4

How Skills Are Used in the Workplace

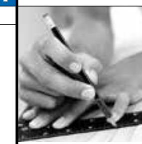
This chapter discusses how information-processing and generic skills are used in the workplace, as measured by the Survey of Adult Skills (PIAAC). It examines the use of these skills across countries and by job and socio-demographic characteristics. It also sheds light on the extent of "mismatch" between the qualifications held by workers or their skills proficiency and the qualifications or skills required in their workplace. Qualification and skills mismatch are then compared, and their effect on wages and the use of skills at work is assessed.

Skills form the bedrock of every country's economy. They are not only linked to aggregate economic performance but also to each individual's success in the labour market. However, having skills is not enough; to achieve growth, both for a country and for an individual, skills must be put to productive use at work. The Survey of Adult Skills (PIAAC) measures both adults' proficiency in key information-processing skills, as described in previous chapters, and how those skills are used in the workplace. It also assesses the use of a variety of generic competencies at work. This chapter presents an analysis of how both information-processing and generic skills are used in the workplace. Among the findings:

- The use of skills in the workplace influences a number of labour market phenomena, including productivity and the gap in wages between temporary and permanent workers.
- Skills-use indicators are only mildly correlated with measures of skills proficiency. In fact, the distributions of skills use for workers at different levels of proficiency overlap substantially. As a result, it is not uncommon that more proficient workers use their skills at work less intensively than less proficient workers do.
- The distribution of workers across occupations is found to be the single most important factor shaping the distribution of skills use. For instance, differences across qualification levels and contract type are explained in large part by differences in the occupations that workers hold.
- Workers tend to use information-processing skills together, often in association with influencing skills. Above-median use of reading, writing, influence and sometimes problem-solving skills at work are jointly observed for at least one-fifth of workers in ten participating countries; in another six countries, ICT, numeracy and reading, and sometimes writing, skills are used in a bundle.
- Mismatches between skills proficiency and the use of skills in the workplace are pervasive, affecting just over one in seven workers. Over-skilled workers – those with higher skills than required by their jobs – tend to under-use their skills, resulting in a "waste" of human capital, while under-skilled workers – those with lower skills than required by their jobs – have to work harder to accomplish their tasks, which could lead to stress and lower job satisfaction, with negative consequences for productivity. Young people are particularly affected by over-skilling, as the incidence of over-skilling generally diminishes with age. In addition, over-skilling has a relatively small negative effect on wages. This suggests either that most employers succeed in identifying their employees' real skills, irrespective of their formal qualifications, and adapt job content accordingly or that wages are negotiated based on skills other than literacy, numeracy and problem solving in technology-rich environments and how those skills are used at work.
- On average across countries, about 21% of workers report that they are over-qualified – that they have higher qualifications than required by their jobs – and 13% report that they are under-qualified for their jobs – that they have lower qualifications than required by their jobs. Over-qualification is particularly common among foreign-born workers and those employed in small establishments, in part-time jobs or on fixed-term contracts. Over-qualification has a significant impact on wages, even after adjusting for proficiency, which, in turn, implies adverse effects on workers' productivity. However, some instances of this kind of mismatch occur when workers have lower skills proficiency than would be expected at their qualification level, either because they performed poorly in initial education or because their skills have depreciated over time. By contrast, under-qualified workers are likely to have the skills required at work, but not the qualifications to show for them.
- While workers with a given level of qualification would be better off if they worked in jobs that better matched their qualifications, this does not imply that either these workers or the economy as a whole would be better off if they had a *lower* level of educational qualification. Qualifications and skills in excess of those *required at work* are still valued in the labour market. On average, a tertiary graduate who holds a job requiring only an upper secondary qualification will earn *less* than if he or she were in a job requiring a tertiary qualification, but *more* than an upper secondary graduate in a job requiring upper secondary qualifications.

USING SKILLS IN THE WORKPLACE

The Survey of Adult Skills (PIAAC) includes detailed questions about the frequency with which respondents perform specific tasks in their jobs. Based on this information, the survey measures the use of a wide range of skills, including both information-processing skills, which are also measured in the direct assessment, and generic skills, for which only self-reported use at work is available.



Given the large amount of information collected in the skills-use section of the questionnaire, it is helpful to construct indices that group together tasks associated with the use of similar skills. Twelve indicators were created (Table 4.1), five of which refer to *information-processing skills* (reading,[1] writing, numeracy, ICT skills and problem solving); the remaining seven correspond to *general skills* (task discretion, learning at work, influencing skills, co-operative skills, self-organising skills, gross physical skills and dexterity).[2]

Table 4.1
Indicators of skills use at work

	Indicator	Group of tasks
Information-processing skills	**Reading**	Reading documents (directions, instructions, letters, memos, e-mails, articles, books, manuals, bills, invoices, diagrams, maps)
	Writing	Writing documents (letters, memos, e-mails, articles, reports, forms)
	Numeracy	Calculating prices, costs or budgets; use of fractions, decimals or percentages; use of calculators; preparing graphs or tables; algebra or formulas; use of advanced math or statistics (calculus, trigonometry, regressions)
	ICT skills	Using e-mail, Internet, spreadsheets, word processors, programming languages; conducting transactions on line; participating in online discussions (conferences, chats)
	Problem solving	Facing complex problems (at least 30 minutes of thinking to find a solution)
Other generic skills	**Task discretion**	Choosing or changing the sequence of job tasks, the speed of work, working hours; choosing how to do the job
	Learning at work	Learning new things from supervisors or co-workers; learning-by-doing; keeping up-to-date with new products or services
	Influencing skills	Instructing, teaching or training people; making speeches or presentations; selling products or services; advising people; planning others' activities; persuading or influencing others; negotiating.
	Co-operative skills	Co-operating or collaborating with co-workers
	Self-organising skills	Organising one's time
	Dexterity	Using skill or accuracy with one's hands or fingers
	Physical skills (gross)	Working physically for a long period

Box 4.1. **How to interpret skills-use variables**

A number of skills-use variables are taken directly from questions asked in the background questionnaire of the Survey of Adult Skills (PIAAC):

- Problem-solving skills: How often are you usually confronted with more complex problems that take at least 30 minutes to find a good solution?
- Co-operative skills: What proportion of your time do you usually spend co-operating or collaborating with co-workers?
- Self-organising skills: How often does your job usually involve organising your own time?
- Physical skills: How often does your job usually involve working physically for a long period?
- Dexterity: How often does your job usually involve using skill or accuracy with your hands or fingers?

For these skills-use variables numerical comparisons between the use of different skills are possible: a value of 0 indicates that the skill is never used; a value of 1 indicates that it is used less than once a month; a value of 2 indicates that it is used less than once a week but at least once a month; a value of 3 indicates that it is used at least once a week but not every day; and a value of 4 indicates that it is used every day.

All other variables described in Table 4.1 have been derived based on more than one question from the background questionnaire using IRT, a statistical method described in more detail in the *Reader's Companion* to this report. These variables have been transformed so that they have a mean of 2 and a standard deviation of 1 across the pooled sample of all participating countries, thus allowing meaningful comparisons across countries. While this transformation implies that the levels of use cannot be easily compared across skill types, such comparisons would be conceptually difficult to make anyway. For example, is using ICT skills every day equivalent to using learning skills every day in terms of how intensively ICT and learning skills are used at work?

Table 4.1 lists the items of the section of the questionnaire on skills use at work that are associated with each of the 12 skills-use indicators. For example, the reading and writing indices are derived from a large set of questions concerning the frequency with which several types of documents (directions, instructions, memos, e-mails, articles, manuals, books, invoices, bills and forms) are read or written during one's regular work activity. Higher values of the indices correspond to more intense levels of use of the individual's ability to read or write (see Box 4.1 on how to interpret skills-use scales).

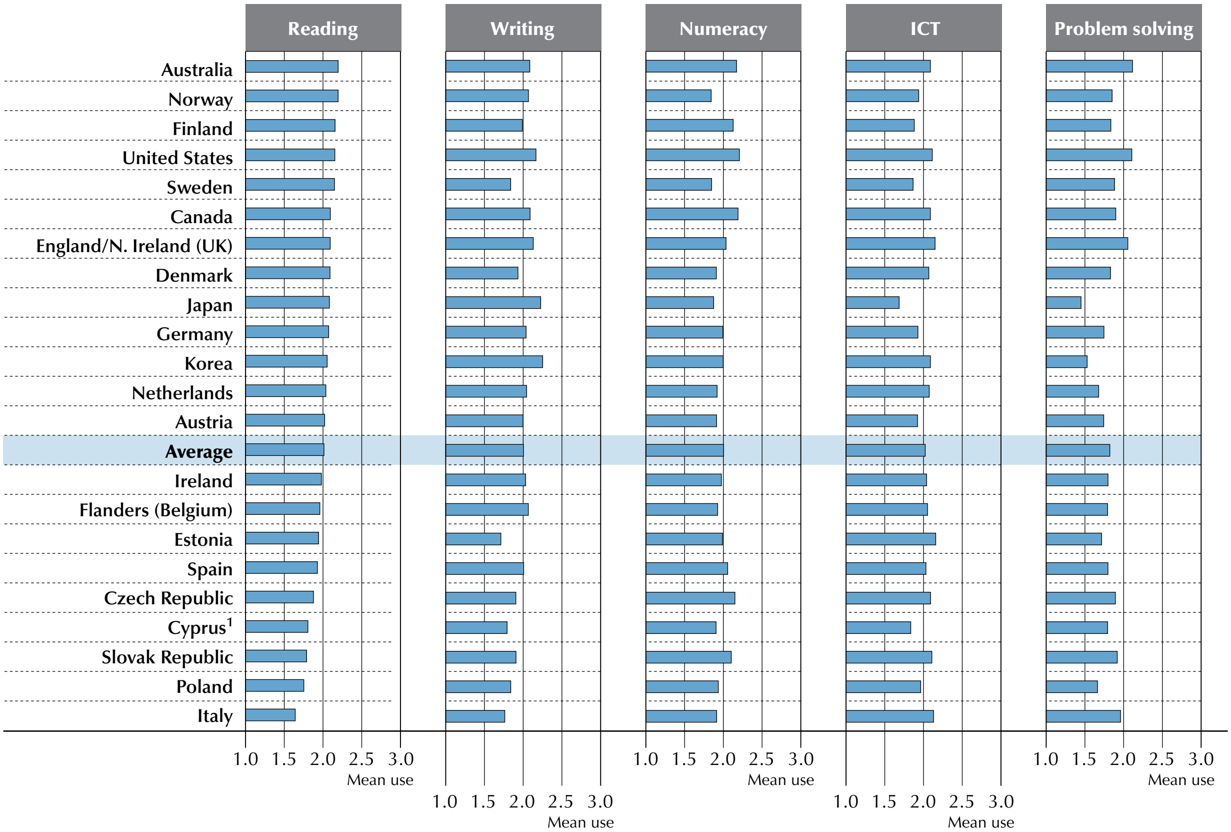
Levels of skills use in the workplace

Countries that make the most frequent use of the skills of their workforce

Reading skills are reported to be used at work most frequently in Australia and Norway, writing skills are used most frequently in Japan and Korea, and numeracy skills are most frequently used in Canada and the United States (Figure 4.1). England/Northern Ireland (UK) and Estonia are the two countries where ICT skills are used the most at work while problem-solving skills are more frequently used in Australia and the United States. These results show surprisingly little connection between the rankings of countries in the average use of each foundation skill at work, emphasising the importance of measuring these skills separately. Australia and the United States are the two countries that rank most consistently near the top of the distribution in all the skills domains measured, but it is more difficult to identify any pattern among the poorest performers.[3]

A similar analysis is conducted for the seven indicators of generic skills (Figure 4.2). As with the use of information-processing skills, the rankings of countries, according to the use of generic skills, vary substantially – even more than for information-processing skills.

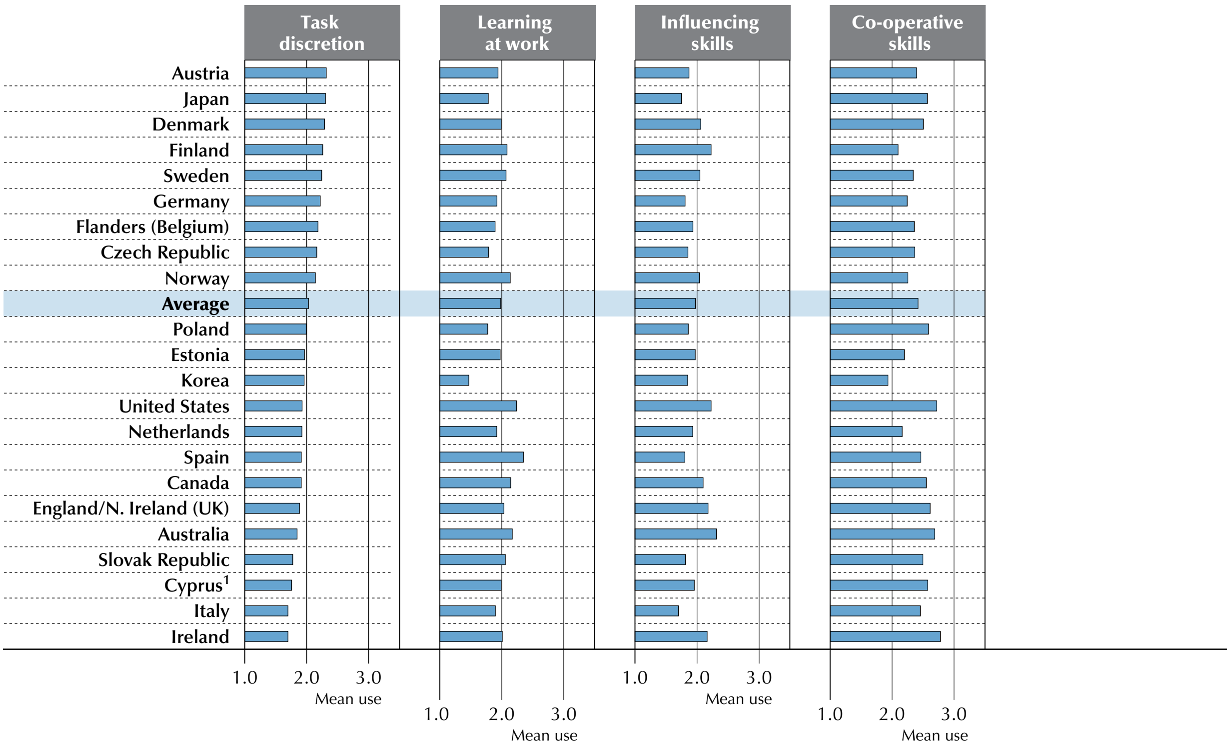
■ Figure 4.1 ■
Average use of information-processing skills at work

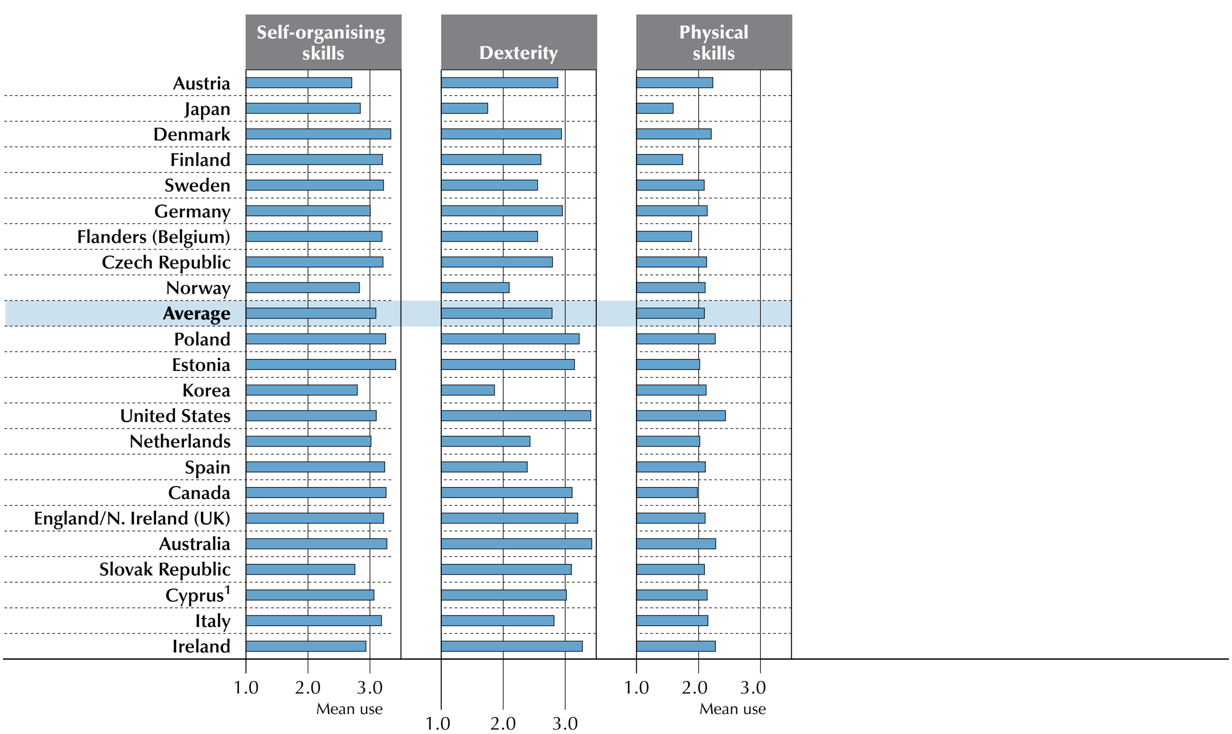


1. See notes at the end of this chapter.
Notes: Skills-use indicators are standardised to have a mean of 2 and a standard deviation of 1 across the entire survey sample.
Countries are ranked in descending order of the average use of reading skills at work.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.1.
StatLink http://dx.doi.org/10.1787/888932901277

■ Figure 4.2 ■

Average use of generic skills at work





1. See notes at the end of this chapter.
Notes: Skills-use indicators are standardised to have a mean of 2 and a standard deviation of 1 across the entire survey sample.
Countries are ranked in descending order of the average use of task discretion at work.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.2.
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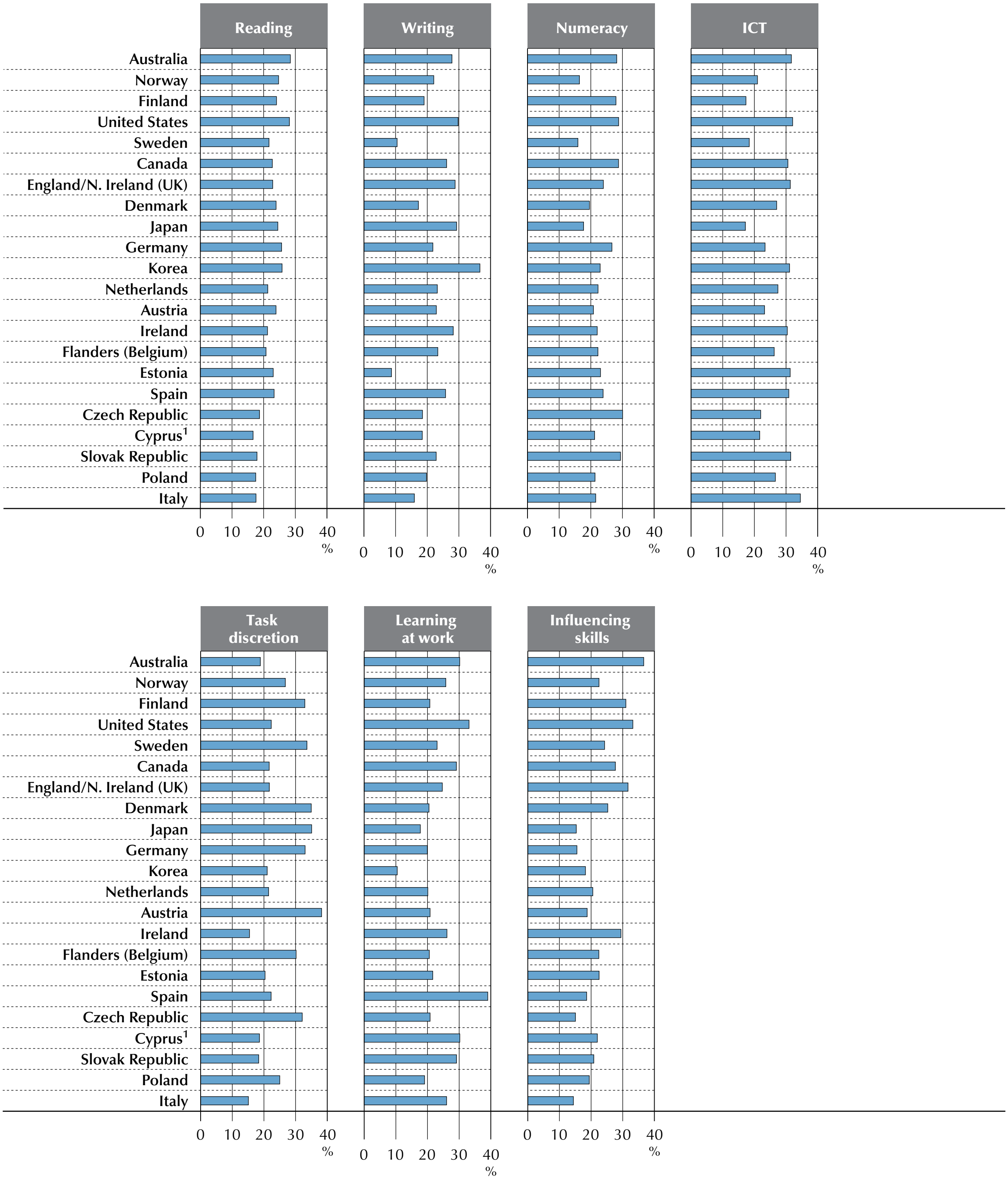
■ Figure 4.3 [1/2] ■

High use of skills at work

A. Percentage of workers in the top 25% of the distribution of the use of skills at work



1. See notes at the end of this chapter.

Notes: The 75th percentile of the overall distribution of skills usage is 2.59 for reading, 2.75 for writing, 2.62 for numeracy, 2.54 for ICT, 2.35 for task discretion, 2.53 for learning at work, 2.54 for influencing skills.

