Chapter 1. The local dimension of job automation

This chapter discusses job automation at the regional level and provides policy recommendations on how to respond to automation. It provides estimates for the risk of automation at the regional level and analyses the factors that are related to this risk. While a significant share of jobs is at risk of automation in all regions, the number varies strongly across countries as well as across regions within countries. Regions with a low share of jobs have a high share of workers with tertiary education, a strong service sector and a large share of urban population.

The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

Box 1.1. Key messages

Disparities across local labour markets are increasing

- Technological progress and globalisation have an uneven impact across local labour markets. Within the same country, some places are able to take advantage of new technologies and greater integration into global markets, thereby attracting firms and workers, while other areas struggle to grow.
- Disparities within countries have increased in terms of the number and quality of new jobs created, unemployment, as well as the educational attainment of the labour force. For example in Turkey, unemployment rates between the best and worst performing regions vary by more than 20 percentage points. Across the OECD, capital regions created 18.1% of all new jobs even though they make up roughly 1% of the number of all regions.
- Demographic disparities are also increasing. More than half of all OECD regions experienced a decline in working age population from 2010 to 2016. Urban areas continue to attract young and educated workers at the expense of rural areas.
- The increasing within-country disparities and the changing nature of work require a flexible and tailored policy response at the local level. Strong policy coordination and complementarities within the management and implementation of employment and skills policies can contribute to the creation of quality jobs.

The uneven impact of automation

- Some jobs are more at risk from automation than others. The geographic distribution of these jobs varies across the OECD. The share of jobs at risk of automation is highest in the West Slovakia region (39%) and lowest in the Oslo and Akershus region (4%) in Norway.
- The magnitude of differences across regions within a country varies, too. Whereas the difference in jobs at risk of automation between the best and worst performing region in Canada is just 1 percentage point, it is 12 percentage points in Spain.
- Regions with smaller risk of automation are characterised by a larger share of workers with tertiary education, a larger proportion of jobs in services, and are highly urbanised.
- From 2011 to 2016, just over half of OECD regions reduced the number of jobs at risk of automation; in the rest of OECD regions, the number of jobs at risk of automation has increased.
- The share of jobs in occupations with a high risk of automation is declining in most regions, whereas the share of jobs at low risk of automation is increasing. This indicates that automation is taking place and easily automatable jobs are being lost. However, in 60% of regions, job creation in occupations at low risk of automation outweighed job losses in occupations at high risk of automation between 2011 and 2016.

- Regions that currently have low productivity growth are likely to be more affected by automation. These regions also tend to have relatively high unemployment rates. This creates a dilemma for policy makers who have to balance the need to foster automation to increase productivity with the need to prevent short-term job losses from automation.
- To address the risk of automation at the regional and local level, training and education of the workforce is essential. However, complementary policies are needed, too. Firms should be encouraged to upgrade their production processes to reduce the risk of automation for a given occupation. Furthermore, the growth of economic sectors with a low risk of automation should be supported. To do this effectively, policy makers need to tailor policies to regional and local economic conditions.

Introduction

Technological progress is rapidly changing the nature of work across the world. It creates new job opportunities and is benefitting consumers. It improves the quality of products while reducing their price and leads to new and innovative products. However, technological progress also threatens established business models and can lead to job losses because it allows the automation of tasks that previously had to be done by manual labour.

Automation has been occurring for centuries. The steam engine is a prominent early example of a technology that saved labour on a massive scale. This labour saving element of technological progress has historically led to fears of 'technological unemployment' (Keynes, 1930). Despite these fears, technological innovations have always given rise to new jobs that provided employment, while the productivity growth from automation has been the most important driver of rising living standards.

Yet, it would be wrong to argue that automation does not pose challenges. In particular, two issues stand out. First, the labour saving effects of automation can be sudden, whereas it might take considerable time until new jobs are created that replace the lost jobs. Second, the skill profiles of jobs that are lost due to automation and the skill profiles of the jobs that replace them are not necessarily the same. Thus, automation can lead to temporary, but possibly prolonged, increases in unemployment. Furthermore, the changing demand for workers with particular skills affects wage levels. It causes permanent gains or losses for some groups of workers

The consequences of sudden and large-scale automation have become the centre of attention in recent years because of new developments in the field of so-called artificial intelligence. New algorithms in combination with the increasing processing power of computers have made it possible for machines to take care of tasks that until now only humans could do. This has raised the spectre that specific functions, which have been impossible to automate until now, could be done by machines instead of people in the future. Importantly, this also affects high-skilled jobs that were in the past largely shielded from automation. While it is impossible to predict precisely how many jobs will be automated in coming years, this report shows that many jobs are threatened by automation.

The impact of automation on regional and local labour markets depends on the characteristics of the local economy; it is therefore asymmetric across places within countries. The geographic dimension of automation has important implications for policy makers trying to design policies that ensure the availability of good quality jobs. When faced with the choice between one-size-fits-all and place-based policies, a series of questions arise. First, as automation gains pace, will jobs disappear evenly across a country or will job losses be concentrated in just a few regions? Second, if job losses are unevenly distributed, what determines which regions will suffer from losses while others thrive? Third, what are the occupations where jobs will be lost or gained? And, finally, how can policies be adapted to meet the individual challenges that each region faces? The analysis conducted in this chapter will attempt to shed light on these questions.

Automation is a critical and perhaps the most important issue affecting labour markets in the near future. Yet, it is not the only change that will affect local employment. Other important trends such as demographic change, increasing international and domestic migration and developments related to international trade also have important implications for local labour markets. The full impact of automation can only be understood in the context of these developments. For example, automation may be considered much more of an opportunity in a place that has an aging population and faces a shortage of workers than in a place that has a high birth rate with many young people entering the labour market in search of jobs.

The chapter is structured as follows. To set the scene, it will start out by describing the most important of these overarching trends and how they affect local labour markets. Subsequently, the chapter will discuss automation within this broader context. It will discuss the implications of automation for different groups of regions. It will provide estimates on the share of jobs at risk of automation at the regional level and of the sectors that are affected by automation.

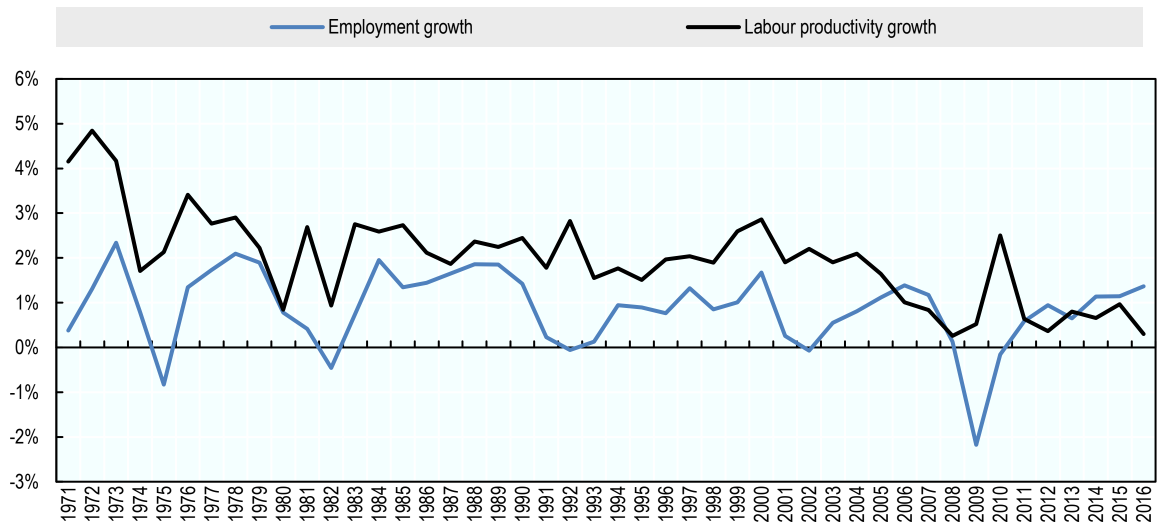
Labour markets are changing across OECD countries

The financial crisis, which erupted in 2008, caused an exceptionally large drop in employment. In contrast to previous recessions, employment recovered only slowly (Figure 1.1) and employment levels only recently reached pre-crisis levels in many countries.

Average labour productivity growth has been in decline since the mid-2000s and labour productivity growth rates have fluctuated around 1% in recent years in major economies. The brief increase in productivity growth rates during the crisis in 2010 was the consequence of the drop in employment in 2009 and is not an indication of a structural change. The decline in labour productivity growth is a concern because labour productivity growth is the most important determinant of long-term economic growth. Without growing labour productivity, sustainable wage growth is impossible in the long term.

Figure 1.1. Long-term trends in labour productivity growth and employment growth

Employment and labour productivity (per hour worked), annual growth rates, G7 countries, 1971 - 2016, %



Source: Calculations based on OECD (2017), "GDP per capita and productivity growth", OECD Productivity.

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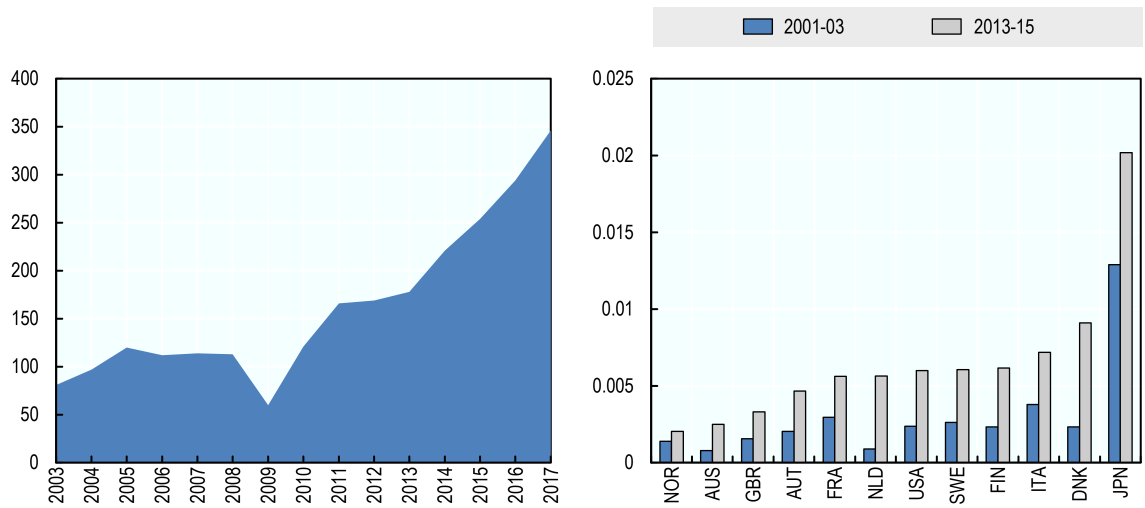
The decline in labour productivity has come despite an increase in digitalisation and automation. At the beginning of the century, 100 000 industrial robots were delivered each year across the world (World Robots, 2016). By 2016, the number of new industrial robots reached 300 000 annually (Figure 1.2, Panel A). This aggregate pattern is reflected in an increase in the use of robots in several OECD countries. In most OECD countries, the number of industrial robots per employee has doubled over the last 15 years (Figure 1.2, Panel B). Many economic models predict that increasing digitalisation and a growing use of industrial robots will lead to higher labour productivity growth. Why this is not the case is an important unresolved question in the economic debate.

Taken together, the slowdown in labour productivity growth and the increasing employment volatility point to the shifting nature of jobs. However, the way in which jobs will change is far from being universal. Some workers will benefit from new technology that makes their jobs more pleasant and leads to rising wages. Other workers will struggle to adapt to the new environment and will face job losses. Since prospective winners and losers are unevenly distributed within countries, some places will fare better than others.

Figure 1.2. The use of industrial robots across the OECD

Panel A. Worldwide annual supply of industrial robots (thousands)

Panel B. Number of robots per worker, all sectors, selected OECD countries



Note: In Panel A, 2017 figures are estimates. In Panel B, the initial period (in blue) refers to an average of the indicator between 2001 and 2003; the last period (in grey) refers to an average of the indicator between 2013 and 2015.
Source: IFR World Robotics 2017 and Calvino et al (2018), "A taxonomy of digital intensive sectors", OECD Science, Technology and Industry Working Papers, No. 2018/14, https://doi.org/10.1787/f404736a-en.

