tasks differentially adopted information technology, reallocated low-skill labour into service occupations (employment polarization), experienced earnings growth at the tails of the distribution (wage polarization), and received inflows of skilled labour. Similarly, Autor et al. (2015) show that local US labour markets more specialized in routine occupations have experienced employment losses in routine task-intensive occupations. These losses are, however, largely offset by local employment growth in abstract and manual task-intensive occupations.[33]

At the industry level, Goos et al. (2014) estimate that routine-biased technological change is mostly responsible for observed patterns of employment polarization in a sample of 16 Western European countries over the period 1993 to 2010. Focusing on automation in the form of industrial robots, however, Graetz and Michaels (2015) do not find that this type of technology is biased against middle-skilled workers. On the contrary, they find that robot density shifts demand from the low-skilled towards the high-skilled. This result could depend on the definition of skills, or on the different ways in which routine jobs are affected by general purpose technologies, like ICTs, as opposed to industrial automation.

In the case of developing countries, there is limited empirical evidence consistent with RBTC. Job polarization in the labour markets of Colombia and Mexico in the 2000s was shown to occur due to reductions in the cost and increased adoption of computer technology (Medina and Posso, 2010). The same, however, does not apply to several other developing countries (Brazil, China, India and the Russian Federation), nor to LDCs (Medina and Posso, 2010; Gimpelson and Kapeliushnikov, 2016; Maloney and Molina, 2016).

(ii) Quantification of the effects of routine-biased technical change

Quantification of the contribution of technology to the decline in middle-skilled employment can be found in Goos et al. (2014) for 16 Western European countries over the period 1993-2010, and in Cortes et al. (2016) for the United States over the period

1979-2014 (or just 1989 to 2014 in an alternative specification). Goos et al. (2014) estimate a model where the routine task intensity index (the standard proxy for RBTC used in the literature) explains most of the observed employment polarization. In particular, for the group of the eight highest-paid occupations, the model predicts an increase in employment shares (hours worked as a share of total hours) of 79 per cent of the increase actually observed (with the estimated increase equal to 4.45 and the increase actually observed equal to 5.62). For the group of nine middling occupations, the model predicts a decrease of 74 per cent of the total observed employment share decrease (with the estimated decrease equal to 6.86 per cent and the increase actually observed equal to 9.27). Lastly, the model predicts an increase for the group of the four lowest-paid occupations of 66 per cent of the observed increase (with the estimated increase equal to 2.41 and the increase actually observed equal to 3.65).

Cortes et al. (2016) calibrate a structural model of the US economy which matches observed occupational reallocations. They find that automation shocks (measured as the deviation of ICT capital from a balanced growth trend) explain at most one-third of the decline in middle-skilled employment. It should be noted, however, that these figures do not provide a quantification of the contribution of technology to the decline of manufacturing employment, because not all manufacturing employment is middle-skilled, and not all middle-skilled employment is in manufacturing.

(iii) The nature of adjustment to RBTC

Recent empirical work on labour market adjustments related to RBTC is available for the United States. Cortes et al. (2014) show that during the 30 years preceding their study, the decline in middle-skilled jobs in the United States was driven mainly by the paucity of transitions from out of the labour force and from unemployment into routine employment, rather than by job losses. In other words, it was very difficult to find employment in routine jobs.

Further insights on low entry rates into routine jobs are provided by Cortes et al. (2016). They document that the decline of middle-skilled occupations in the United States between 1979 and 2014 was primarily driven by the disappearance of routine jobs among workers in specific demographic groups: male high school dropouts of all ages and male high school graduates under the age of 50 in the case of manual employment, and young (20-29) and prime-aged (30-49) females with either high school diplomas or with some degree of post-secondary education in the case of cognitive employment. On the labour supply side, increasing educational attainment and population ageing in the United States have reduced the fraction of workers with these demographic attributes.

However, labour supply alone cannot account for the labour market experience of these demographic groups. Within each group, the propensity to work in routine occupations has decreased dramatically. For instance, while more than 60 per cent of low-educated young men worked in routine manual occupations in 1979, this figure dropped to one-third in 2014 (Cortes et al., 2016). The decline in the probability of routine employment (equal to 8.1 percentage points between 1979 and 2014 for manual employment, and to 1.2 percentage points for cognitive employment in the same period, as shown in Figure C.4) was offset by increases in non-employment and in non-routine manual employment.

The results of Cortes et al. (2016) suggest that, on average, it has been very difficult for US workers employed in routine occupations to find employment in high-paying non-routine cognitive occupations. Cortes (2016) shows that the outcomes vary across workers, depending on their abilities. In particular, he provides theoretical and empirical evidence showing that low-ability routine workers are more likely to switch to non-routine manual jobs, while high-ability routine workers are more likely to switch to non-routine cognitive jobs.

(iv) Can RBTC explain "jobless recoveries"?

Routine-biased technical change has also been linked to so-called "jobless recoveries" (periods following recessions in which rebounds in aggregate output are accompanied by much slower recoveries in aggregate employment). In particular, the argument has been made that routine-biased automation might be responsible not only for job losses during downturns, but also for sluggish employment growth during economic recoveries. In this connection, Brynjolfsson and McAfee (2011; 2014) refer to a "great uncoupling", in which economic growth has become detached from employment growth for the first time in the modern era.

There is, however, no consensus on this issue, since the empirical evidence is mixed. In the case of the United States, the disappearance of employment in routine occupations has been concentrated in economic downturns (Jaimovich and Siu, 2014). Specifically, 88 per cent of job losses in routine occupations since the mid-1980s have occurred within a 12-month window of recessions (all of which have been characterized by jobless recoveries). The displaced workers have then been forced into timeconsuming transitions to different occupations and sectors, resulting in slow job growth during the recovery. Jaimovich and Siu (2014) and Graetz and Michaels (2017) provide empirical evidence of a link between the hollowing out of middle-skill routine occupations and jobless recoveries for the United States.

However, Graetz and Michaels (2017), using data on 71 recessions which took place in 17 developed countries other than the United States from 1970 to 2011, do not find evidence that industries that make more intensive use of routine jobs, and that are therefore more susceptible to technological change, have had particularly slow employment growth during periods of economic recovery. The same result holds for industries in which labour was more exposed to automation by industrial robots. They also find that middle-skill employment grew similarly in routine-intensive industries and other industries during recent recoveries. Graetz and Michaels (2017) therefore conclude that technology is not causing jobless recoveries in developed countries outside the United States.

Summing up the results of Section C.2, it can be argued that technological change impacts workers differently, depending, among other conditions, on their skills and on the work tasks they perform. Current technological change tends to be skill-biased, in the sense that it increases the relative demand for skills, and routine-biased, in the sense that it decreases demand for routine tasks. Therefore, relatively skilled workers performing non-routine tasks tend to benefit from technological change, which can be disruptive for relatively unskilled workers employed in routine tasks.

The next subsection will provide insights into whether these conclusions might still apply in the near future, or whether, with the upcoming wave of advances in smart technology, artificial intelligence, robotics and algorithms, technological disruption might affect ever-increasing numbers of workers at all levels of skills and work tasks.

4. Technology and the future of work

As discussed in Section B, the level and structure of employment depends on the supply and demand of labour. The future of jobs is no exception and hinges on the future of both the labour supply and demand. The future of labour supply depends, among other things, on demographic developments, the future level and distribution of wealth, as well as the meaning and enjoyment of working attributed by workers and the availability and attractiveness of alternatives to working. Similarly, the future of labour demand depends, among other things, on the relative cost of investment goods and financing conditions, product demand, and the existence as well as the affordability of specific technologies.