Countries are ranked in descending order of the average use of reading at work (see Figure 4.1).

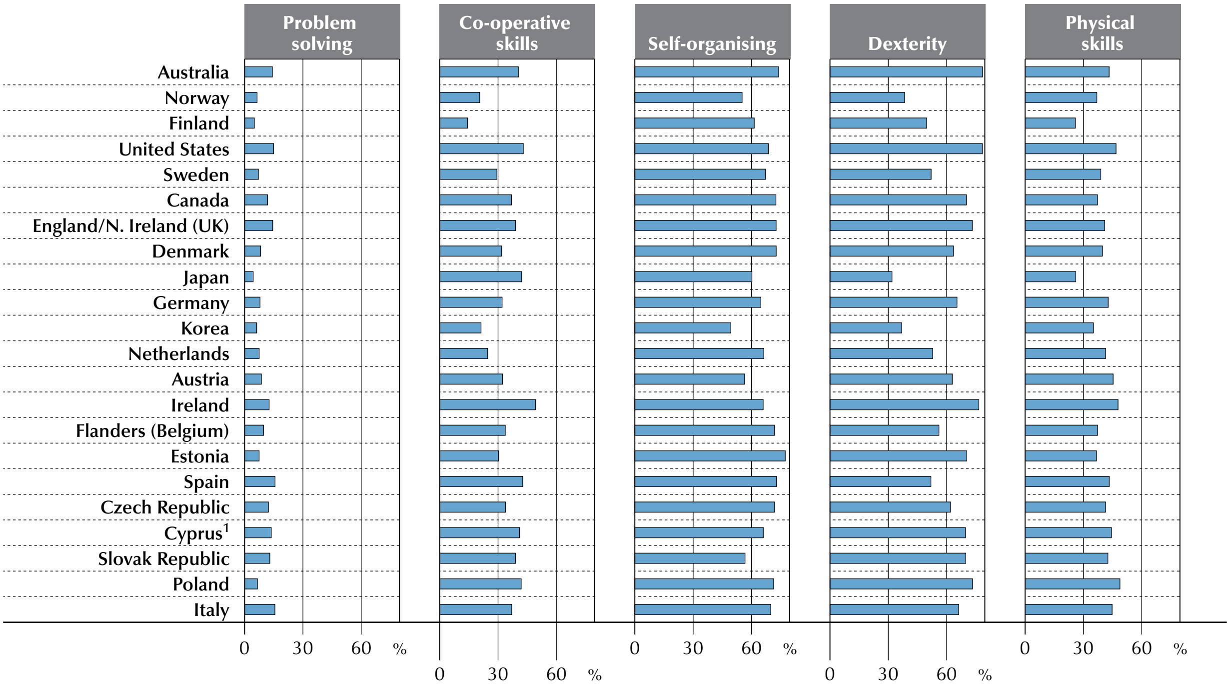
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.3.

StatLink http://dx.doi.org/10.1787/888932901315

■ Figure 4.3 [2/2] ■

High use of skills at work

B. Percentage of workers using the skills shown everyday



1. See notes at the end of this chapter.

Notes: The 75th percentile of the overall distribution of skills usage is 2.59 for reading, 2.75 for writing, 2.62 for numeracy, 2.54 for ICT, 2.35 for task discretion, 2.53 for learning at work, 2.54 for influencing skills.

Countries are ranked in descending order of the average use of reading at work (see Figure 4.1).

Source: Survey of Adults Skills (PIAAC) (2012), Table A4.3.

StatLink http://dx.doi.org/10.1787/888932901315

Another way of looking at skills use at work is by focusing on the proportion of workers who use their skills the most frequently (Figure 4.3).[4] While these findings are similar to those that emerged when looking at *average* skills use, there are some exceptions. For instance, the use of reading skills in Sweden is above average, while the country has a relatively small proportion of jobs that require a high use of reading skills. The opposite is true in Spain, where the use of reading skills is well below average, while the country has a relatively large share of workers who use their reading skills frequently.

Skills used in concert in the workplace

Many of the skills described above are used in concert at work. Cluster analysis suggests that, in ten participating countries, reading, writing, influence skills and, sometimes, problem-solving skills are used together at work. In these countries, at least one in five workers uses these skills at work with above-average frequency (Table 4.2). In another seven countries, ICT, numeracy, reading and, sometimes, writing skills are correlated, with between 17% and 24% of workers using these skills together at work with above-median frequency.[5] Overall, the results of the cluster analysis show that while information-processing skills tend to be used together, generic skills are not. The only exception are influencing skills, which tend to be associated with reading, writing and problem-solving skills. Interestingly, an above-median use of ICT skills is most often associated with an above-median use of numeracy and reading skills.

The extent of skills use at work and productivity

In theory, countries where skills are used more intensively in the workplace also enjoy greater productivity, although the strength of the link depends on a number of factors, such as the capital stock, the quality of production technologies, and the efficiency of matching workers to jobs. Analysis of results shows that the use of reading skills at work correlates most strongly with a standard indicator of labour productivity, namely output per hour worked. Obviously, productivity may also be affected by the use of many other skills or by the nature of the work environment. As a result, the link between reading at work and productivity may reflect the fact that reading is associated with these other skills and/or with capital-intensity in the workplace.

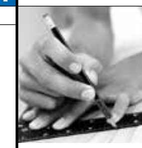
Table 4.2
Skills used jointly at work

	Percentage of workers with high-use of multiple skills[1]	Skills-use clusters
Australia	18.6	Influencing, Reading, Writing, Problem Solving
England/N. Ireland (UK)	18.2	Influencing, Reading, Writing, Problem Solving
Ireland	18.0	Influencing, Reading, Writing, Problem Solving
Austria	24.5	Influencing, Reading, Writing
Denmark	21.7	Influencing, Reading, Writing
Finland	21.9	Influencing, Reading, Writing
Germany	19.5	Influencing, Reading, Writing
Italy	23.8	Influencing, Reading, Writing
Netherlands	23.1	Influencing, Reading, Writing
Norway	21.4	Influencing, Reading, Writing
Czech Republic	17.2	ICT, Numeracy, Reading, Writing
Korea	18.2	ICT, Numeracy, Reading, Writing
Sweden	18.8	ICT, Numeracy, Reading, Writing
Flanders (Belgium)	23.6	ICT, Numeracy, Reading
Japan	25.1	ICT, Numeracy, Reading
Canada	22.3	ICT, Reading, Writing
Estonia	24.2	ICT, Reading, Writing
Cyprus[2]	32.7	Influencing, Reading
Spain	33.0	Influencing, Reading
Slovak Republic	25.0	ICT, Problem Solving, Reading
United States	32.6	ICT, Reading
Poland[3]	-	-

1. High use of skills is defined as above the median of the within-country distribution of the indicator of skills use.
2. See notes at the end of this chapter
3. No skills use cluster is identified for Poland.

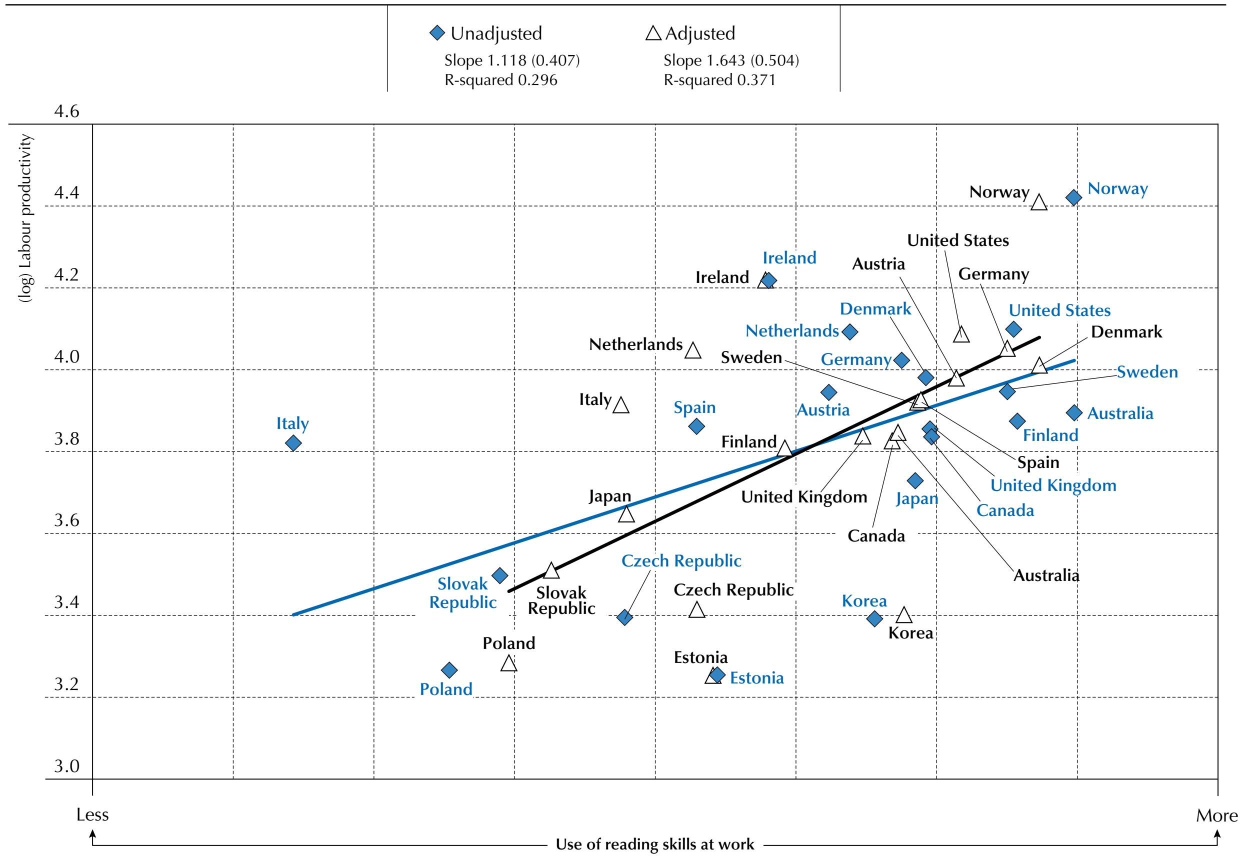
Despite these caveats, labour productivity and the use of reading skills are positively and statistically significantly correlated across participating countries. Differences in the average use of reading skills explain around 30% of the variation in labour productivity across countries (Figure 4.4). In other words, how skills are used at work can affect productivity. One possible explanation for this is that skills use simply reflects workers' proficiency in those skills. If so, the link between the use of reading skills at work and productivity could actually reflect a relationship between literacy proficiency and productivity.[6] But this is not what the data show. The positive link between labour productivity and reading at work remains strong and statistically significant even after adjusting for average proficiency scores in literacy and numeracy.[7] If anything, once these adjustments are made, the average use of reading skills explains more (37%) of the variation in labour productivity across countries.[8] Put simply, the way skills are used at work is important, in itself, in explaining differences in labour productivity over and above the effect of proficiency.

These results emphasise the importance of putting skills to productive use, beyond having a skilled workforce (Hanushek and Woessmann, 2008). Too often workers are not employed in the jobs that make the best use of their skills. This issue will be discussed at greater length below, in the section on mismatch.



■ Figure 4.4 ■

Labour productivity and the use of reading skills at work



Notes: The bold lines are the best linear predictions. Labour productivity is equal to the GDP per hour worked, in USD current prices (Source: OECD.Stat). Adjusted estimates are based on OLS regression including controls for literacy and numeracy proficiency scores. Standard errors in parentheses.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.4.
StatLink http://dx.doi.org/10.1787/888932901334

The distribution of skills use according to workers' and jobs' characteristics

Skills use at work and gender

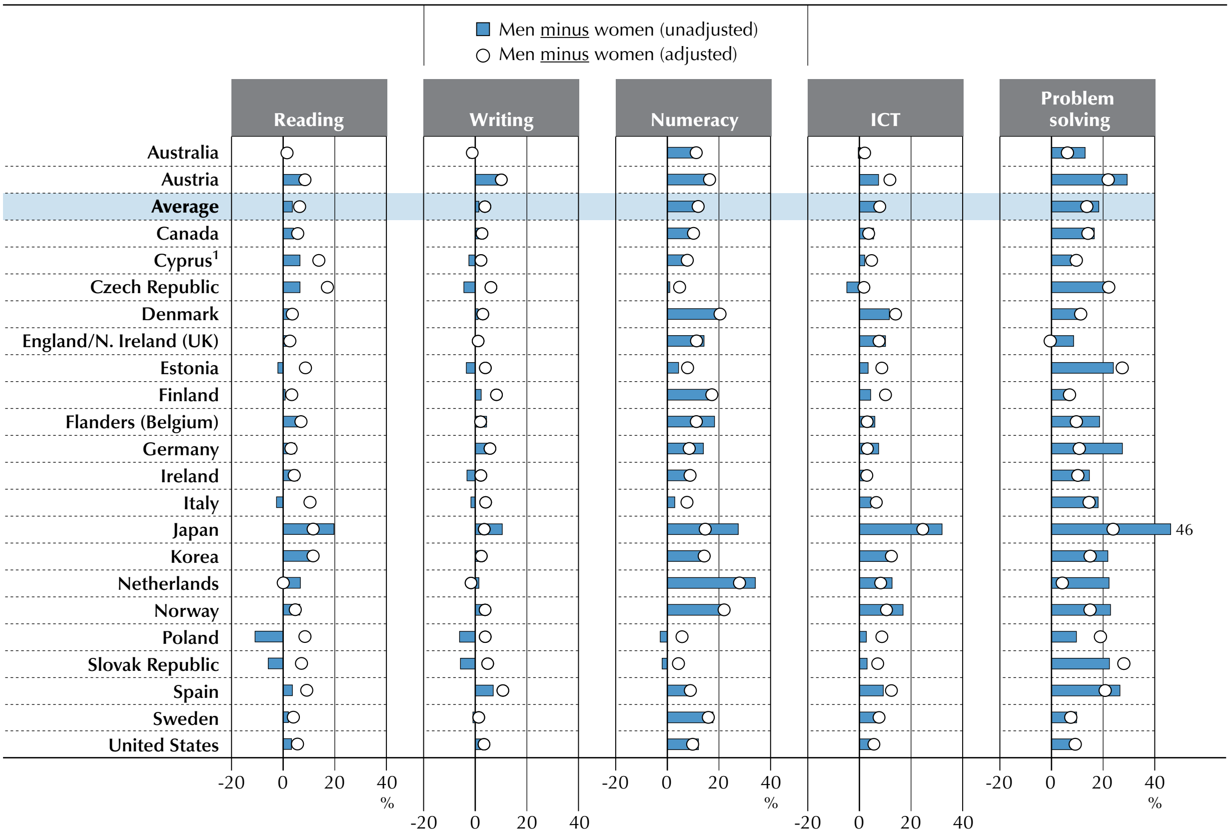
With only a few country exceptions, men use information-processing skills at work more frequently than women, on average (Figure 4.5). This is always the case for problem-solving skills; whereas for reading, writing, ICT and numeracy skills, a small group of countries, often including Poland and the Slovak Republic, shows greater use of these skills among women than among men.

Differences in skills use between men and women may be the result of gender discrimination but may also be explained by differences in skills proficiency (in numeracy and literacy) and/or in the nature of the job (part-time versus full-time, and occupation). For instance, if literacy and numeracy skills were used less frequently in part-time jobs than in full-time jobs, this may explain part of the difference in skills use between genders, as women are more likely to work part-time than men. This reasoning could apply to occupations as well, with women more likely to be found in low-level jobs that presumably require less intensive use of skills.[9] Indeed, when these factors are taken into account (the *adjusted* values in the figure), differences in skills use by gender are smaller.[10] The results confirm that gender differences in the use of information-processing skills are partly due to the fact that men appear to be slightly more proficient and that they are more commonly employed in full-time jobs, where skills are used more intensively.[11] However, this is not the case when adjusting for occupation: when the type of job held is taken into account, the differences in how men and women use their skills at work are larger. This is somewhat surprising, given that the concentration of women in low-paying occupations is often considered one of the key determinants of gender discrimination and the gender gap in wages (Blau and Kahn, 2000 and 2003; Goldin, 1986; OECD, 2012). One possible explanation is that, while women tend to be concentrated in certain occupations, they use their skills more intensively than do the relatively few men who are employed in similar jobs.

■ Figure 4.5 ■

Use of information-processing skills at work, by gender

Adjusted and unadjusted gender differences in the mean use of skills, percentage of the average use of skills by women



1. See notes at the end of this chapter.

Notes: Adjusted estimates are based on OLS regressions including controls for literacy and numeracy proficiency scores, hours worked, and occupation dummies (ISCO 1 digit).

Countries are listed in alphabetical order.

Source: Survey of Adults Skills (PIAAC) (2012), Tables A4.5a and A4.5b.

StatLink http://dx.doi.org/10.1787/888932901353

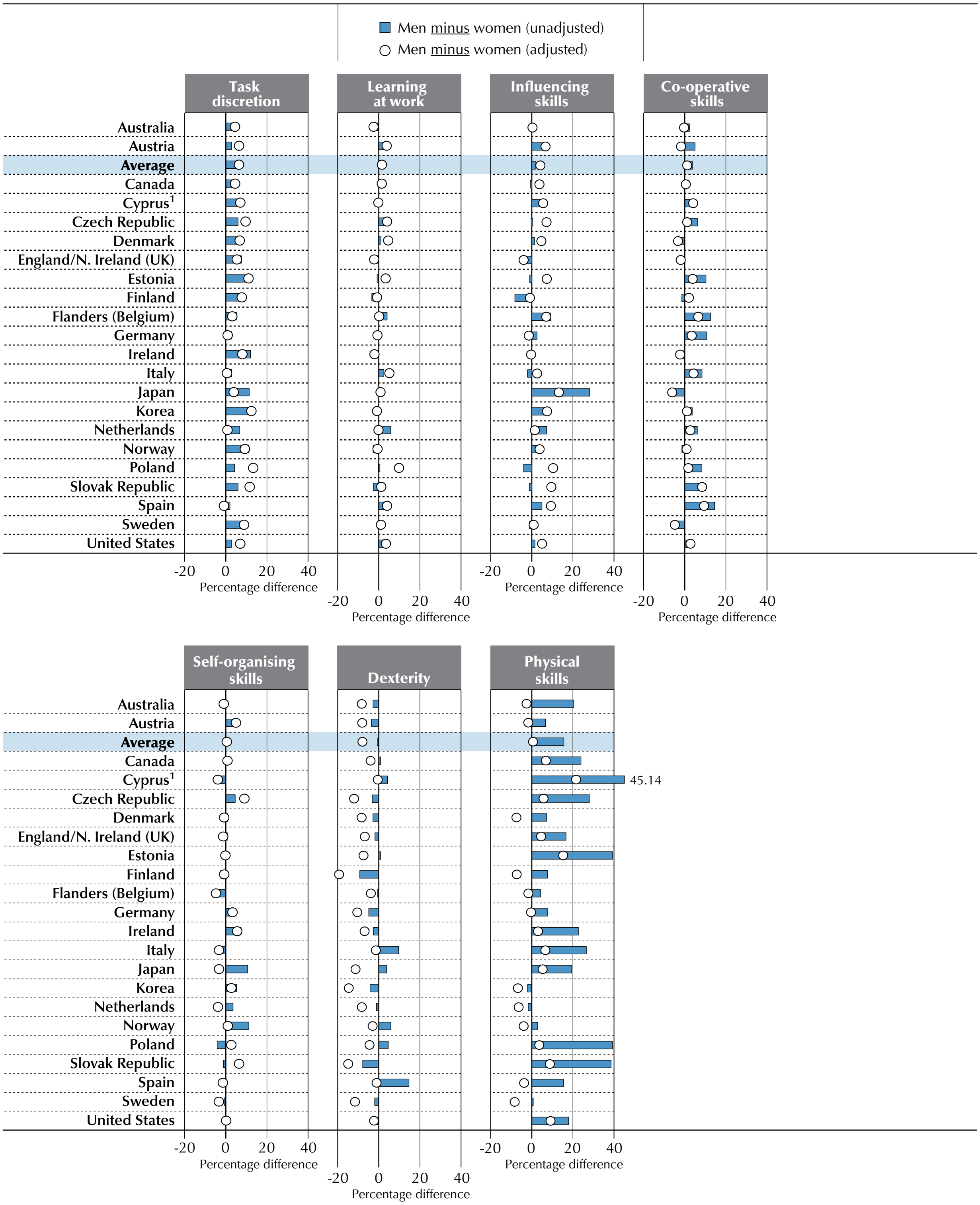
A similar but somewhat more varied picture emerges when considering generic skills (Figure 4.6). Men tend to use some skills, such as task discretion and, particularly, (gross) physical skills, at work more than women; but only small differences are observed for other generic skills and take different signs across countries. The influence of other factors, such as proficiency, part-time or full-time work, and occupation on gender differences in the use of generic skills varies considerably across the skills considered and across countries. Such heterogeneity is, for the most part, due to the different roles played by proficiency and part-time work across types of skills, while adjusting for the distribution of male and female workers across occupation increases differences in the use of generic skills in most countries and for most skill domains, with the notable exception of dexterity.