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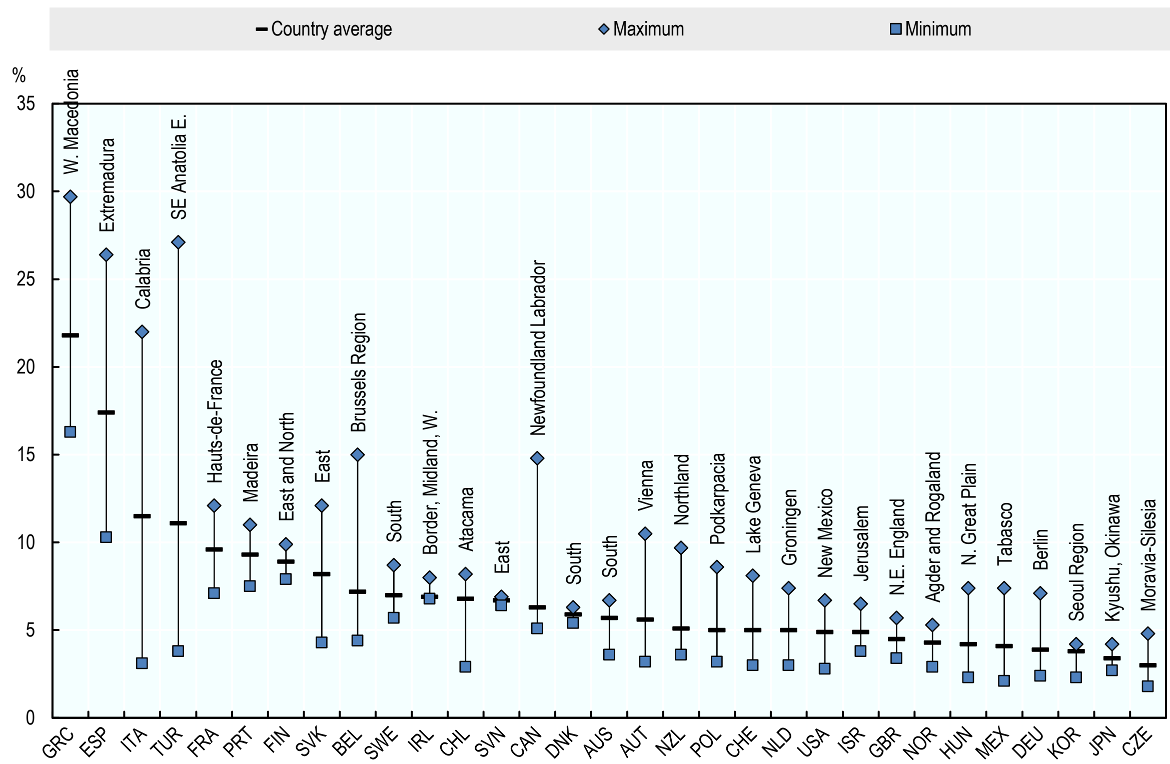
Persistent and substantial differences in unemployment across regions within the same country

Although national unemployment rates have mostly returned to the levels seen prior to the global financial crisis, large differences still remain within countries. National labour policies (e.g. training programmes, employment regulations, etc.) target people wherever they live and work, but job opportunities are not equally distributed across places. Regional disparities are largest in Turkey, Italy, Spain and Greece, where unemployment rates between the best and worst performing region vary by approximately 20 percentage points (Figure 1.3). In other countries, regional disparities are smaller but still around 5-10 percentage points. Naturally, smaller countries tend to have smaller regional disparities. However, some OECD countries prove that even large countries can have small inter-regional labour market disparities. For instance, Japan is the second largest OECD country by population, but has one of the smallest differences in unemployment rates between the best and worst performing regions.

Figure 1.3. Large disparities in unemployment rate across OECD regions

Unemployment rates, TL2 regions and country averages, 2017



Note: The top blue diamond represents the region with the highest unemployment rate, the bottom blue diamond corresponds to the region with the lowest unemployment rate in the country. The short horizontal bar is the national average. It is important to note that the figure reflects regional and not local disparities within countries. However, they can be interpreted as lower bounds for the variation across local labour markets, which is likely to be even higher than the variation shown in Figure 1.3 (see Box 1.3).
Source: Adapted from OECD (2018, forthcoming), Regions at a Glance 2018.

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Box 1.2. The geographic scale of data used in this report

Local labour markets vary in size and shape and often do not correspond to administrative boundaries. This makes it difficult to identify these markets and even more difficult to collect data for them. Even though various OECD member countries work on measuring local labour markets and on collecting data for them, internationally comparable data on local labour markets in particular, and on subnational regions in general, is still scarce.

The OECD collects subnational data at three geographic scales for regions that are designed to be internationally comparable in size. Data at a large regional scale is available at the so-called Territorial Level 2. TL2 regions typically have a population of several million inhabitants. Especially in larger OECD countries, they often correspond to the first level of subnational government. At a smaller regional scale, the OECD collects data at the Territorial Level 3 (TL3). TL3 regions, as defined by the OECD, typically cover several hundred thousand inhabitants. While TL3 regions were not designed to match local labour markets, many are suitable approximations of local labour markets. Lastly, the OECD collects data for metropolitan areas. Whereas TL2 and TL3 regions cover the entirety of a country, metropolitan areas cover only urban agglomerations with more than 500,000 inhabitants.

Generally, data availability is best for TL2 regions, followed by TL3 regions and lastly metropolitan areas. Whenever possible, this report uses data at the TL3 level to reflect its focus on local labour markets.

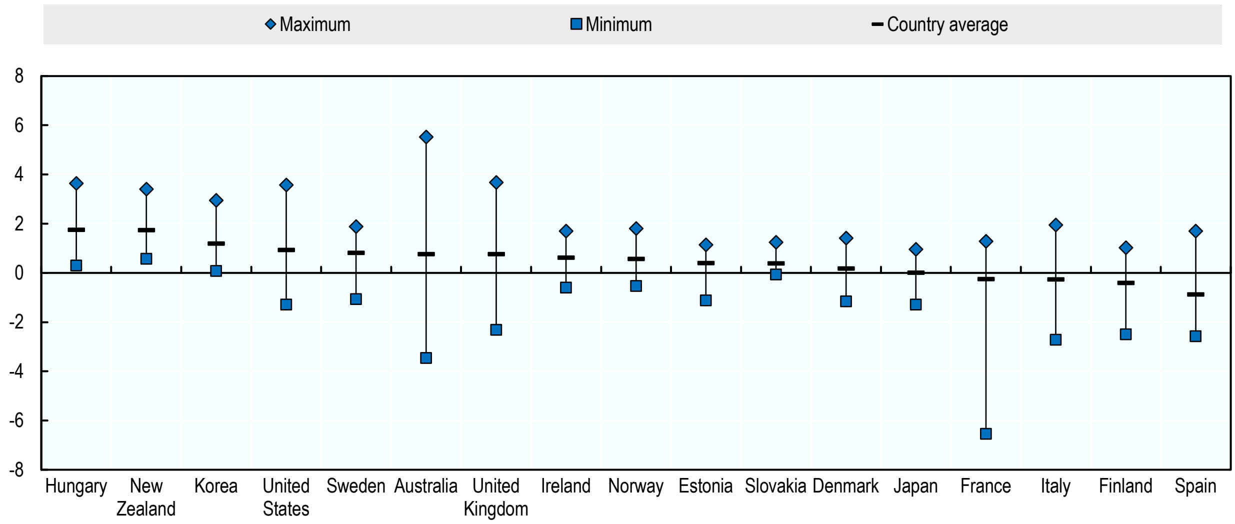
When data at the TL3 level is not available, the report uses TL2 data. In these instances, the data does not reflect local labour markets, but the regional variation that it reflects is indicative of the variation across local labour markets. For many analyses, the regional variation at the TL2 level within a country is a lower bound of the actual variation across local labour markets within the country. In these instances, the variation across local labour markets is at least as high as the variation across TL2 regions and most likely even higher.

Some places manage to take advantage of the changing economic environment. They attract firms and workers while others lag behind and struggle to grow. This is partly because of their existing industrial specialisation and the skills of the workforce that matches the needs of growing economic sectors. For example, many German regions that had a strong industrial base in the manufacturing of machinery managed to benefit from the rise of China’s rapidly growing manufacturing sector by supplying the machines and tools for it. Other regions have advantages because of factors such as population density, geographical location or resource availability. Large cities for example are the preferred location for providers of knowledge-intensive services, which have become much more important compared with previous decades.

However, regional development is not a deterministic process that is driven by laws of nature. Even if some regions have more favourable conditions than others, the wide range of outcomes across regions with similar starting conditions shows that policy choices still play a crucial role in determining regional economic performance. Some regions manage to perform well despite difficult starting conditions, whereas others fail to capitalize on their initial advantages and fall behind.

Figure 1.4. Small aggregate changes in employment growth mask larger changes at the local level

Annual employment growth rate in TL3 regions, average over the period 2011-2016.



Note: Calculations refer to annual employment growth rates for the population aged 15 and older.
Source: OECD (2018), OECD Regional Statistics (database), http://dx.doi.org/10.1787/region-data-en.

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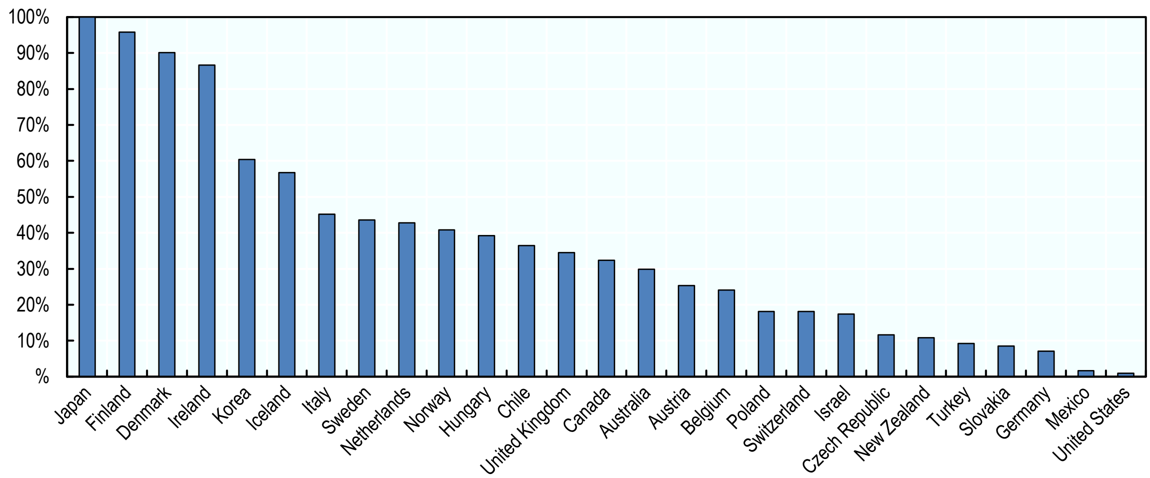
These factors become apparent in the capacity of local economies to create jobs. In some countries, such as Spain, Australia or Italy, the average (aggregate) employment growth was close to zero over the 2011-16 period. Yet, some regions achieved substantial job creation, whereas others suffered significant declines. Figure 1.4 shows that there is often significant regional variation even in countries that see little change in aggregate employment at the national level.

Regional disparities in job creation are reflected in a more unequal distribution of jobs within countries. This implies that jobs are increasingly concentrated in just a few regions. Figure 1.5 shows that in many countries, capital regions were responsible for a substantial share of net job creation. Across the OECD, capital regions created 18.1% of all jobs even though they make up roughly 1% of the total number of regions. This phenomenon cannot be attributed to the global financial crisis that hit most OECD economies in 2007-08, as a similar trend is present also in the period leading up to the crisis.

Figure 1.5. Job creation is largely concentrated in capital regions

Share of net job creation in capital regions relative to total job creation, TL2 regions, 2006-2016 (%).



Note: Capital regions in Portugal, Spain and Slovenia lost jobs over the 2006-2016 period. Due to data availability, the values for Chile, Israel and Mexico cover the 2006-2014 period.
Source: Calculations based on OECD (2018), OECD Regional Statistics (database), http://dx.doi.org/10.1787/region-data-en.

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Globalisation had strong effects on labour markets in some sectors. The combined effects of greater integration into global value chains have accentuated the difference between firms and places that are able to compete globally and those that have struggled with this transition. For instance, in some regions the manufacturing sector benefited from increasing trade openness whereas it suffered in others. For example, regions in the Slovak Republic that have strong automotive clusters were among the beneficiaries of trade openness, whereas many regions across the OECD that had strong textile manufacturing lost out.

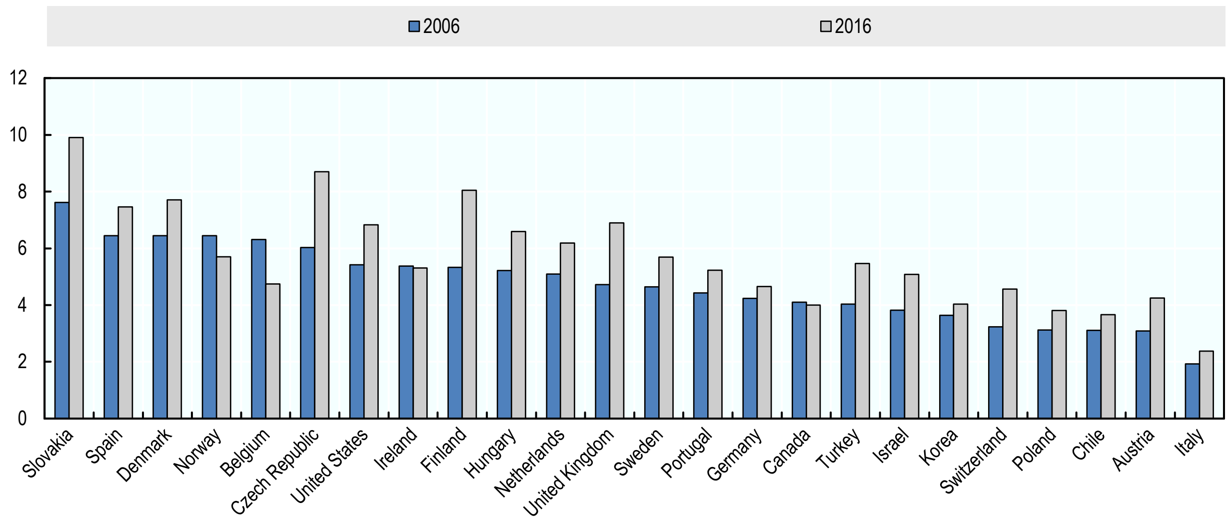
While globalisation had significant effects on some regions it is important not to overstate the impact of globalisation on regional and local disparities. In many cases, regional performance is influenced to a much greater extent by local, regional and national policy choices as well as by technological developments than by global competition.

The demographic composition of regions is changing

Education levels in most regions have been increasing. Often the increase has been larger in absolute terms in regions that already had a high education level in 2006. This has led to a growing gap in terms of tertiary education attainment of the labour force between the top and bottom region within each country over the period 2006-2016 in most OECD countries. These results are in line with similar results from the previous edition of *Job Creation and Local Economic Development 2016* (OECD, 2016b), which also highlighted the increasing gap in the share of workers with tertiary education as one of the main challenges for local labour market policies. Figure 1.6 shows that the increasing absolute difference in education level has led to a growing standard deviation in educational attainment across regions.

Figure 1.6. Within-country variation in education levels of workers is widening

Standard deviation across TL2 regions in the share of tertiary-educated people in the labour force, 2006 and 2016.



Note: The graph shows the standard deviation of the share of tertiary educated people (ISCED 5-9) in the labour force across TL2 regions within the same country.