The ongoing and upcoming wave of advances in smart technology, artificial intelligence, robotics and algorithms, often referred to as the fourth industrial revolution, is gathering increasing expert and media attention. In this context, a debate has emerged about the impact that these emerging technologies will have on the future of jobs. Some experts argue that history will repeat itself and the transformative processes brought by the next wave of technological advances will replace many existing jobs but eventually create new jobs and opportunities. Other experts argue that the impact of the new wave of labour-saving technological change and innovations on jobs will be different this time around, with the replacement of human jobs by artificial intelligence and robotics on a massive scale, leading to a "jobless future". This subsection will review the main arguments put forward by both sides regarding the impact of technology on future jobs, and discuss the implications for skills development.

(a) Moving with or against technological advance?

The view that the new technological advances in artificial intelligence and robotics will not lead to a "jobless future" is based on historical experience. Although each wave of technological change has generated technological anxiety and led to temporary disruptions with the disappearance of some tasks and jobs, other jobs have been modified, and new and often better jobs have eventually been developed and filled through three interrelated mechanisms (Autor and Handel, 2013; Autor, 2015; Bessen, 2015; Mokyr et al., 2015).

First, new technological innovations still require a workforce to produce and provide the goods, services and equipment necessary to implement the new technologies. Recent empirical evidence suggests that employment growth in the United States between 1980 and 2007 was significantly greater in occupations encompassing more new job titles (Berger and Frey, 2017).

Second, the new wave of technologies may enhance the competitiveness of firms adopting these technologies by increasing their productivity. These firms may experience a higher demand for the goods or services they produce, which could imply an increase in their labour demand.[34] Several empirical studies reviewed in Section C.2 above find that the adoption of labour-saving technologies did not reduce the overall labour demand in European countries and other developed economies (Goos et al., 2014; Graetz and Michaels, 2015; Bessen, 2016; Gregory et al., 2016).

Finally, as discussed in Section C.2, the upcoming technological advances may complement some tasks or occupations and therefore increase labour productivity, which could lead to either higher employment or higher wages, or both. The new workers and/or those benefitting from a pay rise may increase their consumption spending, which in turn tends to maintain or raise the demand for labour in the economy. Recent empirical evidence suggests that the use of industrial robots at the sector level has led to an increase in both labour productivity and wages for workers in Australia, 14 European countries, the Republic of Korea and the United States (Graetz and Michaels, 2015).

Conversely, the proponents of a future rise in unemployment due to technological advances recognize that the fear of such unemployment has been proven wrong many times in the past, but consider that the new wave of technological progress represents a sharp departure from earlier innovations. Advances in robotics, artificial intelligence, self-driving vehicles, "big data" (i.e. data sets too extensive for traditional data processing software to process) and 3-D printing are likely to continue to erode lower-skilled employment specialized in routine tasks, but also to impact on medium- and high-skilled jobs involving physical, cognitive and non-routine tasks requiring knowledge, judgment and experience, which were once thought to be exclusively human domains (Brynjolfsson and McAfee, 2014; Ford, 2015).

In particular, they argue that the upcoming technological advances in digitalization and algorithms empowered by big data will continue to reduce the marginal costs of (re)production to a near zero level, making human workers more expensive than the additional costs of using the new technologies (Rifkin, 2015). This would ultimately result in a shrinkage of the total number of available human jobs in the medium to long run.[35] The impact of the new and upcoming wave of technologies on future job losses is, in their view, also distinct from previous ones in terms of speed, scale, and force (Schwab, 2016).

Firstly, empirical evidence suggests that previous technological advances were adopted at a slower pace, providing individuals with more time to adjust (Comin and Hobijn, 2010). For instance, the United States took 30 years to achieve a 10 per cent adoption rate of electricity, while it took less than five years for tablet devices to reach the same level of adoption rate (DeGusta, 2012).

In comparison with previous innovations, the new technological advances are evolving at an exponential pace. Although some experts argue that Moore's Law, according to which the number of components in a specific size integrated circuit has doubled every 18 months since 1965, is approaching its end, it has enabled greater computing power and the ability to automate increasingly complex tasks (Brynjolfsson and McAfee, 2014; Waldrop, 2016). Graetz and Michaels (2015) report that from 1993 to 2007, mean robot density increased by more than 150 per cent in Australia, 14 European countries, the Republic of Korea and the United States. Boston Consulting Group (2017) reports that there are currently between 1.5 and 1.75 million industrial robots in operation, a number that could increase to between 4 and 6 million by 2025. The pace of progress in certain areas, such as biotechnology, has even exceeded Moore's Law (Autor, 2015). According to the World Economic Forum (2016), around 65 per cent of pre-school children will be expected to undertake tasks and jobs that do not currently exist. The speed of technological acceleration could imply that individuals, even those who are flexible and well-adjusted to the labour market, may need to retrain and update their skill sets so as to keep up with the occupational rearrangements and new additional skills that will be required.

Secondly, most previously ground-breaking technological innovation, such as light bulbs and telephones, did not necessarily occur in every industry of the economy at the same time, which allowed affected individuals to look for job opportunities in until then undisrupted industries. For instance, during the agricultural revolution in the 1700s, many individuals who lost their jobs in the countryside moved to cities in search of work. Previous technological revolutions often took a long time to exhibit significant impacts on the entire economy. While investments in railroads generated initially relatively limited benefits and spillovers, the latter have gradually expanded thanks to improvement in railroad productivity and an increase in the share of rail output in economic activity.

Similarly, the speed of adoption of ICT has been different across sectors. Some sectors, such as manufacturing, agriculture, forestry and fishing, hotels and restaurants, and the wholesale and retail trades, have experienced a very rapid increase in the use of ICT capital services per hour worked, while other sectors, such as construction and transport, have recorded a lower ICT intensity growth rate (OECD, 2017). Some experts argue that technological progress in ICT has been less transformative than any of the three main technologies that emerged during the second Industrial Revolution at the end of the nineteenth century and beginning of the twentieth century (namely electricity, cars and wireless communications) (Gordon, 2014). However, a recent study comparing US labour productivity in the electrification era (1890 to 1940) and the ICT era (1970 to 2010) finds that productivity growth in both eras exhibited remarkably common patterns: an initial relatively slow growth in productivity, followed by various decade-long accelerations and then a slowdown in productivity growth (Syverson, 2013). Unlike previous important technological innovations, the new and upcoming ones are not limited to one specific area but combine various elements, such as energy storage, quantum computing, mobile networks, biotechnology, nanotechnology and material science, potentially affecting all areas of the economy at once, including the services sector as well as the agricultural and manufacturing sectors.

Finally, the breadth and depth of these new complex technologies have the potential to transform entire systems of production, management, and governance. For instance, the phenomenon of digitalization has already led to the emergence of new business and employment models, often referred to as the "platform economy", "sharing economy", "peer-to-peer economy", "gig economy" or "on-demand economy". In particular, the establishment and development of new digital transportation, accommodation, and on-demand and freelance labour platforms have enabled the creation of new types of jobs as well as temporary and flexible contracting arrangements.[36] Some experts also anticipate a surge in superstar-biased or talent-biased technological change associated with many digital technologies, where a limited number of firms and individuals capture most of the market share and financial benefits stemming from the adoption and diffusion of these technologies (Brynjolfsson and McAfee, 2014). The emergence of such winner-take-most or -take-all markets could have consequences on the degree of competition of different sectors of the economy and on perceptions of equity and fairness of the consequences of technical change.