The use of problem-solving skills at work explains about half of the gender gap in wages. Despite the extensive literature on wage differences between genders (see OECD, 2012 for a review), little is known about the extent to which the use of skills at work explains such differences. An analysis of survey results finds that about 49% of the cross-country differences in the gender gap in wages can be predicted by differences in the use of problem-solving skills at work (Figure 4.7). This relationship is statistically significant but disappears after gender differences in a number of other factors, namely proficiency in literacy and numeracy skills, educational qualifications, occupation, and industry of the jobs, are taken into account.

■ Figure 4.6 ■

Use of generic skills at work, by gender

Adjusted and unadjusted gender differences in the mean use of skills, percentage of the average use of skills by women



1. See notes at the end of this chapter.

Notes: Adjusted estimates are based on OLS regressions including controls for literacy and numeracy proficiency scores, hours worked, and occupation dummies (ISCO 1 digit).

Countries are listed in alphabetical order.

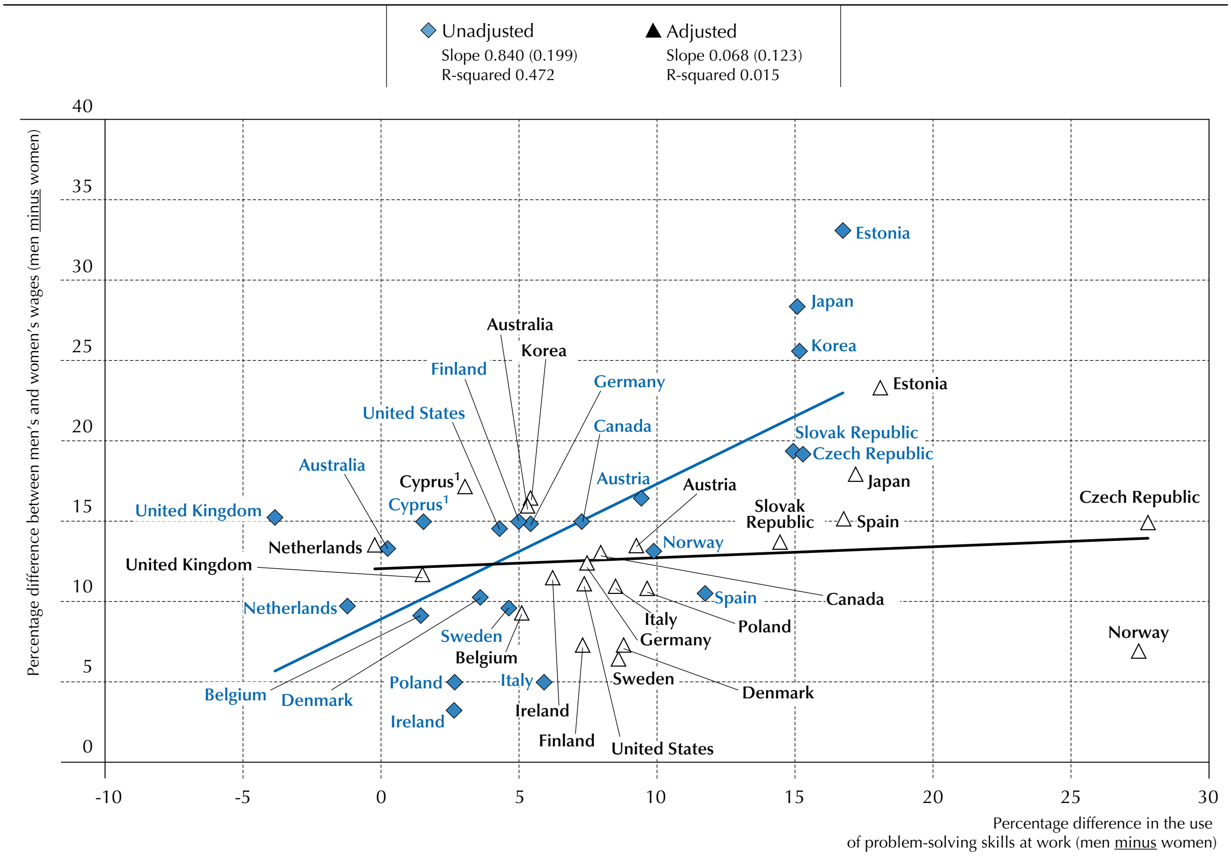
Source: Survey of Adults Skills (PIAAC) (2012), Tables A4.6a and A4.6b.

StatLink http://dx.doi.org/10.1787/888932901372

These findings suggest that detailed understanding of skills use at work can help to identify the roots of the gender gap in pay. As a consequence, policies that aim to improve the match between the skills in the labour supply and those in demand may also affect the gender gap in wages (Black and Spitz-Oener, 2010).

■ Figure 4.7 ■

Gender gap in wages and in the use of problem-solving skills at work



1. See notes at the end of this chapter.

Notes: The gender gap in wages is computed as the percentage difference between men's and women's average hourly wages, including bonuses. The wage distribution was trimmed to eliminate the 1st and 99th percentiles. Adjusted estimates are based on OLS regressions including controls for average literacy and numeracy scores, dummies for highest qualification (4), occupations (9) and industry (10). The bold lines are the best linear predictions. The sample includes only full-time employees. Standard errors in parentheses.

Source: Survey of Adults Skills (PIAAC) (2012), Table A4.7.

StatLink http://dx.doi.org/10.1787/888932901391

Skills use at work and age

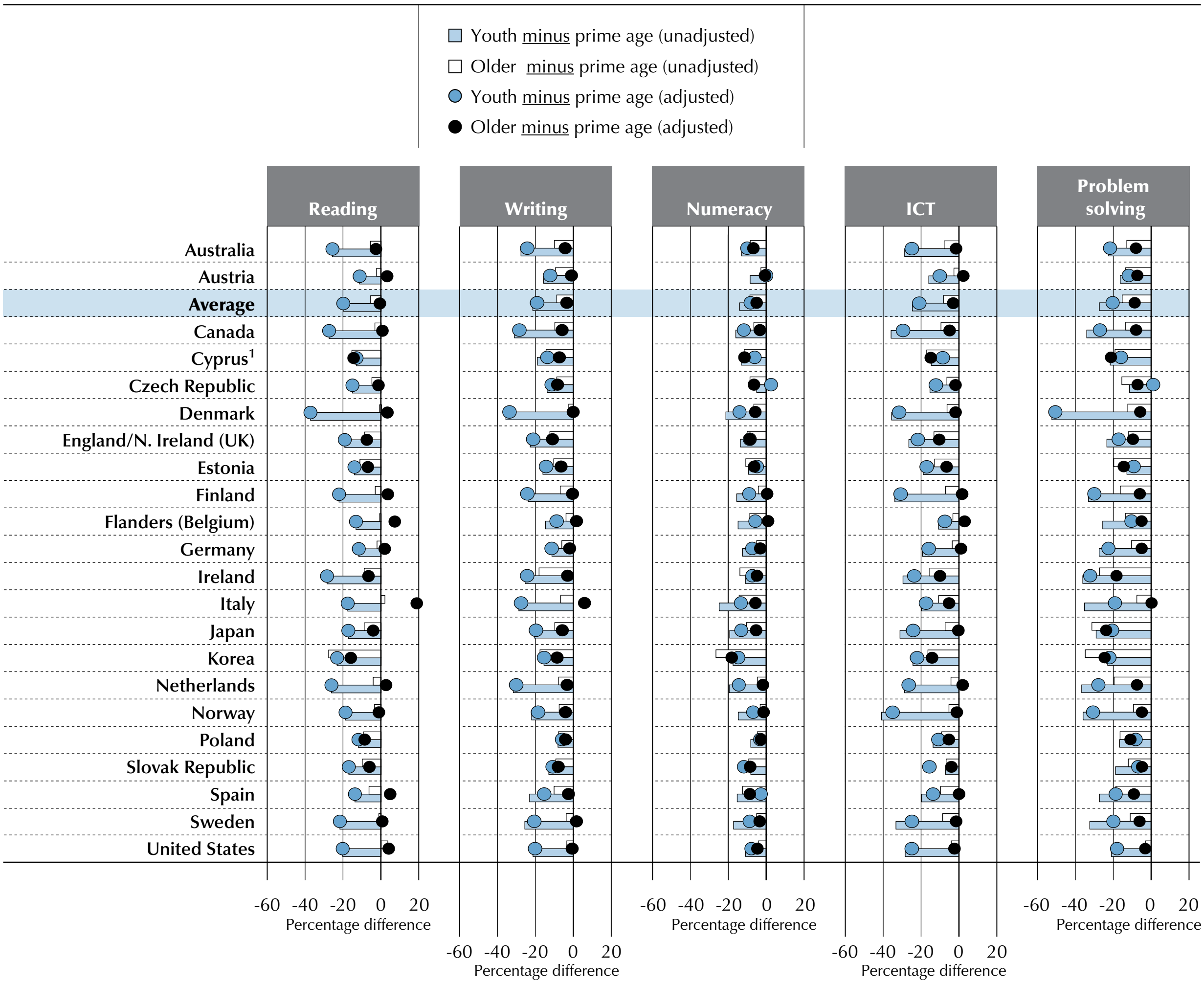
On average, workers aged 16-24 and those aged 55-65 use information-processing skills at work less than do workers of prime age, i.e. aged 25-54 (Figure 4.8; Figure 4.9 shows use of generic skills). This finding can be interpreted in several ways. For instance, it is possible that older workers move into less demanding positions prior to retirement. Alternatively, skills use may decline as skills proficiency does: skills accumulated in the initial stages of one's career may depreciate over time due to a lack of investment in training and lifelong learning activities (see Chapter 3).[12] The latter explanation is likely to be more important for generic skills than information-processing skills, which are less likely to be acquired on the job or outside school.

Interestingly, differences in proficiency levels and in contract types (permanent versus temporary) seem to be substantially more important in explaining the variation in skills use between prime-age and older workers than between prime-age workers and young workers; and proficiency has the strongest effect.[13] Moreover, the difference in skills use is generally larger between younger and prime-age workers than between older and prime-age workers, suggesting that people accumulate skills relatively quickly during the early years of their careers and lose them relatively slowly during the later years. In countries with ageing populations, this may be interpreted as a positive finding, as keeping older people at work may not lower average productivity as much as it is sometimes feared (Feyrer, 2007; Friedberg, 2003; Kotlikoff and Gokhale, 1992).

■ Figure 4.8 ■

Use of information-processing skills at work, by age group

Adjusted and unadjusted age differences in the mean use of skills, percentage of the average use of skills by prime-age workers



1. See notes at the end of this chapter.

Notes: Adjusted estimates are based on OLS regressions including controls for literacy and numeracy proficiency scores and contract type. Youth are 16-25 years old, prime age 26-54 and older workers 55-65.

Countries are listed in alphabetical order.

Source: Survey of Adults Skills (PIAAC) (2012), Tables A4.8a and A4.8b.

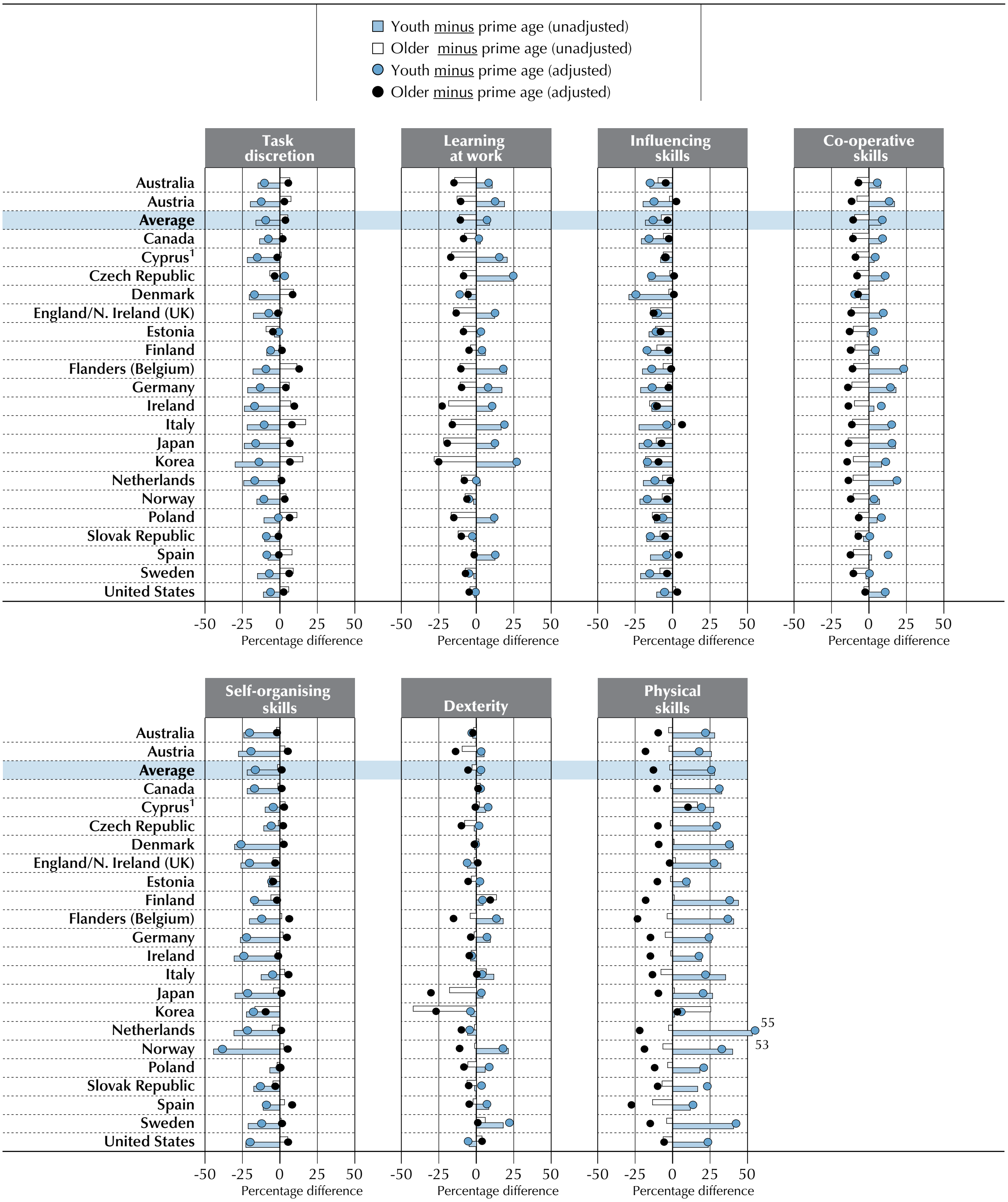
StatLink http://dx.doi.org/10.1787/888932901410

Contrary to the conventional wisdom that young people are more intense users of information and communication technologies, the average index of ICT use among youth is lower than that among prime-age workers in all participating countries. However, the picture is different for home use of ICT. Workers aged 16-24 use ICT consistently more at home than in the office, whereas the opposite is true among prime-age (25-54 year-old) and older (55-65 year-old) workers (Figure 4.10).[14] Of course, some of the computer activities in which young adults engage at home (videogames, Internet browsing, chatting) may not be the same as those required on the job. Nevertheless, it would be useful to explore further the extent to which young people's ICT skills are being underused in the labour market.

■ Figure 4.9 ■

Use of generic skills at work, by age group

Adjusted and unadjusted age differences in the mean use of skills, percentage of the average use of skills by prime-age workers



1. See notes at the end of this chapter.

Notes: Adjusted estimates are based on OLS regressions including controls for literacy and numeracy proficiency scores and contract type. Youth are 16-24 years old, prime age 25-54 and older workers 55-65.

Countries are listed in alphabetical order.

Source: Survey of Adults Skills (PIAAC) (2012), Tables A4.9a and A4.9b.

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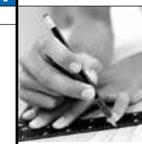
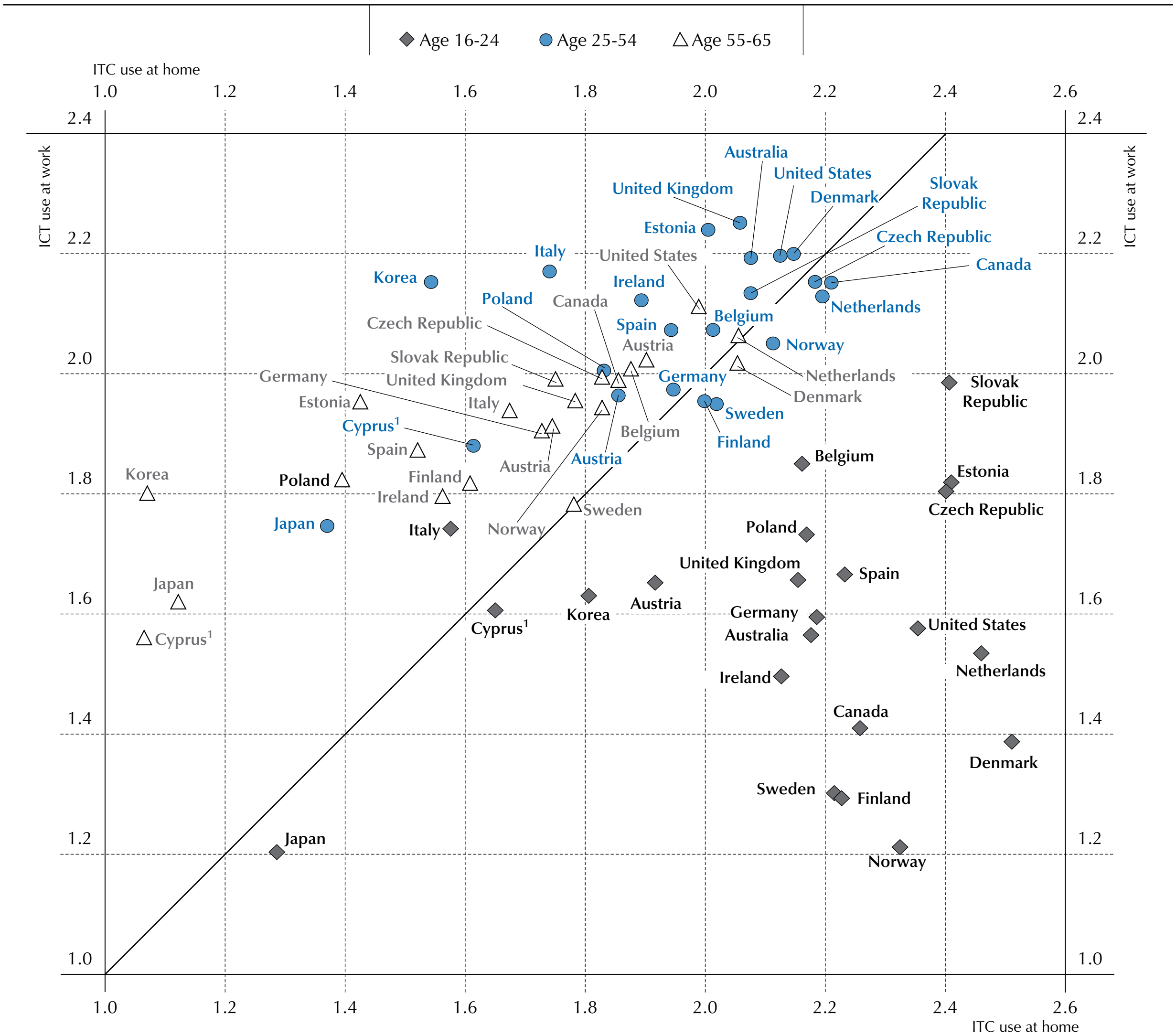


■ Figure 4.10 ■

Mean ICT use at work and at home, by age group



1. See notes at the end of this chapter.
Notes: The sample includes only workers.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.10.
StatLink http://dx.doi.org/10.1787/888932901448

Skills use at work and formal education

Although skills are developed in a variety of settings and evolve with age, formal education remains the primary source of learning, and it seems natural to expect greater use of skills among better-educated individuals.