Source: Calculations based on OECD (2018), OECD Regional Statistics (database), http://dx.doi.org/10.1787/region-data-en.

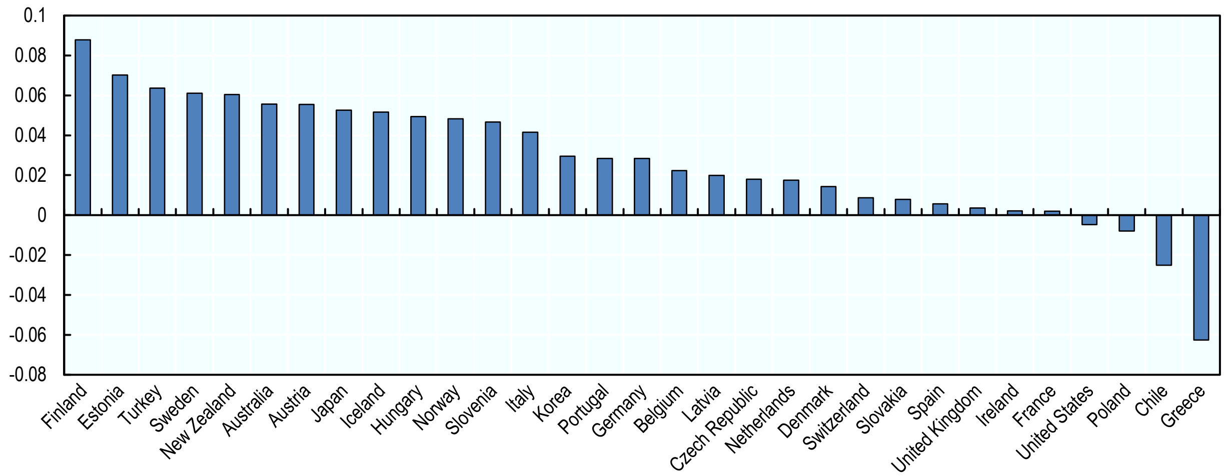
StatLink https://doi.org/10.1787/888933824515

Population aging and intra-regional migration affect the availability of workers in the local economy. Population aging is a source of concern for most developed countries, and it can create significant challenges. Low birth rates and increasing life expectancy shifts the old-age dependency ratio, i.e. the ratio between people of working age and people at retirement age.

While only some OECD countries such as Japan are currently facing shrinking working age populations in aggregate, many individual regions are strongly affected by it. More than half of all TL3 regions experienced shrinking working age populations between 2010 and 2016. Often, such a decline is due to the outmigration of working age people from the region. If the local economy loses workers, especially young and well-educated ones, it may become difficult to promote economic growth. This phenomenon is not uniform across local economies; outflows of working age individuals tend to affect rural regions predominantly. Figure 1.7 shows that the disparities across regions in the number of working age population have increased since 2006.

Figure 1.7. People of working age population are increasingly concentrated in certain regions

Change in the regional disparity of working-age population among TL3 regions, selected OECD countries, 2006-16



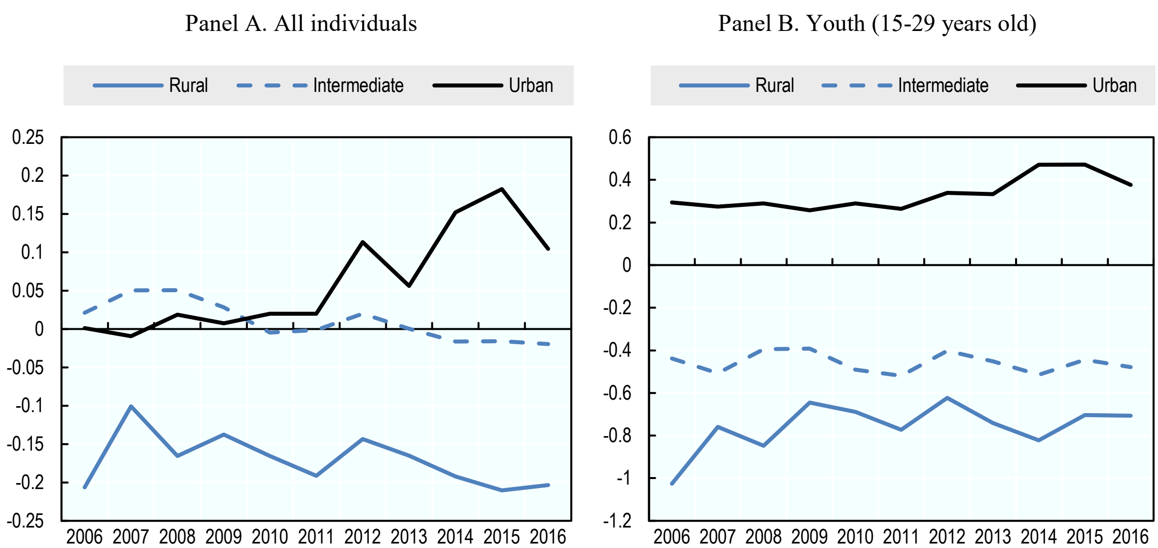
Note: The chart shows the change in the coefficient of variation (see Box 1.2) in working age population (15-64) across TL3 regions within the same country between 2006 and 2016. The values for Turkey correspond to the period 2008-2016.
Source: Calculations based on OECD (2018), OECD Regional Statistics (database), http://dx.doi.org/10.1787/region-data-en.

StatLink https://doi.org/10.1787/888933824534

Figure 1.8 shows the average net population flows in urban, rural and intermediate regions. It is apparent that there are important systematic differences in net migration flows. Whereas urban regions record persistent inflows, intermediate regions have a roughly balanced migration balance and rural regions record persistent outflows. The trend of migration towards urban regions is even more striking among young people aged 15-29.

Figure 1.8. Inter-regional migration flows between urban and rural regions

Inter-regional net migration rate, TL3 regions in selected OECD countries, 2006-2016



Note: Panel A includes TL3 regions in Australia, Austria, Canada, Czech Republic, Denmark, Estonia, Finland, Hungary, Iceland, Japan, Korea, Norway, Poland, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey and United Kingdom. Panel B includes TL3 regions in Australia, Canada, Czech Republic, Denmark, Finland, Hungary, Iceland, Korea, Poland, Sweden, Switzerland and Turkey.
Source: OECD (2018), OECD Regional Statistics (database), http://dx.doi.org/10.1787/region-data-en.

StatLink https://doi.org/10.1787/888933824553

Automation is transforming labour markets

In the context of far-ranging changes to the socio-demographic composition of regions, technological progress and automation are shaping labour markets. They offer regions new opportunities, but can also increase the divergence in labour market outcomes within and across regions.

Automation is a source of productivity growth that increases prosperity and raises living standards. Without labour saving machinery, most people would still be engaged in basic manual tasks and economic output and living standards would have been drastically lower. To increase prosperity further, continued technological progress and automation is needed.

However, rapid automation may create losers. Workers whose jobs have been automated do not always have the skills that are being sought after in changing labour markets and struggle to find new jobs. Likewise, firms that do not keep pace with growing automation may become uncompetitive. Furthermore, automation can lead to growing inequality among people, both because it affects the income distribution across different groups of workers as well as between labour and capital more generally.

Concerns over automation have increased in recent years because of technological progress in so-called artificial intelligence. This has made it possible to automate tasks that could previously only be done by humans. One widely held view is that digital advances have been so great that they have affected workers' comparative advantage, vastly reducing the number of tasks to which human labour is required. Thus, digital advances can potentially lead to the automation of a wide range of tasks that have, until now, been shielded from automation.

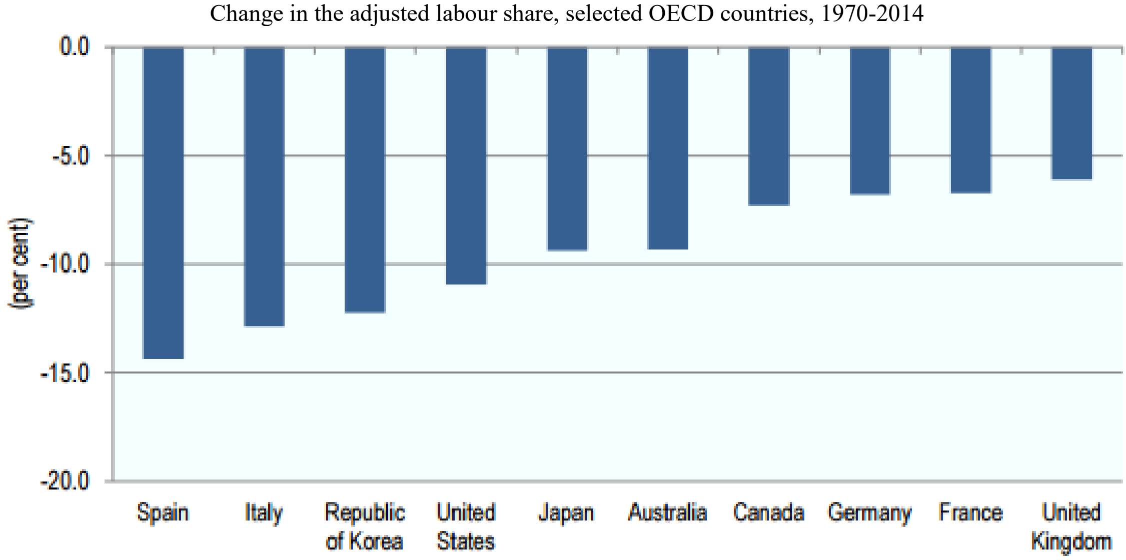
Freeman (2015) argues that the increasing substitutability of human labour with machine labour will exert severe downward pressure on wages. Since the costs of machines that can replace human labour are likely to decline, humans have to accept ever lower wages to compete for jobs. In the past, this effect was mitigated by the fact that many tasks could not be done by machines. However, this moderating factor will be much weaker in the future as machines become increasingly sophisticated. As a consequence, the labour share of total income could decline as most profits accrue to the owners of robots and algorithms.

A series of recent studies have found declining labour shares in many countries, developed and developing alike (Karabarbounis and Neiman, 2013; Piketty, 2013; Schwellnus, Kappeler and Pionnier, 2017). The labour share is the share of total national income that is paid in wages. Historically, it changes only slowly, but a continuous decline can be observed for the last few decades (Figure 1.9). Among the 10 countries for which long-term data exist, the labour share has declined from 65% in 1970 to 56% in 2014.

There are many possible explanations for the decline in the labour share. These may include changes in labour laws and in particular in collective wage bargaining and increasing trade openness. Furthermore, economic activity has been shifting to sectors that have typically a lower labour share. However, the decline in labour was at least partially due to greater automation over that time period (OECD, 2018a). Acemoglu and Restropo (2016) find that the expanding use of robots in the US is associated with a reduction both in wages and in the employment rate. This is particularly true in sectors with a higher concentration of occupations involving routine tasks, which are easier and cheaper to automate (Dao et al., 2017; Autor and Salomons, 2018).

Figure 1.9. The share of wages within national income has declined

Change in the adjusted labour share, selected OECD countries, 1970-2014

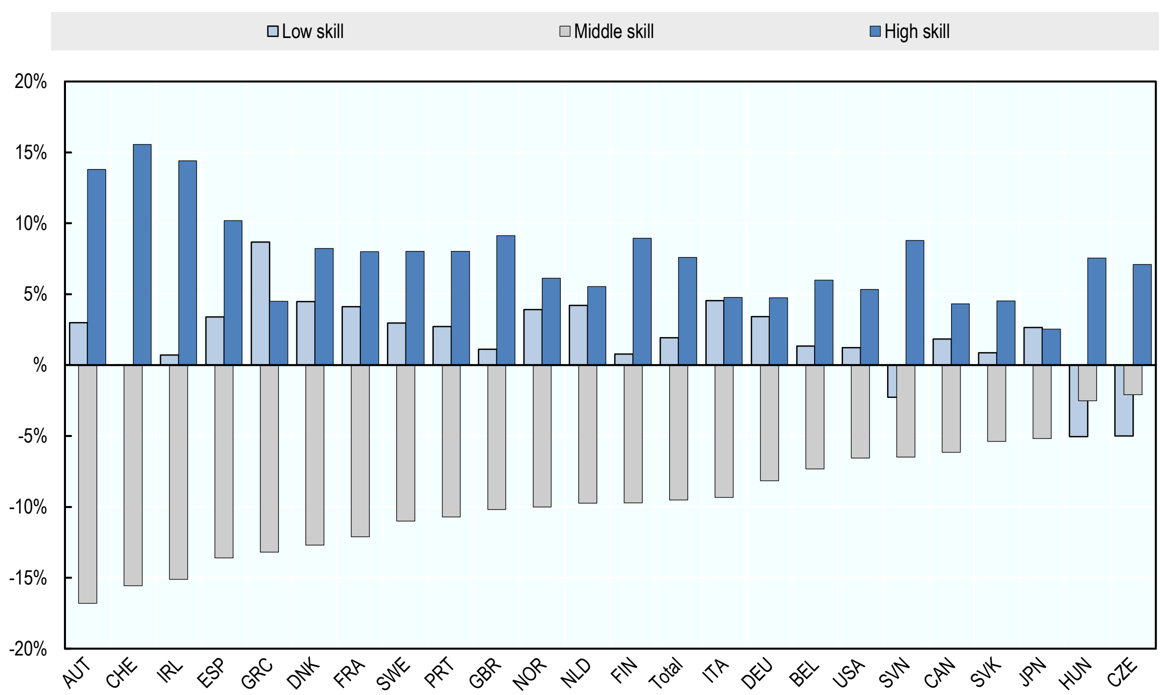


Note: Data for the Republic of Korea only includes the 1991-2014 period. In the case of Germany, prior to 1991 the adjusted labour income share refers to West Germany.
Source: ILO and OECD, *The Labour Share in G20 Economies* (ILO and OECD, 2015).

