Chapter 3. A digital world of work: Adapting to changes through occupation mobility

The chapter assesses the training needed to make it easier for workers to change occupations and estimates how much it will cost countries to help workers move away from occupations at high risk of automation. To examine the feasibility and cost of occupational mobility, this chapter presents a new set of empirical estimates based on the Survey of Adult Skills (PIAAC). The analysis suggests that with about one year of training, an average worker in most occupations at high risk of automation could move to a low- or medium-risk occupation. The total cost of helping workers in occupations at high risk of automation move away from this risk varies between countries. It may range from less than 0.5% to over 2% of one year's GDP in the lower bound estimate and from 1% to 10% of one year's GDP in the upper bound estimate. However, these costs need not be sustained all at the same time or in one year. These are experimental estimates based on available data. They do not attempt to capture the overall training needed to help all workers face changes in their jobs, but only the training needed for the workers most at risk of losing their jobs. Policies that encourage simultaneous working and learning – through flexible education and training programmes and informal learning – are fundamental to mitigate the cost.

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.

New technologies, new business models, the dispersal of production in global value chains, the aging of the population and other megatrends are reshaping labour markets. For some occupations, demand is increasing. New occupations are appearing, such as artificial intelligence specialists, bloggers and value chain managers. Demand for others is declining because of digital technologies, automation in particular. An ever-growing number of workers will need to shift from declining occupations to growing ones. In particular, as applications of machine learning and artificial intelligence advance in many sectors, workers will need to move away from occupations that are highly intensive in routine tasks, which can be easily automated.

This chapter investigates how education and training policies can help workers change occupations. After explaining the role of labour mobility for labour market restructuring, the chapter aims to:

1. assess the distance between occupations in terms of skills requirements;
2. identify transitions from any occupation to others that require the least upskilling or (re)training efforts while maintaining workers in quality jobs that make the best use of their skill sets;
3. understand the size and type of (re)training or upskilling efforts needed to help workers move away from occupations at high risk of automation; and
4. assess the monetary cost of the education and training required to move away from the risk of automation.

Finally, this chapter discusses the policy implications of these findings.

As digital transformation affects regions differently, geographical mobility is also important. Chapter 6 discusses these issues.

This chapter uses several concepts to analyse mobility across occupations:

- (Re)training effort: The analysis considers three training needs scenarios: small (up to six months' training), moderate (up to one year) and important (up to three years).
- Possible and acceptable transitions: Possible transitions are those that can happen with a given (re)training effort. Acceptable transitions would entail, in addition, moderate wage reductions and limited skills excesses.
- Risk of automation: The extent to which available technology and potential technical improvement might lead to automation of tasks and jobs.
- "Safe haven": An occupation that a worker can move to with minimum upskilling or (re)training efforts, moderate wage reductions, limited skills excesses and a low or medium risk of automation. Other aspects of the occupation – such as whether it may become less needed in the future for other reasons than automation or its working conditions – are not taken into account.
- Country cluster: – As the full analysis cannot be done at a country level because of data constraints, countries are grouped in clusters.

The analysis in this chapter builds on several assumptions that can affect the size of the effects presented here. The findings should therefore be seen as experimental estimates, intended to foster reflection while indicating policy directions, rather than precise estimates.

The main findings of the chapter are:

- Most occupations appear to be fairly close to some other occupations in terms of cognitive skills requirements, task content, and knowledge area, so most workers have *possible* transitions to other occupations. However, workers may be unwilling to move if moving entails large drops in wages and significant underuse or loss of skills. *Acceptable* transitions, with moderate wage reductions and limited skills excesses, can be identified for just over half of occupations with a small training effort.
- Countries need to invest in education and training to ensure that those at risk of losing their jobs because of automation are not left behind and can find a new job. Many acceptable transitions to occupations at low or medium risk of automation require moderate or important upskilling or (re)training efforts.
- For some workers in occupations at high risk of automation, a small training effort may be sufficient to provide acceptable transitions to occupations at lower risk of automation. Depending on the country cluster, 20% to 50% of occupations at high risk of automation appear to have at least one acceptable transition to an occupation at lower risk of automation that requires at most six months of (re)training. With a moderate (re)training effort (up to one year), these proportions may climb to 65% to 80%. In countries where workers' skills are dispersed, occupations tend to be more distant from one another in their skills requirements and the training effort required to switch occupation is larger. Designing effective options to learn on the job is crucial in these countries.
- Around ten occupations (depending on countries' specificities) are in a particularly critical situation, as they are at high risk of automation and workers in those occupations would on average require an important training effort (more than one year) to move to occupations at low or medium risk of automation. These occupations on average account for 2% to 6% of employment, depending on the country considered. When considering that only a fraction of workers in these occupations are in job at high risk of automation, these figures drop to a range of 0.3% to 1.5%.
- The cost of training includes direct and indirect components. The *direct cost* is the monetary cost of an education and training programme of a given length. The *indirect cost*, or opportunity cost, reflects the wages workers will not receive while they are (re)training. The indirect cost represents 70% of the total training cost per person. This result underlines the importance of enabling individuals to work and learn at the same time, which would lower the indirect cost of switching occupations.
- Estimates of the country-level minimum cost (direct and indirect) of helping workers in occupations at high risk of automation move to "safe haven" occupations vary across countries and depend on the assumption that is made about the number of workers who may need to change occupation:
    - Assuming that only workers who are today in occupations at high risk of automation and perform tasks that can be automated need to change occupation, cost estimates range from less than 0.5% of one year's GDP in Norway to more than 2% of one year's GDP in Chile (lower bound estimate).
    - Assuming that all workers in occupations at high risk of automation need to move, because those occupations are likely to disappear, cost estimates range

from 1% of one year's GDP to 10% of one year's GDP depending on the country (upper bound estimate).

- Differences between countries reflect several factors, including differences in the share of employment in jobs at high risk of automation, the costs of education and training policies, the indirect costs of training, and the occupational and skills distributions of the population.
- The direct country-level minimum cost of moving workers at high risk of automation to "safe haven" occupations is estimated to range from about 3% of secondary and tertiary education yearly expenditure in Belgium to 23% in the Slovak Republic (lower bound estimate).
- These cost ratios may appear high because they compare costs of training that is likely to occur over several years with yearly GDP or education expenditure. Workers and employers may decide to spread training over multiple calendar years to reconcile (part-time) work and training. Furthermore, policies should not target all workers in jobs at high risk of automation at the same time and within one year, as technology spreads and is adopted at different paces in different countries, industries and companies. Lastly, the cost can be shared between the public and private sectors.
- At the same time, these estimates may appear low compared with other public expenditure. This is because they only encompass the cost of education and training policies needed for the workers most at risk of losing their jobs. However, all occupations may change as a result of digital transformation (Chapter 2). The education and training effort necessary to address this broader challenge is larger.
- Specific types of (re)training or upskilling are required to help workers in occupations at high risk of automation move to occupations with lower risk. In addition to training in general cognitive skills, such as literacy and numeracy, these include training in non-cognitive skills, such as management, communications and self-organisation. They also require some training in ICT. This is mainly because occupations at risk of automation include mostly routine tasks, whereas management, communications and self-organisation are more difficult to automate.
- Policies that promote working and learning at the time through flexible education and training programmes and informal learning are fundamental to mitigate training costs and ensure countries can sustain these costs. Furthermore, education systems need to better prepare the next generation of workers for career changes. As well as limiting the number of students who drop out, policies can ensure that vocational education and training programmes include not only job-specific skills but also a strong component of cognitive skills.
- This chapter shows that workers in occupations at high risk of automation are particularly in need of upskilling or (re)training, yet appear less likely to participate in on-the-job training. Policies need to overcome the barriers that prevent some groups of workers from participating in training activities and learning as much as possible on the job.
- As a mix of skills is generally needed to help workers switch occupations, education providers, employers and unions can better co-ordinate their actions to provide the necessary training. At the moment, employers mainly provide training in job-specific skills and few workers go back to formal education in most countries.

- To ensure that inequalities do not increase, everyone involved in labour market restructuring will need to reflect on how to implement a range of policies that share the costs not only of training but also of social protection. Such a comprehensive approach (see Chapter 6) will also need to revisit some specific policy questions, such as which occupations legitimately require a licence rather than a skills certification.
- Uncertainties surrounding estimates in this chapter mainly come from the lack of data on adult education and training programmes, which makes it difficult to assess the cost of these programmes and their returns in terms of skills. More data on adult education and training would enable these programmes to be better designed to meet the needs and constraints that adults face as they continue to develop their skills.

The role of labour mobility

All workers need to adapt to the continuously evolving demand for skills as digital technologies develop and get adopted in different sectors (Chapter 2). Those in occupations at high risk of automation face bigger challenges, however, and need to become more mobile.

Too little occupational mobility when labour markets are restructuring may lead to situations where workers are trapped in declining occupations, risk becoming unemployed or fail to develop their skill sets to adjust to new skills needs. Moving between jobs or occupations entails several costs, however.

Given the nature of digital transformation, moving to a job in a different firm or industry but the same occupation is unlikely to help a worker cope with labour market restructuring. Remaining in an occupation at high risk of automation may merely postpone the redundancy problem rather than solving it, and entail having to move to yet another job in the near future.

An increase in occupational mobility would signal that restructuring of labour markets is indeed taking place, but recent evidence does not point to such an increase (Box 3.1). Studies have found a declining trend in the United States between 1995 and 2015 (Lalé, 2017[1]) and no clear trend in the United Kingdom (Carrillo-Tudela et al., 2016[2]). However, measuring occupation mobility is difficult because of the lack of comparable and reliable data on changes across occupations.

In addition, available studies do not provide clear evidence that workers who are changing occupation move away from the risk of automation. In the United States, the decrease in the share of employment in routine jobs comes from reduced inflows from unemployment to these types of jobs rather than from increased outflows from these jobs (Lalé, 2017[1]). In the United Kingdom, however, career changes tend to move workers from routine to non-routine employment, although these movements did not accelerate during the Great Recession of the late 2000s and early 2010s (Carrillo-Tudela et al., 2016[2]).

The challenge for governments thus becomes helping workers overcome mobility obstacles and fostering smooth transitions in the labour market, while enabling more efficient allocation of workers and skills among occupations, firms and sectors. Of the many policy tools normally used to make mobility easier (e.g. job search assistance through intensive counselling, redeployment benefits or subsidies for geographical relocation), skills policies play an especially important role in the context of digitalisation. Education and training policies can help workers develop the skills they need to adapt to the ever-changing task content of occupations and to move to other jobs when necessary or desired.

It is still not clear how labour markets will be affected by technological development. At the same time, many factors shape workers' opportunities and willingness to change occupations. Policies should therefore not be too specific or try to reallocate workers across occupations on a large scale. Hence, this chapter aims not to be prescriptive but to: 1) inform countries about how they can better design their education and training policies to help workers switch occupations; and 2) provide information on options for occupational mobility and the associated type and size of the necessary investment in training.

Box 3.1. Occupational mobility: What do empirical studies show?

Globalisation and digital transformation are expected to have at least two effects on occupational mobility. First, they trigger labour market restructuring. Some occupations are needed more, while others are needed less, undergo change or disappear. Mobility reflecting structural change in labour demand is generally captured by *net* mobility, that is changes in the shares of employment by occupation. Second, new business models and technologies, including platforms and online employment offers, can help match workers with jobs, thereby reducing excess reallocations or reallocations of workers between occupations that cancel out, leaving the shares of employment by occupation unchanged. Overall, digitalisation could lead to an increase in net mobility and a decrease in excess reallocations.[1]

How many workers change occupation?

Mobility between occupations is difficult to estimate for several reasons. It varies among countries as it is influenced by several labour, housing, social and infrastructure policies and institutions. Job mobility studies are hardly comparable because of data problems. Finally, the estimated mobility depends on the level of aggregation at which occupations are considered. Mobility appears lower at a high level of aggregation (e.g. one-digit level of occupation classifications) than at a detailed level (three or four-digit level of occupation classifications, which also captures changes between occupations within the same aggregated category). Yet there seems to be a consensus that changes in occupations account for almost half of job changes.

Available estimates give the following results for net mobility and for gross mobility, which is the sum of net mobility and excess reallocations:

- In the United States, net reallocations at the 3-digit level of the OCC1990 Classification (387 categories), hence at a detailed level, amounted to 4.4% of employment between 1976 and 2015 (Lalé, 2017[1]). With excess reallocations, i.e. those that cancel out, amounting to 14.6% over the period, gross reallocations reached to be at 19% of employment.
- Between 2011 and 2014, 3% of European workers changed their occupation (capturing gross mobility) per year at a 2-digit level of the ISCO-08 Classification (43 categories) (Bachmann, Bechara and Vonnahme, 2017[3]). Occupational mobility nevertheless differed by country, reaching 7.4% of employment in Sweden, 5.2% in the United Kingdom and less than 2% in France. Net occupation

mobility is on average around 2%. Some countries exhibit a very high ratio of gross occupational mobility over net occupational mobility (e.g. Slovak Republic, Hungary and Poland), pointing at excess churning, while the ratio is low for countries such as Greece and Portugal, which suggests that structural changes are occurring in these countries.

- In the United Kingdom – one of the OECD countries with the highest labour market turnover – around 50% of workers who changed job between 1993 and 2012 moved to a new occupation at 1-digit level of the SOC 1990/2000 classification (9 categories) (Carrillo-Tudela et al., 2016[2]). In other words, many workers moved to very different occupations. Likewise, around 50% of workers who changed job took a job in a different industry; workers tended to change occupation and industry at the same time.

Trends in occupational mobility

Occupational mobility shows no clear trend. In the United States, worker net reallocation at the one- and two-digit OCC1990 levels (7 and 80 categories respectively) was stable between 1980 and 2015 (Lalé, 2017[1]). At the 3-digit OCC1990 level (387 categories), an upward trend in the 1980s and early 1990s was reversed between 1995 and 2015. Excess reallocations have increased since 1995. In the United Kingdom, mobility has tended to follow economic cycles (Carrillo-Tudela et al., 2016[2]). Two groups of workers with a higher probability of switching careers are driving occupational change dynamics: those who move voluntarily from job to job, as a change in their career path, and those who get employed after an unemployment spell.

A study found that the difference, or distance, between occupations in terms of their task content is a significant component of the cost of switching occupations (Bachmann, Bechara and Vonnahme, 2017[3]). This suggests a role for task-specific training. Across most occupations, however, only 15% of the total transition costs is attributable to the task distance. This percentage was stable between 1994 and 2013.

Occupational mobility and wages

Mobility is often associated with change in wages. In the United Kingdom between 1993 and 2012, workers in the bottom part of the wage distribution who moved from job to job experienced a fall in real wages of about 15%, while wages fell more than 20% from previous jobs for those coming from an unemployment spell (Carrillo-Tudela et al., 2016[2]). Career changes that involved a step down in skill level were more likely after spells of non-employment. Conversely, those in the top of the wage distribution who changed job experienced a large increase in wages. Such increases were larger for those who changed occupations than for those who changed jobs but remained in the same occupation.

In Europe, only 36% of workers who change their occupation remain in the same earnings decile, which is much lower than for all workers changing jobs (53% with no change) (Bachmann, Bechara and Vonnahme, 2017[3]). Downward transitions can be observed for 37% of occupation changers and upward transitions for 28% of occupation changers. The reason for changing occupation is an important determinant of wage transitions. Workers who change occupation voluntarily have a higher probability of increasing their wages than those who are pushed to change occupation.

Sources: Lalé, E. (2017[1]), "Worker reallocation across occupations: Confronting data with theory", http://dx.doi.org/10.1016/J.LABECO.2016.12.001; Bachmann, R., P. Bechara and C. Vonnahme (2017[3]), "Occupational mobility in Europe: Extent, determinants and consequences", http://dx.doi.org/10.4419/86788852; Carrillo-Tudela, C. et al. (2016[2]), "The extent and cyclicality of career changes: Evidence for the U.K.", http://dx.doi.org/10.1016/J.EUROECOREV.2015.09.008.

The distance between occupations in terms of skills needs

Education and training policies can make it easier for workers to change occupations by helping them develop the necessary skills. Most governments face budget constraints, so it is important that these policies be cost-effective. In particular, policies that help workers move to occupations with similar skills requirements would limit the education and training effort needed. This means it is important to assess the "skills distance" between occupations. A related document explains the methodology used to assess skills distances between occupations (Bechichi et al., 2018[4]).

Methodology: assessing the skills distance between occupations

The Survey of Adult Skills (PIAAC) can be used to assess the distance between occupations in terms of cognitive skills and task content:

1. Literacy and numeracy are used to investigate the extent to which occupations differ in terms of workers' cognitive skills.[2]
2. To evaluate the distance between occupations in terms of their task content, the analysis relies on five "task-based skills" indicators of the frequency with which workers performed tasks involving ICT skills, management and communication skills, accountancy and selling skills, advanced numeracy skills and self-organisation skills (Grundke et al., 2017[5]). The construction of these indicators is explained in Chapter 2 (Box 2.3 and Table 2.1).

Distances between occupations in terms of cognitive skills are more likely to be bridged by formal education and distances in task-based skills through learning on the job, on-the-job training and vocational training.

As a first step, the average requirements in cognitive skills and task-based skills were calculated for the 127 occupations at the 3-digit level of the 2008 International Standard Classification of Occupations (ISCO-08) available in PIAAC. As a second step, multidimensional skill distances between any two occupations, e.g. A and B, were further assessed using measures of skill shortage and skill excess. Assuming a hypothetical move from occupation A to occupation B:

- The measure of skill shortage was computed for all skills for which occupation B required higher levels than occupation A. This showed the type and amount of skills that workers would need to move from occupation A to occupation B. The skill shortage measure was calculated as the weighted sum of the skill differences, with weights mirroring the relative importance of the skills in the destination occupation B.

- The measure of skill excess was computed for all skills for which occupation B required lower levels than occupation A. Thus, the excess measure captures the amount of skills needed to a lesser extent in occupation B than in occupation A.

The shortage and excess measures are symmetric: shortage measures for a move from occupation A to occupation B equal the excess measures for a move from occupation B to occupation A. Box 3.2 explains the detailed methodology.

Occupation distances were computed across all 31 countries included in PIAAC. Due to the size of the PIAAC sample (around 3 500 workers on average by country), distances cannot be computed by country at the detailed occupation level chosen for the analysis. However, it is possible to group countries in clusters according to similarities in terms of the distribution of the tasks performed by workers in each occupation group (Bechichi et al., 2018[4]), and perform this analysis by cluster (Table 3.1). If, for all occupations, workers in the same occupation in a considered cluster perform similar sets of tasks with the similar frequencies, it could be expected that distances between occupations in these countries might be similar.