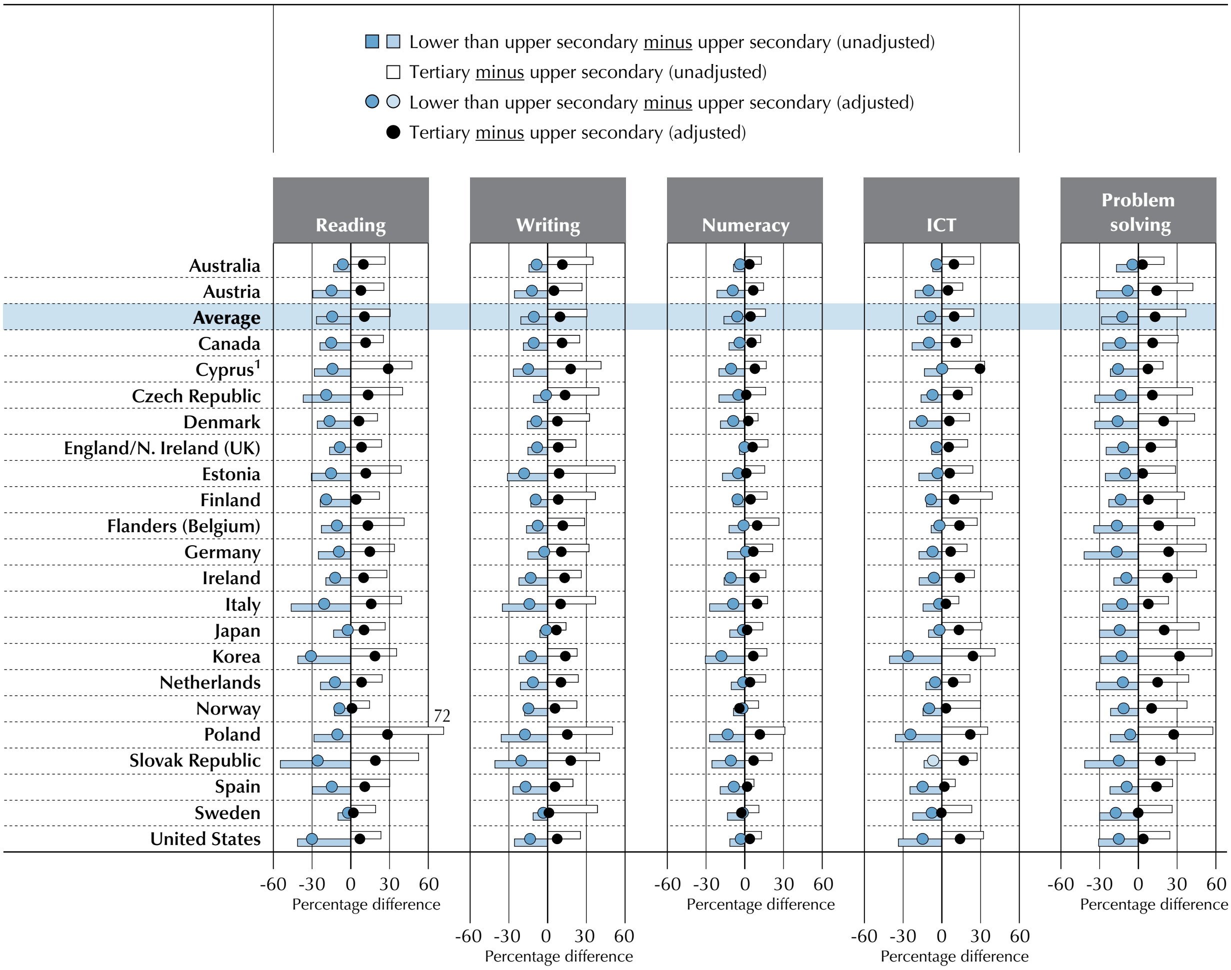
For this analysis, only three groups of workers are considered: those who have less than upper secondary education, those who have completed upper secondary education, and those who have completed tertiary education.[15] With very few exceptions, the results show that workers with higher educational qualifications also use their skills more intensively in their jobs (Figures 4.11 and 4.12). The only obvious exceptions are dexterity and gross physical skills. Beyond this general trend, there are no patterns common to all skills and all countries, especially as concerns the ranking of countries across the different skills domains.

Not surprisingly, differences in skills proficiency and in the distribution of workers across occupations explain most of the variations in skills use among people with different educational qualifications. However, it is the jobs that people hold – as reflected by their occupations – rather than their competency in literacy and numeracy that have the greatest impact on skills use.

■ Figure 4.11 ■

Use of information-processing skills at work, by educational attainment

Adjusted and unadjusted differences in the mean use of skills by educational attainment, percentage of the average use of skills by adults with upper secondary education



1. See notes at the end of this chapter.

Notes: Adjusted estimates are based on OLS regressions including controls for literacy and numeracy proficiency scores and occupation dummies (ISCO 1 digit). Estimates based on a sample size less than 30 are shown in lighter tones.

Countries are listed in alphabetical order.

Source: Survey of Adults Skills (PIAAC) (2012), Tables A4.11a and A4.11b.

StatLink http://dx.doi.org/10.1787/888932901467

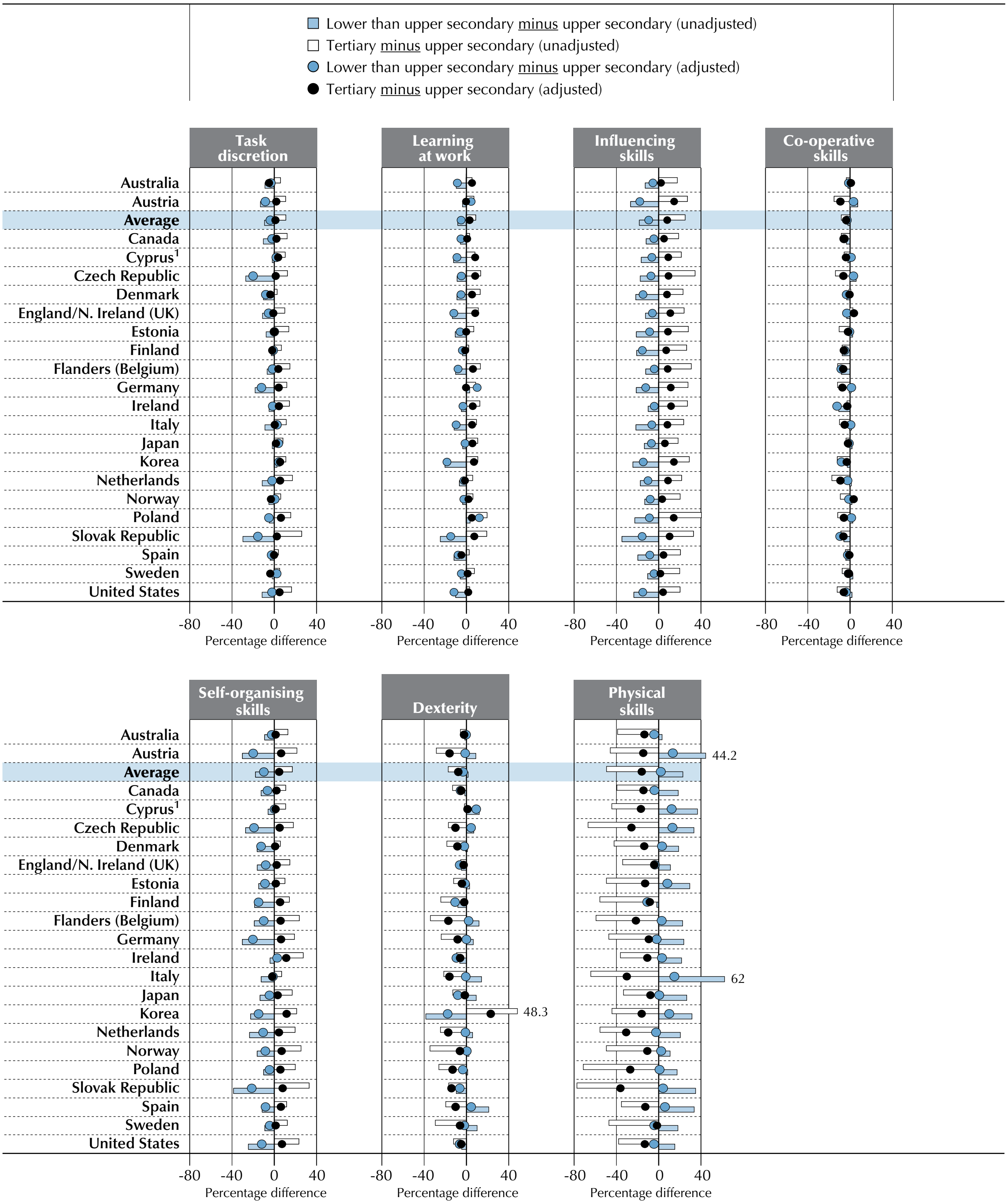
These results have implications for a number of hotly debated issues in labour market policy, particularly regarding the sources and evolution of wage inequality (Card and Lemieux, 2001; Katz and Murphy, 1992; Juhn, Murphy and Pierce, 1993; Lemieux, 2006). One such issue is the college premium in wages, i.e. the average wage advantage of tertiary graduates compared to other employed individuals. The Survey of Adult Skills (PIAAC) allows for an investigation of how this phenomenon correlates with the use of reading skills and task discretion, the two (information-processing and generic) skills that appear to be linked most strongly with it.

The link between skills use and the premium earned by tertiary graduates compared to their less-educated counterparts is primarily due to differences in proficiency and in the type of jobs graduates hold. Across countries, the correlation between the tertiary wage premium and the average difference in the use of reading skills at work is statistically significant; and differences in skills use predict 26% of the variation in the wage premium (Figure 4.13). However, this correlation is almost entirely due to differences in skills proficiency and in the type of jobs and industries in which graduates and non-graduates work. This is also true for the link between the use of task discretion and the tertiary wage premium.

■ Figure 4.12 ■

Use of generic skills at work, by educational attainment

Adjusted and unadjusted differences in the mean use of skills by educational attainment, percentage of the average use of skills by adults with upper secondary education



1. See notes at the end of this chapter.

Notes: Adjusted estimates are based on OLS regressions including controls for literacy and numeracy proficiency scores and occupation dummies (ISCO 1 digit).

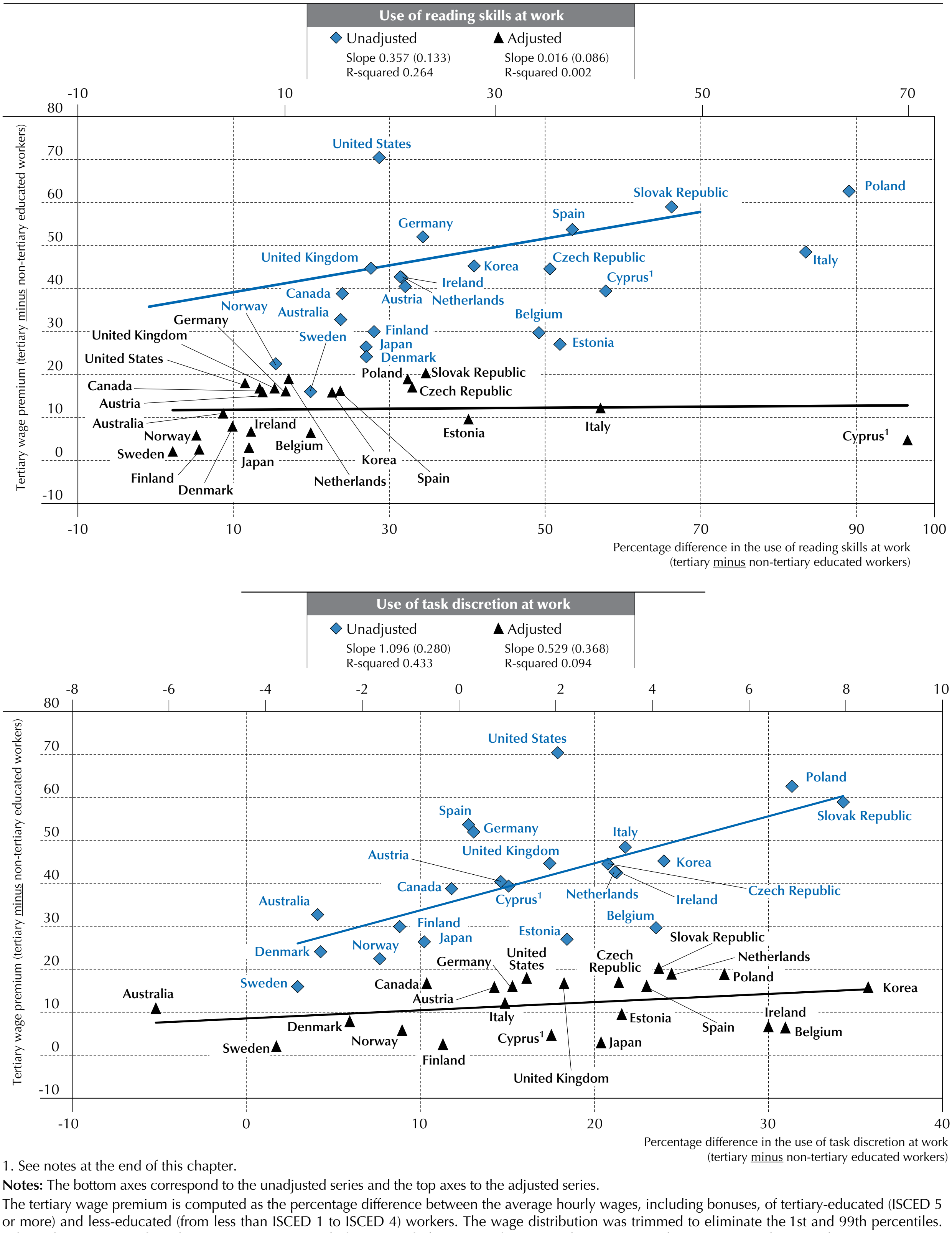
Countries are listed in alphabetical order.

Source: Survey of Adults Skills (PIAAC) (2012), Tables A4.12a and A4.12b.

StatLink http://dx.doi.org/10.1787/888932901486

■ Figure 4.13 ■

The tertiary premium and the use of reading skills and task discretion at work



1. See notes at the end of this chapter.

Notes: The bottom axes correspond to the unadjusted series and the top axes to the adjusted series.

The tertiary wage premium is computed as the percentage difference between the average hourly wages, including bonuses, of tertiary-educated (ISCED 5 or more) and less-educated (from less than ISCED 1 to ISCED 4) workers. The wage distribution was trimmed to eliminate the 1st and 99th percentiles. Adjusted estimates are based on OLS regressions including controls for average literacy and numeracy proficiency scores, dummies for occupations (9) and industry (10). The bold lines are the best linear predictions. The sample includes full-time employees only. Standard errors in parentheses.

Source: Survey of Adults Skills (PIAAC) (2012), Table A4.13.

StatLink http://dx.doi.org/10.1787/888932901505

Skills use at work and type of work contract

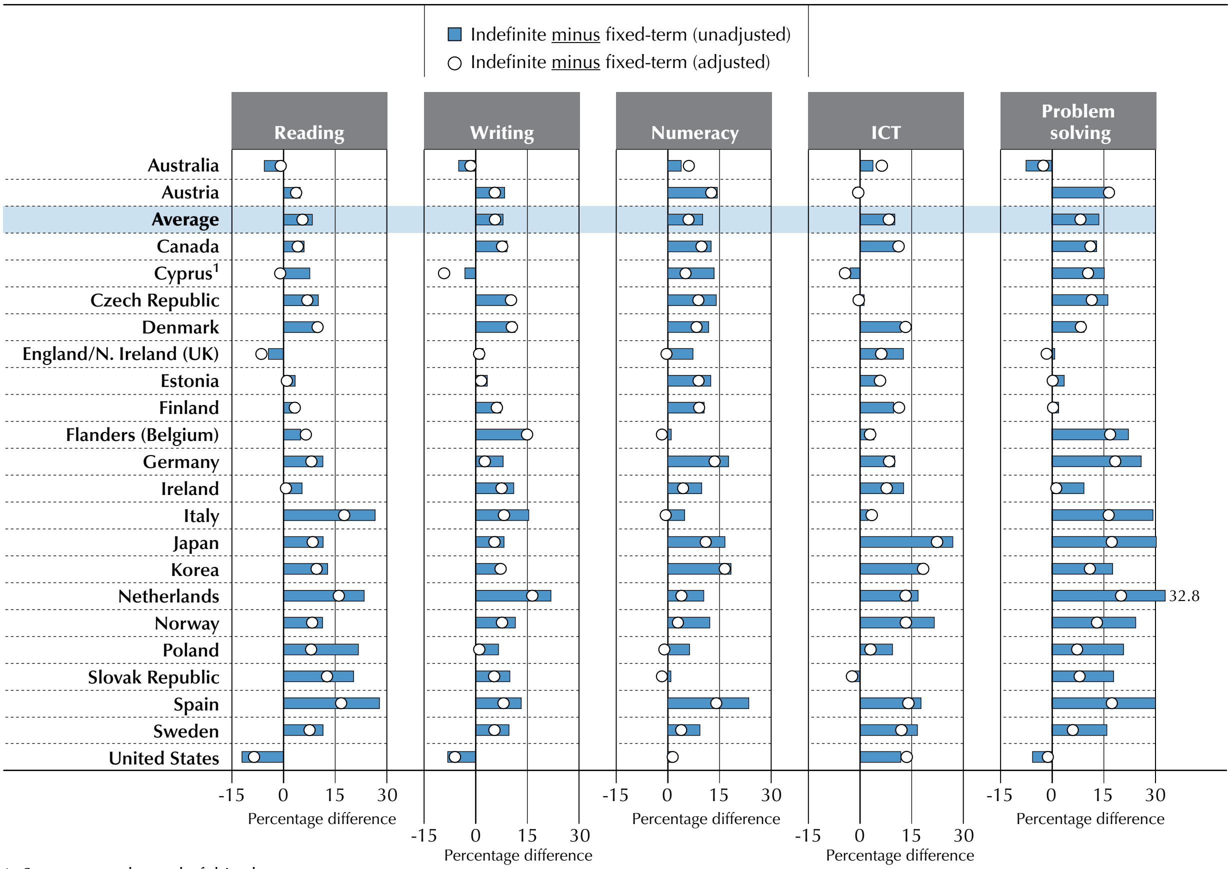
Data on skills use may also help inform the debate on another important labour-market issue: the use of temporary contracts that has become pervasive in several OECD countries in recent years. When combined with low rates of transition to permanent contracts and the fact that a disproportionate share of workers on temporary contracts are young people, greater use of these contracts could have adverse effects on both individual workers and the economy as a whole. For example, it has been extensively documented that workers on temporary contracts receive less training from their employers (Autor, 2001; OECD, 2006) and have fewer opportunities to accumulate job-specific skills, thus potentially reducing their opportunities for career development and jeopardising the growth of labour productivity among the younger generations. Understanding the differences in the tasks performed and the skills used by workers on temporary and permanent contracts is crucial for designing appropriate policies to address this problem.