Beyond putting downward pressure on wages, automation also leads to a polarisation of required skills in the labour market (Autor, Katz and Kearney, 2006; Goos, Manning and Salomons, 2014; OECD, 2016a). Autor (2015) argues that a large proportion of middle-wage occupations, such as manufacturing or clerical jobs, are highly reliant on easily automatable routine tasks. Consequently, OECD countries have seen a decline in middle-wage, middle skill employment as a share of the workforce over the past two decades (Figure 1.10). In contrast, workers who complete non-routine tasks have increased their share of total employment. Typically, these jobs are either high-skilled (e.g. managerial positions) or low-skilled (e.g. basic services). Thus, both ends of the skill-distribution of jobs have increased while the middle has declined. Although jobs in low-skilled occupations have increased, they have borne the brunt of the falling labour share, raising important questions regarding patterns of future productivity, inequality and job quality (Autor and Dorn, 2013; Goos, Manning and Salomons, 2014). These issues are further discussed in Chapter 3.

Figure 1.10. Change in the share of jobs by skill level

Percentage point change in the share of total employment by type of skills, 1995-2015.



Note: High skill occupations include jobs classified under the ISCO-88 major groups 1, 2, and 3. Middle skilled occupations include jobs classified under the ISCO-88 major groups 4, 7, and 8. Low-skilled occupations include jobs classified under the ISCO-88 major groups 5 and 9. For more details refer to the OECD Employment Outlook 2017

Source: OECD Employment Outlook 2017 (OECD, 2017b).

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A major challenge for policy makers will be to help workers adapt their skills to a labour market in which ever more tasks can be completed by machines. Workers in occupations at high risk of automation already suffer from much higher rates of unemployment than their counterparts in low-risk jobs. They also make less money: Nedelkoska and Quitini (2018) find that a 10% increase in automation risk is associated with a drop of over 4% in hourly earnings. But the challenges do not end there. Technological improvements are taking place rapidly. This suggests that the tasks that can be done only by humans may shift very quickly. In recent years, there have been increasing indications that even some jobs in high-skilled occupations could be at risk of automation. Thus, even high-skilled workers need to become more flexible in finding their comparative advantage relative to machines.

Automation has a regional dimension

Previous waves of technological breakthroughs have shown that automation does not spread evenly across space. This is due to the fact that automatable tasks are more prevalent in certain occupations and sectors, and neither occupations nor sectors are evenly distributed within national borders. Thus, areas with a higher proportion of jobs relying on routine tasks are likely to experience more disruption, whereas places where more jobs require tacit skills will face lower levels of risk. Tacit skills are based on experience and intuition instead of formal rules. Thus, they are more difficult to replicate through mechanical processes or standard algorithms.

A recent study by Rahwan et al. (2018) highlights that regional specialisation affects the patterns of risk of automation among US metropolitan areas. In particular, between one-half and three-quarters of workers in metropolitan areas may face severe disruption in the near future. This risk decreases with the size of the city, in part because larger cities have a higher share of employment in occupations whose tasks are more resilient to automation (Rahwan et al., 2018).

Regional labour shocks caused by automation are likely to remain geographically concentrated. As technology penetrates an economy, a high proportion of low- or middle-skill workers in a given region may find themselves forced to transition into a different job over the next few years. In addition, while the jobs lost may be concentrated in a few regions, new jobs may well emerge in entirely different regions. Inter-regional migration is one way in which these regional labour market imbalances can be resolved within national borders. Migration patterns such as the one displayed in Figure 1.8 usually flow from regions with poor job prospects to regions with good job prospects. Workers who recently lost their job due to automation can find work by moving to a different part of the country where demand for labour is higher. Geographical mobility of labour thus increases the dynamism of an economy and helps to reduce spatial inequalities (Blanchard and Katz, 1992).

However, there are several factors limiting the effectiveness of inter-regional migration as an adjustment mechanism. First, while mobility can be an important structural adjustment mechanism in the long term, it is rarely a short-term solution. People may find themselves out of a job and struggle to find a new one; but they also have family obligations, friends, financial responsibilities, etc. that are tied to where they currently live in.

Second, geographical mobility is more restricted for low-skilled workers. This is due to the monetary and non-monetary fixed costs of moving that are proportionally higher relative to income gains from moving for workers with low incomes. The costs of moving are relatively similar for workers at all income levels. This includes monetary costs, for example related to transporting furniture as well as non-monetary costs, such as the effort required to find new friends. For high-income workers these costs are often outweighed by the financial gains of finding a new job rather than staying unemployed. However, for low-income workers the financial gains from moving are frequently not enough to make up for the costs. This is especially a problem in countries where house prices and rents are elevated in economically successful areas and much of the financial gains from higher wages would be absorbed by higher housing costs.

Furthermore, in some countries mobility is limited by administrative hurdles, such as the fact that social insurance benefits sometimes cannot be transferred across regions within a country or professional licensing requirements that vary across regions. Typically, these problems occur primarily in federal countries, where the administrative responsibility for these areas falls to federal states.

Thus, even under the most optimistic assumptions, it is unlikely that labour market mobility can make up for the uneven impact of automation across local labour markets. Thus, public policy needs to respond to shocks at the local and regional level with targeted measures that take the concrete local impact from automation into account. The following section discusses how the impact of automation is distributed across regions. The policy implications that arise from the analysis are discussed at the end of this chapter.

How to measure the risk of automation

The main challenge in the estimation of the number of jobs at risk of automation is the definition of which tasks are actually subject to automation. In recent years several studies have attempted to understand how the development of digital capabilities is likely to affect employment. Starting from a single question: "what is it that computers do – or what is it that people do with computers – that appears to increase demand for educated workers?" (Autor, Levy and Murnane, 2003, p. 1280), the topic has since been extended to tackle the broader issue of how computers complement or substitute for human skills in the workplace.

The most commonly cited study trying to measure of automation is Frey and Osborne (2013). The authors try to find out how susceptible jobs are to being automated through machine learning techniques. Building on expert judgements, the authors themselves use machine learning to identify occupations that can be automated and those that cannot. Jobs that require the following skills are considered to be safe from automation:

a. Tasks linked to *perception and manipulation*, especially if they require being involved in unstructured processes such as working in cramped workspaces.

b. Tasks that require *creativity*, such as artistic activities or coming up with original ideas.

c. Tasks that rely on *social intelligence*, such as being persuasive, negotiating aspects of a project or caring for others.

About 47% of US employment is at high risk of automation according to Frey and Osborne (2013). The authors also warn that "recent developments in machine learning will put a substantial share of employment, across a wide range of occupations, at risk in the near future" (Frey and Osborne, 2013). A summary of their methodological approach is provided in Box 1.4.

However, recent studies by the OECD that build on the methodology of Frey and Osborne (2013) - but use more detailed data - find that the risk of automation is considerably lower. Nedelkoska and Quintini (2018) find that only 14% of all jobs across the OECD are at a high risk of automation, while another 32% are likely to be affected by significant modifications. Arntz, Gregory and Zierahn (2016) even found, for a sample of 21 OECD countries, that only 9% of jobs are at high risk of automation.

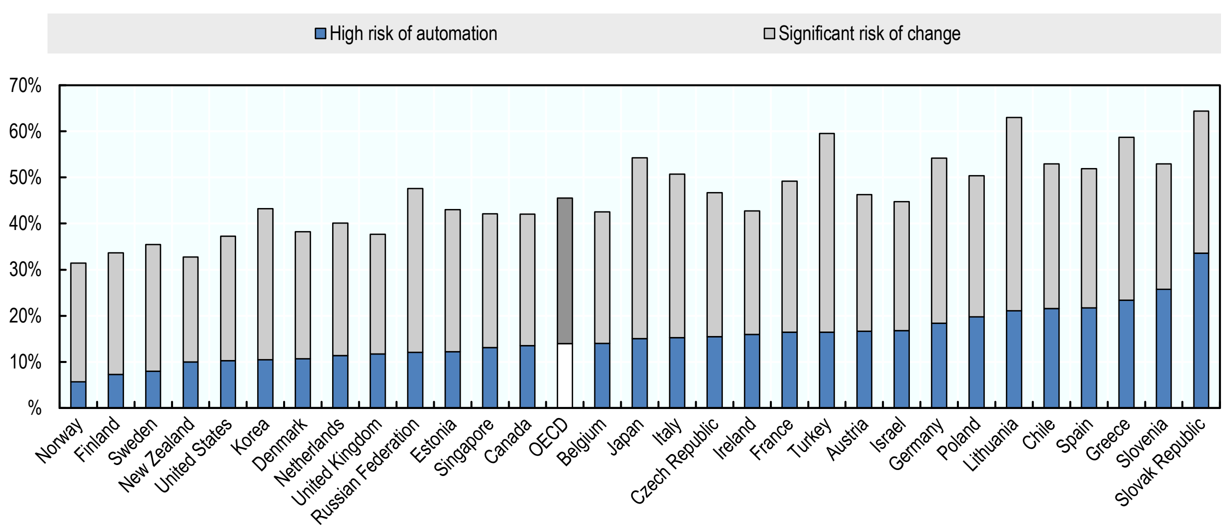
The diverging estimates are due to better occupational data used by the latter studies. Nedelkoska and Quintini (2018) use data from the OECD's PIAAC survey that has a more granular occupational classification than the data used by Frey and Osborne (2013). It also makes it possible to link tasks to occupations on the individual level. Based on this data, Nedelkoska and Quintini (2018) estimate that a larger share of jobs than previously assumed involve tasks that are difficult to automate.

The share of jobs at high risk of automation varies strongly across countries (see Figure 1.11). In line with the literature, a job is considered to be at high risk of automation if it has a 70% or higher probability of being automated. The percentage of jobs at high risk of automation ranges from 5.7% in Norway to 33.6% in the Slovak Republic. More generally, Northern Europe (the Scandinavian countries and the United Kingdom), North America (Canada and the United States) and New Zealand face relatively low levels of risk. At the other end of the distribution, Southern and Eastern Europe face a much higher risk of automation.

Contrary to what may be expected, these differences are not due to sectoral differences in the respective economies. Rather, they are due to the different organisation of jobs in those countries. Jobs in Southern and Eastern Europe are more likely to have automatable aspects than jobs of the same job family in the other countries (Nedelkoska and Quintini, 2018). For example, workers on an assembly line might only do a manual task that is at high risk of automation in one country. In another country, workers in the same occupation might also monitor an industrial robot and take care of quality control measures. In this case, jobs in the occupation in the second country are at much lower risk than in the first country.

Figure 1.11. Jobs at risk of automation by country

Percentage of jobs at significant and high risk of automation by country (%), 2013



Note: 'High risk of automation' refers to the share of workers whose jobs face a risk of automation of 70% or above. 'Significant risk of change' reflects the share of workers whose jobs have a 50-70% chance of being automated.

Source: Nedelkoska and Quintini (2018), "Automation, Skills Use and Training", *OECD Social, Employment and Migration Working Papers*, No. 202, (Nedelkoska and Quintini, 2018).

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Importantly, the methodology to estimate the risk of automation in an occupation can account for differences in the risk across countries but it cannot show how the risk of automation within an occupation changes over time. This introduces an important caveat. Countries or regions might respond to the threat of automation not only by shifting into economic sectors that have a lower risk of automation, but also by adapting the task profile of occupations so that they become less susceptible to automation. With the current methodology, it is impossible to capture the latter effect. Estimates that show how the number of jobs at risk of automation changes over time are based on how the number of jobs in different occupations changes over time. In other words, they show how regions gain or lose jobs in risky and less risky occupations.

Box 1.3. Estimating the risk of automation in OECD countries

Frey and Osborne (FO) estimated the number of occupations at high risk of automation in the United States, using a two-step methodology.

Firstly, they conducted a workshop with a group of experts in machine learning, whom they provided with a list of 70 occupations and their corresponding O*NET task descriptions.[1] They were then asked "Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment?" This allowed for the coding of each occupation either as automatable or non-automatable.

They then used a machine learning algorithm to find out more about the links between the coding to automate and the list of O*NET variables. They were able to identify those variables (and their associated bottlenecks) with higher prediction power (Table 1.1). High scores on these bottlenecks are likely to mean that an occupation is safe from automation. They could then compute a 'probability of computerisation' for each occupation in the US, leading to the aggregate estimate that 47% of US jobs have a probability of automation of more than 70%.

Table 1.1. Bottlenecks to automation

Computerisation bottleneck	O*NET variable
Perception and Manipulation	Finger dexterity
	Manual dexterity
	Cramped workspace; awkward positions
Creative intelligence	Originality
	Fine arts
Social intelligence	Social perceptiveness
	Negotiation
	Persuasion
	Assisting and caring for others

Note: Please refer to the reference below for further details on the definition of the automation bottlenecks.
Source: Frey and Osborne (2013), "The Future of Employment: How Susceptible are Jobs to Computerisation?," *Technological Forecasting and Social Change*, Vol. 114/C, (Frey and Osborne, 2013).

Box 1.4. Estimating the risk of automation in OECD countries (2)

The OECD built on this approach to calculate the risk of automation across 32 countries (Nedelkoska and Quintini, 2018). The analysis was based on individual level data from the OECD Survey of Adult Skills (PIAAC), which provides insight into the skill composition of each person's job as well as their skillset. The methodology used closely follows FO, with four exceptions: first, the training data in Nedelkoska and Quintini (NQ) is drawn from Canada in order to exploit this country's much larger sample in PIAAC; second, O*NET occupational data for FO's 70 original occupations had to be manually recoded into the International Standard Classification of Occupations (ISCO) to allow for the correspondence between countries; third, NQ use a logistic regression model to estimate the risk of automation for every occupation and country instead of FO's Gaussian process classifier; and lastly, equivalents had to be found in PIAAC to match FO's bottleneck variables.

While PIAAC does include variables that broadly address each of the three bottlenecks identified by FO, no perfect match exists for all variables within each bottleneck. Crucially, no questions in PIAAC could be identified to account for job elements related to "assisting and caring for others".[2] Given that this variable is related to occupations in health and social services that account for an important part of employment in most OECD economies, reported risks of automation based on this methodology are likely to be slightly overestimated.