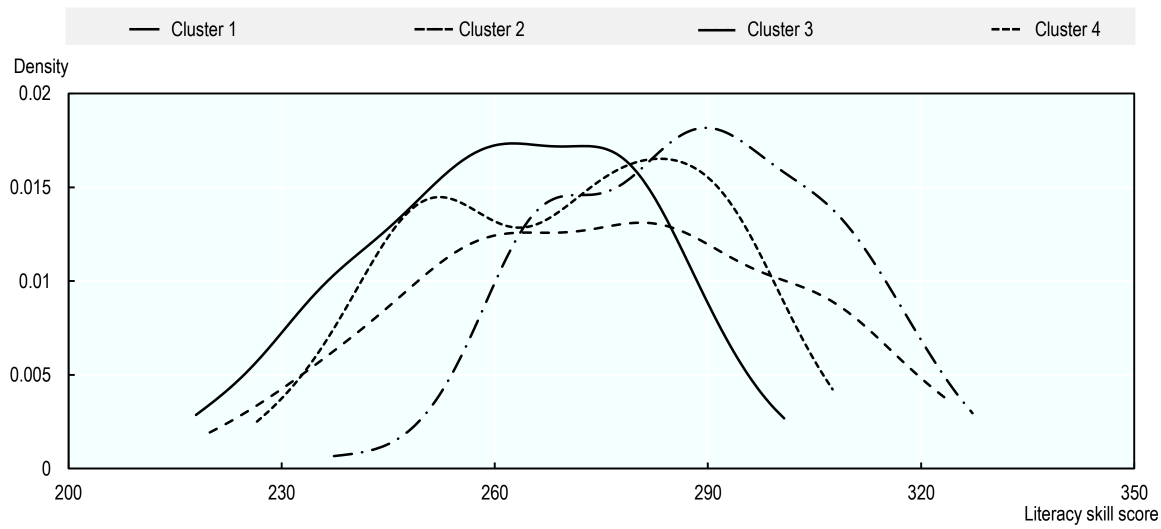
Table 3.1. Grouping of countries according to the cluster analysis

	Countries	Characteristics of skills distribution
Cluster 1	Chile, Greece, Italy, Lithuania, Russian Federation, Slovak Republic, Turkey	Average low skills proficiency; small dispersion
Cluster 2	Australia, Canada, Ireland, New Zealand, United Kingdom, United States	Average medium skill proficiency; large dispersion
Cluster 3	Austria, Belgium, Czech Republic, Denmark, Finland, Germany, Japan, Netherlands, Norway, Sweden	Average high skills proficiency; small dispersion
Cluster 4	Estonia, France, Israel, Korea, Poland, Singapore, Slovenia, Spain	Average medium skill proficiency; medium dispersion

Source: Bechichi, N. et al. (2018[4]), "Moving between jobs: An analysis of occupation distances and skill needs", https://doi.org/10.1787/d35017ee-en.

Clusters of countries differ according to the characteristics of their skills distribution (Figure 3.1). Cluster 1 features countries characterised by low proficiency and a small dispersion. Cluster 2, made up of Anglo-Saxon countries, stands out as having large skills dispersion and medium skills proficiency. Cluster 3 is characterised by the highest skills proficiency and a narrow distribution of skills. Cluster 4 appears similar to what is observed on average across all countries considered.

Figure 3.1. Literacy skills distribution by clusters of countries



Note: Each line represents the kernel density of occupations' average literacy skill in a given cluster. A kernel density can be thought as a smoothed histogram such that approximately, for a given literacy skill score, a greater line height means this literacy skill score is more frequent. That being said, the y-axis cannot be interpreted as actual frequencies. Clusters are defined in Table 3.1.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973418

Box 3.2. Measuring the distance between occupations

Distances between occupations in terms of cognitive skills and task-based skills, as identified in Bechichi et al. (2018[4]), were computed at the three-digit ISCO-08 occupation level using data for 31 countries from the Survey of Adult Skills (PIAAC). Cognitive skills measures rely on the results of two skills assessed through externally administered tests in PIAAC –literacy and numeracy – while task-based skills were computed based on the frequency with which certain tasks are performed by workers following Grundke et al. (2017[5]).

Cognitive skills shortage and excess

Cognitive skills shortage and excess from occupation A to B are defined as the weighted sums of the difference in occupation A and B's average literacy and numeracy skills across countries.

In particular, the shortage is equal to:

$$CogShortage_{A\to B} =$$

$$\omega_{literacy} \times (literacy_B - literacy_A)\boldsymbol{I}(literacy_B > literacy_A) +$$

$$\omega_{numeracy} \times (numeracy_B - numeracy_A)\boldsymbol{I}(numeracy_B > numeracy_A),$$

where $\omega_{\{literacy,numeracy\}}$ is equal to the relative importance of the cognitive skill in occupation B (e.g. $literacy/\max(literacy, numeracy)$), $literacy_{\{A,B\}}$ and $numeracy_{\{A,B\}}$ are occupation A and B's average literacy and numeracy skills, and $\boldsymbol{I}()$ is an indicator function returning 1 if the condition in parenthesis is true and 0 otherwise. As such, cognitive skills shortages arise in the case where the origin occupation is insufficiently skilled relative to the destination occupation, in one or both cognitive skills.

Similarly, cognitive skills excess is defined as:

$$CogExcess_{A\to B} =$$
$$\omega_{literacy} \times (literacy_A - literacy_B)\boldsymbol{I}(literacy_A > literacy_B) +$$
$$\omega_{numeracy} \times (numeracy_A - numeracy_B)\boldsymbol{I}(numeracy_A > numeracy_B).$$

Cognitive skills excesses arise when the origin occupation is more skilled in one or both cognitive skills than the destination occupation. Overall, around 47% of possible transitions involve no cognitive skills shortages.

Task-based skills shortage and excess

The task-based skills shortage and excess from occupation A to B are defined as the weighted sums of the difference in occupation A's and B's average intensities for five task-based skills: ICT skills, management and communication skills, accounting and selling skills, advanced numeracy skills, and self-organisation skills. They were computed following Grundke et al. (2017[5]). The task-based skills shortage is equal to:

$$TaskShortage_{A\to B} =$$
$$\sum_{t=1}^{5} \omega_t \times (Intensity_B^t - Intensity_A^t)\boldsymbol{I}(Intensity_B^t > Intensity_A^t),$$

where t is one of the five task-based skills, ω_t is equal to the relative importance of task-based skill t in occupation B's task portfolio, and $Intensity_{\{A,B\}}^t$ is equal to the average intensity of the task-based skill t in occupation A or B.

Similarly, task-based skills excess is defined as:

$$TaskExcess_{A\to B} =$$
$$\sum_{t=1}^{5} \omega_t \times (Intensity_A^t - Intensity_B^t)\boldsymbol{I}(Intensity_A^t > Intensity_B^t),$$

As with cognitive skills, transitions between occupations are likely to involve both shortages and excesses of different skills, unless one of the two occupations requires strictly more of each task-based skill than the other occupation. Overall, around 23% of transitions involve no task-based skills shortages.

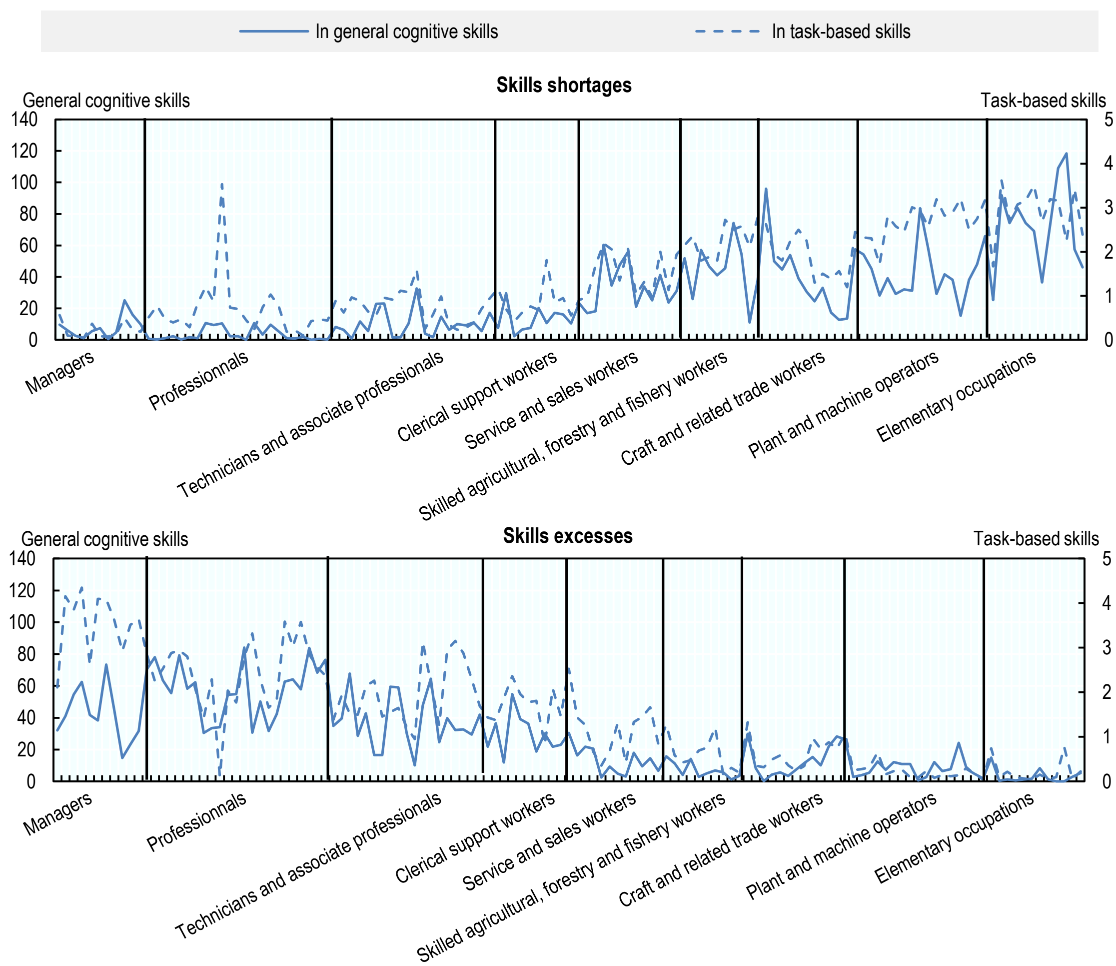
Sources: Bechichi, N. et al. (2018[4]), "Moving between jobs: An analysis of occupation distances and skill needs", https://doi.org/10.1787/d35017ee-en ; Grundke, R. et al. (2017[5]), "Skills and global value chains: A characterisation", http://dx.doi.org/10.1787/cdb5de9b-en.

Results: how distant occupations are from one another

Distances between occupations involve both skills shortages and excesses, and this is true for general cognitive skills (literacy and numeracy) and task-based skills (ICT, self-organisation, advanced numeracy, accounting and selling, and managing and communicating) (Figure 3.2). Moves from high-skilled occupations, such as those belonging to managers and professionals, to other occupations would on average entail small shortages and large excesses in both cognitive skills and task-based skills. Conversely, moves from low-skilled to other occupations would on average entail large shortages and small excesses in both cognitive skills and task-based skills. Mobility for middle-skilled occupations to other occupations generally involves both substantial skills shortages and excesses.

Figure 3.2. Average skills shortage to move to other occupations

Average skills shortages to move from one occupation to any other occupation



Note: Each tick mark corresponds to an occupation within the group of occupations mentioned on the axis and indicated by a blue area.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

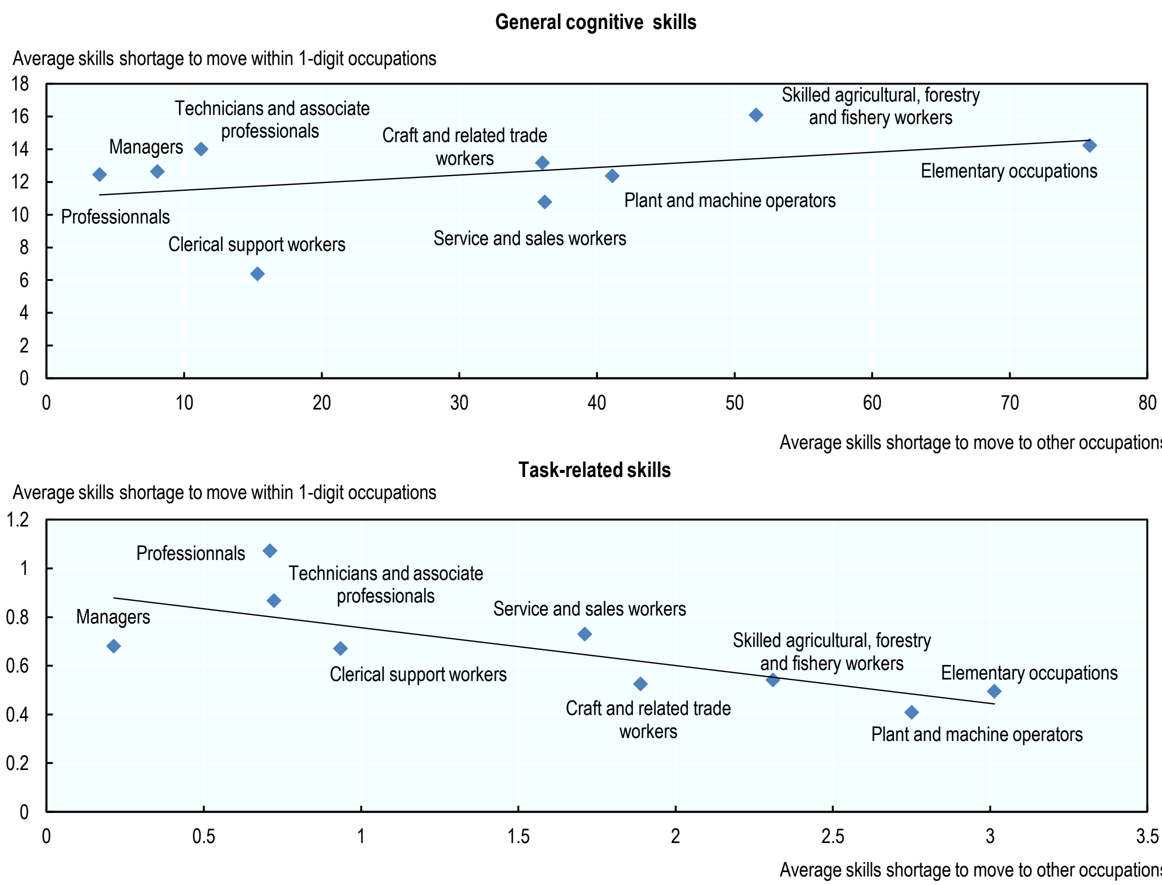
StatLink https://doi.org/10.1787/888933973437

Statistics on distances from one occupation to any other occupation help shed light on the effort that may be needed to move on the labour market. However, workers are more likely to switch to occupations that are closer to their occupation of origin in terms of skills requirements. In particular, transitions within the same (one-digit ISCO-08) group of occupations (e.g. within managerial jobs or elementary occupations) can be considered as "close" transitions, or transitions to similar occupations.

A slightly positive relationship between the average distance to all other occupations and the average distance within the same group of occupations emerges in terms of cognitive skills (top panel of Figure 3.3). This means that close transitions would entail significantly greater shortages in cognitive skills for elementary occupations than for managers. In contrast, distances in terms of task-related skills within the same group of occupations are larger for high-skilled occupations groups such as technicians and professionals than for low-skilled ones such as plant and machine operators, and for elementary occupations (bottom panel of Figure 3.3).

Figure 3.3. Skills shortages to move within the same ISCO-08 one-digit occupation category

Relationship between the average shortage for transitions in the same ISCO-08 one-digit occupations category and the average shortage for transitions to all other occupations

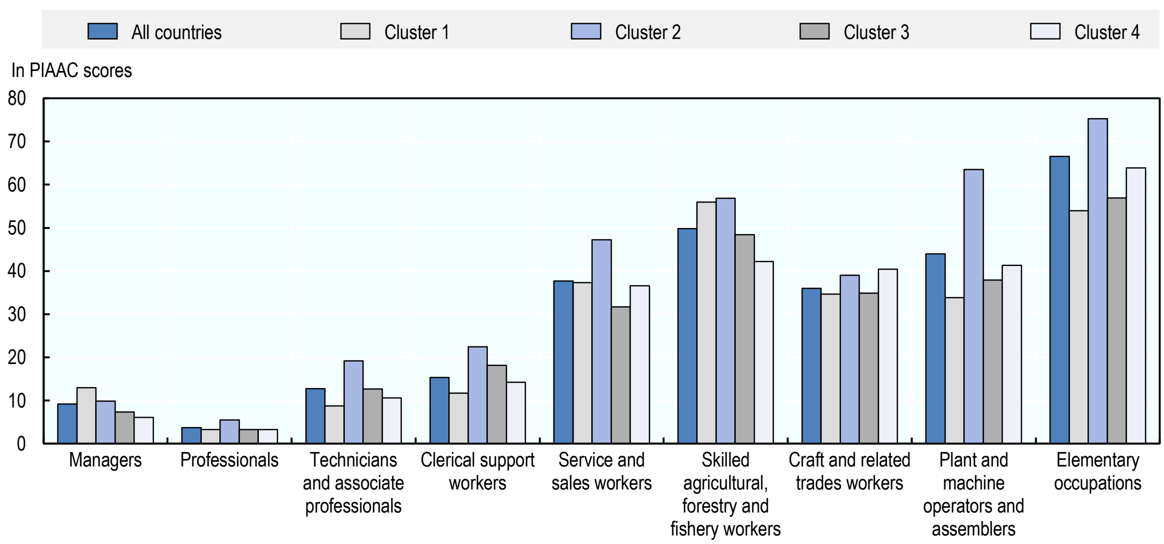


Note: Occupations refer to the three-digit codes of 2008 International Standard Classification of Occupations (ISCO-08), while occupations group refers to the one-digit ISCO-08 codes. The average shortage to all other occupations is calculated as the average of the average shortages of each occupation belonging to that occupations group to all other occupations outside this group. The average shortage to move within one-digit occupations (occupations group) is calculated as the average of average shortage for each occupation to the other occupations belonging to that occupations group.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973456

Distances between occupations vary by clusters of countries. Cluster 2, made up of Anglo-Saxon countries, stands out as having larger distances between occupations than other groups of countries, for almost all groups of occupations, reflecting more dispersed skills distributions (Figure 3.4). Cluster 1, featuring countries characterised by lower proficiency, exhibits small distances between occupations for low-skilled occupations. In Cluster 3, characterised by high skills proficiency and low skills dispersion, distances between occupations are small for most groups of occupations.