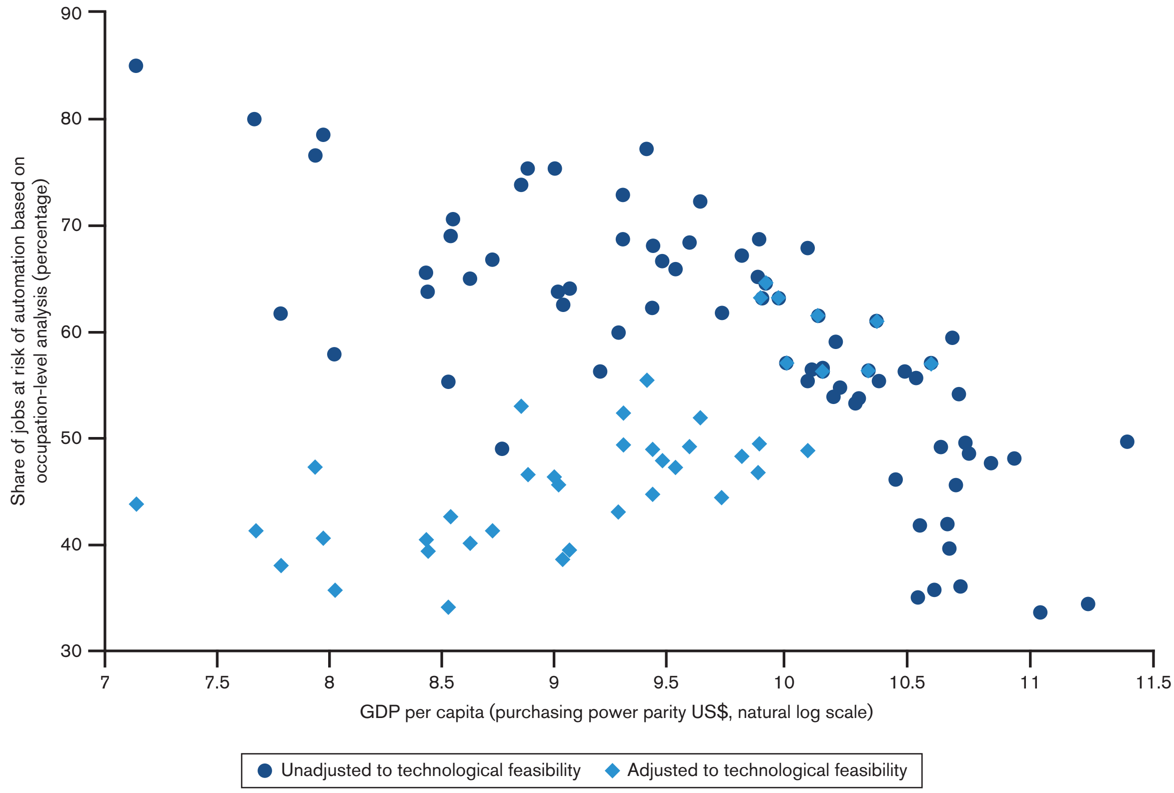
Besides the speed at which the new and upcoming waves of technologies could change the systems of production, distribution and consumption in almost every industry and economy, these new complex technologies will also unfold in a different setting in terms of demographic and life expectancy compared to previous technological revolutions (Clark, 2017). Previous significant innovation occurred in a world characterized by its growing population. Nowadays, an increasing number of developed and emerging countries face an ageing and shrinking working-age population with the potential additional pressure to use non-human labour to compensate for the fewer working-age workers that used to finance the social safety net. Conversely, most developing countries are still experiencing a growing population and face the challenge of creating conditions in which to provide new jobs in addition to existing jobs unaffected by the new technological innovation. Similarly, the improvement of the average life expectancy, thanks to scientific and technological innovations in health and medicine, implies that individuals will, on average, be able to work longer, potentially putting additional pressure on the labour market.

(b) Prospects of automation

One of the studies that reignited the debate about the new wave of technologies, in particular automation, and employment was a 2013 research paper by Frey and Osborne (2017), who classify 702 occupations in the United States in terms of skills that are likely to be automated. The authors conclude that 47 per cent of these occupations are at risk of automation and computerization over the next two decades. In particular, the study identifies retail salespeople, administrative assistants, food counter personnel, cashiers, and transport truck drivers as working at occupations that are at a greater risk of automation.[37] A number of consultancy firms and academics have replicated the analysis for various European countries, Australia, Canada, Japan and New Zealand, and report that the share of jobs susceptible to automation ranges from 30 to 49 per cent (Baert and Ledent, 2015; Deloitte, 2015b; Bouée and El Karoui, 2014; Sproul et al., 2015; Pajarinen and Rouvinen, 2014; Brzeski and Burk, 2015; Citibank, 2016; David, 2017; Durrant-Whyte et al., 2015).[38]

The risk of automation is not only confined to developed economies. As highlighted in Figure C.5, estimates of the share of occupations at risk from automation actually tend to be higher for developing and least-developed countries than for high-income countries. According to the World Bank's *World Development Report 2016*, two-thirds of all jobs could, on average, be vulnerable to automation in developing countries in the next decades. The estimated share of jobs at high risk of automation ranges from 55 per cent in Uzbekistan, 65 per cent in Nigeria and 67 per cent in Bolivia and South Africa,

Figure C.5: Proportion of jobs at risk of automation by economic development



Source: WTO Secretariat based on occupation-level analyses published by Baert and Ledent (2015), Bouée and El Karoui (2014), Brookfield Institute for Innovation + Entrepreneurship (2016), Bruegel (2014), Brzeski and Burk (2015), Centre for Strategic Futures (2015), Chang and Huynh (2016), Chartered Accountants Australia and New Zealand (2016), David (2017), Deloitte (2015a), Deloitte (2015b), Durrant-Whyte et al. (2015), Frey and Osborne (2017), Pajarinen and Rouvinen (2014), Pajarinen et al. (2015), Stiftelsen för Strategisk Forskning (2014), Unionen (2014) and World Bank (2016).

to 74 per cent in Angola, 77 per cent in Bangladesh and 85 per cent in Ethiopia. The estimated share of jobs at risk of automation is also substantial in emerging economies, such as Argentina (65 per cent), India (69 per cent) and China (77 per cent). A recent International Labour Organization (ILO) study estimates also that about three in five jobs face a high risk of automation in Cambodia, Indonesia, the Philippines, Thailand and Viet Nam (Chang and Huynh, 2016).

According to the World Bank, the high share of jobs susceptible to automation could impact negatively on developing economies' ability to develop further. However, the adoption and diffusion of automation could be slower and more limited in developing countries given the higher prevalence of barriers to technology, lower wages, and the number of jobs based on manual dexterity (see Box C.2). Adjusted for the slower pace of technology adoption in developing countries, the World Bank's estimates of the share of jobs at risk of automation decrease significantly for most developing countries analysed. As shown in Figure C.5, the estimated shares adjusted to technological feasibility in low- and middle-income countries range from 34 to 65 per cent, which is relatively similar to the estimates for many high-income countries.

According to more recent studies, the relatively high share of jobs vulnerable to automation estimated and reported in the above-mentioned studies stems from the failure to account for the fact that occupations tend to adjust to technology by adapting their task structure. In fact, most occupations adapt regularly to technological innovation by reallocating routine tasks to automation and refocusing human work on management and on non-routine social, interpersonal and creative tasks. This is what happened with many bank tellers following the introduction of ATMs, as discussed in the previous subsection.

Taking into account the difference in the ability to automate specific jobs and tasks within occupations, a recent study estimates that 12 per cent and 9 per cent of the jobs in Germany and the United States, respectively, could be fully automated (Bonin et al., 2015). Based on the same methodology, an OECD

Box C.2: The future impact of automation on developing countries' labour market

While there is a growing literature on the potential impact of automation and artificial intelligence on the labour market in developed economies, the impact in developing countries has received much less attention. The few occupation-based studies that estimate the share of employment at risk of automation in developing countries conclude that the latter have a larger share of employment in routine occupations that could be automated and computerized (World Bank, 2016; Citibank, 2016). Yet, as pointed out in World Bank (2016), the impact of automation on the labour market of developing countries could occur later and be slower for two main reasons. First, although the speed of technology adoption has increased in developing countries, it remains slower than in developed countries. Second, lower wages and a relatively high share of manual non-routine jobs, which are currently more difficult to automate, could make investment in automation in developing countries less profitable (at least in the short run). However, regardless of the timing, automation raises several issues for developing countries.