With very few exceptions, workers on fixed-term contracts use their information-processing skills less intensively than their colleagues in permanent employment (Figure 4.14).[16] Interestingly, Anglo-Saxon countries, and the United States in particular, stand out with a distinct pattern in which temporary workers use their information-processing skills either more than (reading, writing and problem solving) or similarly to (numeracy) workers on indefinite contracts. This could partly be because of the limited employment protection provided, regardless of the type of job, especially in the United States, where the distinction between temporary and permanent contracts is much more blurred, and where fixed-term contracts refer to a much more distinctive, and relatively uncommon, form of contract, than they do in other countries.[17]

■ Figure 4.14 ■

Use of information-processing skills at work, by type of contract

Adjusted and unadjusted differences in the mean use of skills between types of contracts, percentage of the average use of skills by employees with a fixed-term contract



1. See notes at the end of this chapter.

Notes: The sample includes only employees. Adjusted estimates are based on OLS regressions including controls for literacy and numeracy proficiency scores and occupation dummies (ISCO 1 digit).

Countries are listed in alphabetical order.

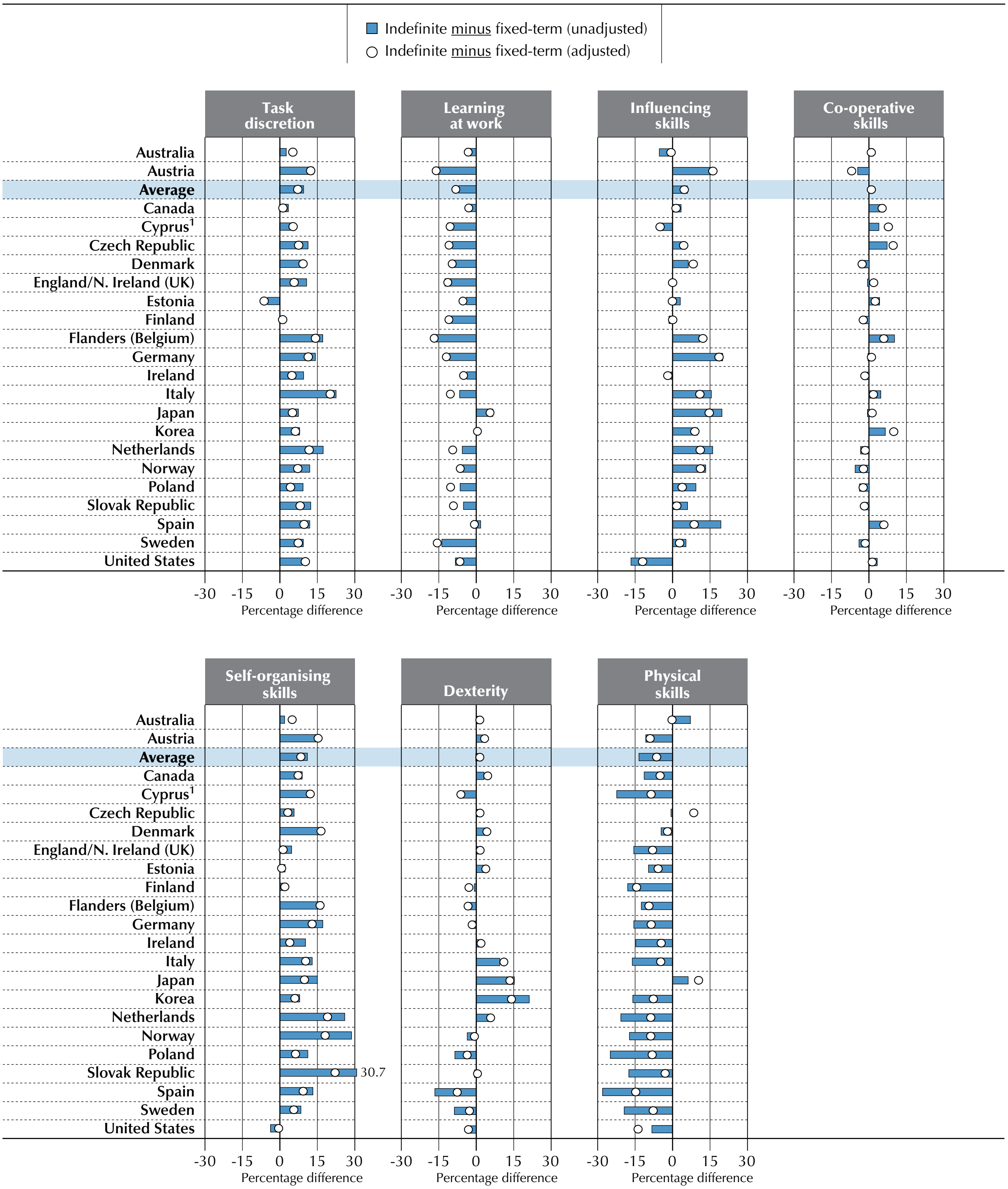
Source: Survey of Adults Skills (PIAAC) (2012), Tables A4.14a and A4.14b.

StatLink http://dx.doi.org/10.1787/888932901524

■ Figure 4.15 ■

Use of generic skills at work, by type of contract

Adjusted and unadjusted differences in the mean use of skills between types of contracts, percentage of the average use of skills by employees with a fixed-term contract



1. See notes at the end of this chapter.

Notes: The sample includes only employees. Adjusted estimates are based on OLS regressions including controls for literacy and numeracy proficiency scores and occupation dummies (ISCO 1 digit).

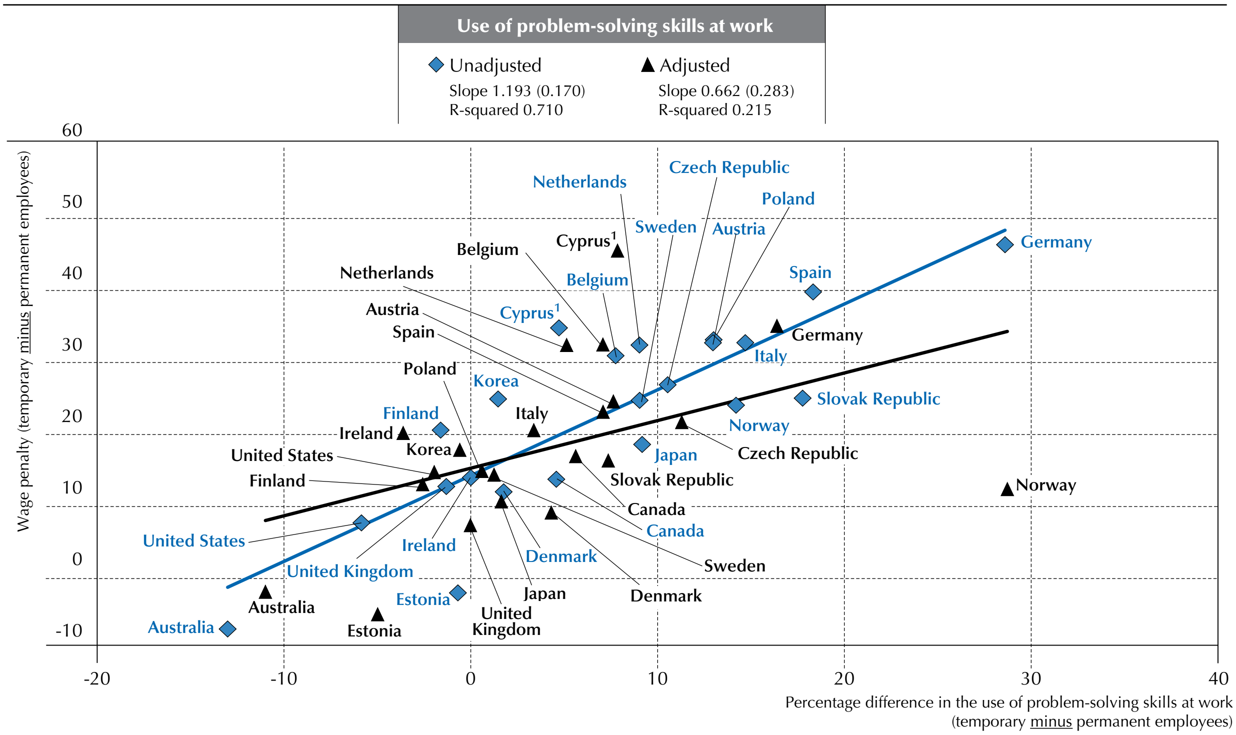
Countries are listed in alphabetical order.

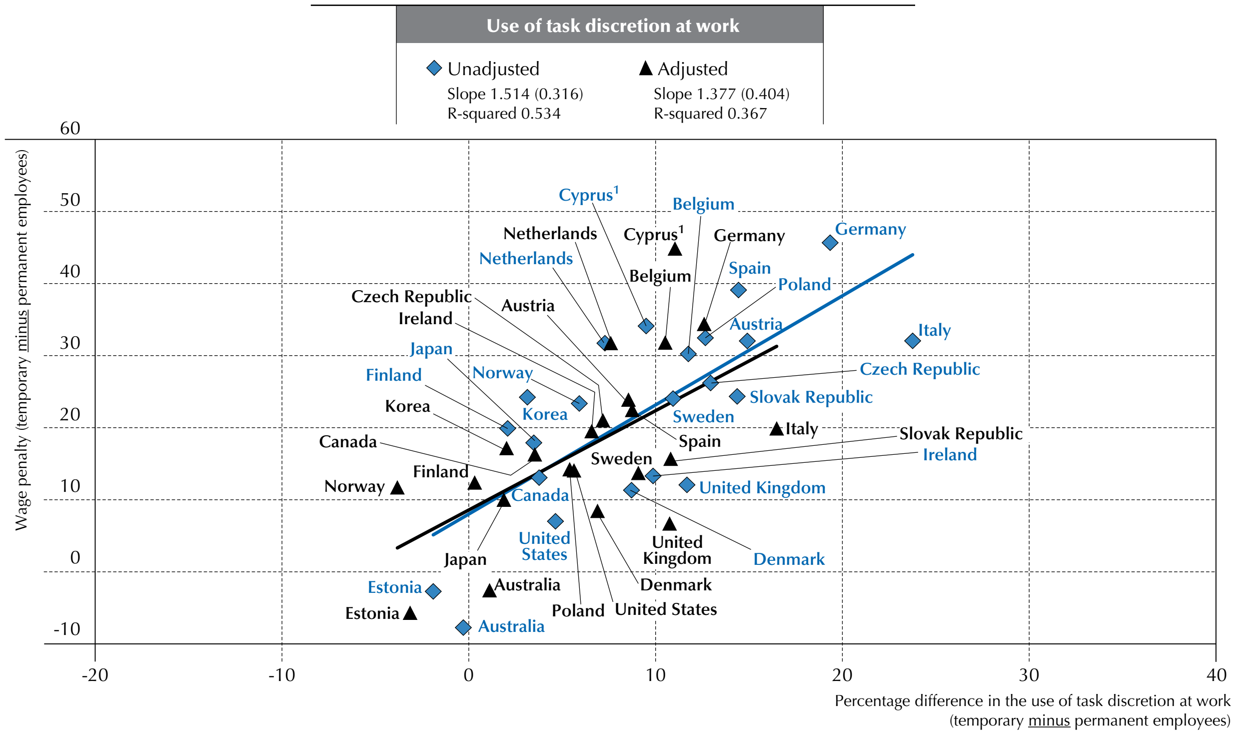
Source: Survey of Adults Skills (PIAAC) (2012), Tables A4.15a and A4.15b.

StatLink http://dx.doi.org/10.1787/888932901543

■ Figure 4.16 ■

The wage penalty for temporary contracts and the use of problem-solving skills and task discretion at work





1. See notes at the end of this chapter.

Notes: The wage penalty for temporary contracts is computed as the percentage difference between the average hourly wages (including bonuses) of temporary and permanent workers. The wage distribution was trimmed to eliminate the 1st and 99th percentiles. Adjusted estimates are based on OLS regressions including controls for average literacy and numeracy scores, dummies for highest qualification (4), occupations (9) and industry (10). The bold lines are the best linear predictions. The sample includes only full-time employees. Standard errors in parentheses.

Source: Survey of Adults Skills (PIAAC) (2012), Table A4.16.

StatLink http://dx.doi.org/10.1787/888932901562

Among generic skills, task discretion, influencing and self-organising skills are more intensively used by workers on indefinite contracts than by workers on fixed-term contracts (Figure 4.15), possibly because such skills are associated with managerial jobs that are often held by experienced workers. Temporary employees, however, appear to be more engaged in learning and in activities requiring gross physical effort. The result on learning at work suggests that, despite the fact that temporary workers are less frequently involved in formal employer-sponsored training, as the Survey of Adult Skills confirms, they nevertheless appear to be learning at work more frequently and intensively than their co-workers in permanent employment. This is partly due to the fact that temporary jobs are often held by young workers, who, being less experienced, learn more on the job.

Analysis of the results re-affirms the idea that temporary contracts are normally associated with jobs where information-processing and other productive generic skills are used less intensively than they are in jobs associated with permanent contracts.[18] This interpretation of the results is consistent with the fact that differences in skills use remain broadly unchanged when comparing workers at similar levels of proficiency who are employed in similar occupations. While sorting across occupations is relatively more important in defining differences in skills use, suggesting that temporary employment is particularly common in certain occupations, even when comparing workers within the same occupations, notable differences in skills use remain.

Close to 70% of the wage differential between temporary and permanent workers can be explained by differences in the use of problem-solving skills at work. Data analysis shows that differences in the use of skills correlate strongly with the average wage penalty associated with temporary contracts compared to permanent contracts (Figure 4.16). Of the five information processing skills that are reviewed in the Survey of Adult Skills, problem solving appears to have a strong power to predict differences in pay between temporary and permanent contracts. This suggests that the type of tasks carried out by workers hired under different contractual arrangements vary substantially. Moreover, this relationship remains statistically significant even after accounting for skills proficiency, education, industry and occupation. The right panel of Figure 4.16 shows a very similar pattern with regard to task discretion, the one generic skill that is most strongly correlated with pay differences.

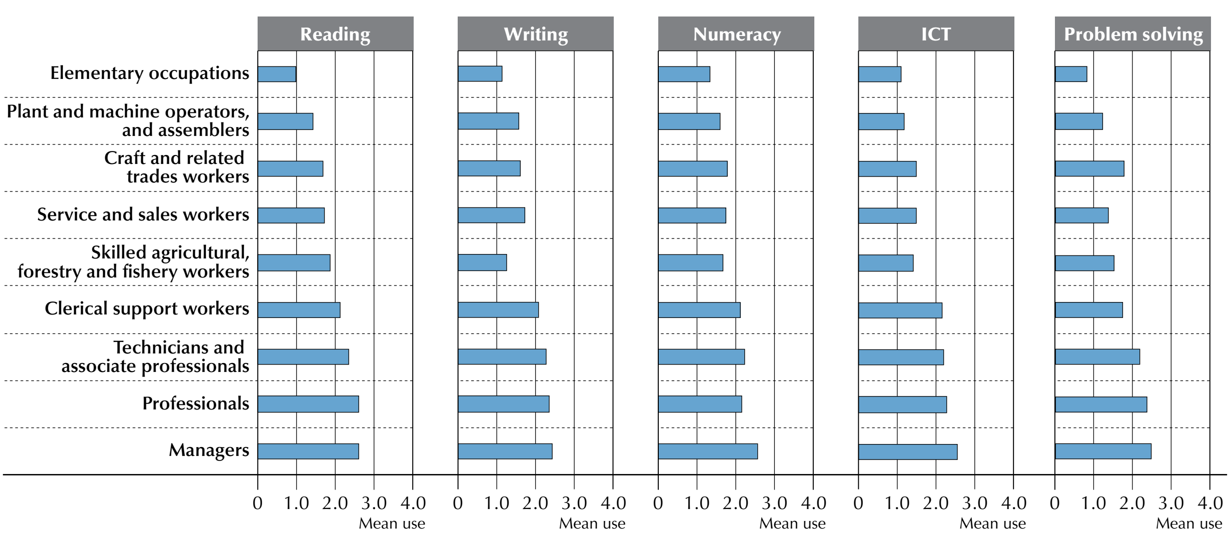
Skills use at work across occupations, industries and firm size

A common theme emerging from the analysis of data is the importance of how workers are distributed across occupations and what that means for skills use (Figure 4.17 and 4.18). Only the average use of skills across countries is shown in the figures, as the high number of occupational categories would make the presentation of results by country too cumbersome.

■ Figure 4.17 ■

Use of information-processing skills at work, by occupation

Average use of information-processing skills, by ISCO-1-digit occupation, in the OECD countries participating in the Survey of Adult Skills (PIAAC)



Occupations are ranked in ascending order of the average use of reading skills at work.

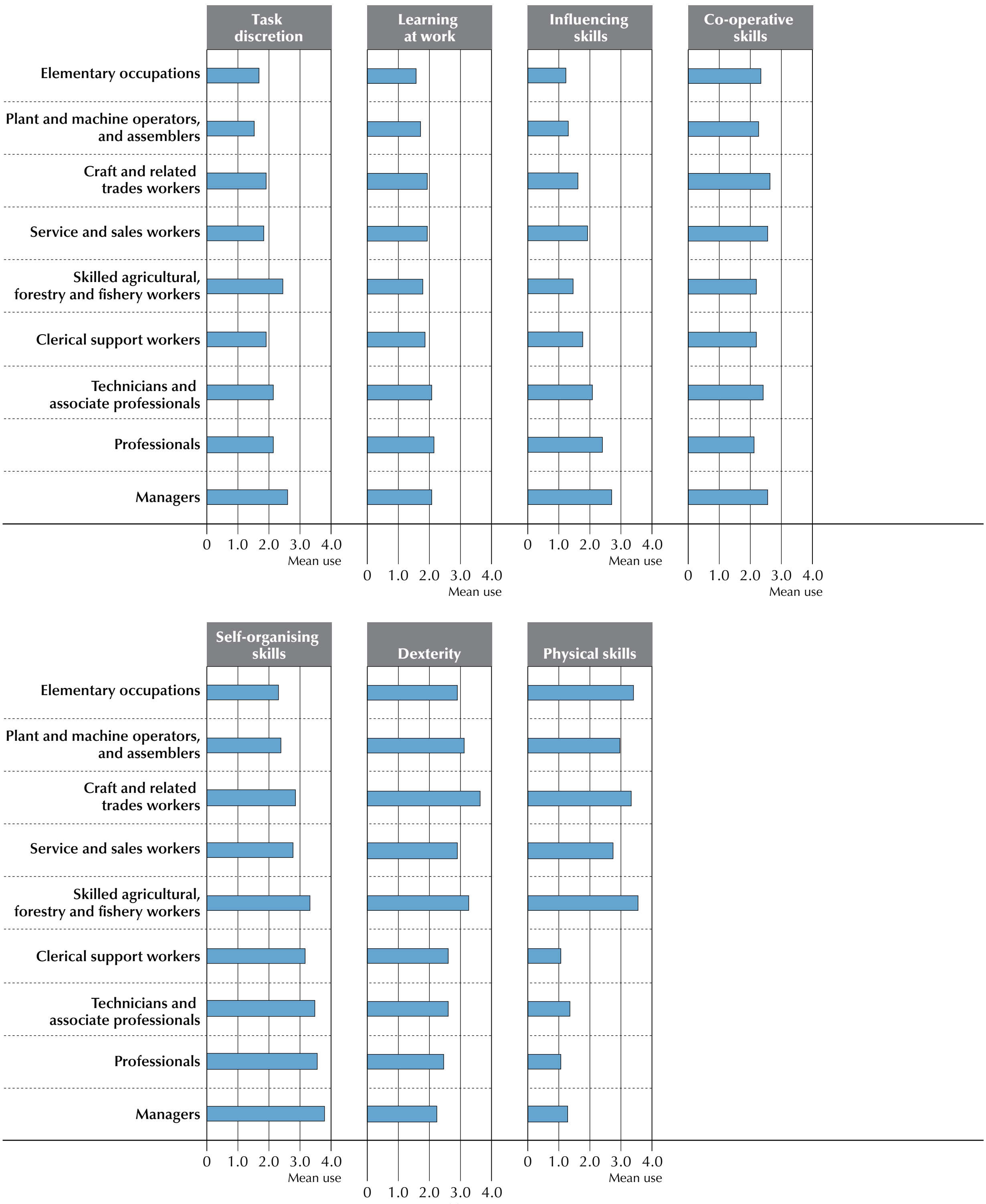
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.17.

StatLink http://dx.doi.org/10.1787/888932901581

■ Figure 4.18 ■

Use of generic skills at work, by occupation

Average use of generic skills, by ISCO-1-digit occupation, in the OECD countries participating in the Survey of Adult Skills (PIAAC)



Occupations are ranked in ascending order of the average use of reading skills at work.