Figure 3.4. Average shortage in cognitive skills to all other occupations, by country clusters and groups of occupations



Note: Each bar shows, for each country cluster, the average shortage for occupations belonging to the indicated group of occupation (e.g. managers) to move to any other occupation. For example, occupations in the group of managers have on average much smaller shortages than occupations in the group elementary occupations to move to any other occupation. The composition of clusters is given in Table 3.1.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973475

Where workers could move: possible and acceptable transitions

Once the distance between occupations is assessed, another question is to identify transitions between occupations that are possible to achieve within a defined upskilling or reskilling effort and are acceptable for workers, economies and societies. Those transitions need to maintain workers in quality jobs that make the best use of their skill sets. A related document explains more in detail the typology of possible and acceptable transitions and the implication for skills needs (Bechichi et al., 2019[8]).

Methodology: Defining neighbourhoods of possible and acceptable transitions

For each occupation, the analysis identifies transitions to other occupations involving (re)training or upskilling needs that could be bridged within pre-determined training effort. To this end, three training scenarios are considered:

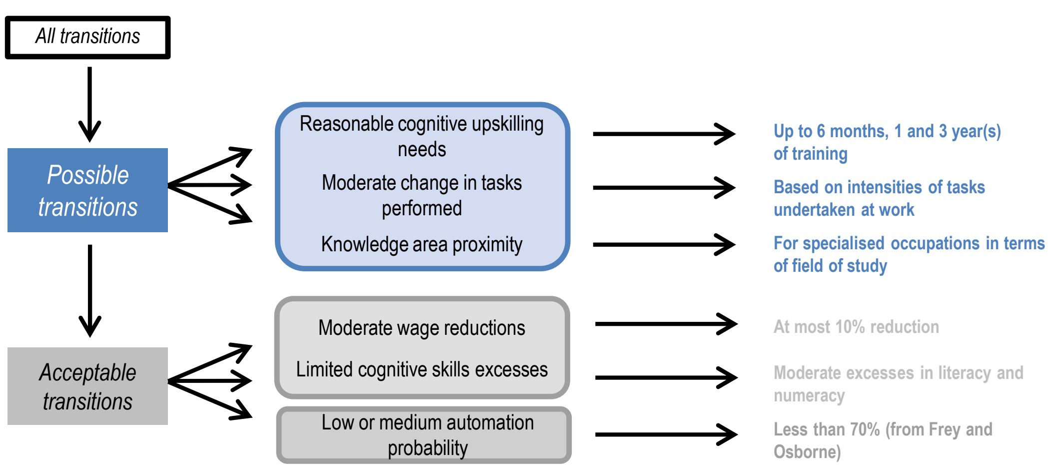
- Scenario 1 *small* training needs, which refers to (re)training or upskilling needs that can bridged within approximately six months of training at most;
- Scenario 2, *moderate* training needs, which could be bridged in approximately up to one year of training;
- Scenario 3, *important* training needs, which could be bridged in approximately up to three years of training.

In the context of any of these three scenarios, two types of transitions are distinguished: possible and acceptable transitions. Possible transitions can be made within the training effort of the scenario considered. These include transitions from high-skilled occupations to much less skilled ones. Acceptable transitions represent the subset of possible transitions that workers, and society more broadly, may be prepared to accept as they entail limited human capital and wage losses. Using a different methodology and data from the United States, a similar analysis is proposed by the World Economic Forum (2018[9]).

More specifically:

- *Possible* transitions are those for which a given upskilling or (re)training effort would close the skills distance existing between two occupations. The skills distance has two components, as explained in the previous section: cognitive skills and task-based skills. In addition, workers are unlikely to move to occupations that involve very different areas and therefore, there should be a proximity in the knowledge area of the occupation of origin and destination.
- *Acceptable* transitions are possible transitions entailing at most moderate wage reductions and limited excess cognitive skills.
- Figure 3.5 and Figure 3.6 explain the concepts used in the following sections.

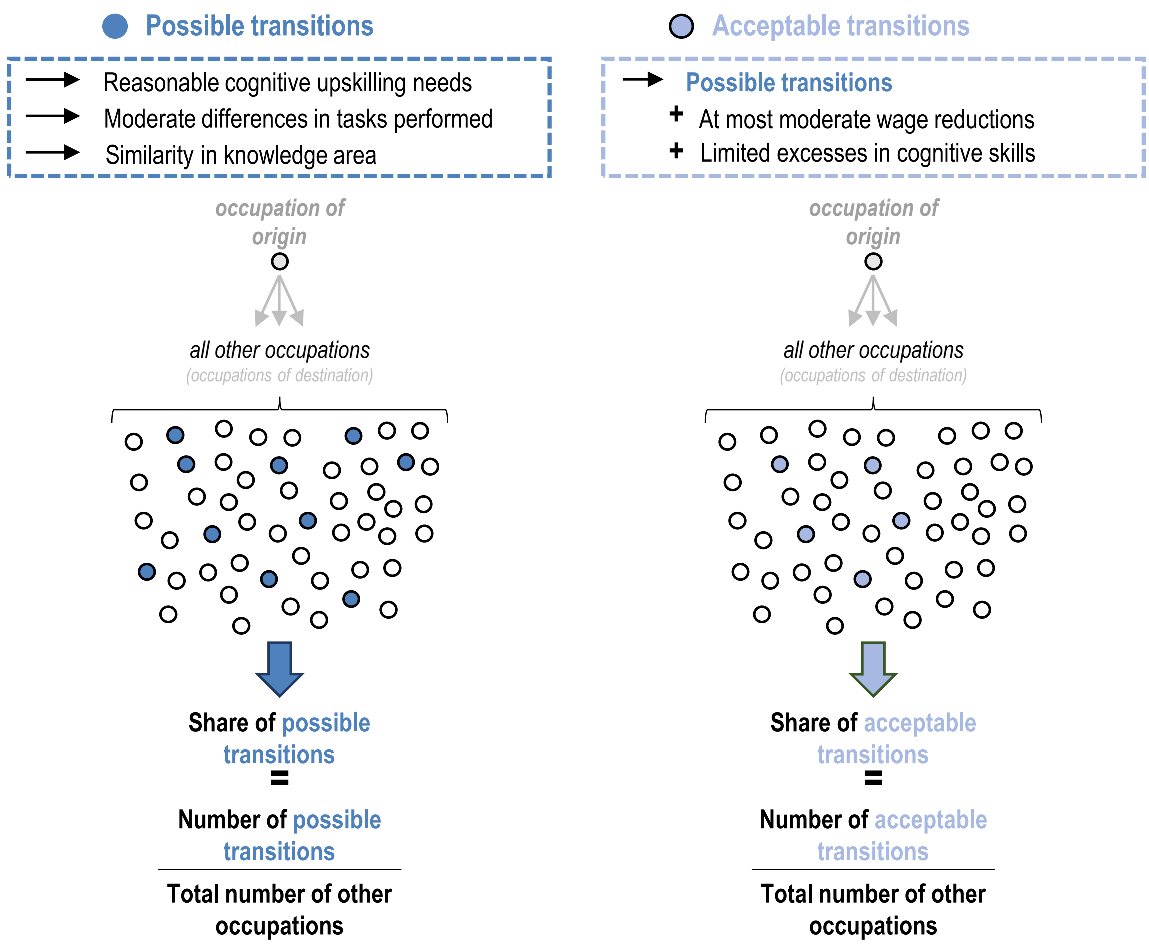
Figure 3.5. Summary of criteria for identifying possible and acceptable transitions



Policies may target acceptable transitions from occupations at high risk of automation to occupations at low or medium risk of automation. Hence, the risk of automation can be added in the analysis as a supplementary criterion guiding the identification of acceptable transitions (in final sections of this chapter). The risk of automation by occupation is taken from Frey and Osborne (2017[10]). These risks were calculated based on machine learning experts' assessment of which tasks could technically be automated and applied to the

Occupational Information Network (O*NET) data from the United States. These estimates assess the intrinsic risk of automation and therefore, are used in this analysis to identify occupations at risk of automation.

Figure 3.6. Concept used in the analysis of possible and acceptable transitions



Identifying transitions that can be made possible by a given (re)training or upskilling effort and can be acceptable is a thorny issue that is central to the analysis. It consists of assessing the extent to which cognitive skills shortages, task-based skills shortages and difference in knowledge areas can be bridged with a given training effort, or scenario. It also consists of assessing the extent to which wage reductions and skills excesses would not be acceptable, from both an individual and economy point of view. Those assumptions are detailed in Table 3.2 and discussed in a related study (Bechichi et al., 2019[8]).

Table 3.2. Summary of conditions for possible and acceptable transitions for each scenario

	Scenario 1 Small training need (up to 6 months of training)	Scenario 2 Moderate training need (up to 1 year of training)	Scenario 3 Important training need (at most 3 years of training)	Explanations
Possible transitions				
Cognitive upskilling	At most 3.5 PIAAC points in literacy and numeracy	At most 7 PIAAC points in literacy and numeracy	At most 21 PIAAC points in literacy and numeracy	The equivalence between years of education and cognitive skills is obtained from regressing PIAAC cognitive skill scores on years of education controlling for a number of factors.
Task up- or reskilling	At most bottom quartile	At most median	At most top quartile	These values correspond respectively to the bottom quartile, median, and top quartile of the distribution of task-based skills shortages (excluding zeros).
Knowledge area proximity	*If specialised destination occupation*: one of the most frequent fields of study of the occupation of origin needs to be among the most frequent fields of study of the specialised occupation of destination *Otherwise*: no restriction		No criteria applied	An occupation's set of most frequent fields of study corresponds to the most common fields of study which together account for at least 50% of the occupation's workers. An occupation is defined as specialised if the workers composing this occupation are concentrated in only a few fields of study.
Acceptable transitions				
Moderate wage reductions	At most 10%			This figure corresponds to approximately the average annual earnings loss one year after displacement in five OECD countries, (OECD, 2013[11]).
Limited cognitive skills excesses	3.5 PIAAC points	7 PIAAC points	7 PIAAC points	For Scenario 1 and Scenario 2, this condition mirrors the maximum allowed cognitive skills upskilling needs. For Scenario 3, the same condition as Scenario 2 is chosen to avoid a large human capital loss.

Source: Bechichi, N. et al. (2019[8]), "Occupational mobility, skills and training needs", OECD, Paris.

In particular, the approach rests on estimates of the cognitive skill shortages that can be bridged within one year of education. Due to data limitations, it is not possible to causally estimate skills returns to education using PIAAC data but only to rely on correlations between cognitive skills and educational level, which account for a number of factors (Bechichi et al., 2019[8]). This approach finds that one year of education makes up for approximately 7 PIAAC literacy and 7 PIAAC numeracy points.

Several caveats surround the choice of the equivalence between years of education and cognitive skills, which is a crucial parameter for the analysis:

- The skills returns to education vary between countries, because some have better education systems than others or because framework conditions differ. As the estimated equivalence is taken over all countries, it represents an average of all the countries included in the analysis and is therefore sensitive to, for example, the inclusion or exclusion of some countries. The main implication of this choice is that, for a given training effort, the transition options may be underestimated for countries with high-performing education and training systems, and overestimated for those with low-performing systems or with large heterogeneity of educational institutions.

- The analysis further assumes that each individual learns at equal pace once in training. Workers are likely to have different learning abilities, however, depending factors such as the type of education they went through as students, their attitude to learning, their skills and knowledge, and their age. The analysis also assumes that individuals complete the education and training programme and that this programme is successful in upskilling.
- Expressing a training effort in terms of duration is questionable in itself as several factors beyond duration affect what participants will actually learn, including resource endowment, curricula and pedagogical approaches. However, the use of an equivalence between cognitive skills shortages and years of education makes it possible to measure training efforts and estimate the cost of training for governments and countries.
- While these estimates cover the training effort required to bridge cognitive skills needs, they cover task-based skills needs only partly. The equivalence between cognitive skills shortages and years of education cannot be reproduced for skills. Task-based skills are more likely to be developed on the job and there is no data on how much an hour of (e.g. vocational) training yields in terms of task-based skills' gain. However, some of the tasks-based skills considered in this study are also partially cognitive, such as ICT, advanced numeracy, and management and communication skills. Hence, it is likely that improving workers' cognitive skills also enhances some of their task-based skills, but the present methodology cannot say how much so. For these reasons, the training effort required to move between occupations may be underestimated.
- Because of the lack of data on non-formal training, estimates build on the skills returns to formal education. The analysis assumes that the training provided to workers, often non-formal training, would lead to the same cognitive upskilling as formal education. This assumption does *not* imply that training needs to be provided by the formal education sector. Years of education data are used as a reference, in the absence of more complete information about training duration and outcomes (and cost for the next sections).

For all these reasons, references to scenarios in terms of duration of training should be considered as tentative and indicative of how small, moderate or important training needs can be.

The analysis identifies neighbourhoods of occupations that can be reached for a given occupation of origin by a given increase in skills. While education and training policies can lead to such skills development, workers can also learn by themselves, from co-workers and by doing. Box 3.3 discusses other caveats related to the analysis presented in this chapter.

Box 3.3. Methodological caveats

This chapter presents estimates of the training needs and costs of education and training policies to facilitate occupational mobility. To identify a typology of occupational transitions and to generate cost estimates for a large number of countries given the data limitations encountered, several simplifying assumptions are made that inevitably influence the results. These aspects are discussed in background studies (Andrieu et al., 2019[12]; Bechichi et al., 2019[8]) and summarised below. Implications for estimates are explained in detail in Annex Table 3.A.1.

Choice of parameters for identifying possible and acceptable transitions

The definition of possible and acceptable transitions relies on a limited number of parameters that workers are likely to consider when changing jobs. Currently these include cognitive and task-based skill excesses or shortages, and differences in wages and field of education specialisation between occupations of origin and destination. However, preferences over the maximum acceptable wage cut or human capital loss that individuals are willing to accept to re-enter employment depend on individuals, countries and the type of transition, either voluntary or involuntary. In addition, preferences about location, contract type, or differences in a worker's match with the position (Groes, Kircher and Manovskii, 2015[13]), to name but a few important ones, are not considered. In this sense, this analysis identifies feasible opportunities for occupational mobility, but cannot predict it.

Lack of worker heterogeneity

The analysis further assumes that workers learn at an equal pace and can acquire at most 7 PIAAC points in both literacy and numeracy in a given year of education. Workers, however, are likely to have different learning abilities. Furthermore, the quality of education and the efficiency of the education sector can differ widely across locations and countries, yielding different training time for different individuals. Relaxing these assumptions, however, requires considering a high level of disaggregation in the PIAAC data and a large quantity of recent data on education systems across countries, which is unfeasible in the context of the present study. Furthermore, "individual proficiency in learning" and the "efficiency" of an education or training system are hard to measure, especially in a uniform way across countries.

Lack of consideration of transitions *within* the same occupation

The analysis only considers the cost of moving from one occupation to another, with a special focus on moving away from occupations at high risk of automation. In reality, transitions within occupations do exist and can entail a cognitive retraining effort, because skill requirements vary between employers a worker's skill set has depreciated or the skill content of an occupation has changed. These transitions may be less costly than those presented in the analysis if the skills distance between jobs belonging to the same occupation is smaller than the skills distance between two different occupations. However, transitions within occupations may not help workers move away from the risk of automation to the same extent as the transitions between occupations considered in the analysis.

Uncertainty surrounding estimates of automatability

The analysis distinguishes between occupations at high versus medium or low risk of automation, while the risk of automation is a continuum that affects all occupations. Furthermore, workers may differ in their risk of displacement due to automation even within the same occupations, depending on the type of technology deployed, the organisation of tasks in their job place, their sector of affiliation or other institutional settings. The analysis cannot account for changes over time in the skill content of occupations, as it relies on cross-sectional data varying between occupations and countries but not over time. This may entail an overestimation of the cost figures presented if occupations at high risk of automation evolve towards a lower risk of automation, or an underestimation if low-risk occupations are quickly automated.

Exclusion of sectoral dimension

The proposed analysis does not consider whether job transitions imply changing the sector of employment. This was mostly driven by data constraints. While much of the economic literature on labour mobility corroborates this assumption (Kambourov and Manovskii, 2009[14]), others disagree and provide evidence of the coexistence of sectoral and occupational switching costs (Sullivan, 2010[15]) or simply of sector-specific costs (Dix-Carneiro, 2014[16]).

Workers transition directly to a different occupation, without going through an unemployment spell

Workers that switch occupations are assumed to move from the original job to education or retraining and then to the new job without discontinuity or unemployment spells. Such frictionless transitions are likely to be unrealistic for most workers, especially for those who are made redundant and did not leave their job voluntarily. Periods of unemployment may depreciate workers' skills and therefore widen the skill gap, which needs to be bridged for workers to re-enter employment. Idle times during transitions increase the opportunity cost of staying out of employment, while longer training times increase the direct cost of transitions.

Lack of general equilibrium or dynamic elements

Lastly, no general equilibrium or dynamic elements are incorporated in this analysis. In other words, no issues are considered that relate to the adequacy between the number of workers needing training (labour supply) and the number of job openings in "safe haven" occupations (labour demand), which in turn affects the relative wages of occupations. Moreover, the analysis does not include in the indirect cost the fact that some workers may move to higher-paying occupations, which influences their future wage profile, to clearly separate the elements that pertain to costs and those pertaining to gains.

Sources: Andrieu, E. et al. (2019[12]), "Occupational transitions: The cost of moving to a "safe haven"", https://doi.org/10.1787/6d3f9bff-en ; Bechichi, N. et al. (2019[8]), "Occupational mobility, skills and training needs", OECD, Paris; Groes, F., P. Kircher and I. Manovskii (2015[13]), "The U-Shapes of occupational mobility", http://dx.doi.org/10.1093/restud/rdu037; Kambourov, G. and I. Manovskii (2009[14]), "Occupational mobility and wage inequality", http://dx.doi.org/10.1111/j.1467-937X.2009.00535.x; Sullivan, P. (2010[15]), "Empirical evidence on occupation and industry specific human capital", http://dx.doi.org/10.1016/J.LABECO.2009.11.003; Dix-Carneiro, R. (2014[16]), "Trade liberalization and labor market dynamics", http://dx.doi.org/10.3982/ECTA10457.