First, by reducing the labour content of the production process, automation in developed countries could compete with countries in which labour costs are low (UNCTAD, 2016). Firms in high-income countries could decide to bring specific manufacturing operations located in developing countries back in order to minimize production costs and enhance their competitiveness. Reshoring could also apply to business process outsourcing in financial services (e.g. accounting), telecommunications (e.g. call centres) and medical services. In such a situation, developing countries may experience a reduction in production and employment opportunities in certain industries (Citibank, 2016). These potential changes could be particularly challenging for those developing countries that are already facing deindustrialization and are becoming service economies sooner and at much lower levels of income compared to countries that were industrialized earlier (Rodrik, 2016). The continuous real wage growth in emerging countries could provide further incentives for potential re-shoring and the adoption of automation. However, for the time being, empirical evidence suggests that reshoring is limited, occurring in specific industries and relatively slowly (UNCTAD, 2016).

Second, the new wave of technologies could provide entrepreneurs and firms in developing countries with the opportunity to establish new business models and offer new goods and services. For instance, additive manufacturing (i.e. industrial 3-D printing) could, thanks to its mobility, flexibility, energy efficiency and increasing affordability, enable small-scale manufacturing to become more competitive and efficient in developing and least-developed economies (Naudé, 2017). However, such opportunities are likely to be challenging for economies without reliable access to electricity and the internet, as well as to relevant skills in the workforce.

Third, automation and advances in ICT could also create new job opportunities in developing countries through the development of online work platforms bringing together potential employers and employees (World Bank, 2016). Such online platforms could provide workers in developing countries, including young people and women, with opportunities to monetize skills which might have limited demand in the local labour market. However, access to and use of these platforms tend to be higher among young people and highly skilled workers, and this, along with automation, could further contribute to the polarization of the labour market, with employment growth at the bottom and top of the skill and income distribution. As discussed in Section B, recent empirical evidence shows that many developing countries, except those with a large share of low-skill employment, large natural resources and commodity endowments, are already experiencing job polarization (World Bank, 2016).

Finally, individuals with low educational attainments and low incomes are most vulnerable to technological changes in the labour market. It is, however, unclear how the informal sector, which, as discussed in Section B, accounts for a large share of the total workforce in many developing countries, will adjust to automation and advances in ICT. Empirical evidence suggests that informal firms tend to innovate or adopt technologies at lower rates than formal firms (Harris, 2014). The literature further shows that as previous technological innovations have improved energy access, telecommunications, and transport systems, they have enabled certain informal workers to make productivity gains by improving their work efficiency and organization, as well as to take advantage of new work opportunities (Casey and Harvey, 2015; 2016). However, for other informal workers who do not have the financial means to acquire the new technologies and/or are unable to upgrade their skills to implement them, the disruptive impact of technologies is much more negative. Several case studies report that informal workers who organize and collaborate with other groups manage to improve considerably their capacity to upgrade and expand their technology options gradually, to keep up with the pace of technological change, and to mitigate the setbacks from the negative impacts of technology disruption in their sector (Casey and Harvey, 2016). Limited and uneven access to future technologies among informal workers, including the most vulnerable, could therefore exacerbate the "digital divide".

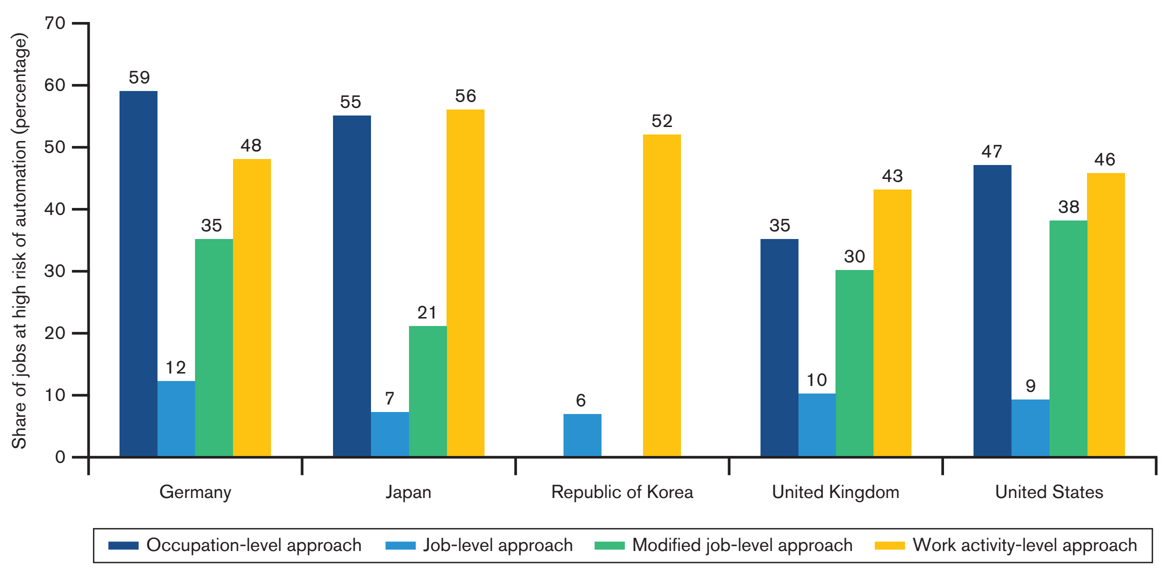
study reports that, on average, 9 per cent of jobs in 21 OECD countries are susceptible to full automation, ranging from 6 per cent or less in Estonia, Finland and the Republic of Korea to 12 per cent in Austria, Germany and Spain (Arntz et al., 2016b). The authors of the study conclude that occupation-level approaches overestimate automation potentials, because three out of four jobs in a particular occupation are, on average, less automatable compared to the median job of the particular occupation, suggesting that workers specialize in non-automatable tasks within their professions (Arntz et al., 2017).

A more recent report prepared by PricewaterhouseCoopers (2017) modifies the methodology used by Artnz et al. (2016b) by applying additional data and developing an algorithm linking automatability to tasks' and workers' characteristics. It estimates that 35 per cent, 30 per cent and 38 per cent of the jobs in Germany, the United Kingdom and the United States, respectively, face a potentially high risk of automation. Two recent studies by McKinsey Global Institute (2016; 2017), based on a different methodology which analyses work activities, suggests that even though 46 per cent of all current tasks in the United States are at risk of automation, and 60 per cent of occupations could encompass 30 per cent or more automated activities, only 5 per cent of occupations could be entirely automated using currently available technologies. At the global level, the estimated percentage of work activities that could be automated ranges from 41 per cent in Kuwait and South Africa to 50 per cent in Brazil and the Russian Federation, 52 per cent in Kenya and Mexico, 55 per cent in Thailand and 57 per cent in Japan. Given the sectoral structure of their economy, the activities mix within these sectors, and their workforce size, China, India, Japan and the United States account for almost two-thirds of the number of workers whose activities could technically be automated by currently demonstrated technologies (McKinsey Global Institute, 2017).

New research also suggests that the future impact of automation could vary significantly across regions and areas within a given country (Morgan et al., 2017; Institute for Spatial Economic Analysis (ISEA), 2017). While digital technologies have enabled firms to enhance their means of communication and further segment their production processes, companies still tend to cluster specific skills and occupations in certain geographical locations to capitalize on the availability of inputs, including labour force and suppliers, and potential spillovers. As a result, areas with a relatively larger concentration of tasks and jobs vulnerable to automation, which tend to be small cities, could be impacted more than other larger metropolitan areas.