Source: Survey of Adults Skills (PIAAC) (2012), Table A4.18.

StatLink http://dx.doi.org/10.1787/888932901600

As expected, the use of information-processing skills increases substantially from elementary occupations up to professionals and managers (Figure 4.17). The magnitude of the difference between skills use in elementary and managerial occupations ranges from 1.2 to 1.7 of a standard deviation – substantially larger than the variation across any of the other personal or job characteristics that have been analysed earlier in this chapter. This supports the notion that the process by which workers are allocated to jobs shapes the distribution of skills use at work. It also suggests that the measures of skills use derived from the Survey of Adult Skills can also be reliably interpreted as measures of skills requirements at work.[19]

The picture for generic skills is more nuanced (Figure 4.18). The degree of variation is still large, particularly for gross physical skills, but the pattern across occupations is not as consistent as occupations move from elementary jobs to professionals and managers. While there is a similar pattern for task discretion, learning, influencing and self-organising skills, it is harder to identify any consistency among the other generic skills. Co-operation at work seems to be a skill that is used pervasively in all types of jobs.

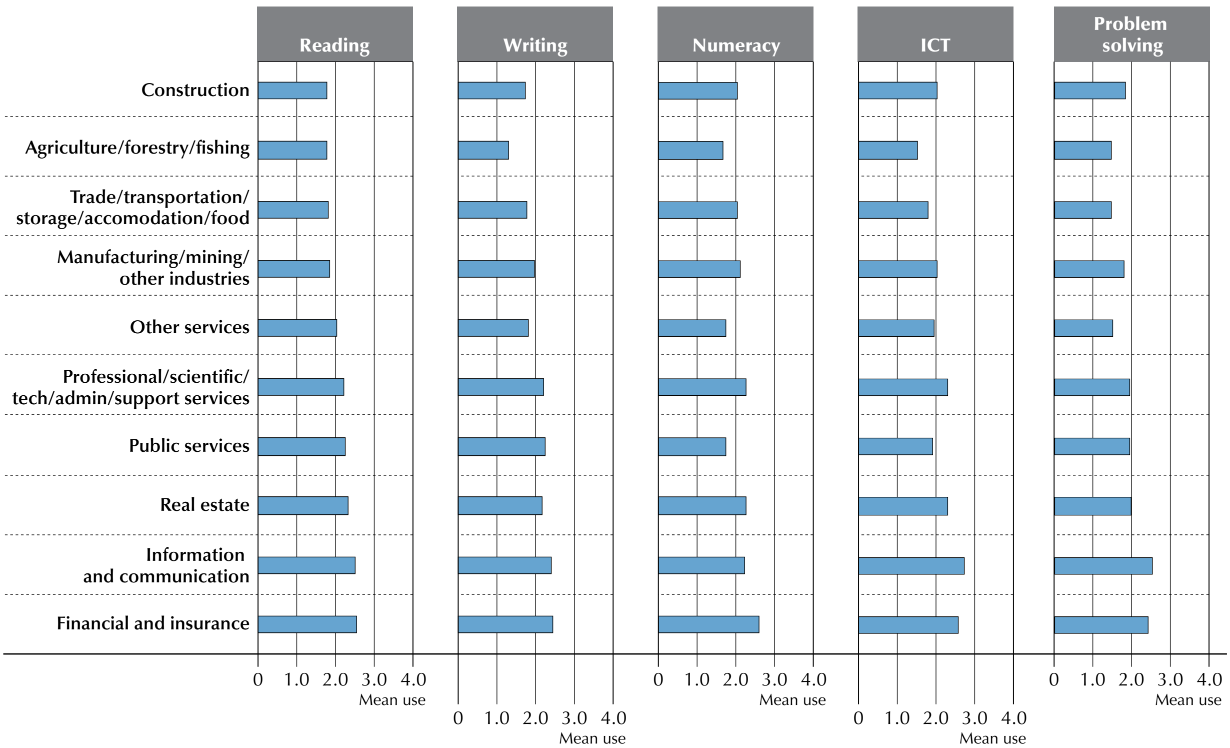
Since the broad occupational categories considered above do not fully capture differences in the types of jobs that workers perform, it is also useful to examine how the use of foundation and generic skills varies by industry (Figures 4.19 and 4.20). As with the analysis by occupations, only average results across countries are reported, as the presentation of country-by-country and industry-by-industry estimates would make it more difficult to identify patterns.

Information-processing skills are most frequently used in the finance and insurance and information and communication sectors and least used in the agriculture, other services and trade and transport sectors (Figure 4.19). The differences across sectors are large, but not as large as across occupations. The differences between the industries with the lowest and the highest levels of use range between 0.7 and 1.3 of a standard deviation, depending on the type of skill.

■ Figure 4.19 ■

Use of information-processing skills at work, by industry

Average use of information-processing skills, by SNA/ISIC industry, in the OECD countries participating in the Survey of Adult Skills (PIAAC)



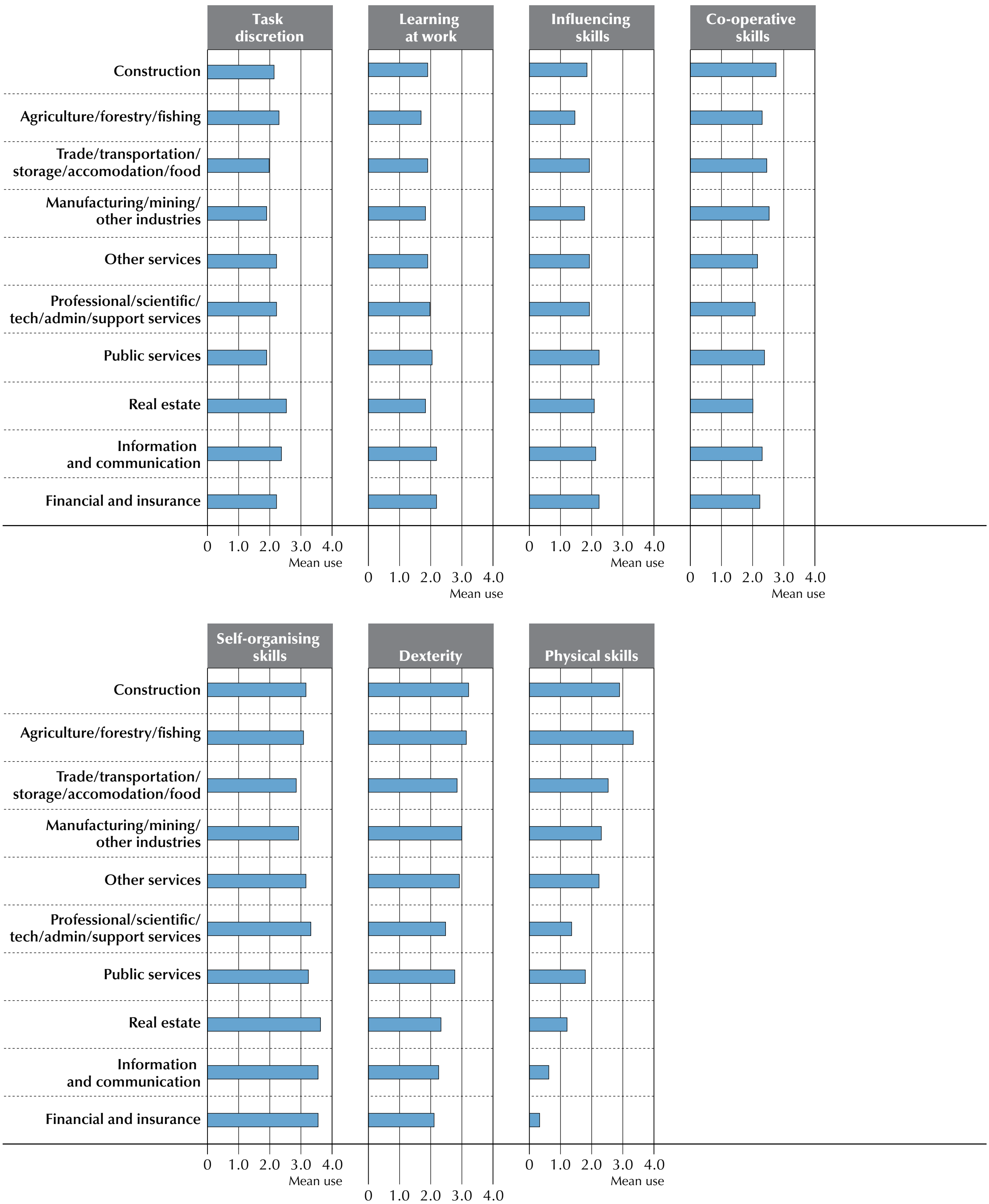
Note: High-level SNA/ISIC aggregation.

Industries are ranked in ascending order of the average use of reading skills at work.

Source: Survey of Adults Skills (PIAAC) (2012), Table A4.19.

StatLink http://dx.doi.org/10.1787/888932901619

■ Figure 4.20 ■
Use of generic skills at work, by industry
Average use of generic skills, by SNA/ISIC industry, in the OECD countries participating in the Survey of Adult Skills (PIAAC)



Note: High-level SNA/ISIC aggregation.
Industries are ranked in ascending order of the average use of reading skills at work.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.20.
StatLink http://dx.doi.org/10.1787/888932901638

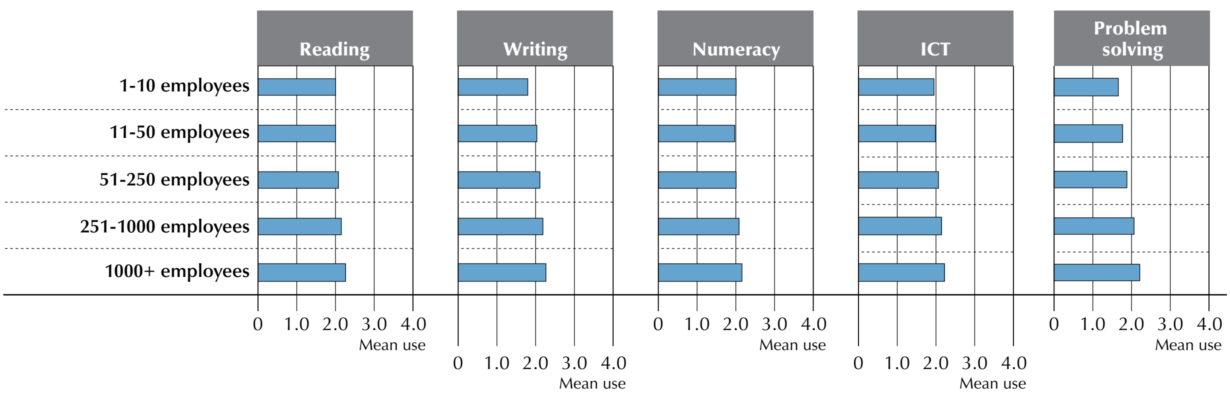
For generic skills, it is harder to identify similarities (Figure 4.20). Learning at work and influencing skills follow a pattern that is similar to most information processing skills. However, self-organising skills are used quite evenly across sectors. Also, workers in sectors with limited use of information processing skills – notably agriculture but also construction – use task discretion at work as much as workers in the finance and insurance sector. The magnitude of the differences between sectors in the use of generic skills, however, is more limited than for the use of information processing skills, with the exception of physical skills, where the difference between the average use in agriculture and finance is very large.

Another factor that determines how workers use their skills is the size of the establishment. It could be expected that workers employed in small establishments use their skills quite differently than do those employed in large establishments, even within the same occupational group and the same industrial sector. Consistent with evidence that large firms employ more skilled workers and adopt more sophisticated production technologies (Brown and Medoff, 1989; Gibson and Stillman, 2009), the use of information-processing skills increases with establishment size across all the domains. The magnitude of the differences ranges between 0.2 and 0.5 of a standard deviation (Figure 4.21).

■ Figure 4.21 ■

Use of information-processing skills at work, by establishment size

Average use of information-processing skills, by establishment size, in the OECD countries participating in the Survey of Adult Skills (PIAAC)



Source: Survey of Adults Skills (PIAAC) (2012), Table A4.21.

StatLink http://dx.doi.org/10.1787/888932901657

Dexterity and physical skills are more commonly used in small establishments (Figure 4.22). A similar but less-pronounced pattern is observed for task discretion, while the reverse is true for co-operation at work. The use of learning, influencing and self-organising skills does not seem to vary much across establishments of different sizes.

What the results indicate

Two themes emerge from the analysis. First, skills-use indicators correlate only weakly with measures of skills proficiency. For example, proficiency in literacy explains only about 6% of the individual variation in the use of reading skills at work across all participating countries, and similar results are found for proficiency in and use of numeracy skills. In fact, across all participating countries, the distributions of skills use among workers with different levels of proficiency overlap substantially (Figure 4.23). While the median use of both literacy and numeracy skills increases consistently as levels of proficiency increase, it is not uncommon, for example, that more proficient workers use their skills at work less intensively than less proficient workers do.

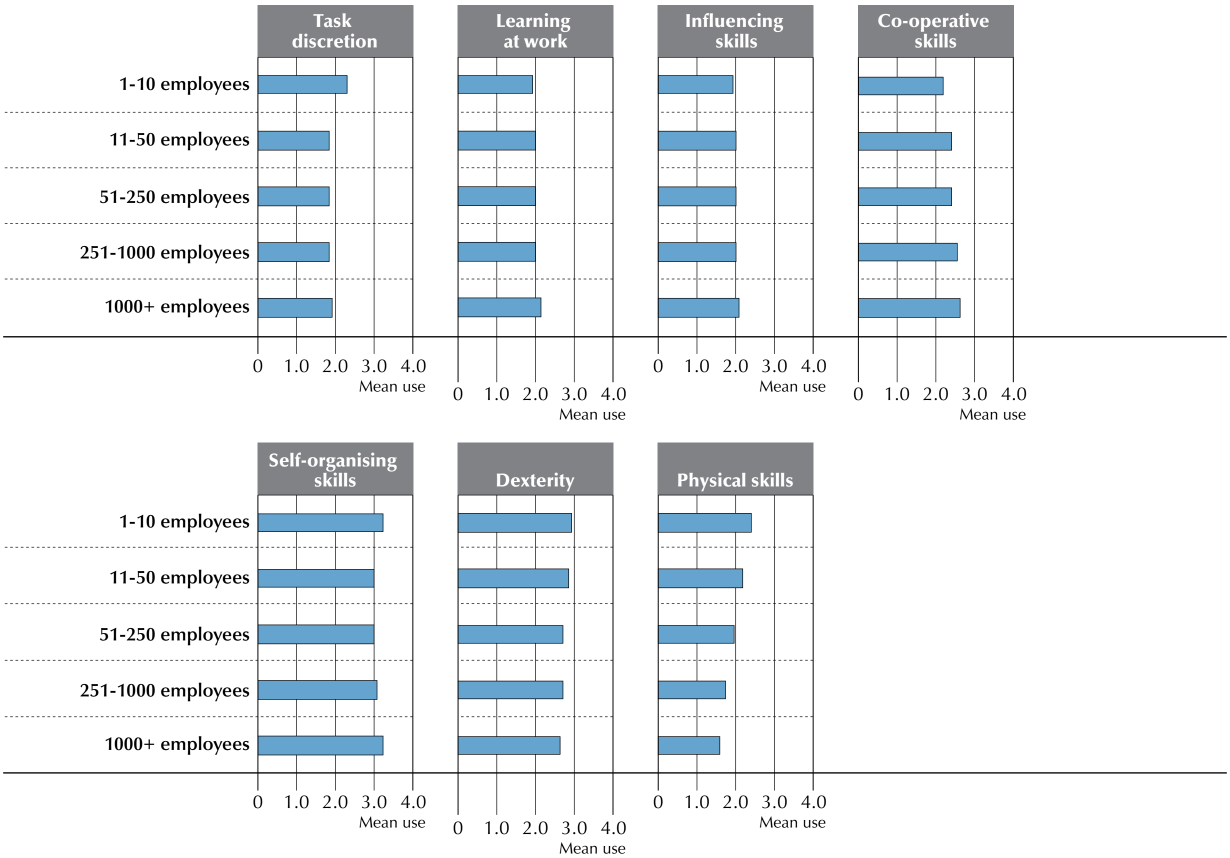
Second, in all the countries covered in the Survey of Adult Skills, the type of jobs held by workers is the single most important factor determining how individuals use their skills at work. As shown in Figures 4.17 and 4.18, differences in skills use across standard occupational categories are larger that the differences between any of the other individual and job characteristics that are considered in this chapter, such as gender, age, education or the type of employment contract.

The implications of these two findings are complex, as the same tasks can be carried out at different levels of complexity. In general, however, the findings imply that improving the efficiency with which workers are allocated to jobs can improve the extent of skills use at work, and thus improve overall productivity and boost economic growth.

■ Figure 4.22 ■

Use of generic skills at work, by establishment size

Average use of generic skills, by establishment size, in the OECD countries participating in the Survey of Adult Skills (PIAAC)



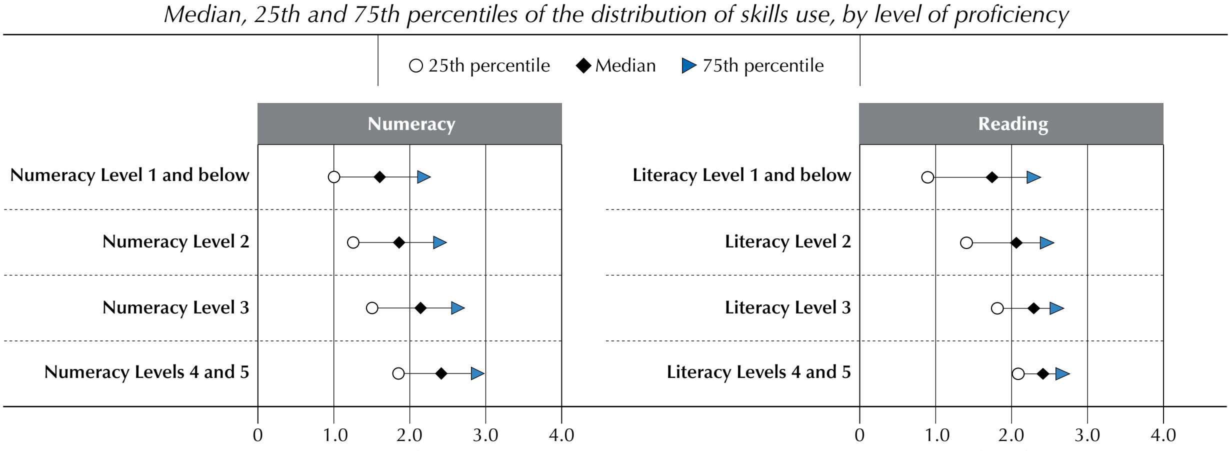
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.22.

StatLink http://dx.doi.org/10.1787/888932901676

■ Figure 4.23 ■

Skills use at work, by proficiency level

Median, 25th and 75th percentiles of the distribution of skills use, by level of proficiency



Notes: Employees only.

Source: Survey of Adults Skills (PIAAC) (2012), Table A4.23.

StatLink http://dx.doi.org/10.1787/888932901695

THE LEVEL OF EDUCATION REQUIRED FOR THE JOB

In addition to measuring the use of skills, the Survey of Adult Skills also questions respondents about the level of education that would be required to get their jobs. This is an important piece of information that is useful for describing the industrial structure of the economy. It is also used to measure "qualification mismatch", or the phenomenon by which workers are often employed in jobs that require a lower or higher level of education than they have (Leuven and Oosterbeek, 2011; Quintini, 2011a and 2011b).