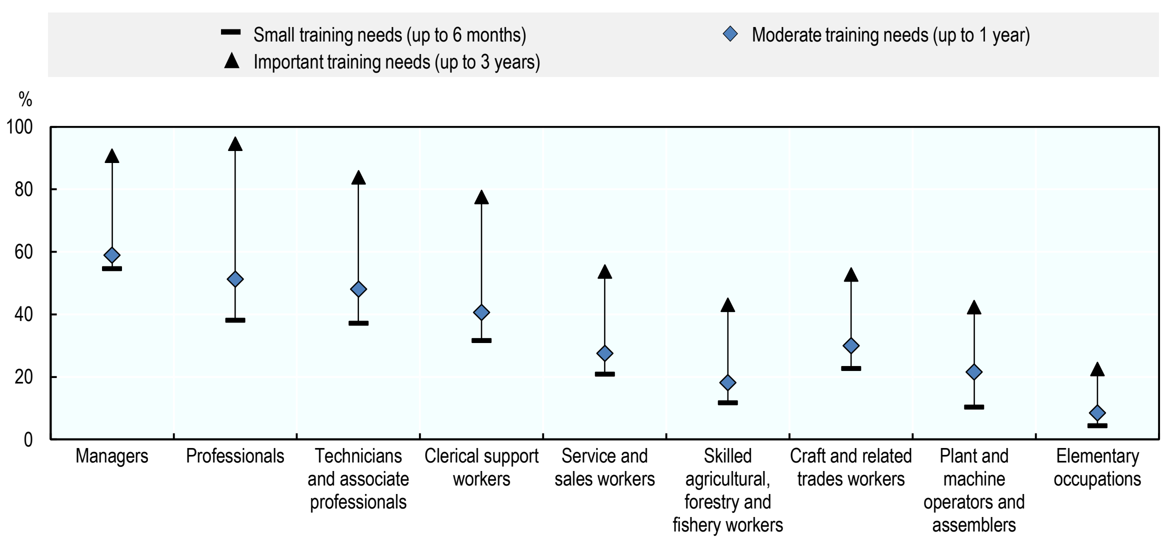
Results: Which transitions for any worker?

In a first step, all occupations and all transitions are considered, without taking into account the risk of automation associated to an occupation.

Most occupations appear to be fairly close to some other occupations in terms of cognitive skills requirements, task content, and knowledge area. This is reflected in the fact that for almost all occupations, it is possible to identify possible transitions in Scenario 1 involving small retraining needs (Figure 3.7). On average, more skilled occupations face several possible transitions in all scenarios, as there are many options to move, even to less skilled occupations. This is true for all three scenarios. For example, within six months of (re)training, managers could move to almost 60% of occupations, whereas workers in elementary occupations could switch to only 5% of all possible occupations, given their skills' endowments and needs. Clerks also have many possible transitions, thanks to their high cognitive skills and the variety and frequency of the tasks they perform on the job (or task-based skills).

Figure 3.7. Average share of possible transitions by group of occupations and scenario

As a share of the total number of occupations, all countries



Note: Each dot shows, for each group of occupations, the average share of possible transitions out of the total number of occupations in the sample, by scenario. For example, in the small training needs scenario, managers, on average, have 55% of possible transitions. In other words, for the average manager occupation, 55% of transitions to all other occupations could technically be bridged within approximately six months. Table 3.2 summarises the conditions used to identify possible transitions.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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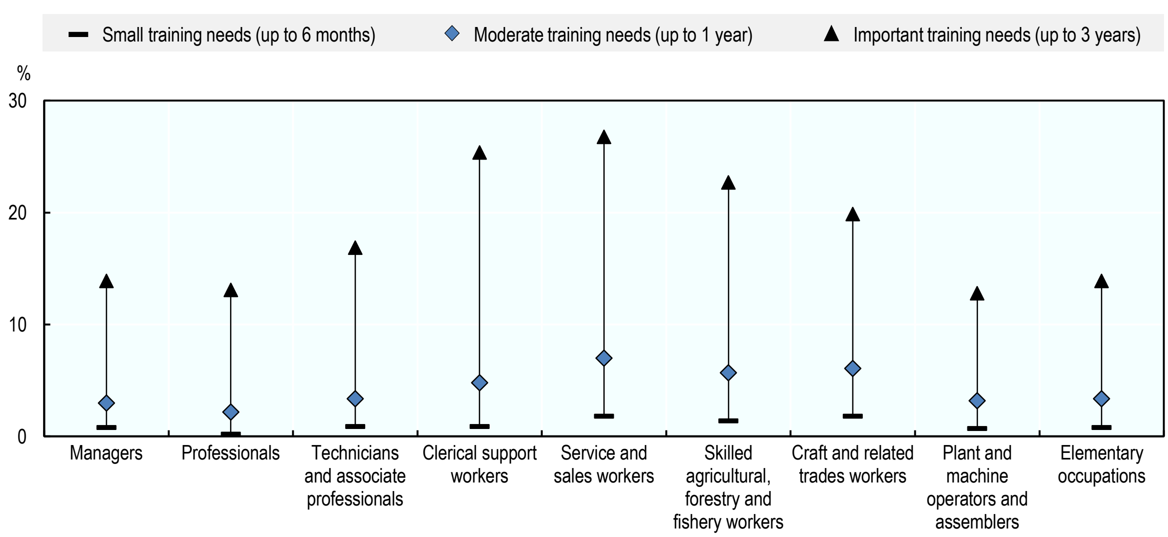
If transitions are required to involve limited cognitive skills excesses and wage reduction, many possible transitions can no longer be considered acceptable, especially for high-skilled occupations (Figure 3.8). For example, within six months of (re)training, less than 1% of the transitions of managers to other occupations could be considered as acceptable.

As the upskilling or (re)training effort increases, it is possible to identify a larger number of acceptable transitions: the share of acceptable transitions increases from Scenario 1 to 3. This is because allowing more (re)training time increases the share of possible transitions. In addition, as it is assumed that workers undertaking longer training spells may transit to occupations that are slightly less cognitively demanding but perhaps involve different task-based skills, the pool of acceptable transitions increases with the retraining effort. With a large training effort of up to three years, some occupations can move to any other occupation, and therefore have 100% of acceptable transitions. This is because the pool of possible transitions is further increased and the condition on the knowledge area is relaxed in Scenario 3.

The relationship between the number of acceptable transitions enabled by upskilling or (re)training efforts and the skill level of occupations is bell-shaped. This finding holds when considering occupation categories as an indication of the skill level (Figure 3.8) or considering directly the average literacy skills of workers of three-digit ISCO-08 occupations (Figure 3.9). There are few acceptable transitions from low-skilled occupations to other occupations because other occupations involve more demanding skills requirements; there are not many acceptable transitions from high-skilled occupations to other occupations because several transitions would entail big wage decreases or skills excesses.

Figure 3.8. Average share of acceptable transitions by groups of occupations and scenarios

As a share of the total number of occupations, all countries



Note: Each dot shows, for each group of occupations, the average share of acceptable transitions out of the total number of occupations in the sample, by scenario. For example, in the small training needs scenario, managers, on average, have less than 1% of acceptable transitions. In other words, for the average manager occupation, less than 1% of transitions to all other occupations could technically be bridged within approximately six months while entailing skills excesses and wage decrease below the limit set for this scenario. Table 3.2 summarises the conditions used to identify acceptable transitions.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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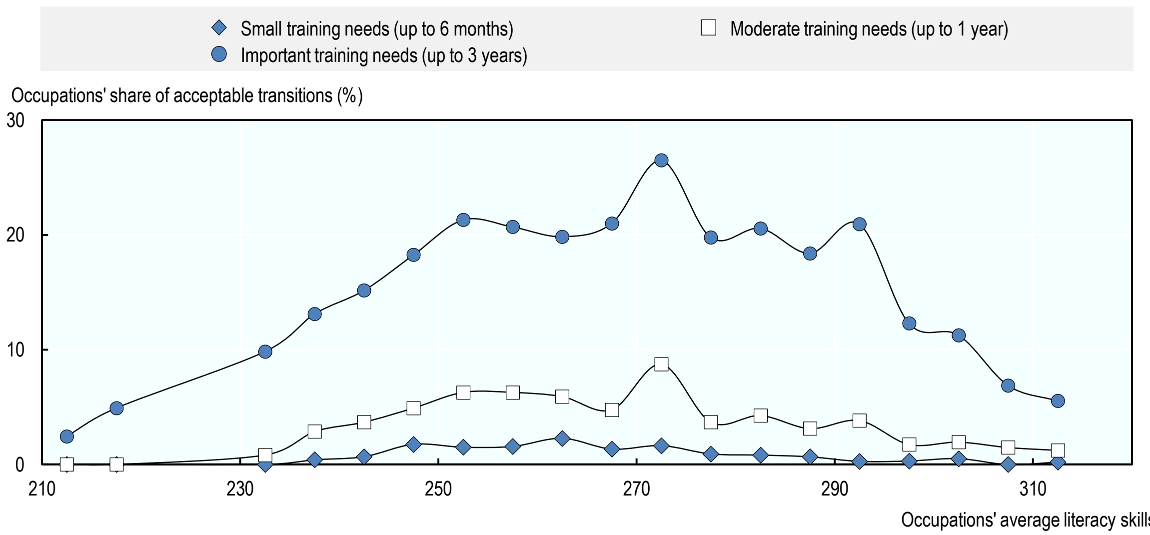
Figure 3.9. Average share of acceptable transitions by literacy skills and scenarios

As a share of the total number of occupations, all countries



Note: This figure displays occupations' share of acceptable transitions as a function of their average literacy skill score, for each scenario. To facilitate readability, literacy scores are grouped in 5-point bins and acceptable transition shares are averaged by 5-point bin. For example, occupations whose average literacy score falls between 270 and 275 points (just to the right of the 270 tick) have an average share of acceptable transitions of 1.6 in the small training needs scenario and 8.7 in the moderate training needs case. Table 3.2 summarises the conditions used to identify acceptable transitions.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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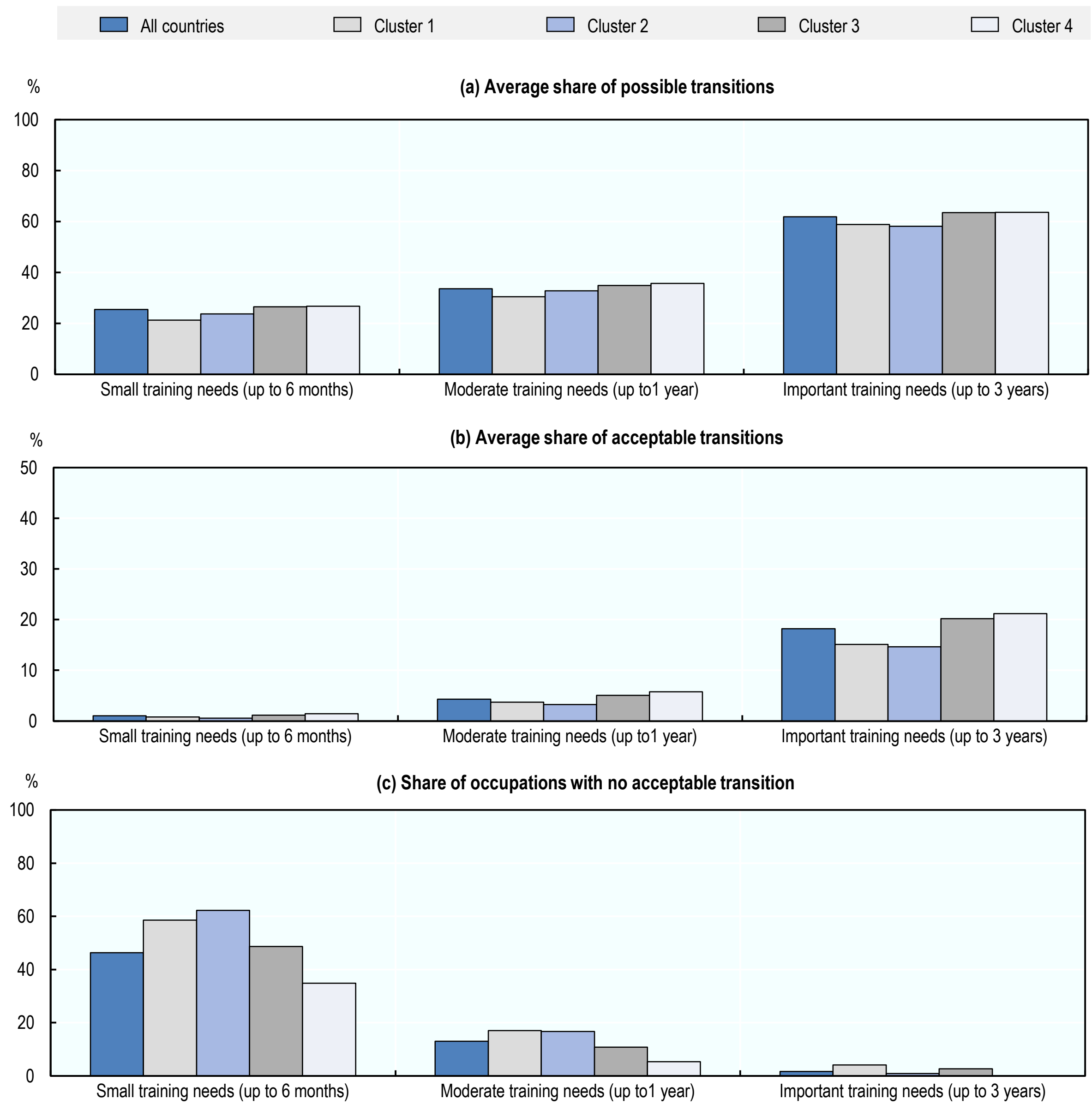
Country specificities of occupational transitions

Opportunities for workers to change occupation depend on several country specificities, including geographical location of economic activity, industry structure and dynamics, institutional barriers (such as occupational licensing), flexibility of labour market arrangements, and skills' distribution. In countries where the distribution of workers' skills is highly uneven, occupations tend to be farther away from one another – and mobility between occupations more difficult – than in countries with narrow skill distributions.

Differences between countries in the distances between occupations affect the numbers of possible and acceptable transitions (Figure 3.10). In countries with larger distances between occupations (clusters 1 and 2), fewer possible transitions can be identified and, consequently, there are also fewer acceptable transitions. In these countries, some possible transitions would entail large skills excesses and wages are more unevenly distributed, so a bigger share of possible transitions involves wage decreases. For clusters 3 and 4, a bigger share of possible and acceptable transitions can conversely be identified. The number of occupations for which no acceptable transitions can be identified with a given training effort also varies by cluster. This is more often the case in clusters 1 and 2 than in clusters 3 and 4.

Figure 3.10. Average share of possible and acceptable transitions, by country cluster



Notes: Panel (a) shows the average share of possible transitions by country cluster and training duration. For example, in the small training needs (up to six months) scenario, for cluster 1, occupations have an average of 21% of possible transitions (out of all transitions), and 30% in the moderate training needs case. Panel (b) shows the average share of acceptable transitions by country cluster and training duration. For example, in the important training needs (up to three years) scenario, for cluster 2, occupations have an average of 15% of acceptable transitions. Panel (c) shows the share of occupations that have no acceptable transition by country cluster and training duration. For example, taking all countries together, there are about 45% of occupations that do not have an acceptable transition in the small training needs case, while this share decreases to 13% in the moderate case.
Possible and acceptable transitions are defined in Table 3.2. Clusters are defined in Table 3.1.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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Which transitions to move away from the risk of automation

While the number of occupations that can be fully automated may not be large, at least in the short-run, education and training policies can aim to facilitate transitions from occupations at high risk of automation to those at a lower risk.

In the following sections, the risk of automation is added to the analysis as a supplementary criterion guiding the identification of acceptable transitions (Box 3.4). The analysis builds on available estimates but large uncertainties need to be acknowledged concerning the number of occupations that would be less in demand in the future and the share of workers who might need to change occupations (Box 3.3).

The analysis identifies "safe havens" or occupations of destination involving a transition with minimum upskilling or (re)training efforts, moderate wage reductions, limited skills excesses and a low or medium risk of automation.

The minimum training effort required to move to a "safe haven" for occupations at high risk of automation is calculated as the average training time in: Scenario 1 if *small* training efforts lead to a "safe haven", Scenario 2 if *small* training efforts do not lead to a "safe haven" but *moderate* training efforts do, Scenario 3 if important training efforts are necessary to move to a "safe haven" (Figure 3.11).

Box 3.4. Estimating occupations' risk of automation

Frey and Osborne's methodology

Frey and Osborne (2017[10]) estimated how potential technological improvements might affect future employment in the United States, with the aim of quantifying the "susceptibility of jobs to computerisation". They focused on the theoretical possibility of automating a task or job rather than on the actual automation of tasks or jobs, and proceeded as follows:

1. During a workshop at Oxford University, they asked a group of machine learning researchers to assess the automatability of 70 occupations based on their O*NET task description. The exact question was "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?" Occupations for which all tasks were confidently considered to be automatable were assigned a 1, while occupations for which none of the tasks were confidently considered to be automatable were assigned a 0.
2. Based on the answers for the 70 occupations of the workshop, they used a machine learning algorithm to better understand the link between their automatability and three "bottlenecks to computerisation" (perception and manipulation; creative intelligence; and social intelligence). The results from the algorithm enabled them to estimate the probability of computerisation for 702 detailed occupations for which employment and wage data are reported by the Bureau of Labor Statistics (BLS).

Automation risk categories

Frey and Osborne (2017[10]) classify occupations into three broad categories, which are also followed in the present work:

- *Low risk of automation*: 30% or less probability of computerisation;
- *Medium risk of automation*: between 30% and 70% probability of computerisation;
- *High risk of automation*: over 70% probability of computerisation.