Table 1.2. Automation bottleneck correspondence

FO computerisation bottleneck	PIAAC variable
Perception and Manipulation	Finger dexterity
Creative intelligence	Problem solving (simple)
	Problem solving (complex)
Social intelligence	Teaching
	Advising
	Planning for others
	Communication
	Negotiation
	Influence
	Sales

Note: Please refer to the source below for further details on the definition of the PIAAC variables.
Source: Nedelkoska and Quintini (2018), "Automation, Skills Use and Training", *OECD Social, Employment and Migration Working Papers*, No. 202, (Nedelkoska and Quintini, 2018).

Just as there are varying risks of automation within the same occupation across countries, it is likely that the risk of automation in an occupation can change significantly over time. National and subnational governments can influence this change. For example, regions might train workers to enable them to do a broader range of tasks within their occupation, which reduces the risk of automation. The estimates in this report cannot capture the effect of such a policy, because they assign a fixed risk of automation to each occupation. However, policies that reduce the risk of automation within an occupation are discussed at the end of the chapter.

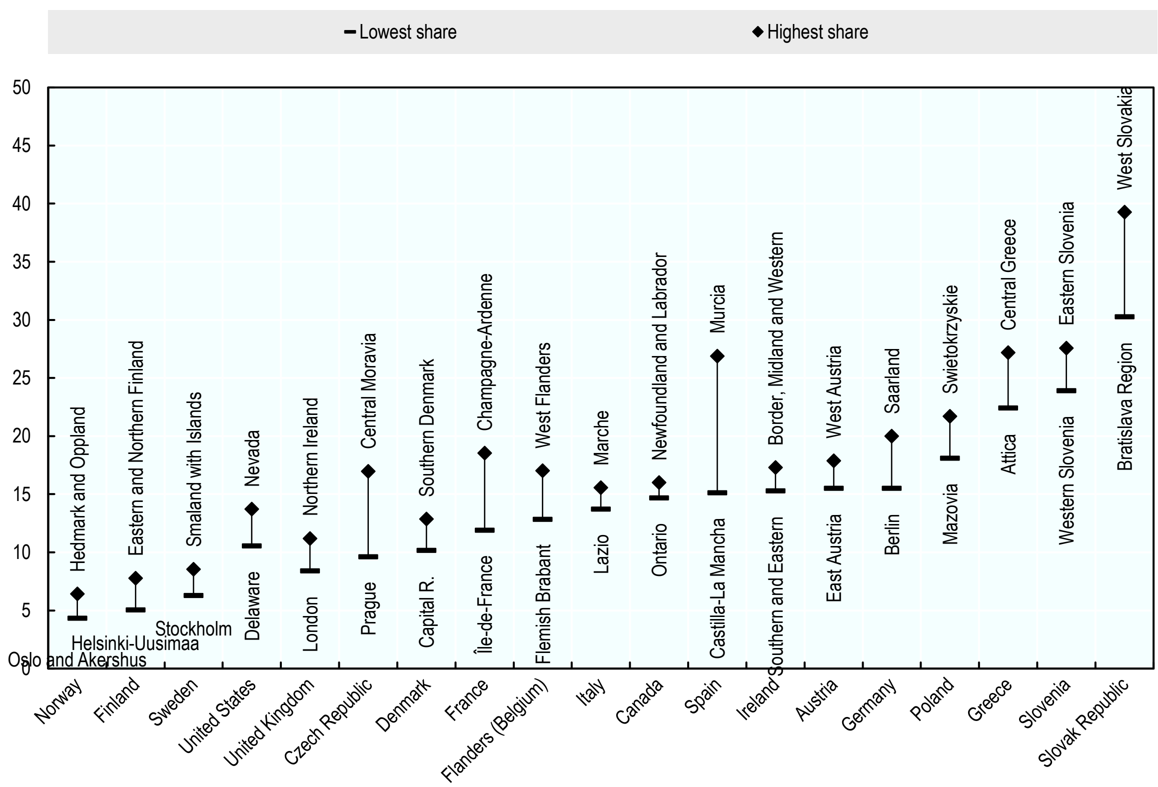
The asymmetric risk of automation at the regional and local level

How high is the risk of automation at the local level?

There are large within-country differences in the number of jobs at risk of automation. To produce subnational estimates, the results of Nedelkoska and Quintini (2018) are applied at the regional scale. For each region, the share of jobs at risk of automation is calculated using data on regional employment by occupation and the estimated probabilities of automation from Nedelkoska and Quintini (2018). As an approximation, the method assumes that jobs within the same job category have the same risk of automation across all regions of a country.

Figure 1.12. Some countries have wide disparities in terms of risk of automation across regions

Percentage of jobs at high risk of automation, highest and lowest performing TL2 regions, by country, 2016



Note: High risk of automation refers to the share of workers whose jobs face a risk of automation of 70% or above Data from Germany corresponds to the year 2013. Except for Flanders (Belgium), for which sub-regions are considered (corresponding to NUTS2 level of the European Classification).
Source: OECD calculations based on (Nedelkoska and Quintini, 2018) and national Labour Force Surveys (2016).

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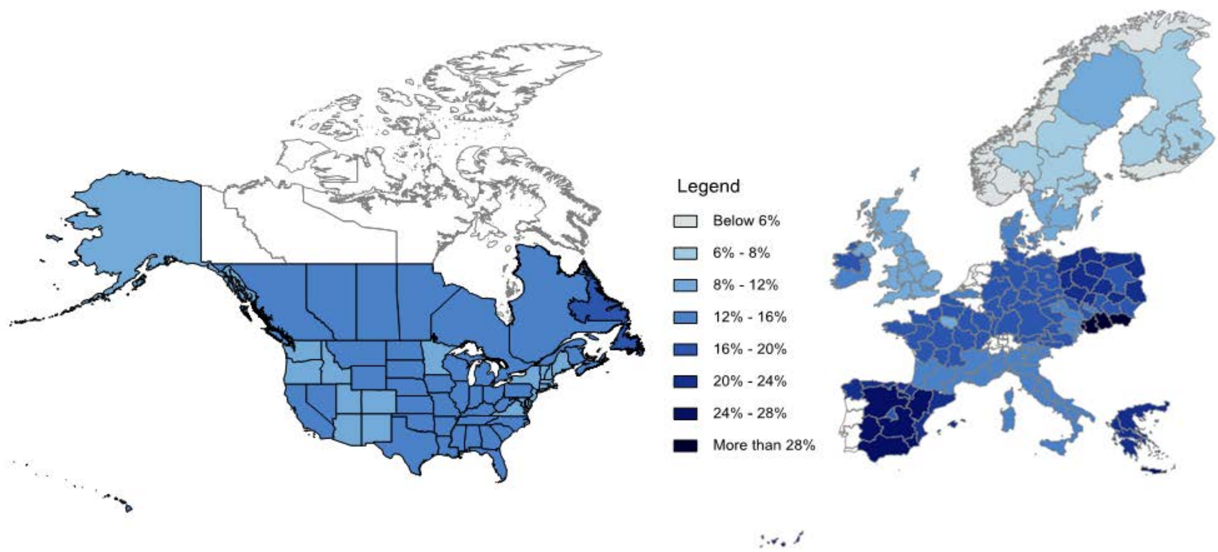
Figure 1.12 shows the regional disparities in the share of jobs at risk of automation. It displays the region with the highest and lowest share in each analysed country. A few countries, such as Spain, the Slovak Republic, the Czech Republic and France, display considerable differences in the share of jobs at high risk of automation. In Spain, the country with the largest regional disparity, the difference between the region with the most and least risky job profile is roughly 12 percentage points. In contrast, other countries such as Austria, Canada and Italy show much smaller disparities in the risk of automation.

A map of the same numbers is presented in Figure 1.13. The share of jobs at high risk of automation is represented by the shading of each region.

Figure 1.13. Share of jobs at risk of automation across selected North American and European TL2 regions, 2016



Note: High risk of automation' refers to the share of workers whose jobs face a risk of automation of 70% or above. Data for Germany correspond to the year 2013.
Source: OECD calculations based on (Nedelkoska and Quintini, 2018) and national Labour Force Surveys (2016).

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Which sectors are at risk of automation?

Some occupations have a particularly high risk of automation. Table 1.3 provides an overview of the occupations with the highest risk of automation and shows the total share of jobs in these occupations. Jobs in these occupations are more likely to be automated on a large scale than in any other occupations. Because of this, automation may prove more disruptive for individual workers - especially if automation occurs quickly and on a large scale - as affected workers will face significant competition from other laid-off workers. Indeed, they will have to compete with a large number of other workers with similar profiles and skill sets who are also looking for new jobs.

Table 1.3. Top 5 occupations in terms of jobs at risk of automation

ISCO occupation group	ISCO occupation name	Share of jobs at high risk of automation, average across TL2 regions
94	Food Preparation Assistants	0.6%
83	Drivers and Mobile Plant Operators	3.5%
93	Labourers in Mining, Construction, Manufacturing and Transport	2.2%
81	Stationary Plant and Machine Operators	2.6%
96	Refuse Workers and Other Elementary Workers	0.8%
	TOTAL	**9.7%**

Note: The table shows the five occupations that have the highest risk of automation (in descending order) as well as their share of total employment, average across TL2 regions in the sample.
Source: OECD calculations based on Nedelkoska and Quintini (2018) and national Labour Force Surveys (2016).

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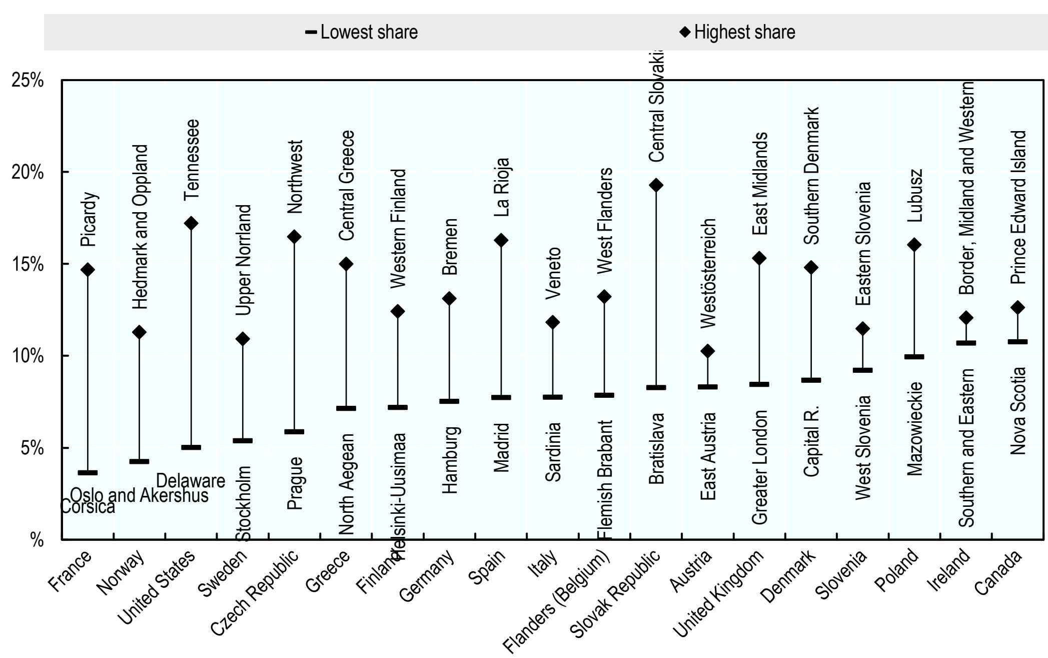
About 10% of workers across all regions are employed in the five "riskiest" occupations. Food preparation assistants, drivers and mobile plant operators, labourers in mining, construction, manufacturing and transport, machine operators, and refuse collectors face a particularly high risk of automation. As technology develops, their jobs are likely to be the first to suffer significant alterations. Targeted reskilling efforts should therefore be focused on these individuals and be implemented in areas where they live and work.

Figure 1.14. Share of jobs in occupations that are highly susceptible to automation

Percentage of jobs in the top five occupations in terms of risk of automation, TL2 regions with highest and lowest share, by country, 2016



Note: Data from Germany corresponds to the year 2013. Except for Flanders (Belgium), for which sub-regions are considered (corresponding to NUTS2 level of the European Classification).
Source: OECD calculations based on (Nedelkoska and Quintini, 2018) and national Labour Force Surveys (2016).

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The occupations most at risk are also highly concentrated in space. The earliest stages of automation will therefore be felt differently across different geographical locations. Figure 1.14 shows the share of jobs in the five abovementioned occupations in the region with the highest and lowest share in each country. Given the likely need to retrain workers in these occupations, policy makers should target regions where they make up a large percentage of overall jobs.

Furthermore, Figure 1.14 reveals an important pattern: Regions where the capital is located are frequently the regions that have the lowest share of jobs in the five riskiest occupations. Thus, large urban areas seem generally less at risk from automation. This is due to the concentration of service sector jobs in the urban economy, which are generally less exposed to automation than other occupations.

A regional classification based on job creation and risk of automation

Creating jobs in occupations at high risk of automation merely defers the problem and increases the risk of higher future public expenditure to help displaced workers. Creating jobs is the aim of many employment and economic development programmes; it is increasingly important, however, to create good quality jobs. This involves several dimensions of the working activity: from salary, to security and environmental conditions of the workplace. An equally important element of job quality is the risk of automation in the near future. As workers lose their jobs, they will likely require unemployment support as well as expensive re-training in order to be able to re-enter the labour market. Consequently, early preparation for any future labour disruptions will be crucial for policy makers trying to implement inclusive growth policies.

Regions can be classified into four categories depending on whether they gain or lose jobs and whether the gains or losses occur in sectors with high or low risk of automation. Regions are classified according to whether they created jobs in the period 2011-2016, and further divided according to the type of occupation in which they created or shed employment (Table 1.4). This classification provides insights into the short-term and long-term employment situation of a region.