Overall, as shown in Figure C.6, the estimated share of country's employment that could be replaced by automation differs significantly depending on the methodology and underlying assumptions considered. Yet, independently of the methodology used, the estimated probability of automation is not equivalent to future unemployment but could still have

Figure C.6: Comparison of approaches to estimate the share of jobs at risk of automation



Source: WTO Secretariat based on occupation-level analyses (Brzeski and Burk, 2015; David, 2017; Deloitte, 2015b; Frey and Osborne, 2017); job-level analyses (Arntz et al., 2016b); modified job-level analyses (PricewaterhouseCoopers LLP, 2017); and work activity-level analyses (McKinsey Global Institute, 2017).

important labour adjustment implications because of compositional changes in the labour market. These estimates should therefore be interpreted with caution for various reasons (Arntz et al., 2016b; McKinsey Global Institute, 2017).

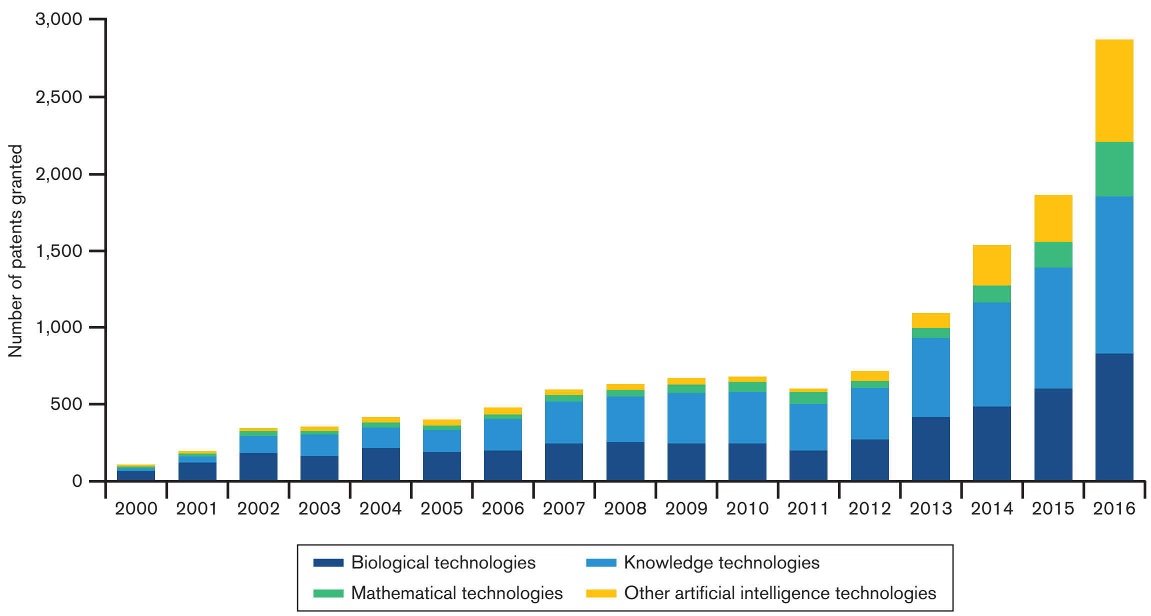
Firstly, the projections of future technological capabilities are based on subjective assessments by experts, who are not certain of how much and at what pace technological progress will eventually be achieved. Technology experts are sometimes viewed as overly optimistic about the forthcoming technological feasibilities in their area of expertise and as potentially overestimating their likely progress (Autor, 2015). A recent survey analysis suggests, however, that experts in artificial intelligence and robotics tend to be more cautious than non-experts when predicting the number of occupations at risk of automation in the next decades (Walsh, 2017).

Many technologies, including artificial intelligence and automation, as shown in Figure C.7, have developed in spurts. Very often, occasional technological advancements are followed by a period of slower progress because of the presence of certain challenging obstacles. As discussed in Section C.2, some scholars also argue that one cannot discard the possibility that rapid automation might also be a transitioning phase towards new technologies benefiting labour by discouraging further automation (Acemoglu and Restrepo, 2016).

Secondly, projections of the development and adoption of future technologies often underestimate the challenges encountered during the development of experimental prototypes and the adjustment of the production process. The degree of stability of a given automation process obtained under laboratory conditions is often difficult to achieve in practice. The automation process very often needs to be tailored and adjusted to the firm's structure and practices. During that process, the firm has to run tests, develop prototypes and adjust and improve the automation system until it can be embedded in the production process. A recent survey analysis of German firms reports that, although the share is increasing, only 5 per cent of firms' production equipment and 8 per cent of firms' office and communication equipment, on average, are based on smart technology, artificial intelligence and robotics (Arntz et al., 2016a). The risk of potential disruptions caused by machine breakdowns, broken or mis-specified parts and worker mistakes can further slow down the adoption process. As a result, the implementation speed of new technologies remains often uncertain and volatile.[39]

More generally, the adoption of a new technology by a firm depends on the cost of software and/or hardware required to implement it and on whether the firm has the necessary financial resources to invest in it. Other factors influencing the decision to adopt the new technology include the availability of relevant skills in the workforce and whether the potential

Figure C.7: Evolution of patents on artificial intelligence granted (2000 to 2016)



Source: Fuji and Managi (2017) based on WIPO Patentscope database.

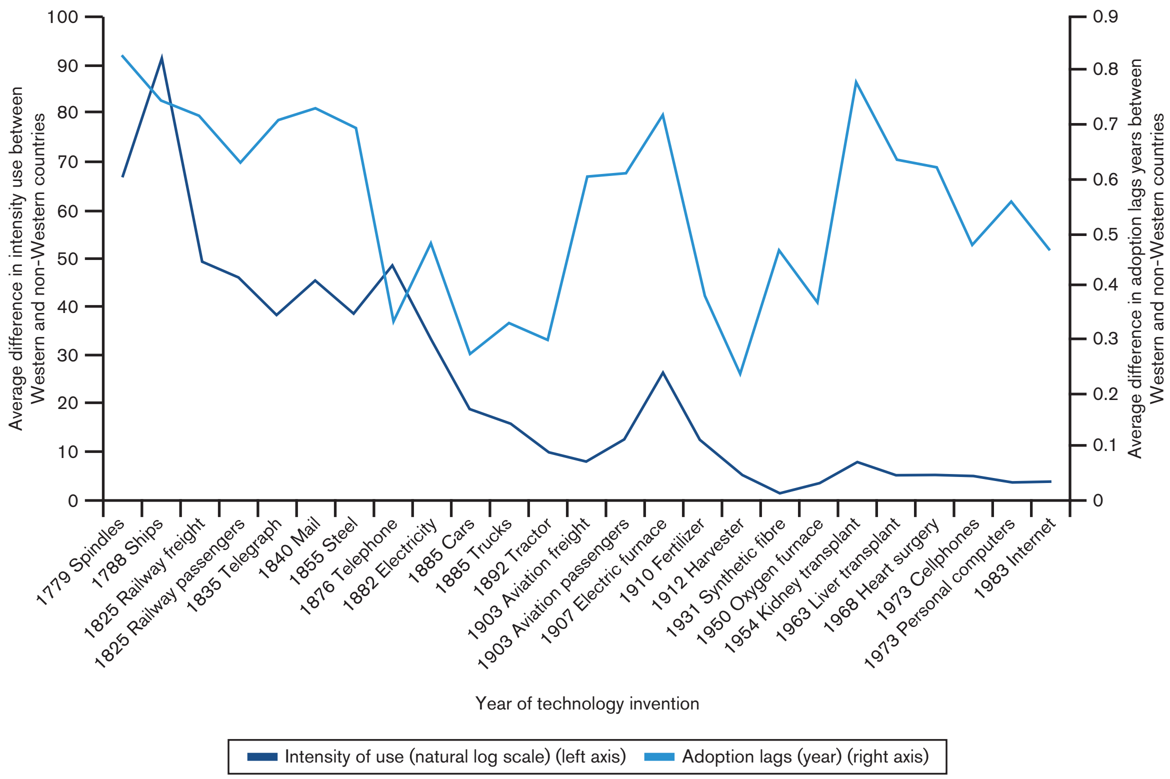
economic benefits in terms of greater efficiency outweigh the costs.