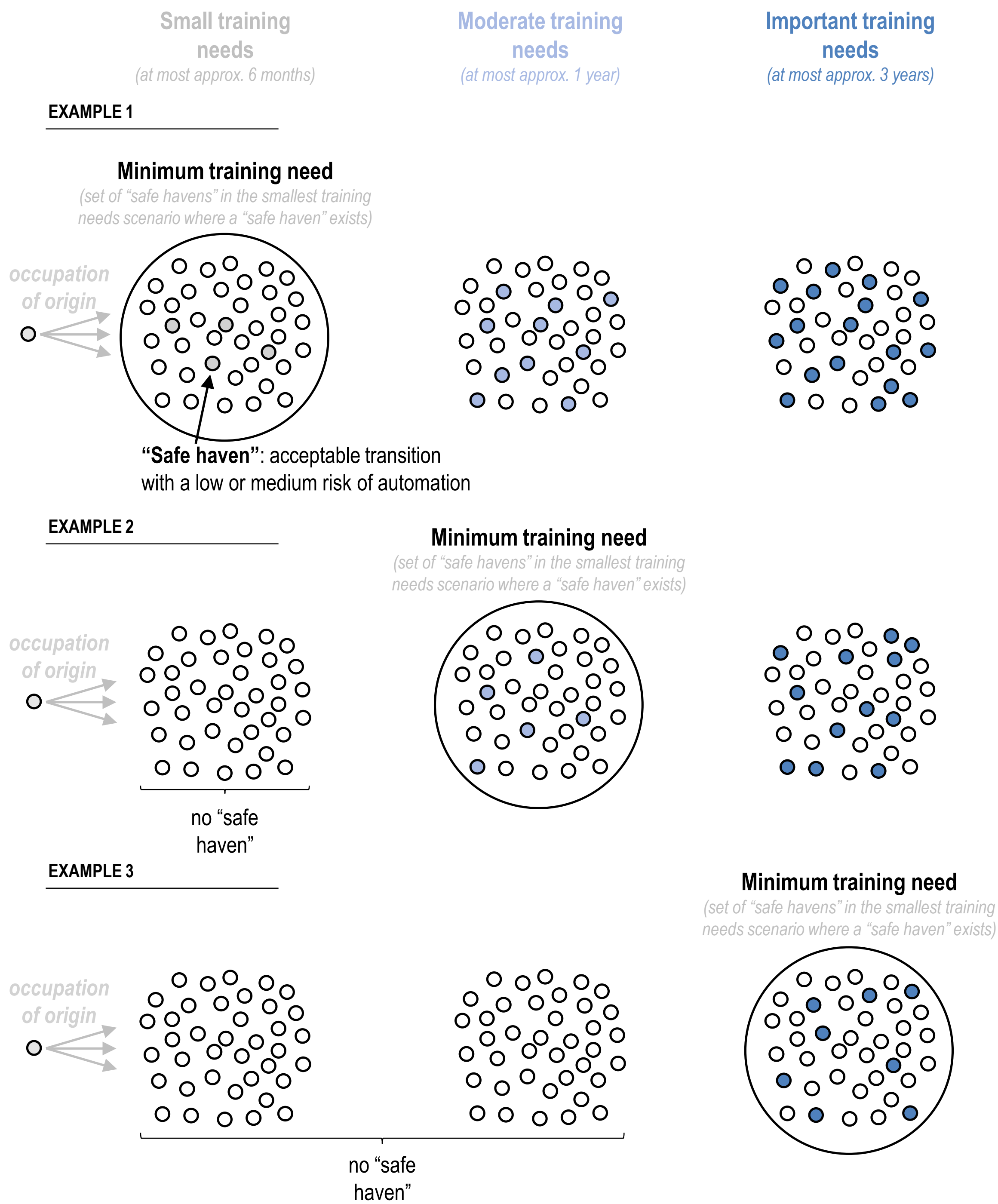
Share of employment at high risk in occupations at high risk of automation

Deriving the share of employment in jobs at high risk of automation requires making an assumption about whether all workers in the same occupation face the same risk or not. Workers in the same occupation may perform different tasks, depending on the organisation of the firm, for example, and the industry in which work, and may therefore face different risks of their job being automated (Arntz, Gregory and Zierahn, 2016[17]; Nedelkoska and Quintini, 2018[18]). Therefore, in the following sections, two cases are considered:

1. Only a proportion of workers in a given occupation at high risk of automation are in jobs at high risk of automation. This assumption leads to lower bound estimates in the following sections, ranging from 4% to 10% of employment depending on the country. The proportions of workers in jobs at high risk of automation for all high risk of automation occupations come from Nedelkoska and Quintini (2018[18]);
2. All workers currently employed in a given occupation at high risk of automation are in jobs at high risk of automation. This assumption leads to upper bound estimates in the following sections, ranging from 19% to 48% of employment depending on the country.

Sources: Frey, C. and M. Osborne (2017[10]), "The future of employment: How susceptible are jobs to computerisation?", http://dx.doi.org/10.1016/J.TECHFORE.2016.08.019; Arntz, M., T. Gregory and U. Zierahn (2016[17]), "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", http://dx.doi.org/10.1787/5jlz9h56dvq7-en; Nedelkoska, L. and G. Quintini (2018[18]), "Automation, skills use and training", https://dx.doi.org/10.1787/2e2f4eea-en..

Figure 3.11. Minimum training needed to find a "safe haven": Definition



Note: In Example 1, an acceptable transition to an occupation with a low or medium risk of automation is identified in the scenario as involving approximately six months of training, hence the minimum training needed to find a "safe haven" is small (around six months). The minimum training needed to reach a "safe haven" is moderate in Example 2 as no "safe haven" can be reached with a small training effort and important in Example 3 as no "safe haven" can be reached with a small or moderate training effort.

Occupations at high risk of automation requiring important investment in training

Occupations at high risk of automation display, on average, shares of possible and acceptable transitions similar to those of occupations at low risk of automation, i.e. the two groups of occupations of origin have similar potential for mobility (Bechichi et al., 2019[8]). When the set of acceptable occupations *of destination* is constrained to occupations displaying low or medium risk of automation (less than 70%) – "safe haven" occupations – this restricts further the set of acceptable transitions.

The (re)training or upskilling efforts necessary to identify acceptable transitions from occupations at high risk of automation to low- or medium-automation-risk occupations varies by country cluster (Figure 3.12). When all countries are considered together, within up to six months of (re)training (i.e. Scenario 1), about half of the occupations at high risk of automation do not have any acceptable transition to an occupation at lower risk of automation. This share climbs to close to 80% for clusters 1 and 2, and just over 65% for cluster 3. Results for cluster 4 are similar to those obtained for all countries. These shares are halved or more when extending the duration of (re)training to up to one year (Scenario 2). With a large training effort (Scenario 3), acceptable transitions to occupations at smaller risk of automation can be found for all occupations in clusters 2 and 4, and for most of them in clusters 1 and 3.

Differences between clusters partly reflect those observed for acceptable transitions in general. For countries with a dispersed cognitive skills distribution (clusters 1 and 2), it is difficult to find transitions when small (re)training efforts are considered, and even more so when restricting transitions to those occupations at low or medium risk of automation.

These findings highlight the role of the skills distribution for occupational mobility and the implications for education and training policies. When workers' skills are dispersed, occupations tend to be more distant from one another in their skills requirements and the training effort required to switch occupations is larger. Designing effective options to learn on the job is crucial in these countries. In countries with a small skills dispersion but a low level of skills, workers may find options to move to other occupations with a small retraining effort in the short term, but in the long term the development and adoption of new technologies needed to maintain or increase countries' competitiveness and growth would require larger investment in education and training.

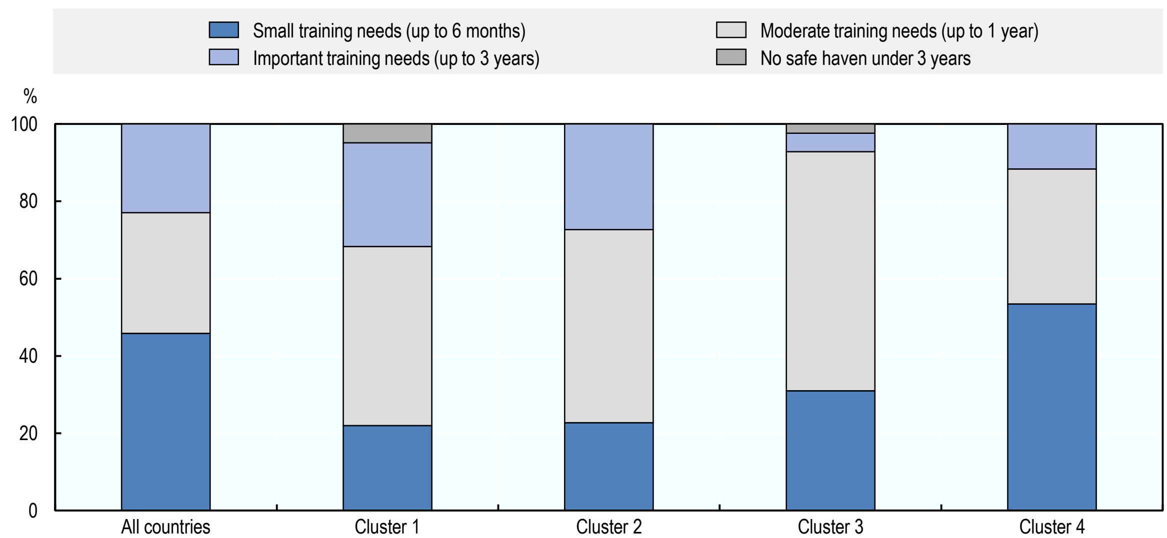
The analysis enables the identification of occupations at risk that education and training policies may need to focus on: those at high risk of automation for which a training effort of more than one year is required to move to occupations at low or medium risk of automation (Table 3.3). Occupations at high risk of automation can be considered as being less at risk if it is possible to identify acceptable transitions to occupations at lower risk of automation with a small or moderate training effort (six months to one year).

The share of employment in occupations at high risk of automation for which an important training effort is required to move to occupations at low or medium risk of automation varies across countries. This share also depends on whether it is assumed that all workers in those occupations are at high risk (upper bound) or that only some of them are at high risk (lower bound) (Arntz, Gregory and Zierahn, 2016[17]; Nedelkoska and Quintini, 2018[18]).

Overall, the share of employment that may be of specific concern for policies ranges between 0.4% and 1.5% for the lower bound and between 2% and 6% for the upper bound (Figure 3.13).

Figure 3.12. Share of occupations at high risk of automation with at least one acceptable transition to occupations at low or medium risk of automation by smallest training need for which such a transition can be found

For all countries and by cluster, as a share of occupations at high risk of automation



Notes: For each country cluster, this figure displays the share of occupations at high risk by the training needs to find its closest acceptable transition with a low or medium risk of automation. For example, when all countries are considered together in the analysis, 45% of the occupations at high risk of automation need a small training effort to find an acceptable transition to an occupation with a low or medium risk of automation, around 30% need a moderate training effort to find such a transition, and the remaining 25% require an important training effort. The risk of automation of origin occupations is computed based on estimates by Frey and Osborne (2017[10]) and described in Box 3.4. Occupations with a low risk of automation have an automation probability below 30%, medium automation risk between 30% and 70%, and high automation risk over 70%. Acceptable transitions are defined in Table 3.2. Clusters are defined in Table 3.1.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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Table 3.3. Occupations that may need to be targeted by training programmes

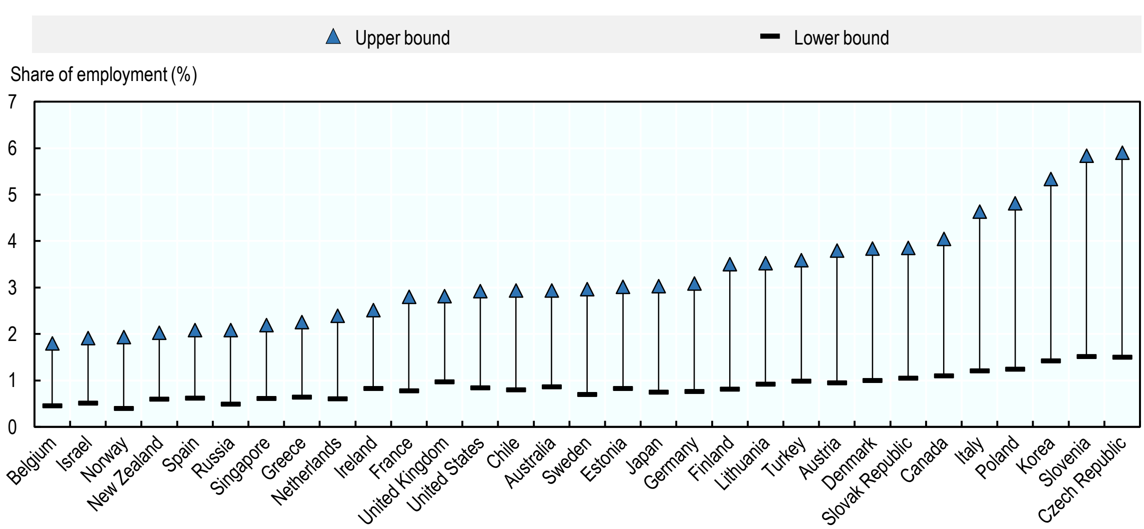
Occupations at high risk of automation not having any acceptable transition to occupations at low or medium risk of automation with training of up to one year

Occupations	Risk of automation
Blacksmiths, toolmakers and related trades workers	84.8
Chemical and photographic products plant and machine operators	85.0
Keyboard operators	96.6
Medical and pharmaceutical technicians	78.8
Metal processing and finishing plant operators	88.0
Mining and construction labourers	80.0

Occupations	Risk of automation
Mining and mineral processing plant operators	80.4
Rubber, plastic and paper products machine operators	86.7
Street vendors (excluding food)	94.0
Subsistence livestock farmers	87.0
Wood processing and papermaking plant operators	82.1

Note: These occupations are occupations at high risk of automation and without any acceptable transition to occupations at low or medium risk of automation, when training spells of up to one year are considered (Scenario 2). The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]) and described in Box 3.4. Low automation risk occupations correspond to occupations with an automation probability below 30%; medium automation risk: between 30% and 70%; high automation risk: over 70%. Acceptable transitions are defined in Table 3.2. Calculations are based on results when countries are considered together.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

Figure 3.13. Share of employment in occupations at high risk of automation for which an important training effort is needed to transition to occupations at low or medium risk of automation



Note: For the lower bound estimate, only workers in jobs currently at high risk of automation are considered while for the upper bound estimate, all workers currently employed in occupations at high risk of automation are considered. The proportion of workers in jobs at high risk of automation in an occupation is taken from Nedelkoska and Quintini (2018[9]). The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]). Those aspects are described in Box 3.4.
Sources: Authors' own calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973589

Assessing the cost of education and training needed to move away from the risk of automation

The final question is to estimate the costs of the training efforts required, in each of the 31 OECD member countries in the analysis, to help workers in occupations at high risk of automation move to "safe havens". A related document explains how to assess the cost of the education and training needed to help workers switch occupations (Andrieu et al., 2019[12]).

Methodology: Defining total, direct and indirect training costs

For each occupation at high risk of automation in each country, the analysis calculates the monetary cost of transitions for an average worker from these occupations of origin to an average "safe haven".

The minimum cost is the cost corresponding to the minimum training effort/need.

Occupations' per-worker total cost of training in a country is equal to the sum of two types of costs:

- *Direct cost:* the actual cost of providing training to a worker to move to a given "safe haven" for the length of the considered training spell. An occupation's direct cost is equal to the training time required to move to a "safe haven" multiplied by the education and training cost per year (proxied by the country's per-pupil annual education expenditure), averaged over all of the occupation's "safe havens" given a certain training effort.
- *Indirect cost:* the opportunity cost of training, corresponding to the wages foregone by a worker during the training spell, assuming that workers do not work during training. An occupation's indirect cost is equal to the training time required to transition to a "safe haven" multiplied by the occupation's median annual wage, averaged over all of the occupation's "safe havens" given a certain training effort.

Once direct and indirect costs have been computed for each occupation in each country, the country-level direct and indirect costs are obtained by summing over all occupations' direct and indirect costs, multiplying by occupations' number of workers in the country. The methodology is explained in Box 3.4.

To compute these estimates several simplifying assumptions were made. First, the cost of training was assumed to be the same for all workers in the same occupation in the same country. In other words, no hypothesis is made regarding how a worker's characteristics, such as their skill or education level, their age, their geographical location or their professional experience, would affect their training cost.

Second, due to the lack of reliable data on countries' expenditures on training, countries' education expenditures are used as a proxy. This assumes that workers retrain through formal or non-formal education and training programmes, but not through learning at work or at home with open educational resources, or though informal learning (e.g. learning from co-workers). Additionally, this assumes that the cost of non-formal training (e.g. on-the-job training) is the same as that of formal training in an education institution (e.g. a vocational education and training programme leading to a degree). Other methodological caveats are discussed in Box 3.3.

In sum, the total cost per occupation and country varies with: (1) the length of the training spell considered; (2) the occupational composition of the cluster; (3) the direct cost of training, which is country-specific; and (4) the wages underlying the indirect cost, which are cluster-specific.

Box 3.5. Computing countries' costs of occupational mobility

Total cost decomposition

The total cost for an average worker to move from occupation o in country i to another occupation is decomposed into two elements, the direct and indirect cost:

$$Total\ Cost_{i,o} = Direct\ Cost_{i,o} + Indirect\ Cost_{c_i,o},$$

where $TotalCost_{i,o}$ is the total training cost of occupation o in country i, $DirectCost_{i,o}$ is the direct cost of occupation o in country i, and $IndirectCost_{c_i,o}$ is the indirect training cost of occupation o in country i's cluster c_i.

Step 1: Computing direct and indirect cost at the occupation-country level

To compute training costs at the country level, it is first necessary to calculate the direct and indirect costs for every occupation in every country.

Direct cost

The direct cost of an acceptable transition from occupation o in country i to occupation d is equal to the training time required to transition to occupation d times education and training cost per year:

$$Direct\ Cost_{i,o,d} = \left(training\ time_{c_i,o,d}\right) \times (per - pupil\ education\ cost_i),$$

where $training\ time_{c_i,o,d}$ corresponds to the training time in years needed for an acceptable transition from occupation o in country i's cluster c_i to occupation d given a certain training effort, and $per - pupil\ education\ cost_i$ is country i's yearly per-student primary to secondary or tertiary cost in USD (expressed in purchasing power parities, or PPP) in 2014 as reported in the Education at a Glance (2017[19]) dataset.

Education expenditure covers the "core services", i.e. total education spending net of research and development (R&D) and ancillary service expenditure, for both private and public education institutions.[3] Thus, it does not correspond only to tuition fees paid by students. If either the occupation of origin or of destination has a majority of tertiary-educated workers, the cost of tertiary education is used. Otherwise, the cost of primary to secondary education is used. This corresponds to assuming that a worker having attained a tertiary degree does not retrain at the secondary level, while the reverse is possible. The analysis does not take into account the possibility that countries with high education expenditure per student achieve better education and training outcomes.