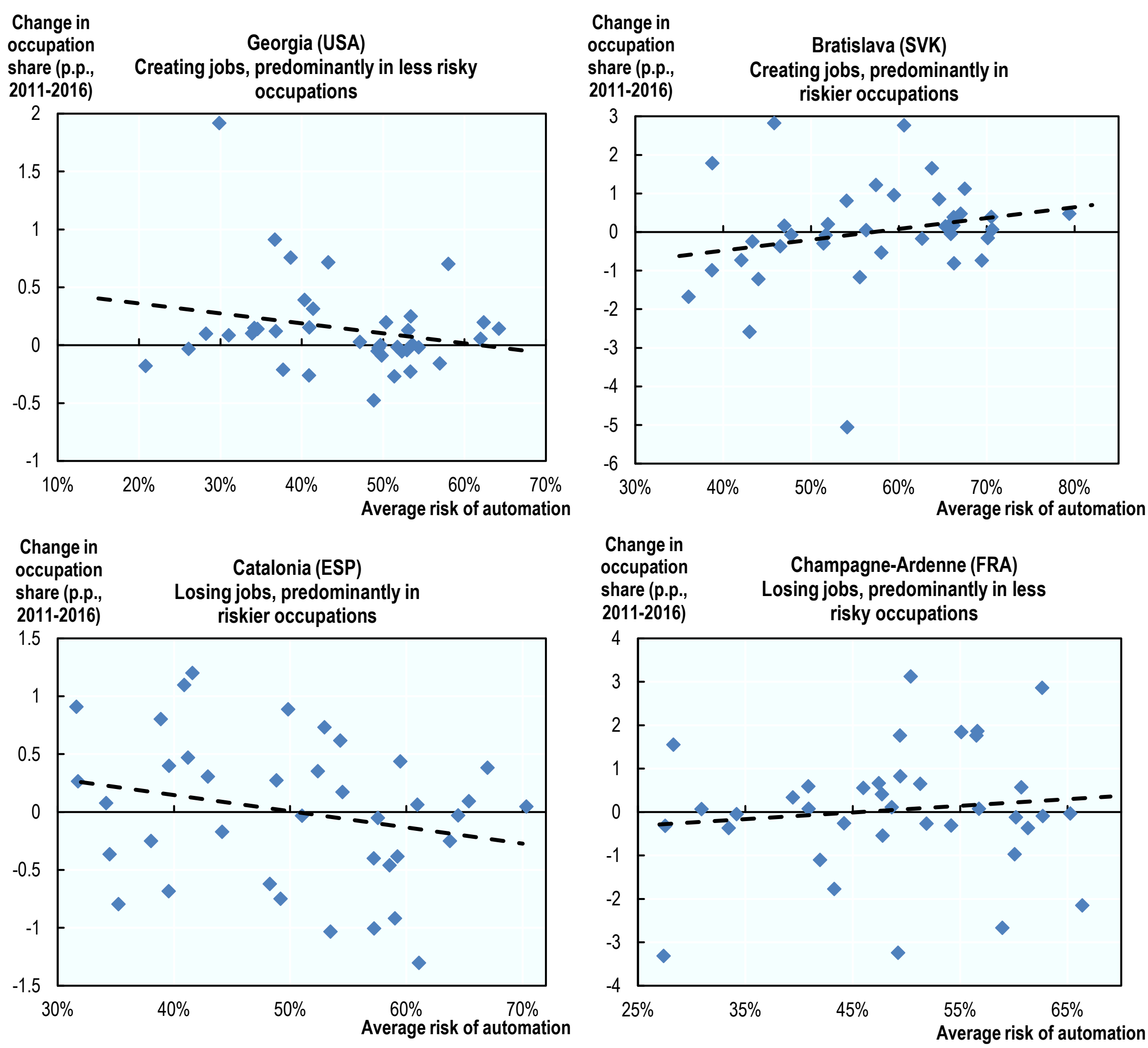
Table 1.4. A new regional typology for employment creation in the face of technological disruption

Type	Description
A	Creating jobs, predominantly in less risky occupations
B	Creating jobs, predominantly in riskier occupations
C	Losing jobs, predominantly in riskier occupations
D	Losing jobs, predominantly in less risky occupations

Regions that create jobs in occupations with a low risk of automation (Type A) improve their job situation in the short term and also reduce their long-term risk of unemployment from automation. In contrast, regions that create jobs in occupations at high risk of automation (Type B) improve their short-term job situation, but do so at the expense of moving towards a riskier job profile in the future. Regions that are losing jobs primarily in areas that are at high risk of automation (Type C) have the typical profile of regions in the process of undergoing a structural change caused by automation. While jobs are being lost to automation today, the risk of further job losses due to automation decreases. Lastly, regions that are losing jobs predominantly in occupations that are at low risk of automation (Type D) face the greatest challenge. They suffer current job losses combined with an increasing risk of further job losses in the future due to automation.

Plotting job creation in the period 2011-16 against the risk of automation by occupation makes it possible to break regions down into four categories. Figure 1.15 shows examples of a region in each category. Each dot represents an occupation, the position on the vertical axis indicates how many jobs were created or lost in the occupation and the position on the horizontal axis indicates the estimated risk of automation. The straight line indicates the estimated relationship between job creation and risk of automation. Its slope indicates whether more jobs have been created in occupations with high risk of automation or with low risk of automation. If the line is upward sloping, more jobs have been created in jobs with high risk of automation. If it is downward sloping, more jobs have been created in occupations with low risk of automation.

Figure 1.15. Four types of regions, according to employment growth in occupations and their risk of automation



Note: Each of the blue dots in the graphs corresponds to an occupation category under the European Union's ISCO (two-digit) classification. "Change in the occupation share (in percentage points, 2011-2016)" refers to the difference between 2011 and 2016 in the share of total employment that belongs to each occupation category.

Source: OECD calculations based on national Labour Force Surveys and Nedelkoska and Quintini (2018).

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Several regions managed to transition towards low-risk jobs in the period 2011-2016. Generally, a majority of regions in Europe have been creating new jobs after the financial crisis. Exceptions to this rule include some of the areas which were hit harder by the economic downturn: those in Southern European countries along with Slovenia and parts of France. In addition, in most countries, more than half of the regions have been shifting towards employment that is at lower risk of automation (Table 1.5).

For example, Georgia (United States) and Catalonia (Spain) in Figure 1.15 are two regions where a shift towards a less risky job profile occurred. In both regions jobs were created predominantly in occupations with a low risk of automation. In Georgia (United States), job creation across all occupations outnumbered job losses, which caused a net growth of jobs in the region. In contrast, Catalonia (Spain) lost more jobs in aggregate than it created.

In contrast, Bratislava in the Slovak Republic (upper right-hand panel in Figure 1.16) has been creating employment in occupations at high risk of automation. This is reflected in the fact that occupations with strong job growth lie predominantly on the right-hand side of the chart. An example of regions that face the most challenging situation is the case of Champagne-Ardenne in France. The region experienced a 6.5% decline in the number of jobs over the period 2011-2016. In addition, the jobs that were lost were predominantly at low risk of automation. Thus, the region has become more reliant on jobs that are more likely to be automated in the future.

Table 1.5. Most regions have been creating jobs in lower risk occupations

Number of TL2 regions per country (% of all regions within the country, 2011 - 2016)

	A. Creating jobs, predominantly in less risky occupations	B. Creating jobs, predominantly in riskier occupations	C. Losing jobs, predominantly in riskier occupations	D. Losing jobs, predominantly in less risky occupations
Austria	2 (66.7%)	-	1 (33.3%)	-
Canada	6 (60.0%)	1 (10.0%)	3 (30.0%)	-
Czech Republic	8 (100.0%)	-	-	-
Denmark	4 (80.0%)	1 (20.0%)	-	-
Estonia	1 (100.0%)	-	-	-
Finland	2 (40.0%)	-	3 (60.0%)	-
Flanders (Belgium)	2 (40.0%)	2 (40.0%)	1 (20.0%)	-
France	9 (40.9%)	3 (13.6%)	4 (18.2%)	6 (27.3%)
Germany	4(25%)	5(31%)	2(13%)	5(31%)
Greece	1 (7.7%)	-	11 (84.6%)	1 (7.7%)
Ireland	2 (100.0%)	-	-	-
Italy	6 (28.6%)	3 (14.3%)	6 (28.6%)	6 (28.6%)
Lithuania	-	1 (100.0%)	-	-
Norway	7 (100.0%)	-	-	-
Poland	12 (75.0%)	-	4 (25.0%)	-
Slovak Republic	1 (25.0%)	3 (75.0%)	-	-
Slovenia	-	-	2 (100.0%)	-
Spain	4 (21.1%)	3 (15.8%)	9 (47.4%)	3 (15.8%)
Sweden	7 (87.5%)	-	1 (12.5%)	-
United Kingdom	11 (91.7%)	1 (8.3%)	-	-
United States	49 (96.1%)	1 (1.2%)	1 (1.2%)	-

Note: Each cell reflects the number of regions of a country in the category. The percentage among all regions within the country is indicated in parenthesis. Except for Flanders (Belgium), for which sub-regions are considered (corresponding to NUTS2 level of the European Classification).
Source: OECD calculations based on EU Labour Force Survey and (Nedelkoska and Quintini, 2018).

Table 1.5 shows the number of regions that fall into each category by country. A few countries, such as the Czech Republic and Norway, managed to generate overall employment growth and shift towards less risky occupations in all regions. However, most countries experienced either a decline in employment or a move towards more risky jobs in some regions. Five countries had regions where both trends occurred in parallel, i.e. overall employment declined while the share of risky jobs increased.

Are jobs actually lost to automation?

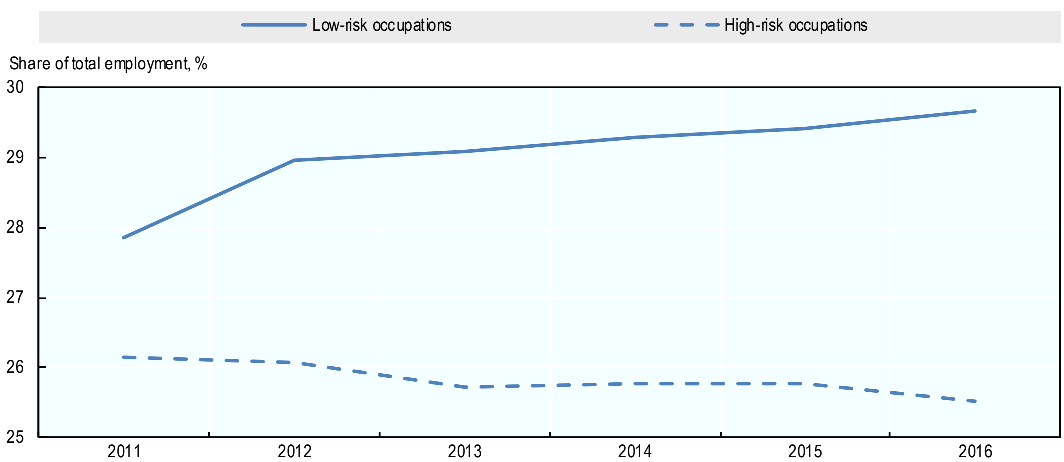
The main concern about automation is the risk of technological unemployment and increasing inequality across workers. Although the analysis in this chapter cannot establish the motivation for job creation or losses, it is reasonable to assume that a reduction of employment in occupations at high risk of automation is the consequence – direct or indirect – of increasing automation. Firms can directly substitute workers with machines. Alternatively, jobs might be indirectly lost because firms that do not automate are driven out of the market.

There are strong indications that jobs are actually being lost to automation in most OECD regions. The analysis conducted on the trend of employment over the period 2011-16 shows that 82% of regions in our sample (excluding Flanders for which we only have NUT2 regions) experienced a reduction in the share of jobs in occupations at high risk of automation relative to jobs in occupations at low risk of automation (Table 1.5). The empirical evidence also shows an increase in the occupations at low-risk of automation. In about 60% of TL2 regions in our sample the reduction of jobs in occupations at high risk of automation was compensated by a greater increase in the share of jobs at low risk of automation.

These findings provide some support to the optimistic view that automation creates opportunities, as jobs lost to automation are replaced by (potentially) better jobs in other occupations. Indeed, the average trends across OECD regions show an increasing share of employment in low-risk occupations and a decline in the share of employment in high-risk occupations (Figure 1.16).

Figure 1.16. Employment is declining in occupations at high risk of automation

Share of employment in low- and high-risk occupation, average across TL2 regions, 2011-16



Note: Low-risk occupations refer to the share of employment in the least risky 3 deciles of the distribution of occupations for each country; high-risk occupations refer to the share of employment in the 3 riskiest deciles of the distribution of occupations for each country; values are averaged across all regions in the sample. The sample consists of TL2 regions in the following countries: Austria, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Lithuania, Norway, Poland, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom and the United States. Except for Flanders (Belgium), for which sub-regions are considered (corresponding to NUTS2 level of the European Classification)
Source: OECD elaborations based on data from National Labour Force Surveys.

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Still, in 10% of regions employment growth over the 2011-16 period was mainly driven by jobs in occupations at high risk of automation; and in about 9% of regions the decline of employment was driven by the loss of jobs in occupations at low risk of automation. In these regions, the risk of future job losses due to automation is growing.

As discussed at the end of this chapter, employment policies should target the specific challenge of each type of region. For instance, in regions that successfully manage the transition towards low-risk occupations, policies should focus on workers that are displaced in the process. Most probably not all workers that lost their jobs due to automation will be able to find jobs in other occupations. In contrast, in regions where no transition towards a lower risk of automation is occurring, policies should help firms to shift towards jobs at lower risk of automation. This can reduce the future risk profile of regions and also lead to higher productivity growth.