Past experience suggests that the adoption of specific technology, such as the use of personal computers, can be relatively slow and challenging, because firms adopting new technologies frequently need time to learn and become familiar with specific practical implementation. For instance, although cloud computing was first commercialized in the 1990s, less than 30 per cent of small and medium-sized enterprises in OECD countries have currently adopted it (OECD, 2016d). An economy's level of economic development and firms' absorptive capacity also seem to play an important role. Although technology adoption lags across countries appear to have declined significantly over the past two centuries, the degree to which new technologies diffuse across firms and consumers following their initial adoption seems to have widened between developed and developing countries over the same period, as shown in Figure C.8 (Comin and Mestieri, 2017).

Thirdly, and as discussed in the previous subsection, even when new technologies are increasingly being adopted and used, their effects on employment prospects depend to a large extent on whether the firms adjust to new divisions of labour made possible by these new technologies. Each industry, and in some cases each firm, develops its own set of job roles over the years, which often also encompass their own sets of tasks. While some of these tasks can potentially be automated or digitalized, others cannot. Moreover, different production tasks can often involve different types of automated functions, some of which may require more complex and expensive automated systems than others.

The impact of new technologies on employment also depends on a firm's managerial and corporate culture, including its human resource management, as well as on organizational and social constraints. The adoption of a new labour-saving technology could result in a reduction in the number of hours worked and not necessarily in a reduction in the

Figure C.8: Average difference in adoption lags and penetration of significant technological innovations between Western and non-Western countries (1779 to 2008)



Source: WTO secretariat based on Comin and Mestieri (2017).

Notes: Western countries include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, New Zealand, Norway, Sweden, Switzerland, the United Kingdom and the United States. The right axis represents the average lags (expressed in years) with which significant technological innovations arrived to developing countries compared to Western countries from 1780s to the present. The left axis represents the average difference in the penetration of significant technological innovations between Western countries and developing countries from 1780s to the present. Penetration is defined on the basis of the intensive margin of adoption for each new technology (expressed in logarithm).

number of jobs. Workers might also adjust to the new technologies by increasingly performing tasks complementary to the new technologies. Empirical evidence suggests that most of the adjustments caused by technological innovation tend to occur within, rather than between, occupations through tasks-restructuring (Spitz-Oener, 2006). The mechanisms by which technology complements human work are, however, less well understood in the literature than those by which technology substitutes for human work. A recent survey-based analysis of Japanese firms operating in the manufacturing and services sectors suggests that the surveyed firms with a relatively larger share of high-skilled workers tend to express more positive views on the impact of artificial intelligence and robotics on the prospective number of their employees, while firms with a larger share of low-skilled workers tended to anticipate a negative impact on employment (Morikawa, 2017a).

Fourthly, the studies attempting to quantify the share of jobs vulnerable to automation consider only existing jobs. They omit to analyse the new jobs that these new technologies could create. According to the World Economic Forum (WEF) (2016), a large number of today's most in-demand jobs did not exist 10 years ago. For instance, technological progress in digitalization has created requirements for app developers, big data analysts and social media managers. The upcoming wave of new technologies could thus support the growth of different types of jobs, including those in charge of developing the new technologies, implementing them, and/or supervising and repairing them (Executive Office of the President of the United States, 2016). In addition, new technologies are likely to require changes in legal frameworks and physical infrastructures, which would create specific new occupations and jobs.

New technologies may also have positive effects on labour demand by raising the demand for existing and new products and/or services if they lead to improve firms' productivity and increase workers' wage and income. As discussed in Section B, frictions in the labour market can alter the process of allocating individuals to jobs and increase unemployment. In this context, further advances in ICT could also facilitate the matching of the labour demand and supply by reducing the time and resources spent by firms and individuals and improving firms' efficiency (Dehaze, 2016).

Fifthly, the adoption and diffusion of new technology does not take place in a vacuum but in a specific legal and regulatory framework. Some labour market regulations may make it difficult and costly for firms to replace workers with new labour-saving technologies, such as robotics. The decision to adopt a new technology may also be resisted by those who expect to be negatively affected. Recent empirical research suggests that individuals in European countries and in the United States facing economic positions that are more likely to be negatively affected by robotics are more likely to be fearful of robots at work (Dekker et al., 2017; McClure, 2017). Similar findings were found in the case of Japan, where workers with limited professional experience, non-regular contracts, and who were engaged in clerical and manufacturing occupations, tended to perceive a higher risk of being replaced by artificial intelligence and robotics (Morikawa, 2017b).

Empirical evidence further suggests that the perceptions of workers in the services sector in New Zealand regarding potential changes in their workplaces due to artificial intelligence and robotics seem to be negatively related to their commitment and career satisfaction and positively related to their turnover intentions and pessimism (Brougham and Haar, 2017). In that context, some experts argue that some professional occupations, such as those of engineers, lawyers and doctors, may have a greater negotiating power in a firm than other types of occupation to ensure that new technologies extend and complement their work (Brynjolfsson and McAfee, 2014; Hughes, 2017).[40]

More generally, public acceptance of technologies can be a key factor in determining their impact on society, including on the labour market. Acceptance of new technologies encompasses political acceptance by public and key stakeholders, but also by consumers and investors, and by the communities and regions in which the new technologies are being developed and implemented. Past experiences show that high public concern can determine the direction, speed and diffusion of technological advances and, in some cases, impede their progress even when technical and economic feasibility have been established, the rationale for adoption seems sound, and important investments have been made. Empirical evidence shows that public ignorance about the true benefits of particular technologies is often not the main reason for public opposition to these technologies. Other, more important, factors include value conflicts and distributive concerns related, among others, to jobs and welfare, as well as failures of trust in institutions, such as regulatory authorities and technical advice bodies (Winickoff, 2017). Public opposition to technologies can, in some cases, lead to the adoption of new regulations that improve trust and confidence, and orient technological progress along pathways that become acceptable to the public (Davis, 2014).

(c) Implications for skills development

While a definitive conclusion on the exact outcome of the new wave of technological innovation on labour markets remains elusive at the present time, the upcoming technological advances will certainly continue to have an effect on the labour supply, especially skills development through changes in labour demand, work organization and skills requirement. In particular, technological advances are likely to continue to be disruptive by rendering specific qualifications and skills less relevant and obsolete whilst requiring and enhancing other and new ones.

Several recent studies, many of which are based on the methodology used to estimate the share of jobs at risk of automation, attempt to identify the types of skills less likely to be subject to automation. Some of these studies identify the jobs least vulnerable to automation as those occurring in dynamic and changing environments and involving non-routine manual and cognitive skills that have so far been proven difficult to automate. These skills include perceptual judgment and manual dexterity skills (used by nurses and surgeons, as well as housekeepers and cooks), social-emotional intelligence skills, such as empathetic and negotiating skills (used by educators, managers and social workers) and creative skills (used by scientists, designers and artists) (Frey and Osborne, 2017; McKinsey Global Institute, 2017).

As explained above, some experts also anticipate that automation will be applied to tasks and jobs located at increasingly elevated levels of the skills ladder (Susskind and Susskind, 2016). For instance, the “Internet of things”, which enables smart devices to send and receive data, could apply to higher-skilled and complementary tasks undertaken by skilled workers, such as providing online instructions to workers. Where complex digital technologies increase the importance of experiential knowledge, some specific experiential knowledge could also be eroded or become obsolete. Given the potentially shorter life cycle of skills, the development of deep soft skills, such as adaptability and learnability, defined as the desire and ability to learn new skills, has been identified as essential to grasp complexity, handle unexpected situations under time pressure, and take the right actions in those situations without necessarily having clear information (OECD, 2016c). In other words, the ability to get and keep certain types of jobs is likely to depend less on what the individuals already know and more on how and what new knowledge and skills they are likely to learn.