The direct cost of moving away from occupation o in country i is obtained by averaging direct costs over all occupation o's acceptable transitions given a certain training effort.

Indirect cost

The indirect training cost of an acceptable transition from occupation o in country i's cluster c_i to occupation d is equal to the training time required to transition to occupation d times the occupation's median annual wage:

$$Indirect\ Cost_{c_i,o,d} = training\ time_{c_i,o,d} \times \left(wages_{c_i,o}\right),$$

where $training\ time_{c_i,o,d}$ is defined in the same way as above, and $wages_{c_i,o}$ is occupation o in country i's cluster c_i's median annual wage expressed in USD PPP.

Again, the indirect cost of moving away from occupation o in country i's cluster c_i is obtained by averaging indirect costs over all occupation o's acceptable transitions given a certain training effort. While the direct cost for a given occupation varies across countries, the indirect cost for a given occupation varies across clusters but not across countries belonging to the same cluster.

Step 2: Aggregate direct and indirect costs at the country level

Once the (average) direct and indirect costs are computed at the occupation-country level, these can be aggregated at the country level. In particular, country i's direct and indirect cost is a weighted sum of occupations' direct and indirect costs:

$$Direct\ Cost_i = \sum_{o=1}^{O_{c_i}} emp_{i,o} \times Direct\ Cost_{i,o},$$

$$Indirect\ Cost_i = \sum_{o=1}^{O_{c_i}} emp_{i,o} \times Indirect\ Cost_{c_i,o},$$

where O_{c_i} is the total number of occupations in country i's cluster c_i, and $emp_{i,o}$ is the number of workers employed in occupation o in country i calculated from the Survey of Adult Skills (PIAAC).

Finally, country i's total training cost given a certain training effort is:

$$Total\ Cost_i = Direct\ Cost_i + Indirect\ Cost_i.$$

The cost of moving to a "safe haven"

The minimum cost of training per worker (associated to the minimum training need, Figure 3.11) required to move away from an occupation at high risk of automation is larger if the move has to be to occupations at low or medium of risk of automation than if all acceptable transitions are considered (Table 3.4). This is because acceptable occupations at low risk of automation are on average characterised by higher cognitive skill requirements.

The average minimum cost of training per worker to move away from the risk of automation varies across clusters of countries. It is higher in countries in cluster 2 (English-speaking countries) because per-student total education expenditure tends to be higher in these countries, leading to a high direct cost, and wages are also higher, leading to high indirect cost.

Table 3.4. Average minimum training costs for a worker in an occupation at high risk of automation

In '000 USD (PPP), by type of occupations of destination

	All destinations			Only low or medium risk of automation destinations		
	Indirect	Direct	Total	Indirect	Direct	Total
Cluster 1	8.0	2.8	10.8	12.5	4.5	17.0
	(0.7)	(0.2)	(0.9)	(0.9)	(0.3)	(1.1)
Cluster 2	15.8	5.4	21.2	21.1	7.4	28.6
	(1.8)	(0.5)	(2.3)	(2.0)	(0.6)	(2.5)
Cluster 3	5.9	2.4	8.3	10.2	3.8	14.0
.	(0.3)	(0.1)	(0.4)	(0.7)	(0.2)	(0.9)
Cluster 4	3.4	1.4	4.7	9.2	3.4	12.6
	(0.2)	(0.1)	(0.3)	(0.8)	(0.3)	(1.1)

Note: This table shows the average minimum training cost for a worker in an occupation at high risk of automation, by country cluster and risk of acceptable occupation of destination. For example, the average *total* minimum training cost for a worker in a high risk occupation in Cluster 1 is USD 10 800 (PPP) if all occupations of destination ("All destinations") are considered and USD 17 000 (PPP) when restricting occupations of destination to those with a low or medium risk of automation ("Only low or medium risk of automation destinations").

Costs are per worker: "Direct" is the education cost of retraining workers; "Indirect" refers to the foregone wages during the training period; "Total" denotes the sum of the direct and indirect costs. Standard errors in parentheses. The composition of clusters is given in Table 3.1.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis and data from OECD (2017[19]), *Education at a Glance 2017: OECD Indicators*, https://doi.org/10.1787/eag-2017-en (accessed on 06 November 2017)

The aggregate training cost is obtained by multiplying the number of workers who are currently employed in high risk of automation occupations and perform a majority of tasks that can be automated (Nedelkoska and Quintini, 2018[18]) by the per-worker, occupation-specific cost of moving to a "safe haven", and by summing over all occupations at high risk of automation.

The aggregate cost can be expressed as percentages of a country's yearly GDP or total annual secondary and tertiary current education expenditure (Figure 3.14).[4] It should be noted that these ratios compare costs of training that is likely to occur over several years (as numerator), with a yearly aggregate (as denominator). Transitions may require training spells longer than a year, if no acceptable transition to low- or medium risk of automation occupations can be reached after a small or moderate training effort. Furthermore, workers and employers may decide to spread the training time over several years, to reconcile (part-time) work and training. Lastly, policies should not target all workers at high risk of automation at the same time and within one year, as technology spreads and is adopted at different paces in different countries, industries and companies.

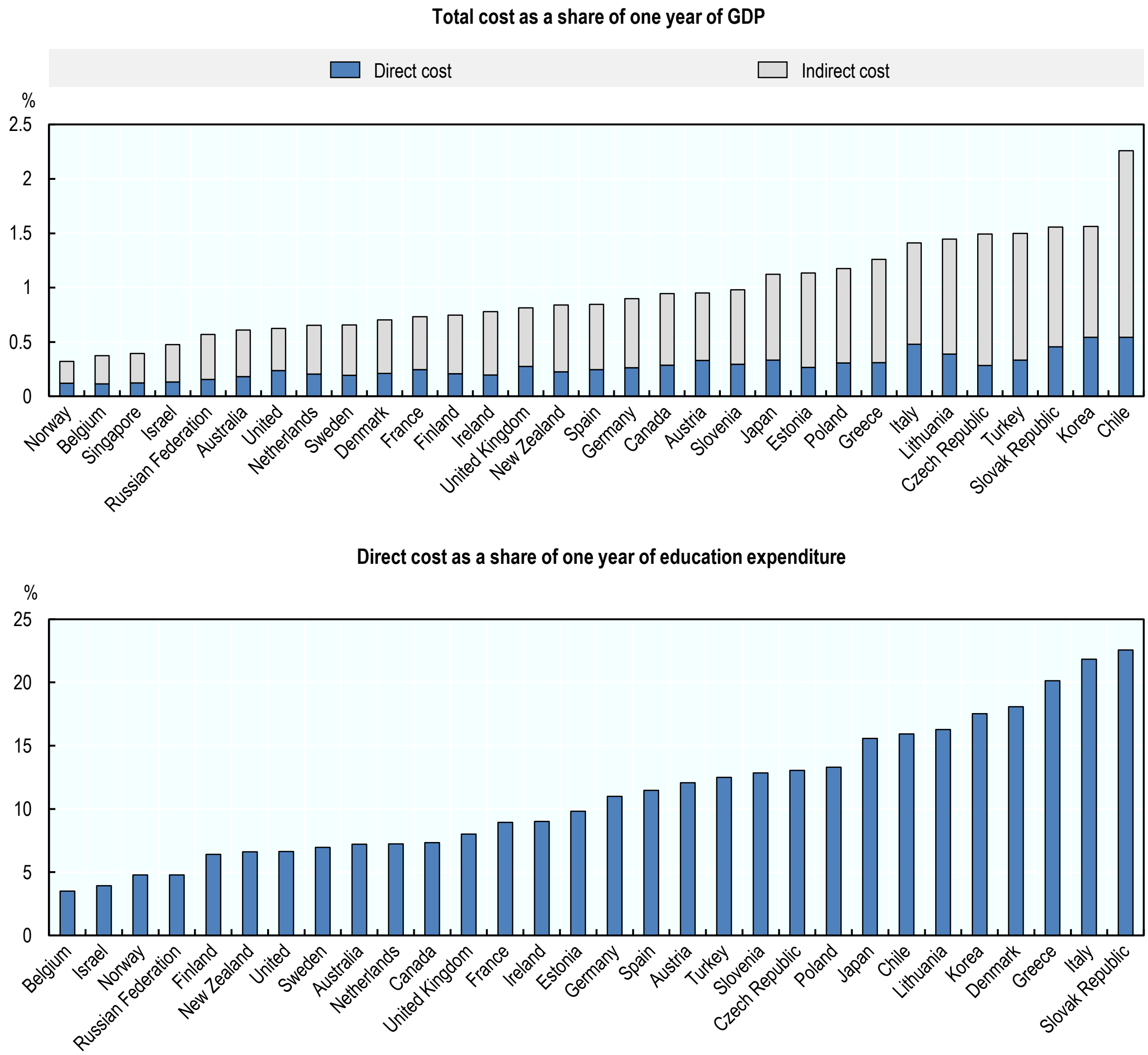
The aggregate cost of moving to a "safe haven" varies between countries from less than 0.5% to over 2% of one year of GDP, of which around 30% is accounted for by direct costs and 70% by indirect costs. Direct costs range from 3% to more than 20% of yearly education expenditure, depending on the country.

The indirect component of the cost of training coming from foregone workers' wages represents approximately 70% of the per-person total cost, and is therefore larger than the direct cost of undertaking the training spell in the education system itself. This result underlines the importance of enabling individuals to be able to train and learn while continuing to work, to lower the indirect cost of moving and mitigate the overall cost of education and training policies that can help workers move away from occupations at high risk of automation.

Estimates are heterogeneous across countries, no matter the denominator chosen to rescale them. Cross-country variation mainly originates from differences in (i) median wages across clusters, which underpin indirect costs; (ii) country-specific education expenditures per student; (iii) average skills distances for occupations at high risk of automation and the set of acceptable occupations of destinations they support, which depend on the cluster countries belong to; and (iv) the proportion of workers in the country employed in occupations at high risk of automation.

The share of employment in occupations at high risk of automation is a major driver of the aggregate costs (Table 3.5). Countries with a high share of employment in those occupations (Chile, Greece, Italy, Korea, Slovenia and Turkey) feature the highest aggregate costs. Differences in direct and indirect costs between countries play a smaller role in explaining differences in costs. In addition, as the direct cost of education and training relies on education expenditure per student and the analysis builds on an average skills return to education, countries with high per student education expenditure have a higher estimated direct cost of training.

Figure 3.14. The aggregate cost of moving to a "safe haven", lower bound estimate, by country



Note: The graphs show the aggregate costs of the minimum training effort necessary to help workers in occupations at high risk of automation find at least one acceptable occupation of destination that is not at high risk of automation. The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]) (Box 3.4).These costs are computed only for the proportion of workers currently in jobs at high risk of automation, which varies by country and occupation (Nedelkoska and Quintini, 2018[18]).
Costs are represented as a percentage of yearly GDP and annual total expenditure for secondary and tertiary education (ISCED levels 3 to 8) in the country. The construction of the direct and indirect costs is explained in Box 3.4.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis, OECD (2018[20]), OECD, *Structural Analysis (STAN) Database*, http://oe.cd/stan and data from OECD (2017[19]), *Education at a Glance 2017: OECD Indicators*, https://doi.org/10.1787/eag-2017-en (accessed on 06 November 2017).

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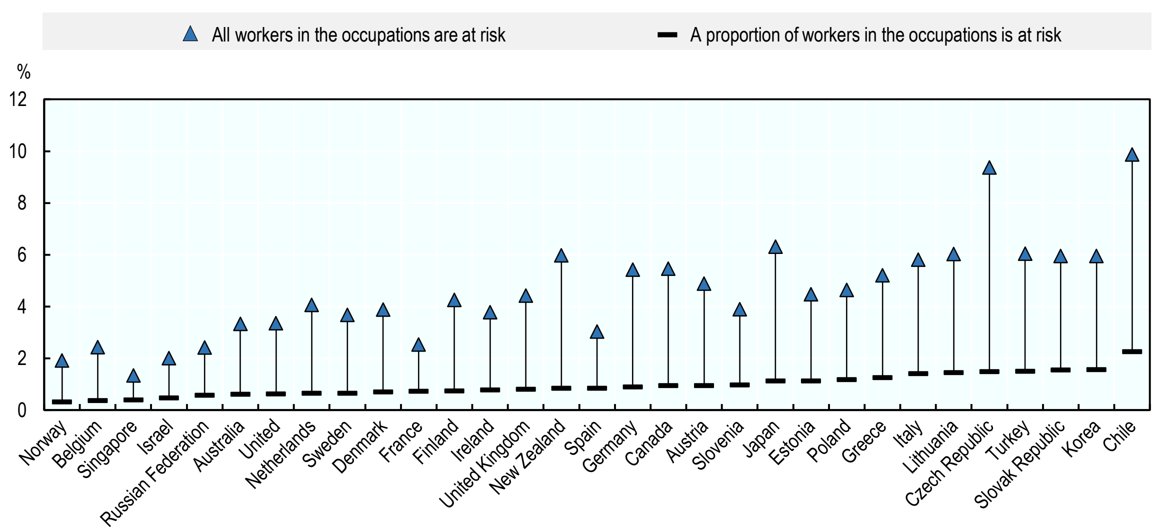
Table 3.5. Factors driving aggregate cost of moving to a "safe haven", by country

Note: For example, the total cost for Australia is low (in the first quartile of the cost distribution). Australia has a low share of employment in occupation at high risk of automation and low direct and indirect cost of training while it belongs to a cluster with large distances across occupations.
The indirect component corresponds to average foregone wages as a share of GDP and the direct component to average education and training cost as a share of GDP. Calculations of the share of employment currently in jobs at high-risk of automation is explained in Box 3.4. "Training duration" corresponds to the average training duration required to reach "safe havens" in the minimum training needs scenario.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis, OECD (2018[20]), OECD, *Structural Analysis (STAN) Database*, http://oe.cd/stan and data from OECD (2017[19]), *Education at a Glance 2017: OECD Indicators*, https://doi.org/10.1787/eag-2017-en (accessed on 06 November 2017).

The cost greatly depends on the number of workers who may need to participate in education and training. Estimates in Figure 3.14 assume that only a proportion of workers employed in occupations at high risk of automation are actually at risk and would need training, which gives a lower-bound estimate. Assuming that all workers in these occupations are at risk gives an upper-bound estimate of the education and training cost (Figure 3.15). This would correspond to a longer-term situation in which those occupations tend to be almost fully automated and to disappear. In such a case, the training costs entailed by moving to a "safe haven" would be fivefold, with the average overall cost ranging from 1% to 10% of GDP depending on countries.

Figure 3.15. Lower bound and upper bound estimates of the cost of moving to a "safe haven"

% of GDP, upper-bound and lower-bound estimates



Note: The graph shows the aggregate costs of the minimum training effort necessary to help workers in occupations at high risk of automation to find at least one acceptable occupation of destination that is not at high risk of automation, as a percentage of GDP and considering two different sets of workers. For the lower bound estimates, the cost only includes workers currently in jobs at high risk of automation, while the upper bound includes all workers currently employed in occupations at high risk of automation. The blue bar therefore represents the range of possible cost between upper- and lower-bound estimates. The proportion of workers at high risk of automation in an occupation is from Nedelkoska and Quintini (2018[18]). The construction of the total costs is detailed in Box 3.4.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis, OECD (2018[20]), OECD, *Structural Analysis (STAN) Database*, http://oe.cd/stan and data from OECD (2017[19]), *Education at a Glance 2017: OECD Indicators*, https://doi.org/10.1787/eag-2017-en (accessed on 06 November 2017).

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Many uncertainties surround these estimates. As discussed in methodological sections of this chapter and further in Box 3.3, the methodology relies on several assumptions that affect the size of the estimated effects. In particular, there are large uncertainties concerning the number of occupations that would be less in demand in the future and the share of workers who might need to change occupations, which are crucial drivers of these estimates. Some workers in occupations at high risk of automation may never be displaced by automation, because the nature of their job evolves, or because automation pervades economies in unexpected ways. For these reasons, lower and upper bound estimates could be different from those in this analysis.

This approach also assumes that workers complete their education and training programmes and that these programmes are successful in raising skills. There is no data on the completion rates of workers and adults. However, data on students (and therefore on youth) show completion rates of 75% for upper secondary education and 72% for tertiary education. By assuming fully efficient education and training programmes with full completion rates, the analysis tends to under-estimate the cost.

The estimates proposed thus far mostly relate to the cost of training individuals to endow them with the cognitive skills needed in the occupation of destination. Different occupations, however, require workers to acquire several task-based skills, e.g. management and communication skills or ICT skills. Occupational distances in such task-based skills are accounted for in the analysis since it is assumed that, in all the scenarios considered, workers can only move to occupations with a given distance in such task-based skills (Table 3.2). However, cost estimates only include those related to bridging cognitive skills distances.

Information from Eurostat's Continuing Vocational Training Survey (CVTS) can be used to tentatively assess the extra resources needed to enable workers to gain some job-specific skills needed to move to different occupations. This survey collects data on the employer-based training of workers.[5] Training types include general and professional IT, management, team working, customer handling, problem solving, office administration, foreign languages, literacy, numeracy, communication and technical job-specific skills. However, only a small share of employers provide training in literacy and numeracy skills. The average participant across all countries covered received 26 hours of training in 2015.

This survey does not break down cost data by type of skills. Furthermore, those data are not at the occupational level. Finally, those data cannot be used to assess the skills distance that may be bridged by participating in those training opportunities. For these reasons, the same cost needs are assumed for all workers regardless of the type of skill gap to be filled and of the occupations of origin and destination. These estimates do not include the indirect cost incurred by employers as workers generally continue to receive their wages while training on the job.

The extra cost component calculated on the basis of CVTS data can be added to the country-level cost of training workers to move from occupations at high risk of automation to occupations at medium or low risk. The top-up cost is calculated as the country-specific cost of training per participant as reported in the CVTS, multiplied by the number of individuals at high risk of automation who are working in the country. The extra cost component amounts to 0.06% to 0.3% of GDP on average across the considered countries (Andrieu et al., 2019[12]). This extra cost is small because the training duration is short according to this survey.

What type of training is required to move away from the risk of automation?

In addition to the need for upskilling in general cognitive skills (literacy and numeracy), occupations at high risk of automation are predominantly in need of training in non-cognitive skills, such as management and communications as well as self-organisation. They also require some training in ICT (Table 3.6). This is mainly because occupations at risk of automation perform mostly routine tasks, while management, communications and self-organisation are more difficult to automate.