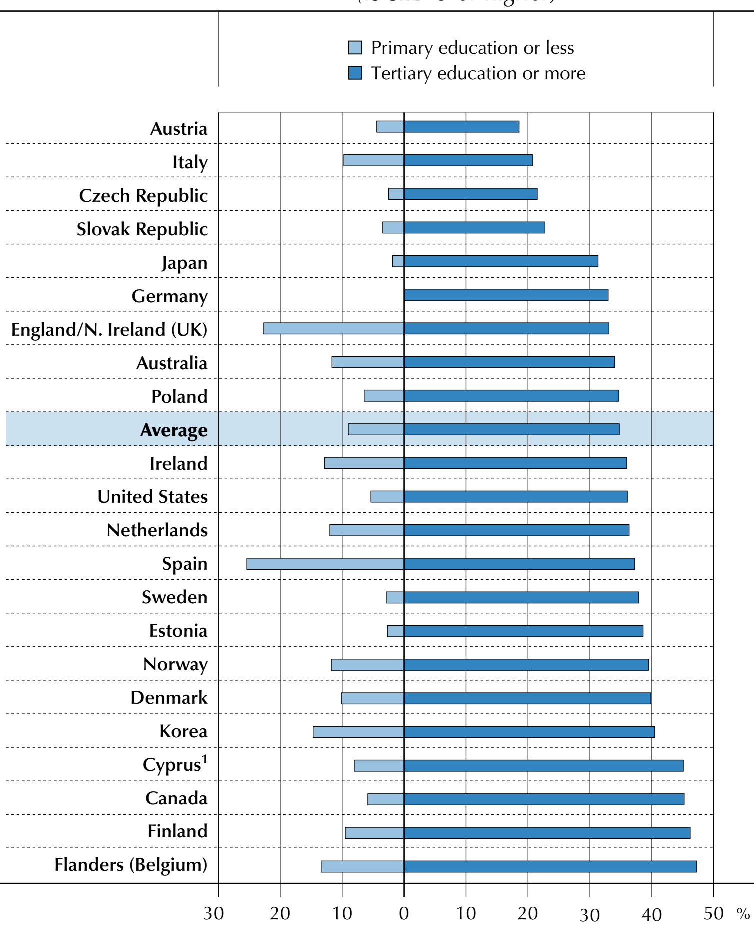
Across all participating countries, 9% of existing jobs are characterised as having low educational requirements (primary education or none), whereas almost 35% require tertiary qualifications (Figure 4.24).

In many countries, the fewer the jobs requiring low levels of education, the more the jobs requiring high levels of education. However, this is not always true. In Spain and England/Northern Ireland (UK), the distribution of jobs by educational requirements is highly polarised: there are many jobs with low educational requirements and many with high educational requirements (Autor et al., 2006; Goos and Manning, 2007; Goos et al. 2009; Wilson and Homenidou, 2012). By contrast, in Austria, Italy, the Czech Republic and the Slovak Republic, jobs characterised by medium-level educational requirements seem to be most prevalent.

■ Figure 4.24 ■

Workers in high-skilled and unskilled jobs

Percentage of workers in jobs requiring primary education (ISCED-1) or less and in jobs requiring tertiary education (ISCED-5 or higher)



1. See notes at the end of this chapter.
Note: Required education is the qualification the worker deems necessary to get his/her job today.
Countries are ranked in ascending order of the percentage of workers in jobs requiring tertiary education.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.24.
StatLink http://dx.doi.org/10.1787/888932901714

These results are based on self-reported information provided by workers and therefore may not reflect the employers' views nor the actual outcomes of the recruitment process (Green and James, 2003). Moreover, the survey specifically asks about the qualifications required to obtain the job at the time of the interview, which may not necessarily be the same as the requirements demanded of the respondents when they were hired. Despite these caveats, these results illustrate both the demand for workers with post-secondary education and the level of complexity of jobs, as perceived by currently employed workers.

The differences across countries in job requirements could be due to at least two different phenomena. First, the more technologically advanced countries are also likely to be those where jobs require more knowledge and where different hiring strategies may be used for different jobs. Second, in some countries, job requirements might not necessarily be linked to task complexity. To the extent that employers use educational qualifications to sort out the best candidates for the job (Spence, 1973), rising levels of educational attainment in the population would force recruiters to raise hiring standards, even if the jobs are not necessarily more complex.

EXPLORING MISMATCH BETWEEN WORKERS' SKILLS AND JOB REQUIREMENTS

Ensuring a good match between the skills acquired in education and on the job and those required in the labour market is essential if countries want to make the most of their investments in human capital and promote strong and inclusive growth. A mismatch between the two has potentially significant economic implications. At the individual level, it affects job satisfaction and wages. At the firm level, it increases the rate of turnover and may reduce productivity.[20] At the macro-economic level, it increases unemployment and reduces GDP growth through the waste of human capital and/or a reduction in productivity. That said, some mismatch is inevitable. Requirements regarding skills and qualifications are never fixed. The task content of jobs changes over time in response to technological and organisational change, the demands of customers, and in response to the evolution of the supply of labour. Young people leaving education and people moving from unemployment into employment, for example, may take jobs that do not necessarily fully match their qualifications and skills. Thus, for a number of reasons, some workers are likely to be employed in jobs for which they are too qualified and others may be in jobs, at least temporarily, for which they lack adequate schooling.

Mismatch, understood as a poor fit between an individual worker's qualifications or skills and those demanded or required by his or her job, needs to be distinguished from aggregate balances or imbalances in the supply of and demand for different types of qualifications and skills in the labour market, such as skill shortages or the over- or under-supply of people with different educational qualifications or skills. Although these two phenomena are distinct, they are, nevertheless, related. Imbalances (e.g. shortages or over-supply of individuals with particular qualifications or skills) are likely to have an effect on the incidence and type of mismatches observed at the individual level. But that relationship is not automatic: a balance between the supply of and demand for workers at a given qualification level does not guarantee that individual workers will be matched to jobs that require the level of education they have attained. A high level of mismatch at the individual level does not imply any particular level of imbalance between aggregate supply and demand.

The discussion of qualification and skills mismatch that follows focuses on the question of mismatch at the individual level, that is, on the outcomes of allocating individuals to jobs and adapting job tasks to workers' skills. It does not address the extent of the balance or imbalance in the supply of and demand for individuals with particular educational qualifications or skills. From this perspective, any evidence of mismatch between workers' qualifications and skills and those required by their jobs should be interpreted primarily as suggesting that there are economic benefits (and benefits in terms of the well-being of workers) to be gained from better management of human resources, including practices that involve hiring workers, designing jobs and providing training, apart from action concerning the adjustment of supply and demand in the aggregate. The evidence should not be interpreted as indicating the existence of too many highly qualified or highly skilled workers in the economy as a whole.

Constructing better indicators of mismatch using the Survey of Adult Skills (PIAAC)

The Survey of Adult Skills provides a rare opportunity to measure more precisely both qualification and skills mismatch. Qualification mismatch is determined based on a comparison of a worker's qualification level – expressed as the International Standard Classification of Education (ISCED) level corresponding to his or her highest educational qualification – and what is thought to be the required qualification level for his or her occupation code – the International Standard Classification of Occupations (ISCO) code attached to the job he or she holds. Because ISCED levels do not accurately reflect skills – not even those acquired in initial education – and ISCO codes do not accurately describe jobs, the resulting measure does not precisely describe how a worker's skills set matches the skills needed to carry out his or her tasks at work. Skills mismatch, however, refers more precisely to a worker's actual skills and to the skills needed in his or her specific job.

Despite these important differences, the two measures of mismatch overlap to some extent, in the same way as education and skills do. Some researchers use the term *genuine mismatch* to indicate when a worker is both over-qualified and over-skilled (or both under-qualified and under-skilled) for his or her job. The term *apparent qualification mismatch*[21] is used to refer to workers who are over-qualified/under-qualified but not over-skilled/under-skilled, i.e. there is a discrepancy between their skills and their qualifications and/or a discrepancy between the skills and the qualification requirements of their specific jobs.

Although qualifications are an imperfect proxy for skills, qualification mismatch should not be simply dismissed as a "bad" measure of skills mismatch. First, by uncovering the causes of *apparent* qualification mismatch, for example when there is a mismatch between the skills learned in school and those required in the labour market, the areas requiring policy intervention are revealed. Second, workers have many different skills, ranging from information-processing skills, to occupation-/sector-specific knowledge and abilities, to generic skills. As a result, any concept of mismatch based on individual skills offers only a partial view of the match between a worker and his or her job. Qualifications reflect several different skills, including both information-processing and job-specific competencies, and could complement narrower, though more precise, skills measures. In addition, skills use depends, at least partly, on the effort that workers decide to put into their jobs, making it difficult to define precise skills requirements; qualification requirements are easier to define.

Thus, several measures of qualification and skills mismatch can be derived using the data available from the Survey of Adult Skills on qualifications, skills requirements and skills use (Table 4.3).

Deriving measures of qualification mismatch

The key way of determining the extent of qualification mismatch is to measure the level of education required at work.[22] The most frequently used measure is the modal qualification of workers in each occupation and country. However, this measure combines current and past qualification requirements as it reflects the qualifications of people who were hired at different times.

Table 4.3
Glossary of key terms

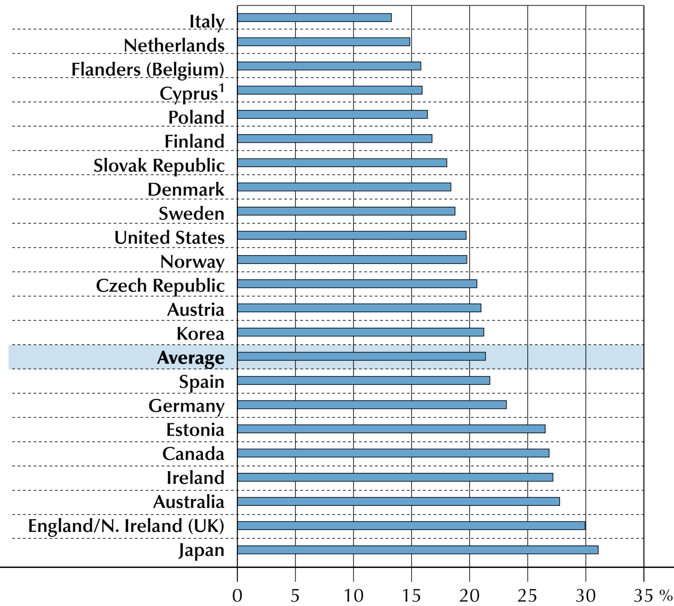
	Mismatch concept	Measure used in this chapter
Qualification mismatch	**Over-qualification**	A worker is classified as over-qualified when the difference between his or her qualification level and the qualification level required in his or her job is positive.
	Under-qualification	A worker is classified as under-qualified when the difference between his or her qualification level and the qualification level required in his or her job is negative.
	Required qualification	Based on respondents' answers to the question "If applying today, what would be the usual qualifications, if any, that someone would need to get this type of job?"
Skills mismatch in literacy, numeracy or problem solving	**Over-skilling in literacy, numeracy or problem solving**	When a worker's proficiency is above the maximum required by his or her job.
	Under-skilling in literacy, numeracy or problem solving	When a worker's proficiency is below the minimum required by his or her job.
	Skill requirements	The minimum and maximum skill levels required correspond to the minimum and maximum observed proficiency of workers who answer negatively to the questions: "Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job?"; and "Do you feel that you need further training in order to cope well with your present duties?"

The Survey of Adult Skills, however, asks workers to report the qualification they consider necessary to get their job today. The comparison between workers' qualifications and this self-reported requirement shows that, on average, 21% of workers are over-qualified while about 13% are under-qualified (Figures 4.25a and 4.25b). The incidence of qualification mismatch varies significantly across countries: the share of over-qualified workers ranges from less than 15% in Italy and the Netherlands to 30% or more in Japan and England/Northern Ireland (UK); while the incidence of under-qualification varies between less than 10% in the Slovak Republic, the Czech Republic, Japan, Poland and Spain to just over 20% in Italy and Sweden.[23]

■ Figure 4.25a ■

Incidence of over-qualification

Percentage of workers whose highest qualification is higher than the qualification they deem necessary to get their job today

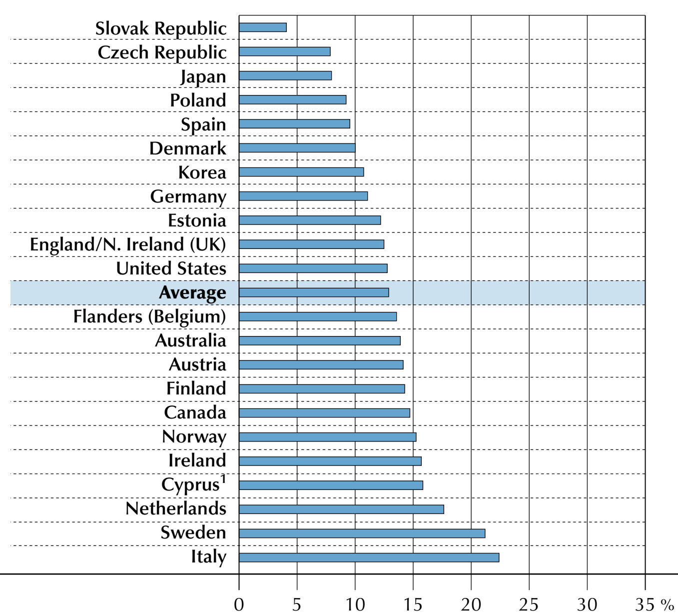


1. See notes at the end of this chapter.
Countries are ranked in ascending order of the share of over-qualified workers.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.25.
StatLink http://dx.doi.org/10.1787/888932901733

■ Figure 4.25b ■

Incidence of under-qualification

Percentage of workers whose highest qualification is lower than the qualification they deem necessary to get their job today



1. See notes at the end of this chapter.
Countries are ranked in ascending order of the share of under-qualified workers.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.25.
StatLink http://dx.doi.org/10.1787/888932901752

Mismatch in literacy

The measures of skills mismatch that have been used in previous research all suffer from various problems, most of which are related to the difficulty of measuring the skill requirements of jobs from surveys of employees. A novel approach to measuring skills mismatch in literacy (or numeracy) is now possible thanks to the wealth of information provided by the Survey of Adult Skills.

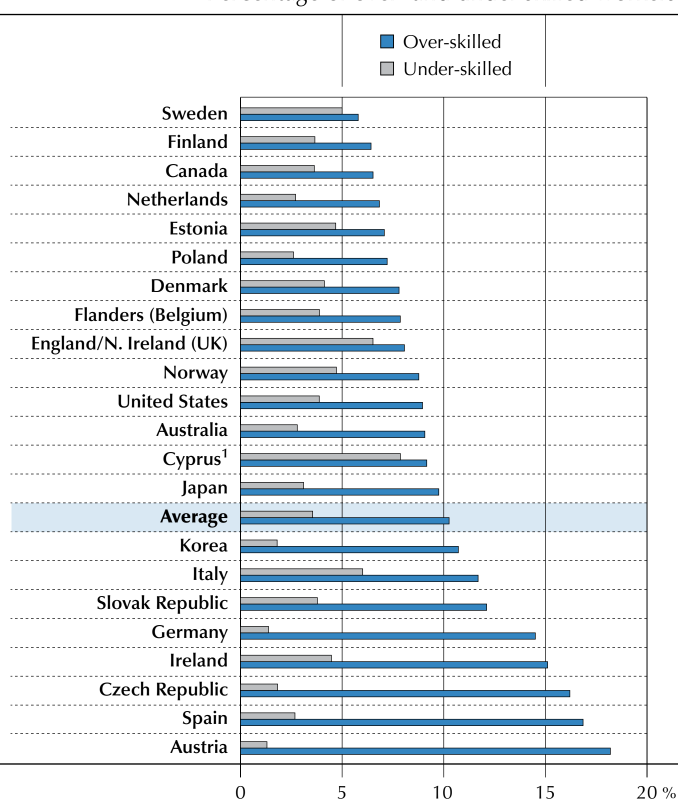
The survey asked workers whether they feel they "have the skills to cope with more demanding duties than those they are required to perform in their current job" and whether they feel they "need further training in order to cope well with their present duties". To compute the OECD measure of skills mismatch, workers are classified as well-matched in a domain if their proficiency score in that domain is between the minimum and maximum score observed among workers who answered "no" to both questions in the same occupation and country.[24] Workers are over-skilled in a domain if their score is higher than the maximum score of self-reported well-matched workers, and they are under-skilled in a domain if their score is lower than the minimum score of self-reported well-matched workers.

The OECD measure of skills mismatch is an improvement over existing indicators as it is more robust to reporting bias, such as over-confidence, and it does not impose the strong assumptions needed when directly comparing skills proficiency and skills use.[25] However, this approach does not measure all forms of skills mismatch; rather, it focuses on mismatch in the proficiency domains assessed by the Survey of Adult Skills, leaving out mismatch related to job-specific skills or that involving generic skills. (A detailed discussion of the survey's measure of skills mismatch, its advantages and disadvantages as well as its underlying theoretical framework is presented in Fichen and Pellizzari [2013]).

■ Figure 4.25c ■

OECD measure of skills mismatch in literacy

Percentage of over- and under-skilled workers



1. See notes at the end of this chapter.

Notes: Over-skilled workers are those whose proficiency score is higher than that corresponding to the 95th percentile of self-reported well-matched workers – i.e. workers who neither feel they have the skills to perform a more demanding job nor feel the need of further training in order to be able to perform their current jobs satisfactorily – in their country and occupation. Under-skilled workers are those whose proficiency score is lower than that corresponding to the 5th percentile of self-reported well-matched workers in their country and occupation.

Countries are ranked in ascending order of the percentage of workers over-skilled in literacy.

Source: Survey of Adults Skills (PIAAC) (2012), Table A4.25.

StatLink http://dx.doi.org/10.1787/888932901771

On average among the countries participating in the Survey of Adult Skills, about 11% of workers are over-skilled in literacy while about 4% are under-skilled in this proficiency domain (Figure 4.25c). Austria, the Czech Republic and Spain show the highest incidence of over-skilling in literacy, while Canada, Finland and Sweden are at the low end of the scale. On the other hand, the highest incidence of under-skilling in literacy is observed in Italy and Sweden, while the lowest is found in Austria and Germany.

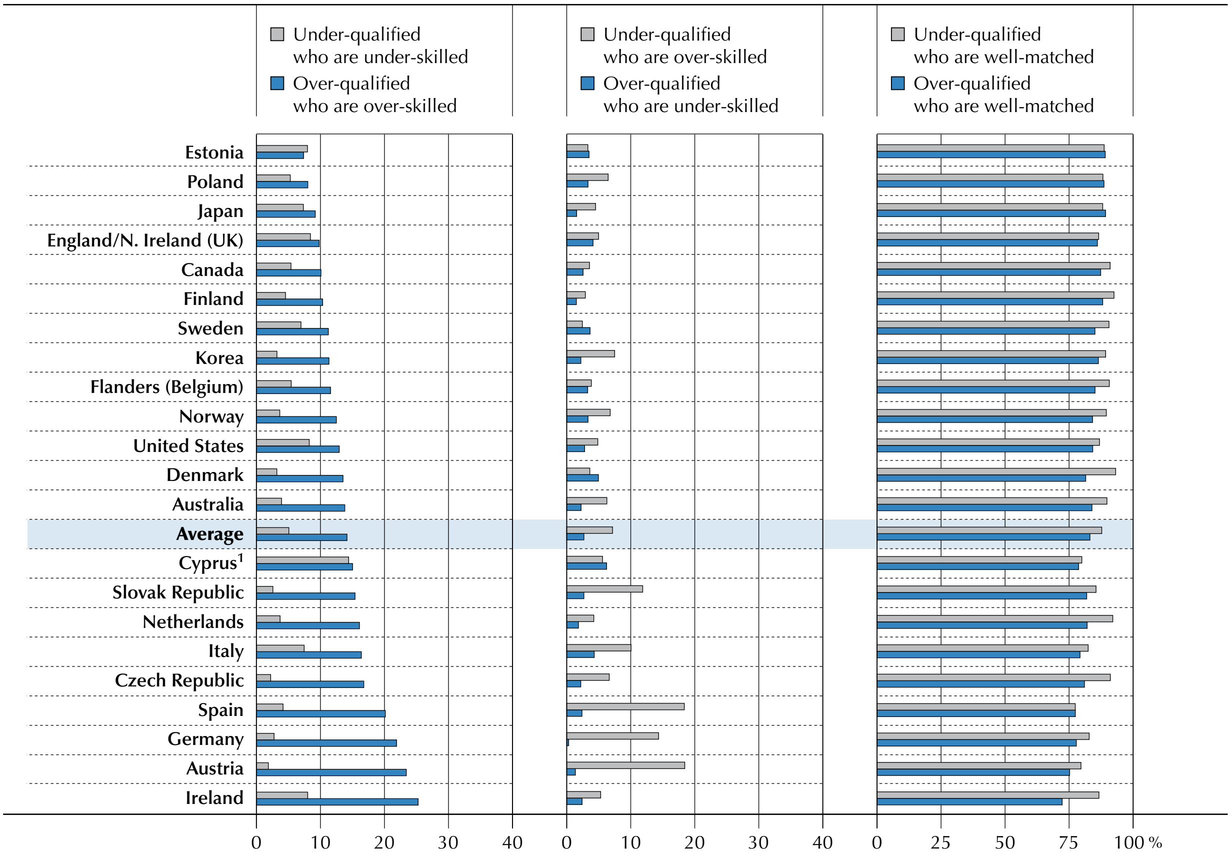
Interaction between skills and qualification mismatch

There is little overlap between qualification mismatch and skills mismatch in literacy.[26] On average, 14% of over-qualified workers are also over-skilled, based on the OECD measure of skills mismatch in literacy (Figure 4.26). This varies between 25% in Ireland to just 7% in Estonia. Overall, only a subset of over-qualified workers has literacy skills that exceed those required for their jobs. This confirms that qualifications are an imperfect proxy for skills, and also suggests that over-qualification may reflect the under-use of skills other than literacy.