Empirical evidence shows, however, that the demand for some of the skills that are considered by many experts to be immune to automation, such as perceptual and supervisory skills, has been experiencing a decrease in the United States (MacCrory et al., 2014). This seemingly contradictory result could be explained by the fact that workers may take on more managerial and organizational responsibilities within the same occupations. On the other hand, interpersonal skills and workers’ facility with technology have gained importance in the last few years. Recent empirical research further suggests that individuals who are more intelligent and show an interest in the arts and sciences during high school in the United States are less likely to select jobs that are more likely to be automated in the future (Damian et al., 2017).

Many of the skills potentially less exposed to automation are already being highlighted as important by many firms. A recent survey of employers conducted by the WEF (2016) highlights an important increase in the future demand for cognitive abilities, systems skills and complex problem-solving skills, such as mathematics and logical reasoning, visualization, systems analysis and creative thinking, by 2020.[41] As discussed in section E, access to higher education, digital literacy and quality training have been identified by some countries as important means to providing individuals with the responsive, flexible and complementary skills needed to alleviate and respond, at least in part, to the current and future challenges of the labour market.[42]

5. Conclusions

This section has considered the effects of technology on the level and composition of employment and wages. Technological progress is the ultimate source of economic growth, as it allows for the production of the same amount of output with fewer resources, or more output with the same amount of resources.

Technological progress has ambiguous effects on aggregate employment. When such progress takes the form of a new product (such as flat screen televisions) which replaces an old product (such as cathode ray tube televisions), firms producing the old product go out of business, but labour demand may increase due to additional demand from firms producing the new product. When such progress takes the place of labour-replacing automation, technological change leads firms to adopt more capital-intensive technologies and to substitute labour for capital. However, various compensation mechanisms (e.g. price-productivity effects, scale-productivity effects, additional demand in other sectors of the economy) can counterbalance this type of reduction in labour demand. The evidence reviewed in this section shows, with some exceptions, few overall effects of technology on the level of employment.

While having few effects on the level of employment, technology strongly affects its composition. This is because technological change has different effects on different workers, depending, for example, on their skills and on the work tasks they perform. This section has presented theoretical and empirical evidence showing that current technological change tends to be skills-biased, in the sense that it increases the relative demand for skills, and routine-biased, in the sense that it decreases demand for routine tasks. Therefore, skilled workers performing non-routine tasks tend to benefit from technological change, while the latter can be disruptive for unskilled workers employed in routine tasks.

Technological progress is ever-increasing. There is indication that advances in smart technology, artificial intelligence, robotics and algorithms, often referred to as the fourth industrial revolution, are taking place at an unprecedented pace. However, technological revolutions often take a long time to have significant impacts. The maximum impact of steam power on British productivity growth was not felt until the third quarter of the nineteenth century, nearly 100 years after James Watt's patent. The benefits of railroads were fairly small initially, but grew as railroad productivity improved and rail output rose as a share of economic activity. Similarly, investments in electrical capital equipment did not have important spillovers until the 1920s. Initially, factory owners simply replaced large steam engines with large electric ones. It took nearly 40 years after electricity was widely available in the United States for organizational methods to catch up and develop more efficient decentralized production lines.

This implies that current technological change is likely to have long-lasting and potentially disruptive effects on the world of work. This section has evaluated the arguments put forward by both technology optimists and by technology pessimists. Technology optimists recognize that each wave of technological change in the past generated technological anxiety and led to temporary disruptions with the disappearance of some occupations and jobs, but note that other jobs were modified and new, and jobs which were often better were eventually developed and filled. Technology pessimists, while recognizing that the fear of technological unemployment has been proven wrong many times in the past, consider that the new wave of technological progress represents a sharp departure from earlier innovations in terms of speed, scale and force. Definitive conclusions on the exact outcome of the new wave of technological innovation on labour markets, however, remain elusive for the present.

Endnotes

1 Automation refers to the use of technologies and automatic control devices that results in the automatic operation and control of production processes (Electrical Technology, 2017).

2 In this case, labour productivity increases go hand in hand with improvements in working conditions.

3 The expression "technological unemployment" was coined by Keynes.

4 Evidence of a declining share of manufacturing employment in several other developed economies is presented in Section B.

5 Industrial robots are defined by the International Organization for Standardization (ISO) as "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes" – see the website of the International Federation of Robotics (IFR) at www.ifr.org

6 IFR data, as elaborated by Graetz and Michaels (2015).

7 Other factors behind the falling shares of employment but ever-increasing output in agriculture include more effective land use through crop cycling and fertilization, following soil analysis.

8 Another typical reason why occupations disappear is lack of demand, such as in the case of boarding-house keepers (Bessen, 2017).

9 Similarly, Harrison et al. (2014) show that product innovation has an ambiguous labour displacement effect (which depends on productivity differences between old and new products), and a positive compensation effect (related to demand enlargement). Overall, product innovation can therefore have net positive or negative employment effects.

10 Non-tradable sectors are those which do not trade internationally. Typically, the non-tradable sector comprises services where the demander and producer must be in the same location, such as electricity, water supply, all public services, hotel accommodation, real estate, construction and local transportation. Commodities which have low value relative to either their weight or volume can also be non-tradable if the transportation charges prevent producers from profitably exporting their goods (Jenkins et al., 2011). Due to advances in ICTs, however, the distinction between tradable and non-tradable sectors becomes ever thinner, particularly if one considers all the modes of services supply contemplated in the General Agreement on Trade in Services (GATS).

11 A list of ICT sectors is provided by OECD (2002, Annex 1).

12 A list of ICT occupations is provided in ILO (2006).

13 Brynjolfsson and McAfee (2014) report the telling example of Instagram, a photo-sharing app. When it was bought by Facebook in 2012, Instagram had just 13 employees, while Facebook had 5,000. These numbers are only a tiny fraction of the number of people employed by Kodak (around 145,000) at the peak of its success in photographic film in the 1990s.

14 Among the various other factors affecting technology adoption by firms, there is uncertainty over future profit streams, sunk costs, the opportunity to delay (Hall and Khan, 2003) and the structure of incentives within firms (Atkin et al., 2017).

15 Lewis (2004) investigates the technology adoption effects of the Mariel boatlift. The Mariel boatlift, which occurred in April 1980, authorized Cubans to leave their country for a limited period of time. It brought 125,000 Cubans from Mariel to Miami, creating a 7 per cent increase in the local labour force in five months in the American city (see Card, 1990). Lewis finds that post-boatlift computer use at work was lower in Miami than in other cities with similar levels of computer-based employment before the event. This suggests that the boatlift induced Miami's industries to employ more unskilled intensive production technologies and supports the idea that markets adapt production technology to local factor supplies.

16 For other theoretical contributions on the overall employment effects of labour-saving technologies, showing that the net effects are indeed ambiguous, see Blien and Ludewig (2016), Benzell et al. (2015), Sachs et al. (2015) and Nordhaus (2015). Blien and Ludewig (2016) show that although labour-saving technology may generate unemployment initially, it may also attract higher product demand. The relative strength of the two forces depends on the demand conditions on product markets. Benzell et al. (2015) and Sachs et al. (2015) show that a rise in robotic productivity which substitutes for labour can result in declining product demand if the output produced by robots is sufficiently substitutable for the output produced by humans. In the paper by Nordhaus (2015), a situation in which technological change makes human labour obsolete, denoted "economic singularity", can arise either if product demand is elastic, so that demand restructures to only ICT-produced goods, or if production is elastic, shifting production to ICT-inputs only.

17 For instance, demand rigidities may prevent product demand to increase as prices fall. For a more detailed discussion, see Vivarelli (2015) and Ugur and Mitra (2017).