Table 3.6. Relative task-based skills training needs involved for acceptable transitions to occupations at low or medium risk of automation

For occupations at high risk of automation, in the scenario with the smallest training need necessary to identify such transition

	ICT skills	Advanced numeracy skills	Accountancy and selling skills	Managing and communication skills	Self-organisation skills
Cluster 1	16	12	14	29	29
Cluster 2	23	13	12	33	19
Cluster 3	20	7	11	38	24
Cluster 4	22	9	15	31	23
All countries	22	10	16	33	20

Note: These tables display the relative minimum training need in terms of task-based skills necessary to help workers in occupations at high risk of automation to find at least one acceptable occupation of destination that is not at high risk of automation. For example, when all countries are considered together, for workers in occupations at high risk of automation to move to an occupation at low or medium risk of automation, the minimum training need would include upskilling mostly in managing and communication skills (33%), ICT skills (22%) and self-organisation skills (20%) and to a lesser in accountancy and selling skills (16%) and in advanced numeracy skills (10%).

Task-based skills are explained in Box 2.3 in Chapter 2. The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]) and described in Box 3.3. Low automation risk occupations correspond to occupations with an automation probability below 30%, medium automation risk: between 30% and 70%, high automation risk: over 70%. Acceptable transitions are defined in Table 3.2. The composition of clusters is given in Table 3.1.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

Policy implications

Mitigating and sustaining the cost

The analysis in this chapter gives an indication of the cost of education and training needed to help workers move away from the risk of automation. These costs can be sizeable, even if they do not need to be sustained all in the short run or for all workers together.

The most important general policy implications of the analysis are to reaffirm the importance of:

- *Policies encouraging learning and working at the same time* through flexible education and training programmes and informal learning. Two-thirds of the estimated training cost comes from the indirect cost of foregone wages, so important savings could be made by enabling learning and working at the same time. First, flexible training options can be combined with work, for example through broader use by firms of open education and massive open online courses (MOOCs) (Chapter 5). Second, working environments and practices that facilitate learning by doing, learning from co-workers and other forms of informal learning can help workers develop the skills they needed as jobs evolve, while entailing little indirect and direct costs. Conversely, sending workers back to formal education is unrealistic on a large scale and would entail large costs.

- *High-quality initial education for all* to equip all future workers with a solid mix of skills, including a strong readiness to learn. Young people leaving education with low basic skills may become trapped in low-skilled occupations at high risk of automation, with a large cost of moving to another occupation if they lose their jobs. As well as limiting the number of students who drop out, policies can ensure that vocational education and training programmes include a strong component of cognitive skills in addition to job-specific skills. Improving the efficacy of educational institutions and the quality of education and training services would lower the direct cost of these policies.

To make it easier for workers move to jobs, an array of policies are needed, all of which require important monetary resources from policy makers. These include policies shaping initial education, skills development, life-long learning, support for worker re-deployment and improved social protection. Resources for industrial and regional policies should be taken into consideration, too, because the concentration of job transitions and the adoption of technologies vary among industries and regions. However, most governments already spend a significant share of their budget on those areas. The effort needs to be on developing a better co-ordinated and more comprehensive approach to facilitate lifelong learning and occupational and geographical mobility (Chapter 6).

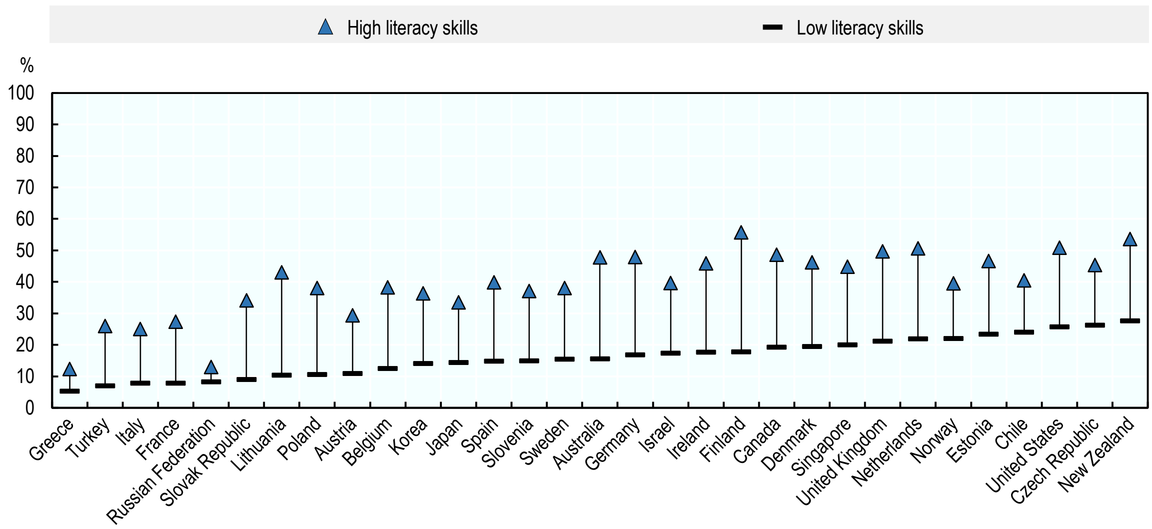
Improving the design and targeting of on-the-job training programmes

Overall, this analysis in this chapter shows that it is important to ensure that workers in occupations at risk of automation, especially those in low-skilled occupations, participate in education and training so they can change occupations and find a "safe haven". However, these workers are less likely to participate in training than workers in occupations with a lower risk of automation (Nedelkoska and Quintini, 2018[18]). More generally, workers with lower skills levels participate less in on-the-job training than more skilled workers (Figure 3.16).

This analysis also show the need for training that helps workers develop a mix of skills, including cognitive, ICT and social and emotional skills, to make it easier for them to switch occupations. Policies that aim to develop task-based skills through learning or training on the job are sometimes not enough to help workers change jobs. Such policies need to be complemented by policies that aim to develop general cognitive skills, through specific programmes or by enabling workers to go back to formal education. Employers mainly provide training on job-specific skills, however, (Figure 3.17) and few workers go back to formal education in most countries because options to combine work and study are scarce.

Figure 3.16. Participation in on-the-job trainings by skill level

Share of workers with low or high literacy skill levels who have participated in on-the-job training over the 12 months before the survey, by country



Note: Share of workers answering "Yes" to the question "During the last 12 months, have you attended any organised sessions for on-the-job training or training by supervisors or co-workers?", for those with low (at or below *Level 1*) or high (*Level 4/5*) literacy skill levels. Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: Year of reference 2015. All other countries: Year of reference 2012. Data for Belgium refer only to Flanders and data for the United Kingdom refer to England and Northern Ireland jointly.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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Overcoming the barriers to participate in adult learning

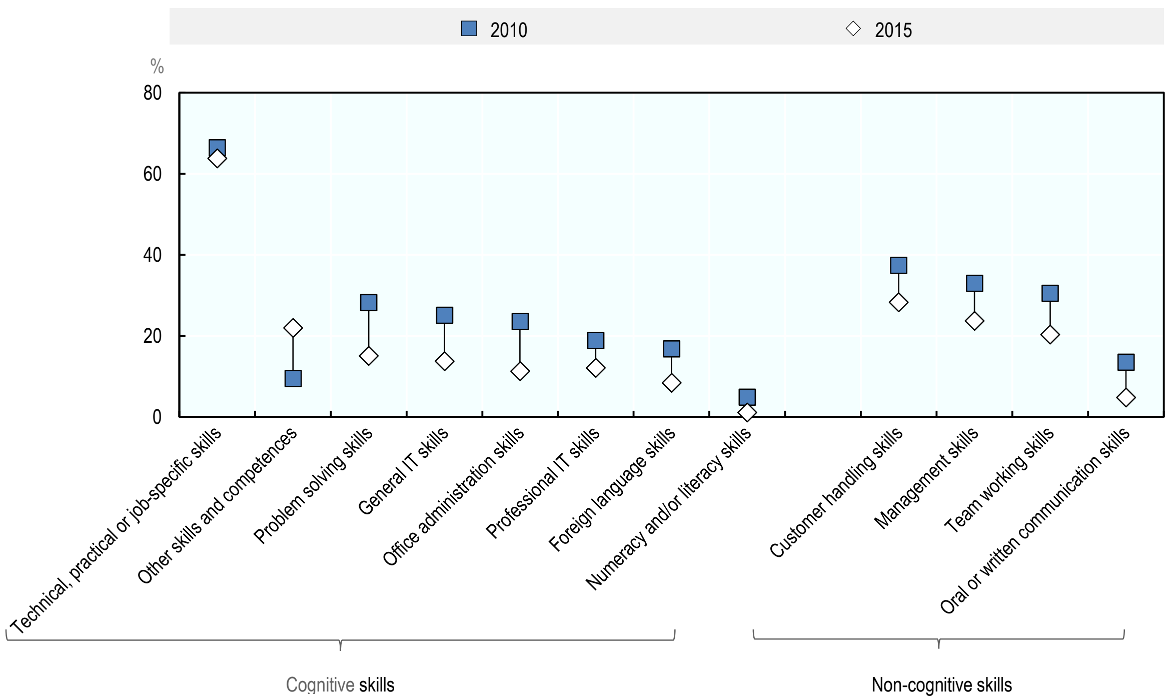
There are many barriers to participation in adult learning, including financial disincentives, time constraints, and the motivation and willingness to learn (Chapter 6).

The analysis in this chapter sheds light on the possible financial incentives of occupational mobility by comparing wages in occupations of origin and destination. An average worker in a significant majority of occupations at high risk of automation would, on average, experience a median hourly wage increase when moving to the closest set of "safe havens" (Figure 3.18). In fact, there is a somewhat decreasing relationship between initial wage and average wage change, implying that workers with smallest wages would possibly have the greatest financial incentives to retrain. Thus for most workers in these occupations, the financial burden of training would at least be partly compensated by an increase in wages in the future occupation.

However, this wage gain is an average and compares hourly wages not annual wages. Actual wage changes will depend on several other factors, such as number of hours worked, geographical location and worker preferences. In addition, the analysis does not incorporate the fact that if more workers try move to the same groups of occupations, raising labour supply for these occupations, wages may decrease. Workers in occupations that appear not to experience positive wage changes will find it much harder to afford and be willing to train. In such cases, workers may be willing to incur small wage losses if moving from a highly automatable occupation to a lower risk occupation appears to imply greater job stability.

Figure 3.17. Main skills targeted by vocational training in enterprises

European Union OECD countries, share of employers providing training related to each type of skills



Sources: Eurostat (2010[21]) and (2015[22]), *Continuing Vocational Training Survey (CVTS)*, https://ec.europa.eu/eurostat/web/education-and-training/data/database.

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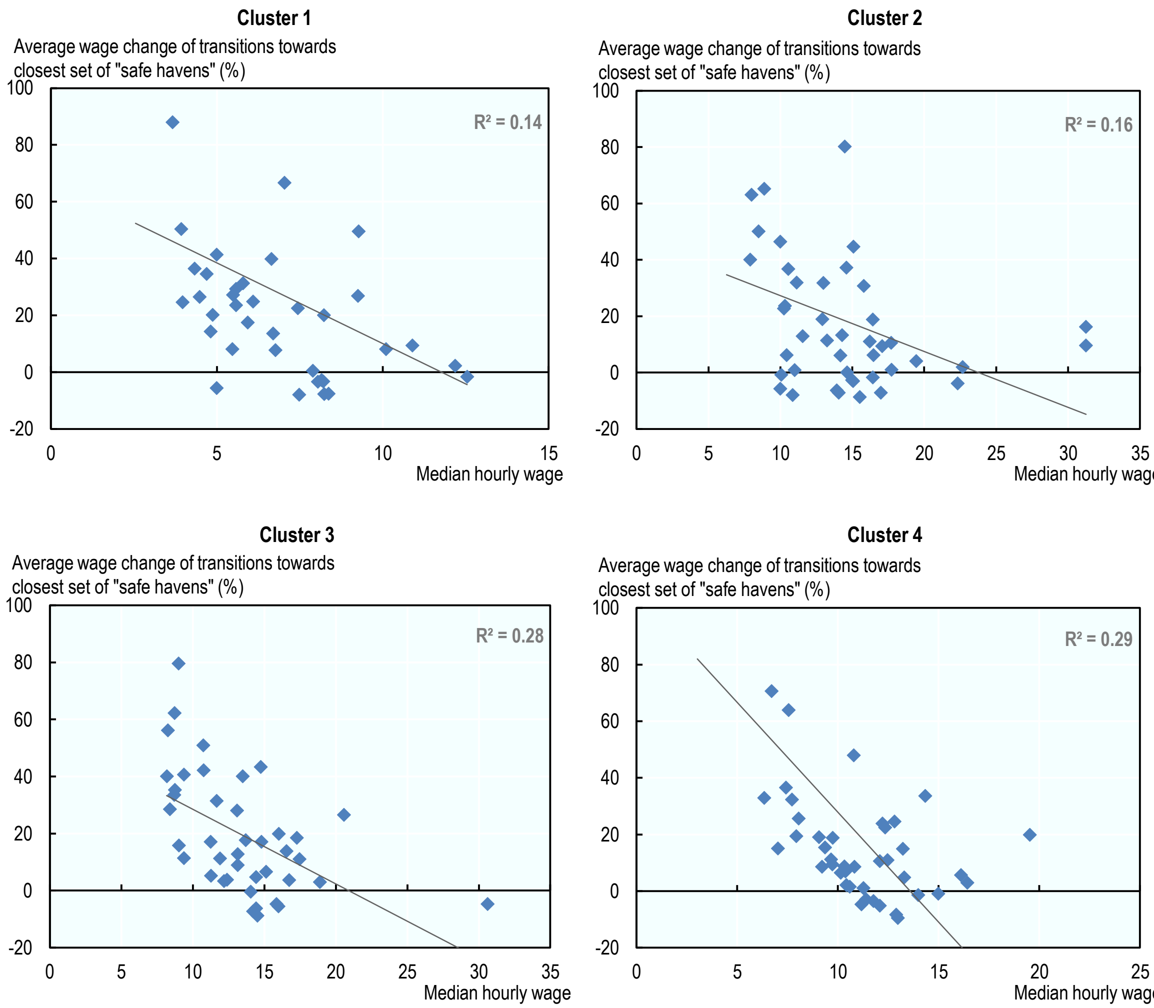
Raising educational attainment?

Most of the occupations at high risk of automation have a majority of workers with at most a post-secondary non-tertiary degree (Figure 3.19). Only a few occupations have a majority of workers with a tertiary education degree. This is the case for all country clusters, though the magnitudes vary slightly.

However, raising educational attainment and enrolling more people in tertiary education can be costly and is not necessarily a good solution as having a tertiary degree does not guarantee having the required skills (Chapter 6). In addition, the analysis in this chapter finds that moving to a "safe haven" from occupations at high risk of automation that have a predominantly tertiary-educated workforce does not appear to require particularly lower average training durations than other occupations (Figure 3.20). Many of these occupations require small training needs, just like predominantly non-tertiary educated occupations.

Figure 3.18. Average wage change induced by transitions to minimum training need "safe havens"



Note: For each cluster, these figures plot the relationship between high-risk occupations' average hourly wage change implied by transitions to the closest set of "safe havens" and their median hourly wage. In all clusters, the relationship is downward sloping, suggesting that, on average, the lower-paid a high-risk occupation the greater the wage change implied by moving to "safe havens". The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]) and described in Box 3.4. The composition of clusters is given in Table 3.1. The R^2 corresponds to the share of the variation in average hourly wage changes that is explained by median hourly wage.

Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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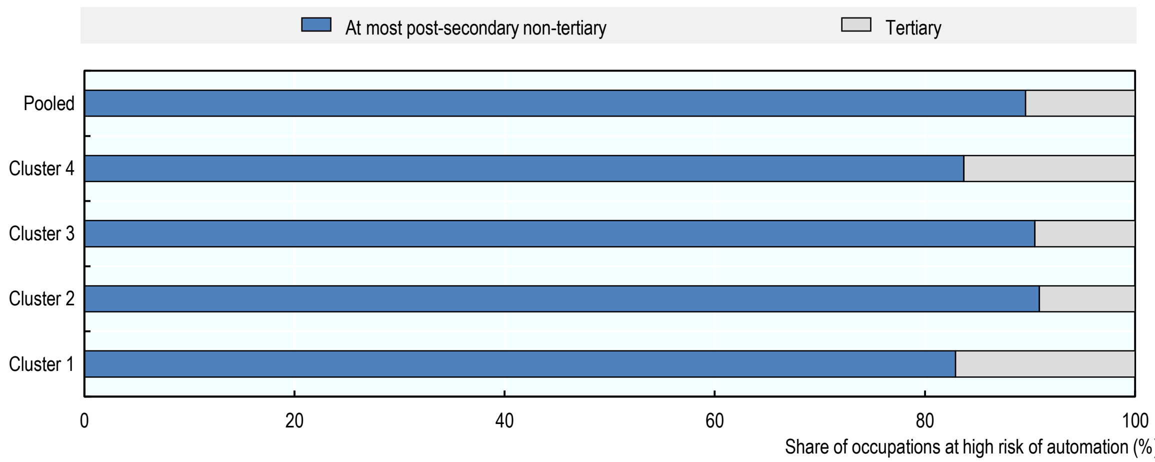
Figure 3.19. Most common education level of occupations at high risk of automation

Occupations' education level is that which represents the majority of workers

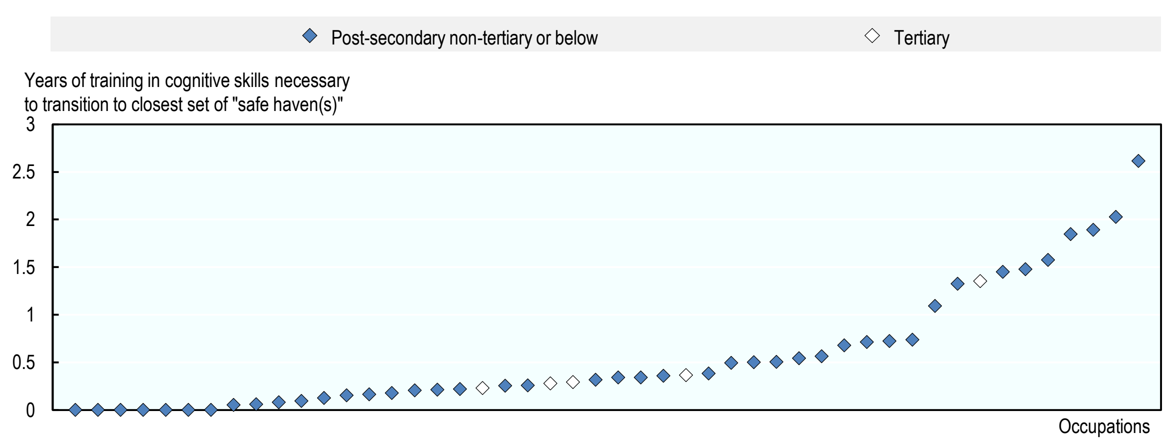


Notes: For each country cluster, each bar shows the share of occupations at high risk for which a majority of workers have at most a post-secondary non-tertiary degree or a tertiary degree. For example, in cluster 3, 90% of occupations at high risk have a majority of workers with at most a post-secondary non-tertiary degree while this share is 83% in cluster 1.
Occupations at high risk of automation have an automation probability greater than 70%. The risk of automation of origin occupations is computed based on estimates by Frey and Osborne (2017[10]) and described in Box 3.4.
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

StatLink https://doi.org/10.1787/888933973703

Figure 3.20. Occupations' average number of years of training for closest "safe havens", by education level

Occupations at high risk of automation are ranked by the average number of years of training necessary to transition to closest set of "safe havens"



Notes: Calculations are based on results when countries are considered together. The risk of automation of the occupation of origin is computed based on estimates by Frey and Osborne (2017[10]).
Sources: OECD calculations based on OECD (2012[6]) and OECD (2015[7]), *Survey of Adult Skills (PIAAC)*, www.oecd.org/skills/piaac/publicdataandanalysis.