Factors that explain the risk of automation at the regional level

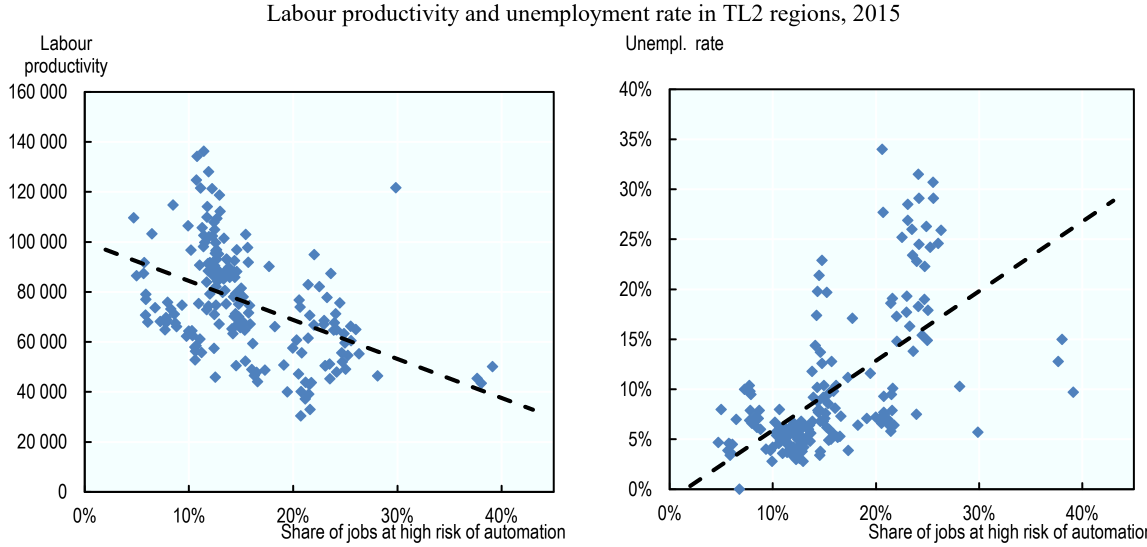
The uneven distribution of risks linked to automation raises the question of which kinds of regions will be most affected by it. Identifying the characteristics of these regions will help policymakers concerned with inclusive growth to target policy interventions to the most disadvantaged areas.

Highly automatable jobs are more likely to be concentrated in regions where productivity is low (see Figure 1.17). At least partially, this is because regions with low productivity make less use of advanced machines. Since automation tends to increase labour productivity, regions with low levels of productivity also tend to have low levels of automation. This implies that these regions have more potential for further automation and hence a higher risk of future job losses.

The challenge for low productivity regions is especially daunting because they often have high levels of unemployment in parallel with low productivity levels. These regions face a dilemma. One the one hand, they have to provide jobs in the short term. On the other hand, they also have to encourage efforts to increase labour productivity to ensure high employment levels and prosperity in the long term. In many cases, this requires increasing automation, which can harm employment in the short run. This pattern is also reflected in Figure 1.7, which shows that regions with higher unemployment levels have more jobs at risk of automation.

Figure 1.17. Regions highly affected by automation display higher unemployment and lower productivity

Labour productivity and unemployment rate in TL2 regions, 2015



Note: Data reported is from 2015 and corresponds to regions (TL2) in Canada, the Czech Republic, Denmark, Estonia, Greece, Spain, Finland, Ireland, Italy, Norway, Poland, Sweden, Slovenia, the Slovak Republic, the United Kingdom, and the United States. Labour productivity is defined as GVA per worker, PPP, constant prices, base 2010. Data from the District of Columbia in the United States stands at almost USD 300 000 per worker and has been excluded from the graph.
Source: OECD calculations based on national Labour Force Surveys and Nedelkoska and Quintini (2018).

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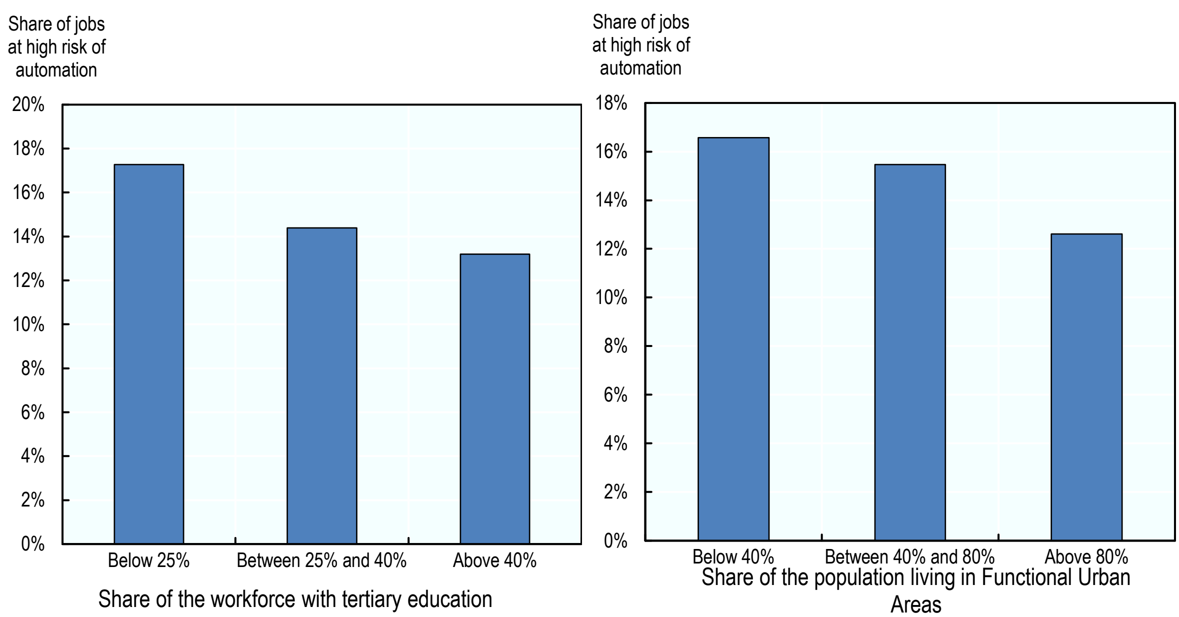
Places with highly educated workforces are less affected by automation. With some exceptions, the risk of automation decreases as educational attainment required for the job increases. Thus, it is no surprise that regions that have a highly educated workforce have a low share of jobs at risk of automation. Figure 1.18 shows the share of jobs at risk of automation for three types of regions; those with less than 25% of the workforce with tertiary education, those with between 25% and 40% of the workforce with tertiary education and those with more than 40% of the workforce with tertiary education. There is a negative relationship between the risk of automation and the share of workers with tertiary education. Regions that have the highest share of jobs at risk of automation also have the lowest share of workers with tertiary education. Reducing the risk of automation in those regions will therefore require efforts in training and education.

Figure 1.18. Urban regions with a highly educated workforce have a lower risk of automation

Average share of jobs at high risk of automation, by TL2 regions, 2016



Note: Data reported in the education chart corresponds to regions (TL2) in the Czech Republic, Germany, Denmark, Estonia, Greece, Spain, Ireland, Italy, Lithuania, Poland, Slovenia, the Slovak Republic and the United Kingdom.
Source: OECD calculations based on (Nedelkoska and Quintini, 2018) and national Labour Force Surveys.

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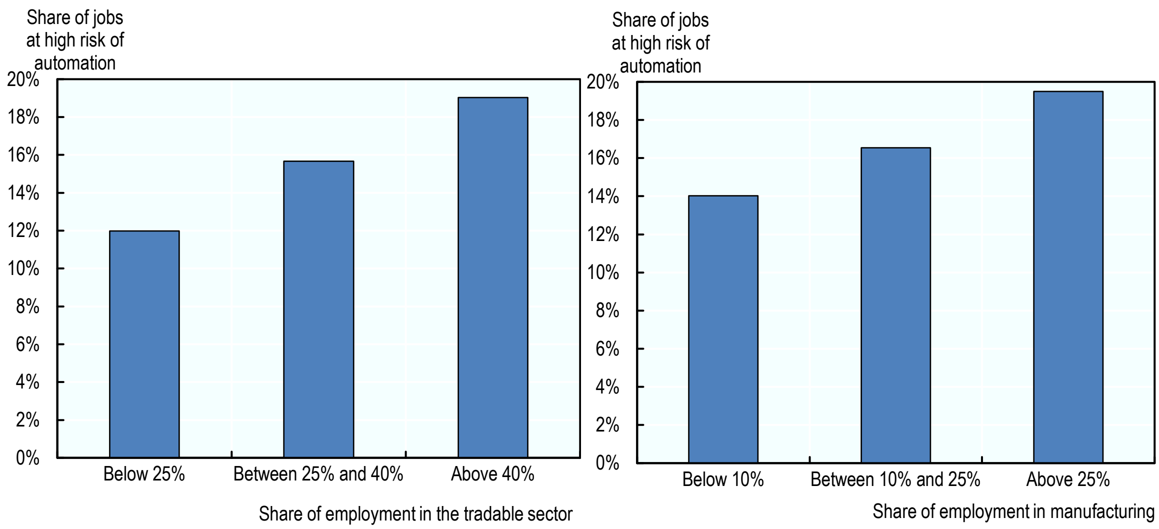
Rural economies are especially at risk of automation. Figure 1.18 shows that regions, which have a low share of the population living in urban areas, have a higher share of jobs at risk of automation. Rural economies have a lower share of service sector jobs that are better protected from automation. Smaller towns and rural areas are also more likely to be highly reliant on a handful of employers or on a single industry. While this does not necessarily increase the risk of automation in and of itself, it makes it more difficult to absorb displaced workers if one of the employers automates on a large scale.

Figure 1.19. More employment in the tradable sector means more automatable jobs

Average share of jobs at high risk of automation, by TL2 regions, 2016



Note: The tradable sector is defined by a selection of the 10 industries defined in the SNA 2008. They include: agriculture (A), industry (BCDE), information and communication (J), financial and insurance activities (K), and other services (RSTU). Data reported corresponds to regions (TL2) in Canada, the Czech Republic, Denmark, Estonia, Finland, Greece, Ireland, Italy, Norway, Poland, Slovenia, the Slovak Republic, Spain, Sweden, the United Kingdom and the United States.
Source: OECD calculations based on (Nedelkoska and Quintini, 2018) and national Labour Force Surveys.

StatLink https://doi.org/10.1787/888933824743

Overall, jobs in the tradable sector are more at risk of automation (Figure 1.19). This is mostly due to the fact that the tradable sector includes many economic sectors that have an especially high risk of automation, such as agriculture and manufacturing (Figure 1.19). Tradable services, which form a small but growing part of the tradable sector, are most likely at much lower risk of automation.

Again, this points to a dilemma for policy makers. On the one hand, strengthening the tradable sector is needed to foster sustained productivity growth. OECD (2018b) shows that the tradable sector has higher productivity growth rates and helps lagging regions to catch up with more productive ones. On the other hand, moving into the tradable sector also increases the risk of automation. Likely, this is because the potential for higher productivity growth in the tradable sector comes from greater opportunities for automation.

This dilemma can only be solved by taking two considerations into account. First, policy makers need to embrace automation insofar as it is an important mechanism to increase labour productivity and thus, an important source of long-term prosperity. Second, policy makers have to help their local workforce and businesses to deal with the potential downsides of automation. The following section will provide examples and recommendations on how they can do so.

Policy response: how can regions deal with the challenges of automation?

Regions and cities should be at the forefront of local responses to the future of work

National labour market policies should be designed in a flexible manner to create bottom-up innovation

The analysis in this chapter has highlighted the uneven impacts of automation across regions and its potential to exacerbate regional inequalities. For those places that are more vulnerable to structural changes, targeted efforts must be made to create an environment that is attractive to highly skilled people and firms. Local employment and training organisations play an important role in facilitating the adaptation of workers' skills to the changing needs of the economy but they require greater room for manoeuvre to respond to mega trends. It is therefore important that national policies provide mechanisms for cities and regions to take a leadership role in responding to the future of work.

Flexibility in the management of national policies can provide local actors, such as local employment services, vocation education and training organisations, as well as city and regional authorities, with the necessary tools to tailor programmes to their unique local labour market challenges. The need to target policies to specific groups of people is also recognised by other OECD contributions (OECD, 2018a). Flexibility encompasses the ability to make changes to national programme eligibility criteria, budget management, as well as accountability provisions. In general, awarding greater flexibility to local and regional stakeholders must be accompanied by guarantees regarding the accountability of decision-making and the efficiency of service delivery at the national level. In many cases, cities and regions can be viewed as "policy spaces" to test new ways of working and innovation approaches to address on-going labour market changes resulting from automation.

An example of a flexible approach to policy management can be found in the devolved skills system in the UK. The region of Leeds is revising its Employment and Skills Plan to take into account the changing work conditions and prospects in the local labour market. Recently, a key focus has been on developing an understanding of sectors and occupations within the local economy that are most susceptible to automation. With the input of leading employers and elected members of the local authority, the region is focusing on providing low-paid workers with access to high quality training opportunities to re-skill for jobs in new and emerging occupations.

In Denmark, the Regional Education Pool, introduced as part of employment reform in January 2015, aims to strengthen the skills of unemployed people, enabling them to adapt to changing labour market conditions. For instance, it provides subsidies to municipalities so that they can purchase short-term vocational training programmes to help unemployed individuals get back in the labour market. At the national level, the Agency for Labour Market and Recruitment (STAR) allocates funding to municipalities according to national criteria. Job centres within each municipality then actively allocate funds and manage the programme.

Local ecosystems can nurture economic diversification in skills-related activities

Across many OECD countries, there is renewed interest in industrial policies as a means of supporting and strengthening key sectors of the local economy (Warwick, 2013).

OECD work has shown that promoting activities in tradable sectors is key to boosting productivity and regional convergence (OECD, 2016c). However, this potential comes at the cost of a higher risk of automation. Thus, policy makers need to embrace the long-term benefits from a shift towards the tradable sector, while also addressing the risks related to automation that come from this shift.

In the context of the future of work, policies should therefore look *inside* the tradable sector and identify how to steer support towards occupations with tasks that are less vulnerable to automation. In practice, there may be benefits to be generated by focusing on clusters of expertise as well as regional strengths through a local skills ecosystem, which encompasses aspects of industrial policy.