18 Equating technological change with routine task specialization has advantages and disadvantages. If the aim is to measure automation technologies, routine task measures capture such technologies more broadly than robotics data, as the former include computers, machines, algorithms, robots and the like. However, task allocation is affected by several factors other than technological change, including offshoring, migration and organizational change.

19 These results are subject to the same methodological critiques as those of Autor et al. (2013), which are detailed in Section D of this report, and should be interpreted with caution. In particular, only differential effects between locations, and not a national effect, can be identified by the underlying "difference-in-differences" econometric approach.

20 Put differently, the labour demand effects of technology substantially depend on who owns the capital, as highlighted by Benzell et al. (2015) and by Sachs et al. (2015).

21 Several single-country firm-level studies for developing countries also find that introduction of new products is associated with employment growth. Moreover, they find no negative employment effects of process innovation (see Crespi and Tacsir, 2013 for a comparative analysis of firm-level studies for Argentina, Chile, Costa Rica and Uruguay).

22 Technology can also have an impact at the level of other individual characteristics. For instance, it has been argued that younger cohorts are more productive than older ones because they are more adept in using new technologies and keeping up with technological change (Meyer, 2011). In this sense, technology might be biased in favour of young generations. There are also some studies on gender showing that, especially in developing countries, women are much less likely to work in ICT sectors or occupations, which are well paid, because they are less likely to receive education in subjects such as science, technology, engineering and mathematics (World Bank, 2016, Box 2.10). Technology can, therefore, also be biased in favour of male workers.

23 Goos and Manning (2007) introduce a finer distinction in the sphere of non-routine non-manual tasks, distinguishing between cognitive tasks (e.g. testing hypotheses) and interactive tasks (e.g. managing others). This distinction is not crucial for the results discussed in this section and will therefore not be considered here.

24 The skill premium is the wage of skilled (or production) workers relative to the wage of unskilled (or non-production) workers.

25 Evidence that computer technology is complementary with human capital is presented by Krueger (1993), who shows that more skilled workers, especially those with higher educational attainment, are more likely to use computers on the job.

26 It should be emphasized that different technology indicators have been used in the literature, making it difficult to directly compare the different studies.

27 The combination of computerization and occupation demand shifters explain roughly 80 per cent of the rise in the skill premium, and almost all of the rise in inequality across more disaggregated education groups (Burstein et al., 2015).

28 For an alternative theoretical approach to the routine-biased nature of technical progress, see Jung and Mercenier (2014). Cortes et al. (2016) demonstrate analytically that advances in automation cause workers to leave routine occupations in favour of non-routine manual jobs and non-employment.

29 Recall from Section C.2 that labour-saving technology substitutes labour for capital (substitution effect). This substitution effect operates mostly in the upper row of Table C.1, because it mostly applies to workers that perform routine tasks.

30 The elasticity of labour supply is the percentage change in labour supply following a 1 per cent change in wages. The more elastic the labour supply, the more employment responds to wage changes. Graphically, an elastic labour supply is flatter than an inelastic labour supply. A perfectly inelastic labour supply, represented by a vertical curve, implies a fixed supply of labour at any wage rate.

31 Middle-skilled workers displaced from routine occupations can also compete with middle-skilled workers in non-routine occupations with cognitive content and low market entry barriers. Hsieh and Moretti (2003) show socially inefficient new entries into the occupation of real estate broker (a non-routine cognitive occupation with low entry barriers) in response to rising house prices in the United States. Some middle-skilled workers may also compete with high-skilled workers, conditional on getting adequate training (Autor and Dorn, 2013; Brynjolfsson and McAfee, 2014).

32 For the United States, evidence that routine employment has declined, while non-routine manual employment has expanded, is also provided by Autor and Dorn (2013) and Mazzolari and Ragusa (2013). The World Bank (2016) shows that employment is shifting away from occupations that are intensive in routine tasks in most countries, both high-income and low- and middle-income.

33 Autor et al. (2015) conclude from this that technology affects local labour markets only by shifting occupational composition within sectors. This is in line with the conclusions of Section C.2 that the overall employment effects of technological change are very small and even positive.

34 According to "Baumol's disease", industries with occupations for which it is difficult to enhance workers' productivity or in which productivity does not increase as fast as the economy's growth, tend to capture a larger share of the economy's workforce.

35 Besides the fear that many jobs could be lost to automation and robots, other forms of anxiety related to technological advancements have been discussed in the literature. One of them relates to the potential risk of dehumanization of work and society. Conversely, another fear expressed by some experts is that technological progress is too slow because the greatest technological advances have already occurred. The lack of technological progress could limit the prospect of future productivity gains and ultimately of economic growth.

36 Recent literature also discusses how the changes associated with the "gig economy" offer opportunities for some individuals, including those excluded from traditional work modes, such as economically inactive or long-term unemployed individuals, but also present a series of challenges for other individuals (De Stefano, 2016).

37 Driverless vehicle technology is one area that has attracted increasing research interest given its potentially large disruptive impact on the labour market of truck drivers (Executive Office of the President of the United States, 2016; Davey and Toney, 2016).

38 A different approach was adopted in a 2016 report published by the WEF (2016), in which the results of a survey of the main global employers in 15 developed and emerging economies were used to estimate the expected level of changes in job families. The report concludes that technological advancements, including automation, could lead to a net loss of more than 5.1 million jobs between 2015 and 2020 (WEF, 2016). Similarly, Willcocks and Lacity (2016) surveyed a large number of firms in the United Kingdom and conclude by extrapolation that for every 20 jobs lost through robotic process automation, 13 new ones would be created. In addition, the authors estimate that robotic process automation is expected to change at least 25 per cent of each job in the economy in the next five to seven years. Combining the projected likelihood of skills becoming outdated with survey information regarding the occurrence of previous technological change in workplaces, the European Centre for the Development of Vocational Training Combining (2016) estimates that about 10 per cent of the jobs of EU employees could be at risk of technological skill obsolescence. Another approach, adopted by Elliott (2017), is based on a literature review of recent computer science research studies in order to

identify the IT capabilities related to skills used in different jobs that have already been demonstrated to work. The author estimates that occupations representing 82 per cent of current employment in the United States could be vulnerable to displacement by IT over the next few decades.

39 From a labour market perspective, uncertainty and volatility in technology adoption may create an additional burden on the labour market as it needs to absorb excess labour turnover beyond the long-term trend.

40 A strand of the literature also analyses the attitude of trade unions towards technological changes, including with respect to the risk of job displacement, reorganization of work routines and wage formation (Lommerud et al., 2006), and the mechanisms by which trade unions can influence a firm's technology choices (Haucap and Wei, 2004; Addison et al., 2017).

41 Some governments and firms already lament a current labour supply shortage in some science-, technology-, engineering-, and math-related skills required to fill the new job openings fostered by the recent technological developments (Dehaze, 2016). However, several academics and experts have questioned the validity of the claim of these particular labour market shortages, in particular in the United States, by noting the increasing number of studies that directly contradict such claims (Charette, 2013). In particular, the real wage evidence in the United States over the past decade is not suggestive of a strong increase in skill demand in science and engineering occupations. If skill demands were strong and matching skill supplies weak, wage growth should have been faster over the past decade.

42 Some experts argue that while education and training have made it possible to adapt to previous disruptive technological innovations, they are unlikely to mitigate the impact of future automation, because the new wave of technologies are likely to substitute rather than complement skills, implying that that the number of jobs requiring an advanced degree could become limited. In addition, increasing educational attainment, which is already high in many developed and emerging economies, would increase the supply of highly skilled workers and potentially reduce the wage levels of highly skilled workers because of greater competition in the labour market. Lower high skill wages could further reduce the incentive to actually acquire higher education (Avent, 2016; Brynjolfsson and McAfee, 2014).