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Young versus older workers

Older workers may find it more difficult than young ones to switch jobs, on average. They have a higher incidence of long-term unemployment and lower hiring rates, take longer to get back to work after an unemployment spell and experience larger earning losses after being displaced (OECD, 2013[11]). As the average age of the population in OECD countries keeps increasing, occupational mobility is likely to represent a greater challenge for older workers and, consequently, a significant concern for policy makers.

Older workers also tend to be over-represented in occupations for which larger education and training costs are needed to help workers move jobs (Andrieu et al., 2019[12]). This finding is not driven by the fact that older workers may be in occupations with higher wages and therefore incur higher indirect costs of training.

Licensed occupations

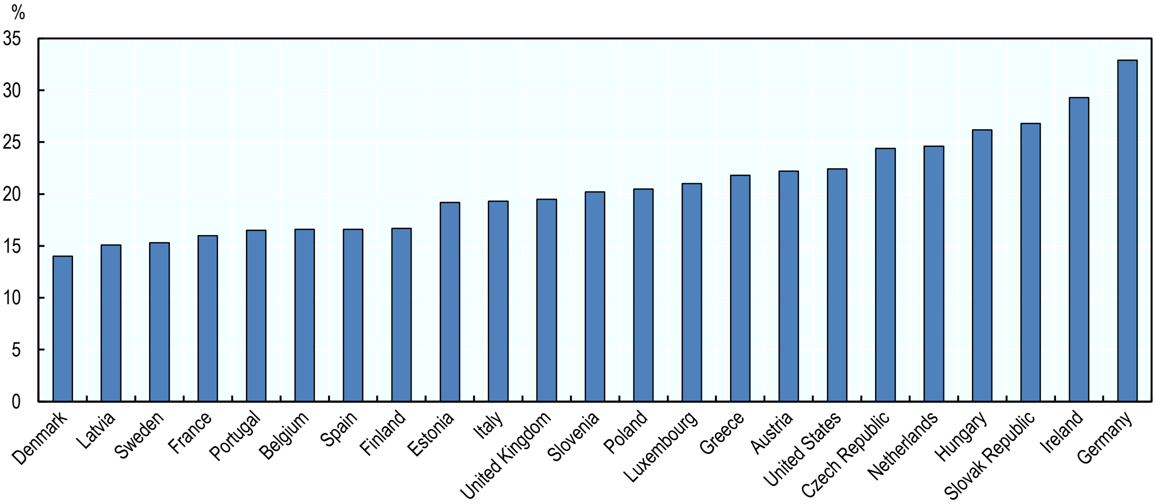
Occupational licensing – the legal requirement to obtain a licence to undertake a certain occupation – is intended to protect consumers through higher quality and skill requirements. Yet it can also constitute a barrier to occupational mobility and career progression. Workers wishing to switch to a licensed occupation may find the requirements too time-consuming or financially burdensome. Conversely, workers in licensed occupations may find it costly to switch occupation as they would lose the benefit of the licence they have obtained. Licensed occupations may tend to experience lower employment growth, therefore affecting the allocation of workers (Kleiner, 2017[23]). This is of significant importance since about 25% of US workers and 22% of EU workers hold a license (Figure 3.21). Regulatory authorities could consider which occupations should legitimately require a license (legal restriction) rather than a certificate (no legal restriction), which can just equally act as a signal for skill and quality.

Sharing the cost of training between stakeholders

As discussed in this and other chapters of this publication, improving the design and efficiency of a range of policies can reduce the overall cost if a significant share of workers need to be retrained to move occupations and escape the risk of unemployment.

In addition, however, it is likely that countries may need to increase their investment in education and training, to face changes in skills requirements and higher demand for workers with a well-rounded set of skills. This raises the question of how to share the burden of the cost between governments, firms and workers themselves. There is no single answer to this question, as it depends on countries' cultures, financial positions, institutions and arrangements, but a debate on this question needs to take place. At the moment, the allocation of education expenditure between public and private sources varies greatly among countries (Figure 3.22).

Figure 3.21. Percentage of licensed workers in selected OECD countries in 2015



Note: This figure displays the percentage of licensed workers in selected OECD countries in 2015. The percentage of licensed workers is computed as the percentage of employed individuals aged 15 and over (16 for the United States) who require a licence to work.
Sources: For all countries except the United States, estimates come from Koumenta, M. and M. Pagliero (2017, p. 28[24]), "Occupational licensing in the European Union: Coverage and wage effects", http://sites.carloalberto.org/pagliero/Pagliero_Koumenta_wages.pdf (accessed on 08 June 2018), based on questions from the EU Survey of Regulated Occupations. For the United States, the estimate comes from the Bureau of Labor Statistics (2017[25]), *Table 49. Certification and Licensing Status of the Civilian Noninstitutional Population 16 years and Over by Employment Status*, https://www.bls.gov/cps/cpsaat49.htm (accessed on 29 August 2018), based on questions from the Current Population Survey.

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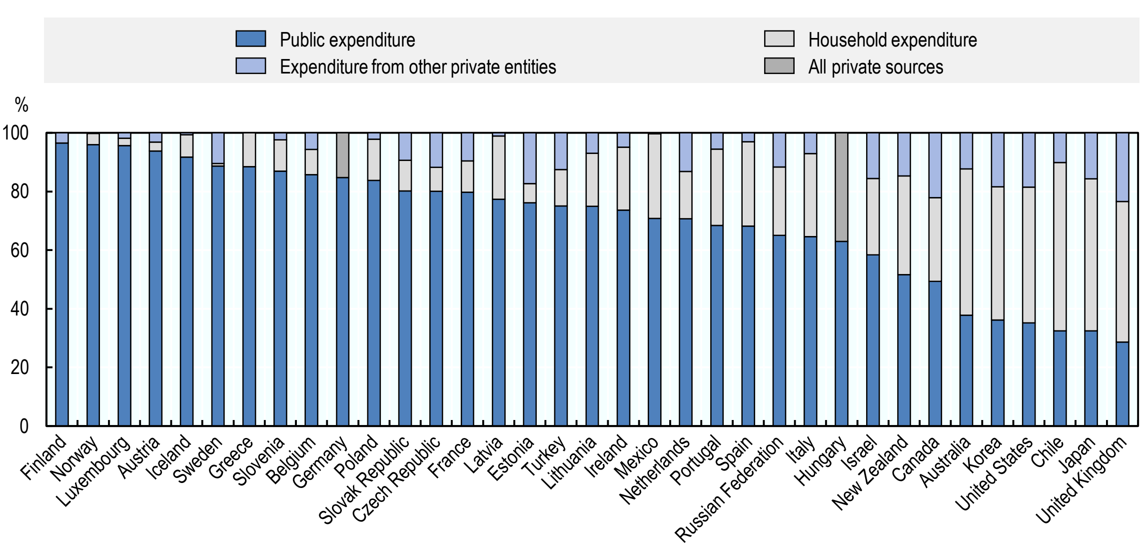
Figure 3.22. Distribution of public and private expenditure on tertiary education in 2015



Note: Excluding international sources: Canada, Chile and Korea. Data from 2016: Chile.
Source: OECD (2018[26]), *Education at a Glance 2018: OECD Indicators*, https://dx.doi.org/10.1787/eag-2018-en, Figure C3.2.

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Summary

This chapter investigates how education and training policies can help workers move occupations, while maintaining them in quality jobs that make the best use of their skill sets. In addition, it sheds light on the magnitude and type of training needed to help workers move away from occupations at high risk of automation, and the associated costs.

Not all occupations at high risk of automation require the same policy effort. Some of these occupations are close to others that require similar skills but have a smaller risk of automation. Simply providing information about options for transitions or making a small retraining effort may be sufficient to help workers in these occupations find a "safe haven". The main policy effort needs to focus on workers in occupations at high risk of automation that are distant from other occupations in terms of their skills requirements and tasks contents. Hence, this chapter suggests directions for better targeting the policy effort at workers who need it the most.

The chapter also estimates the possible costs of education and training policies to help workers move from occupations at high risk of automation to "safe havens". The costs are substantial for several countries but need not all be sustained immediately, as workers in occupations at high risk of automation will not all move to a "safe haven" at the same time.

There are several ways to reduce this cost. Important savings could be made by enabling learning and working at the same time, improving the efficacy of educational institutions, and improving the quality of education and training services more broadly. Learning and working at the same time can be encouraged through policies that promote flexible education and training programmes, the use of open education and massive open online courses (MOOCs) by firms, and the adoption of working organisation practices that favour co-operation, learning from co-workers and other forms of informal learning. Special training efforts may be needed for low-skilled workers, who tend to benefit less from technical change and adapt to it less well than highly skilled workers. Curricula may need to be adapted more frequently and to reflect a holistic approach to skills in order to cater for the numerous competencies that are demanded from workers. More broadly, additional efforts may be needed to bridge the information gap so that employers, workers and educational institutions are aware almost in real time of the successful skills mixes needed on the labour market.

Workers, employers, education institutions and governments all have roles to play in responding to the reskilling and upskilling challenge, including its financial aspect. How these stakeholders will meet the demand for resources, however, remains an open question. The split in the costs of retraining could reflect the sharing of the costs and benefits of mobility, be they in the form of changes in wages, productivity of labour, or tax receipts. Employers, for instance, could be encouraged to invest in transferrable (rather than only firm-specific) skills, to establish work-education partnerships with the education sector, or to create training programmes that are better tailored to individual workers.

Notes

[1] Assuming an employment gain of 10 in one occupation is achieved by 15 hires of workers coming from another occupation and 5 separations towards other occupations, then the net occupation mobility is 10, the gross mobility is 20 and the excess reallocations are 10.

[2] The third cognitive skill measured in PIAAC, problem solving in technology-rich environments, is not included in the analysis because many individuals with generally lower literacy and numeracy skills did not take the assessment test for problem solving. Excluding these individuals from the analysis would lead to a strong selection bias. In addition, France, Italy and Spain have not participated in the assessment tests for problem solving and would be excluded from the analysis when using problem solving as a third cognitive skill.

[3] Data are from 2015 or 2014 when 2015 is not available. When core services expenditure are missing, they are replaced: for primary to secondary expenditure by total expenditure minus the OECD average ancillary services (Canada, Denmark, Greece, Ireland, Japan, New Zealand); for tertiary expenditure by total expenditure minus countries' expenditure on R&D activities when they exist (Finland, Greece, New Zealand) or OECD average (without outliers) expenditure on R&D activities otherwise (Denmark, Japan). For Canada for which tertiary education expenditure per student is missing, the average expenditure of other countries in the same cluster is applied.

[4] Education expenditure by ISCED2011 level by private and public institutions is sourced from the Education at a Glance (2017) database and refers to 2015 or 2014. Data on GDP are sourced from the OECD Structural Analysis (STAN) database and refer to the year 2014.

[5] The CVTS collects data on vocational training within EU enterprises with at least 10 or more employed persons and belonging to a certain group of economic activities.

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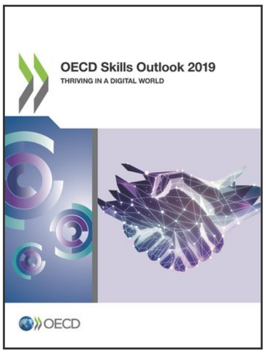
Annex 3.A. Methodological Assumptions

Annex Table 3.A.1. Main hypothesis and their implications for the estimates

	Hypothesis	Motivation	Implications for the estimates
1	Training costs are estimated based on bridging cognitive skills shortages, and only partly on task-based skills shortages.	Data which would allow assessing how much an hour of education/training would yield in terms of all task-based skills included in the analysis is lacking.	This hypothesis underestimates training cost, as occupational transitions can imply shortages in both cognitive and task-based skills. However some task-based skills are likely picked up while developing cognitive skills (e.g. the correlation between numeracy and ICT and advanced numeracy is high).
2	The cost of training is derived using information on education expenditures rather than actual training costs. In particular, data from OECD Education at a Glance on per-pupil core expenditure for secondary and tertiary education is used. Moreover, in the absence of reliable data on adults' learning abilities, education and training are assumed to cost the same for all individuals, regardless of their age.	This assumption does *not* imply that training needs to be provided by the formal education sector. Education expenditure data are used as reference costs, in the absence of more complete information about training costs. No international comparable data exist on adult training. For European countries, the Eurostat's Continuing Vocational Training Survey (CVTS) gives information on the cost per hour but no information on the outcome of training is provided. These data show a higher hourly cost of training than data on education from OECD Education at a Glance but the hourly cost is likely inflated given that the training performed is of a short term nature (average of 36 hours per year).	This hypothesis may overestimate training costs if: • Education expenditure figures include a range of expenses which do not apply to adult learning/training or include the development of some skills that is not needed for occupational transition. • Adults learn faster/more effectively than young people, because of experience or knowledge accumulated on the job. This hypothesis may underestimate training costs if: • Alternative data sources like the CVTS are used to estimate yearly costs, though CVTS figures refer to short duration training programmes. • Education and training systems enjoy "economies of scale" relative to training provided in different shapes or forms (e.g. on a firm-by-firm basis). This may depend also on different bargaining power and purchasing of big versus small companies, the type of training providers, etc.

	Hypothesis	Motivation	Implications for the estimates
			• Adults learn more slowly than young individuals.
3	Working and learning at the same time is ruled out: when in training, individuals are assumed to not work.	Learning here is intended as structured learning aimed to improve cognitive skills. Improving such an assumption would require having information about the time that working individuals can devote to structured learning.	This hypothesis overestimates training costs, as allowing the possibility to learn and work at the same time would decrease the indirect cost of training, which accounts for a large share of total costs.
4	Training is effective, in that all individuals acquire the necessary skills within the estimated training spell duration.	The assumption that all individuals are able to learn and acquire skills is a necessary condition without which the training time needed to bridge the skills shortages between any two occupations cannot be estimated. Data on type, duration and success rates of adult learning/training is lacking.	This hypothesis may underestimate training costs if training is only partially effective, i.e if only a part of the adult population is able to learn or if adults learn to different extents.
5	All individuals manage to bridge the same cognitive skills shortage within a certain training spell.	The regression based approach adopted (which controls for a number of covariates known to affect learning) is needed to translate skill shortages into a training duration. While accounting for all individuals' learning specificities would be impossible, availability of relevant data might help improve the accuracy of the current estimates.	This hypothesis may overestimate training costs if adults learn at a faster pace than estimated and underestimate training costs if adults learn at a slower pace than estimated.
6	All countries' education systems have the same effectiveness.	Up-to-date and comparable data on the effectiveness of education systems is lacking.	This hypothesis may overestimate training costs for countries that have relatively more effective education and training systems and underestimate training costs for those featuring relatively ineffective education and training systems.
7	Workers transit directly to a different occupation, without going through an unemployment spell.	The objective of the work presented in this chapter is to find alternative occupations and estimate the cost of moving workers away from jobs at "high" risk of automation. The focus is not on workers who are already unemployed. If data were available about previous occupations, unemployment spell characteristics and skills depreciation over time, among others, the proposed analysis could be used to also inform the discussion on how to help individuals move out of unemployment.	This hypothesis may overestimate training costs for: • Individuals moving out of unemployment, as the opportunity costs would be lower than those estimated for workers. This hypothesis may underestimate training costs if: • Unemployment spells depreciate workers' competencies and therefore increase the skills shortages to be bridged.
8	The opportunity cost is represented by foregone wages.	Given hypotheses 3 and 7, workers are assumed to transit to the next occupation upon receiving training while being formally employed in the occupation of origin. This entails that they receive their salary while on training.	This hypothesis may overestimate training costs if workers can learn or train while working or receive a lower wage while training.

	Hypothesis	Motivation	Implications for the estimates
9	The analysis refers to “acceptable” transitions, which are identified on the basis of skills shortages and excesses as well as wage conditions.	Estimates rely on available information. Information on a number of aspects known to impact occupational transitions (e.g. location, industry structure, family setting, workers’ preferences, contract type, etc.) are not available and thus cannot be taken into account.	This hypothesis may overestimate training costs if: • Workers are willing to accept greater unused human capital and wage losses to transition away from a “high” risk of automation. This hypothesis may underestimate training costs if: • Acceptable transitions are unavailable in a certain region and workers would need to train for a longer spell.
10	Wage decreases of more than 10% are considered unacceptable.	This figure corresponds approximately to the average annual earnings loss of workers one year after displacement in 5 OECD countries. Workers facing high risks of displacement may accept larger wage cuts.	This hypothesis may overestimate training costs if: • Workers are willing to accept higher wage cuts. This hypothesis may underestimate training costs if: • 10% is a too high wage pay cut to accept, and workers need to train for longer spells to find acceptable transitions.
11	The labour market will be able to absorb workers in one or more of the occupations of destination identified as acceptable transitions.	For simplicity, the analysis does not take into account general equilibrium effects. Indeed, as workers progressively move out of certain occupations to others, labour demand and returns in the occupations of destination will adjust to the inflow and outflow of workers.	How these effect would increase or lower the overall cost of retraining, will depend on the design of the general equilibrium model.



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