A local skills ecosystem within a region can create a thicker labour market providing access to relevant specialised knowledge and skills. A local skills ecosystem is a cluster of firms working horizontally across a value chain with the education and training system to foster knowledge exchange and coordination. Local skills ecosystems can emerge organically and in some cases, government can play a role in providing incentives for their development. The establishment of a local skills ecosystem is often dependent on a strong anchor institution, such as a higher education or vocational education institution, strong local networks among stakeholders, as well as a catalyst for change (e.g. evidence suggesting that the region is likely to experience significant adjustment as a result of automation).

Public policies should promote diversification into activities that are closely related and connected to the existing skills base of the population. As communities respond to structural adjustments resulting from automation, there is evidence suggesting that the local network connecting industries with overlapping skill requirements is highly predictive of where firms are most likely to diversify economic activities. According to this research, diversification is found to be over 100 times more likely to occur into industries that have ties to a firm's core activity in terms of skills than into industries that do not (Neffke and Svensson Henning, 2009).

A good example of this diversification approach can be found in Akron, Ohio, which was the location of four major tyre companies in the 1990s. After experiencing a major economic decline in those activities, the city reinvented itself investing in polymer technology, establishing a National Polymer Innovation Centre, which has since been a new source of job creation in the city. This is an example of leveraging the existing skills base and local knowledge and applying it to new technology and production processes. Similarly, Manufacturing Extension Partnerships in the United States have also been successful in establishing local collaboration to work with manufacturers to develop new products, expand and diversify markets, adopt new technologies, and enhance value within local supply chains (National Institute of Standards and Technology , 2018).

"Smart Specialisation" strategies may be a useful policy instrument for concentrating local development activities in areas where there is a critical mass of knowledge and innovation potential. In Slovenia, the Smart Specialisation Strategy has been focused on creating "factories of the future" through investments to raise the level of automation, and robotics within the manufacturing sector (Slovenia Government Office for EU Cohesion Policy, 2015).

Target lifelong learning opportunities to those most vulnerable to automation

Low-skilled people require access to lifelong learning opportunities in order to remain relevant in a changing labour market

The analysis conducted in this chapter underlines the importance of education and skills of the workforce in reducing the risk of automation. In an age of extensive automation and increasing use of artificial intelligence, it is critical to provide skills training (both work-based or classroom focused) and access to lifelong learning programmes so that workers' skills remain relevant in a rapidly evolving labour market. Individual Training Accounts (or Lifelong Learning Accounts) can help workers to manage disruption in the labour market. The overarching principle of these accounts is that workers use available funding at any point in their careers to invest in training – either to help them with career advancement or to adjust to a new job as a result of automation.

In Scotland (UK), the government has recently announced the launch of Individual Training Accounts to make it easier for job seekers and low paid workers to gain access to skill training, giving people up to GBP 200 per year for training and skills development. Another good example can be found in Singapore, which has established a programme to provide individuals with access to funding for lifelong learning and training (see Box 1.5).

Similarly, Spain has recently established a training plan for digital skills. This is mainly a subsidy (EUR 60 million in the 2018-19 period) for the acquisition and improvement of professional skills related to technological changes and digital transformation. The plan primarily targets employed people but is also open to unemployed people.

Box 1.5. Individual Training Accounts in Singapore

In Singapore, the Skills Future Programme provides Singaporeans with opportunities to develop their fullest potential throughout life, regardless of their starting points. Skills Future targets skills training to early and mid-career professionals, recognising that technology and globalisation are changing the nature of jobs at a rapid pace. As part of the programme, all Singaporeans aged 25 and above receive an opening credit of SD$ 500 to use towards lifelong learning and training. The programme also offers guidance on industry-relevant training programmes that focus on emerging skills such as: (i) data analytics, (ii) finance, (iii) tech-enabled services, (iv) digital media, (v) cyber security, (vi) entrepreneurship, (vii) advanced manufacturing, and (viii) urban solutions.

Encourage partnerships with employers to stimulate both the supply and demand of skills

Apprenticeship programmes can improve business-education connections and rebuild middle skill jobs

OECD research has highlighted the importance of better engaging employers in skills development programmes to ensure that training programmes are well aligned with the skills needed by the local labour market. Several countries are currently promoting apprenticeship programmes, which combine on-the-job as well as off-the-job training to smooth the school-to-work transition (OECD, 2017a). Apprenticeship programmes often lead to decent and good "middle class" jobs in occupations such as welding, plumbing, electricity and other repair type services. Many employers across the OECD continue to complain that these types of jobs remain unfilled.

Broadening the availability and accessibility of apprenticeships can fill potential shortages in "hands-on" occupations, which are less vulnerable to automation. It is important to avoid the promotion of apprenticeship programmes within occupations at serious risk of automation, such as food preparation assistants, truck drivers and mobile plant operators as well as machine operators.

At the local level, much can be done to coordinate outreach and market apprenticeship programmes to employers, especially SMEs, who often face unique barriers to participation. Local Apprenticeship Hubs in Manchester, United Kingdom have been successful in coordinating the range of government actors involved in delivering apprenticeship programmes (see Box 1.6) (OECD, 2017a).

Box 1.6. Local apprenticeship hubs in the United Kingdom

Local Apprenticeship Hubs provide a "one-stop" offer to local employers. In Manchester, United Kingdom, the number of young people participating in apprenticeship programmes has increased as a result of efforts undertaken by local stakeholders to "persuade" employers to participate in apprenticeship training.

The local apprenticeship hub model demonstrates how a decentralised approach to apprenticeship can be effective in bringing on board SMEs, which often face unique barriers to participating in training. In some cases, local employers require "hand holding" to participate in these types of training arrangements. This is clearly an area where the local level can play a strong role in facilitating stronger connections between businesses and the education system.

Boosting the demand for skills should be a clear policy priority to improve the quality of jobs

Governments have addressed the issue of skills primarily from the supply side – namely, focusing on the need to improve the number of people with post-secondary and tertiary academic or vocational qualifications. However, there is an increasing recognition that policy makers must also promote the demand for skills. This involves understanding the nature of the skills demanded by employers and the optimal utilisation of those competences in the workplace (OECD/ILO, 2017). Stimulating the demand for skills should be a priority for those regions that have a number of occupations at low risk of automation but are not seeing sustained employment growth.

Public policies will need to find new ways of working with employers to move them into higher skilled and more productive economic activities. From the point of view of firms, better skills use in the workplace is typically associated with higher labour productivity. For example, the use of reading skills explains a considerable share (26%) of the variation in labour productivity across countries participating in the OECD Adult Skills survey (e.g. PIACC), after adjusting for average proficiency scores in literacy and numeracy. In other words, how skills are used at work can have a major impact on productivity, even above and beyond that of proficiency (Quintini, 2014).

Local policies that aim to improve the use of skills in the workplace usually involve a mix of programmes focused on work organisation, job design, technology adaptation, innovation, employee-employer relations, human resource development practices and business product market strategies. Those regions whose primary economic activities are concentrated in the retail sector would also benefit from a greater focus on the demand for skills. In these regions, more must be done to work more closely with employers to look at how to maximise business performance and embed skills development into the company's business model. Vocational education and training institutions, sector councils, human resources consulting firms and other business associations are critical brokers at the local level who often have specialised expertise to help firms think over the long-term about their training activities.

Public policies can stimulate the development of networks among firms to encourage investment in skills training

Creating or leveraging local employer networks can promote skills upgrading in the workplace. Employer's associations can also play a key role in fostering trust-based relationships between firms that stimulate knowledge-sharing and collaborative investment in training. Collaborative relationships across firms can foster innovative diffusion along a supply chain within a region with the added benefit of potentially linking firms along a production Global Value Chain, making a region less vulnerable to automation (OECD, 2018b). As an example, the POSCO Human Resource Development Consortium based in Gwangyang, Korea, facilitates joint connections between large firms and SMEs that are mostly situated within the same supply chain as suppliers or contractors of the larger firms. Through this consortium, SMEs are encouraged to increase investment in their own training programmes and to implement a Human Resources Development plan to create conditions for the long-term employment of workers (OECD/ILO, 2017).

In Ireland, Skillnets has been effective in actively supporting and working with businesses to address their current and future skills needs. The programme funds 65 training networks which operate locally, supporting over 14,000 companies and 50,000 trainees. Member companies actively participate in determining their own training needs and how, when and where training will be facilitated. Programmes are optimised to suit the needs of employed learners, through both formal and informal learning that spans further education and higher education provision (OECD, 2014).

Embrace digital technologies to improve service delivery and regional development planning

Digital technology can enable efficient job matching and training services

In a number of OECD countries, online vacancy databases are the primary platform for filling jobs, complementing public employment service databases. In Germany, around 50% of all vacancies are reported to the public employment service (Arbeit, 2015). In many OECD countries, public employment services are now using online applications to enable workers and employers to connect in a more efficient manner. This technology can also be used to provide more robust and accessible labour market information to potential workers on job opportunities available, expected wages, as well as the required education and training for employment.

Digitalisation and automation may provide opportunities to improve the implementation of local employment and training programmes where the Internet has become an increasingly important channel for service delivery. Online technologies can be used for standardised procedures such as initial registration and posting job vacancies, personalised interactions between public employment services (PES) staff and clients, casework counselling functions, and skills training and development.

Box 1.7. Embracing digital technology to improve the service delivery of employment and training programmes in Sweden and Mexico

In Sweden, a campaign has been launched by the public employment services to make people better at using digital services. The idea is that jobseekers and employers should be able to access the various services of the Swedish Public Employment Service (Arbetsförmedlingen) via Internet or a mobile phone without having to visit an unemployment office.

In Mexico, the Secretariat of Labour and Social Welfare has launched the Distance Training Program for Workers (PROCADIST), which offers online courses for training of workers who wish to acquire or improve their skills and increase their work productivity. It consists of a virtual interactive teaching and learning environment, managed on a technological platform, where courses can be taken by personal computer or a mobile device (tablet, cell phone, etc.). The programme has national coverage and promotes the training of workers through flexible and modular learning units.

Robust local labour market information can deliver real-time intelligence on future job demands

Artificial Intelligence (AI) can help elaborate and analyse big data on workers skills and employment opportunities. Local labour market information and skills anticipation systems will be fundamental to guide individuals and workers in making well-informed career choices. At both the national and local level, employment and skills policies can respond to the future of work by better anticipating needs and preparing individuals with relevant competences that will be less vulnerable to automation.

Actions to develop real time labour market information can inform monitoring and evaluation mechanisms within the policy development cycle. Real time labour market information includes regular data on wages, job openings, hiring and salary trends, as well as information about employers who most frequently list job openings.

In Belgium, the Flemish public employment service (VDAB) has initiated structured dialogue with local governments and social partners to discuss labour market information with the goal of establishing stronger intelligence on current and future labour market needs. VDAB is engaging with educational institutions to develop study and career orientation tools that are shared with schools and students to prepare for future skill needs in the economy.

In the Czech Republic, the KOMPAS project is focused on building a comprehensive system of labour market anticipation, which aims to predict future qualification needs by taking into account the expected impacts of technological change. The outputs serve government actors as well as employers and training organisations, especially in setting up the education system and focusing on retraining courses, as part of career guidance and career counselling.

Latvia has recently introduced a labour market forecasting system to determine changes and trends across occupational groups and sectors. At the same time, the Latvian Ministry of Economy prepares a medium- and long-term forecast that focuses on future mismatches. This forecasting system contains regional information to identify which sectors are likely to experience job growth over the next 5-10 years.

Conclusion

Automation has taken place for centuries. However, due to recent technological developments in the field of so-called artificial intelligence the pace of automation is likely to accelerate. Furthermore, technological progress changes the profile of jobs that can be automated. Whereas previously it was mostly low- and medium-skilled occupations that could be automated, new technological developments raise the possibility that even high-skilled occupations will be automated in the near future.

This chapter has shown that a large number of jobs are at risk of automation. However, there are important differences in how this risk is distributed across countries and regions. Across countries, the share of jobs at high risk of automation varies between 6% and 34%. Within countries, the differences can be considerable, too. The difference between regions within a country that have a high share of jobs at high risk of automation and those that have a low share is frequently more than 5 percentage points and sometimes more than 10 percentage points.

Regions with a similar share of jobs at risk of automation have certain characteristics in common. Regions that have a high share of urban population, of workers with tertiary education and of economic activity in the service sector generally have a lower share of jobs at risk of automation than other regions. Regions that have a high share of jobs at risk of automation often have lower levels of productivity and high unemployment. This creates a dilemma for policy makers. On the one hand, automation is needed to foster productivity growth, but on the other hand, automation also raises the spectre of further job losses in regions that already suffer from high unemployment.

Automation is not a process that takes place in isolation. It occurs during a time in which socio-economic disparities and differences in labour market outcomes across regions have been increasing. Policy makers need to take this broader picture into account when developing policies to respond to automation. While education and lifelong learning is an important component of any policy response to automation, it should not be the only element. Policy makers at regional and local levels also need to implement policies to help firms grow to foster the demand for jobs.

Finally, policy makers at all levels of governments need to target more than just the availability of jobs. The quality of jobs and the wages that they are paying are important determinants of social inclusion and well-being, too. The local and regional dimensions of these important aspects of labour markets will be discussed in the following chapters.

Notes

[1] O*NET provides a set of 277 quantitative variables that serve as descriptions of the skill requirements for each of the 702 occupations in the US classification of occupations. O*NET was originally made up of labour market analysts, although it now also uses continuous surveys of workers and experts in order to keep track of changes in the nature of jobs.

[2] Nedelkoska and Quintini (2018) find that the variables that explain most of the variance in automatability are planning for others, selling, influencing, communicating and advising, respectively.

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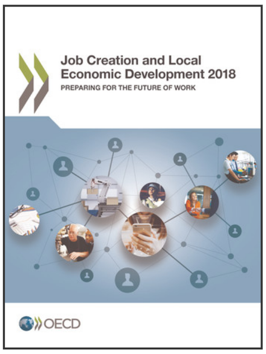
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