■ Figure 4.26 ■

Overlap between qualification- and skills-mismatch measures

Percentage of qualification-mismatched who are in each literacy mismatch status



1. See notes at the end of this chapter.

Notes: Over- and under-qualification are defined relative to the qualification needed to get the job, as reported by the respondents. Literacy mismatch is defined according to the OECD measure.

Countries are ranked in ascending order of the percentage of over-qualified workers who are over-skilled in literacy.

Source: Survey of Adults Skills (PIAAC) (2012), Table A4.26.

StatLink http://dx.doi.org/10.1787/888932901790

Under-qualification and under-skilling in literacy also appear to be two distinct phenomena, with very little (on average, just 5%) overlap. This suggests that under-qualified workers actually have the literacy skills required to carry out their jobs, but do not have the corresponding qualifications. This hypothesis is supported by the fact that, in several countries, a relatively large share of under-qualified workers is actually over-skilled: just under one in five under-qualified workers in Austria and Spain. For these workers, under-qualification could be due to what is known as "qualification inflation", when having a larger number of graduates in the labour force inflates qualification requirements, or to the fact that workers have acquired the necessary skills and knowledge on the job, but these skills are not certified by an official educational qualification.

How mismatch interacts with proficiency and other individual and job characteristics

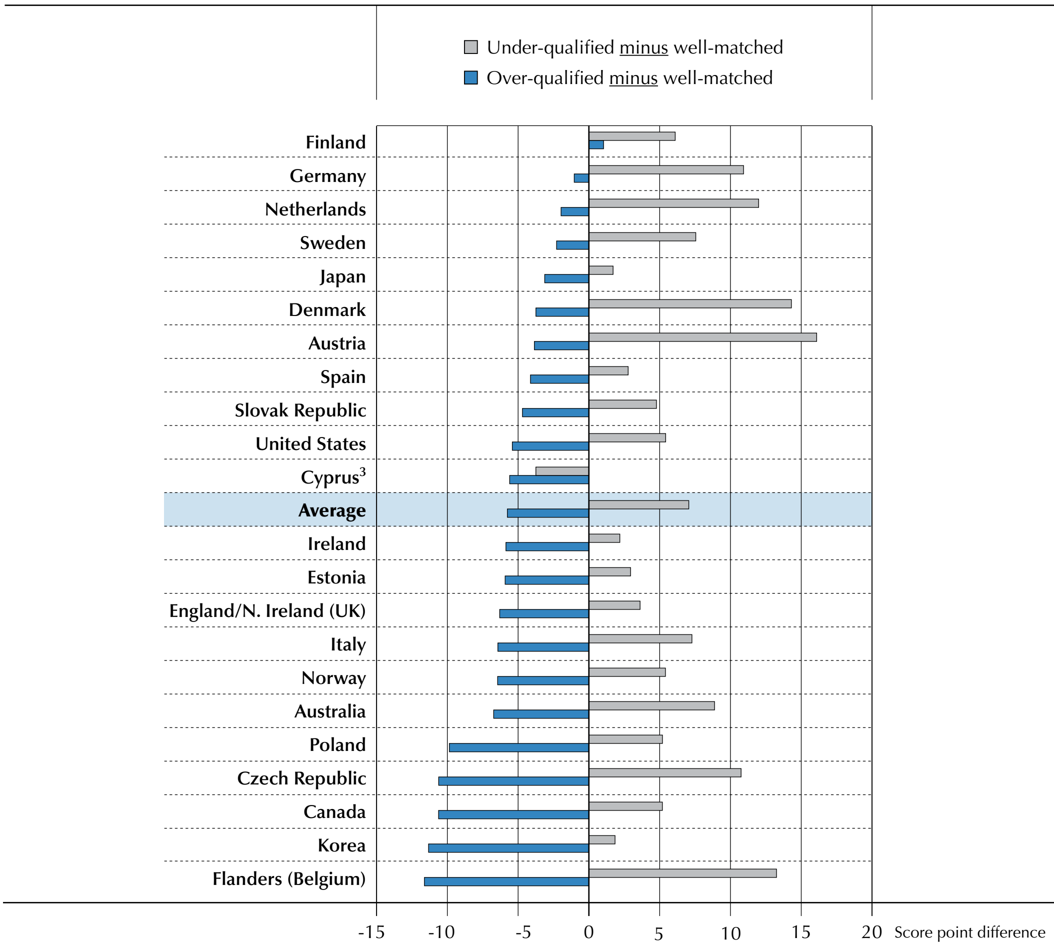
Qualification mismatch and proficiency

Several studies show that there are significant differences in skills proficiency among workers with the same qualifications. In the context of qualification mismatch, the best-skilled individuals in a given qualification category may get jobs that require higher formal qualifications while the least-skilled will only be able to get jobs requiring lower formal qualifications. Hence, individuals in the former group will appear as under-qualified, despite having the skills required for their jobs, while those in the latter group will appear as over-qualified, even though they lack some of the key skills needed to get and do a job with higher qualification requirements.[27]

■ Figure 4.27 (L) ■

Literacy proficiency scores among over- and under-qualified workers

Difference in literacy scores between over-qualified[1] and well-matched workers and between under-qualified and well-matched workers, adjusted by socio-demographic characteristics[2]



1. Over- and under-qualification are defined relative to the qualification needed to get the job, as reported by the respondents.
2. The scores presented in the figure are adjusted for years of education, gender, age and foreign-born status.
3. See notes at the end of this chapter.

Countries are ranked in decending order of the difference in literacy score between over-qualified and well-matched workers (over-qualified minus well-matched).

Source: Survey of Adults Skills (PIAAC) (2012), Table A4.27 (L).

StatLink http://dx.doi.org/10.1787/888932901809

On average, under-qualified individuals score higher in literacy proficiency than their well-matched counterparts (Figure 4.27 [L]), while over-qualified workers have lower scores than their well-matched peers.[28, 29] This *supports the theory that differences in proficiency within qualification levels could explain some qualification mismatch.* And the differences in average scores are not negligible: each year of schooling corresponds to around seven points on the literacy proficiency scale.

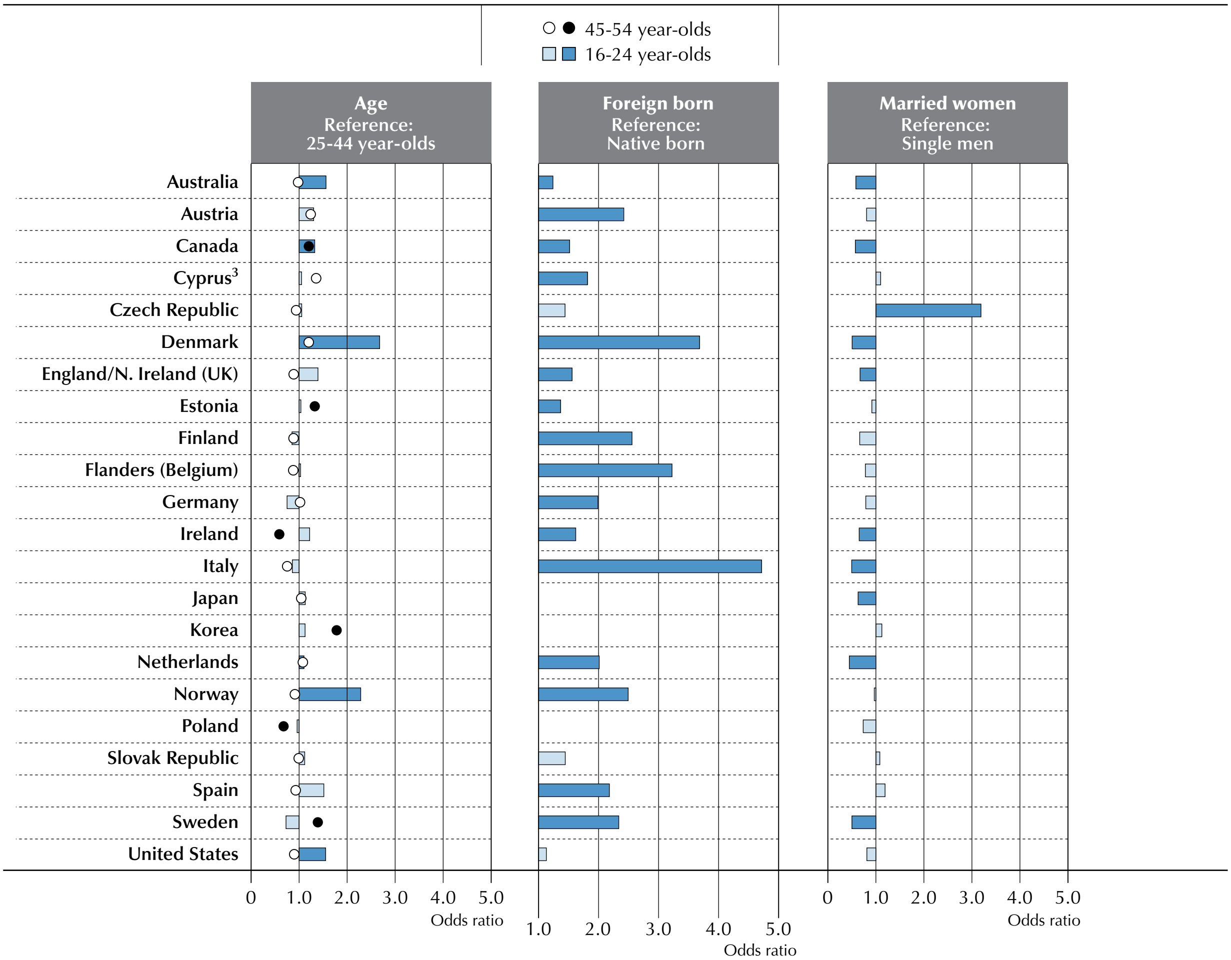
Socio-demographic and job characteristics and mismatch

Individual and job characteristics may influence the likelihood of qualification mismatch too. For example, it may take young people, as new entrants to the labour market, some time to sort themselves into well-matched jobs. Or, some workers may choose to accept a job for which they are over-qualified. This can happen when workers wish to remain close to their families or better reconcile work and family life and accept part-time jobs. An analysis of the impact of socio-demographic characteristics on qualification mismatch shows clearly that foreign-born workers are more likely to be over-qualified than their native counterparts (Figure 4.28a). This could be because qualifications acquired outside the host country are not recognised, and so highly-qualified migrants are relegated to working in low-skilled jobs.

■ Figure 4.28a ■

Over-qualification, by socio-demographic characteristics

Adjusted odds ratios showing the likelihood of over-qualification[1], by socio-demographic characteristics[2]



1. Over-qualification is defined relative to the qualification needed to get the job, as reported by the respondents.
2. From logit regressions including controls for years of education, age, gender and marital status, foreign-born status, establishment size, contract type, hours worked. Statistically (at the 10% level) significant values are shown in darker tones. Estimates based on a sample size less than 30 (odds ratio of foreign born with respect to native born for Japan, Korea and Poland) are not shown.
3. See notes at the end of this chapter.
Countries are listed in alphabetical order.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.28.
StatLink http://dx.doi.org/10.1787/888932901828

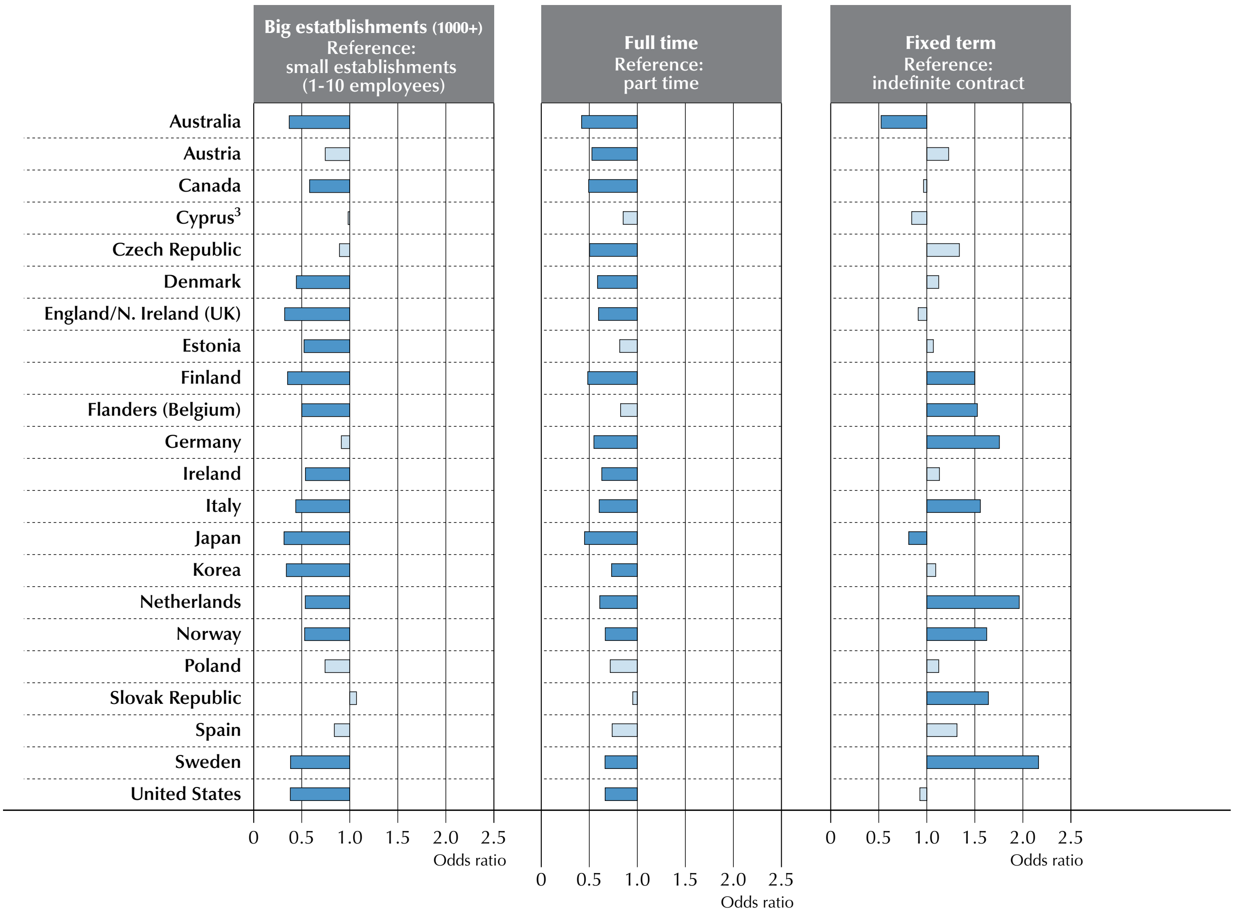
In addition, 16-24 year-olds are more likely to be over-qualified than prime age workers (aged 25-44) although by little and the relationship is often not statistically significant. And, contrary to the assumption that women are more likely to be over-qualified because of family constraints, once socio-demographic and job characteristics are controlled for, married women (and single women, though this is not shown in Figure 4.28a) are less likely to be over-qualified than their single male counterparts, with the only exceptions found in the Czech Republic.[30]

An analysis of results also finds that working for a large firm reduces the likelihood of over-qualification in most countries, as does working full-time (Figure 4.28b). One possible explanation for this is that firm size is a proxy for the quality of human-resource policies, with larger firms being better at screening candidates and at understanding how over-qualification may affect satisfaction at work and, ultimately, productivity. Large firms also have larger internal labour markets through which workers can be transferred to better matches inside the firm. Part-time jobs may have lower skills content, but they attract qualified workers because they are more compatible with personal/family life. Fixed-term contract jobs could be expected to have lower qualification requirements than permanent jobs, but they often attract tertiary-educated workers who cannot find a permanent position. This hypothesis is supported by the data in most countries.

■ Figure 4.28b ■

Over-qualification, by job characteristics

Adjusted odds ratios showing the likelihood of over-qualification,[1] by job characteristics[2]



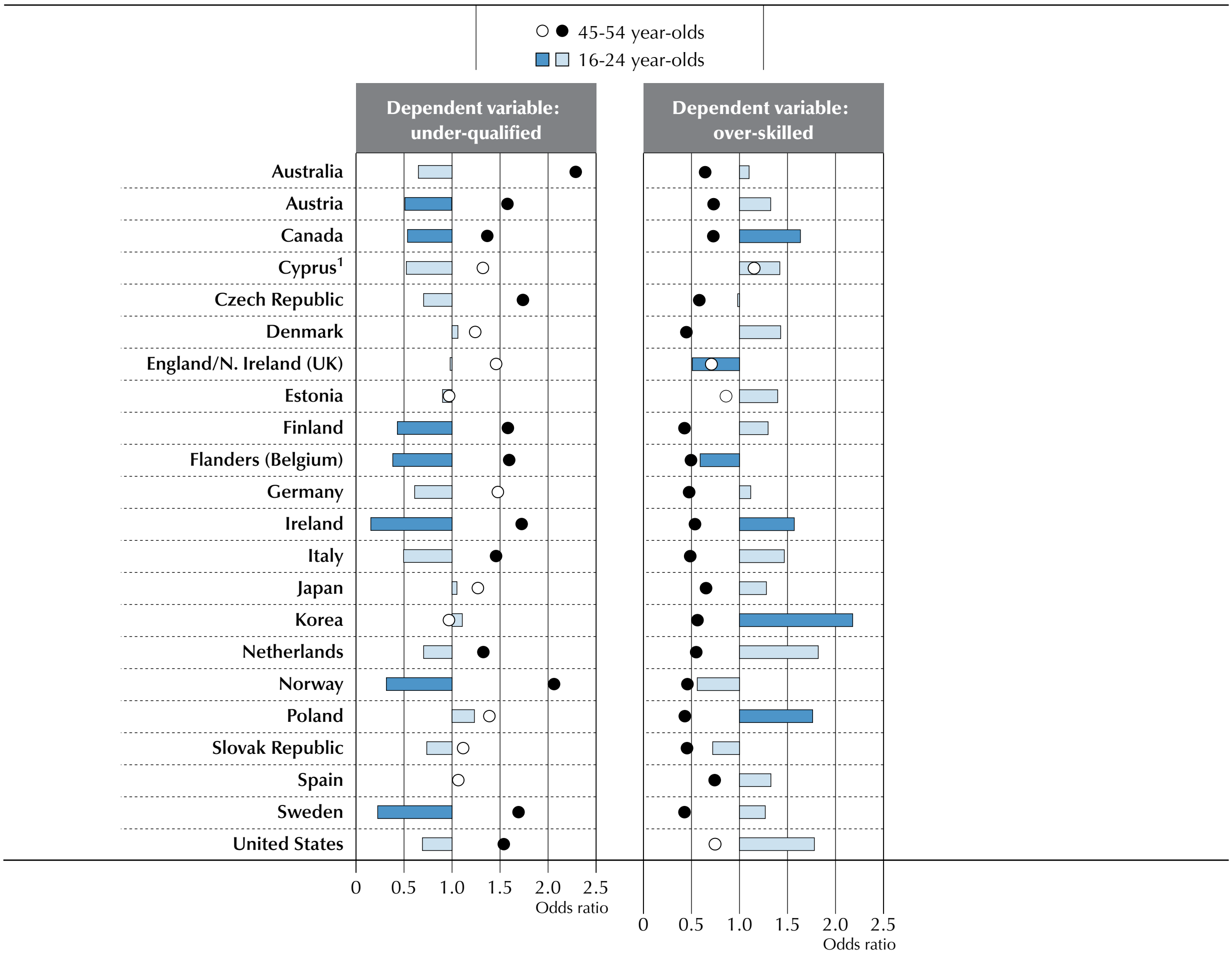
1. Over-qualification is defined relative to the qualification needed to get the job, as reported by the respondents.
2. From logit regressions including controls for years of education, age, gender and marital status, foreign-born status, establishment size, contract type, hours worked. Statistically (at the 10% level) significant values are shown in darker tones.
3. See notes at the end of this chapter.
Countries are listed in alphabetical order.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.28.
StatLink http://dx.doi.org/10.1787/888932901847

No statistically significant patterns emerge across countries for under-qualification or skills mismatch, with the only exception of the association with age. The likelihood of over-skilling declines with age (Figure 4.29). Also, older workers are more likely to be under-qualified than prime-age workers with the same skills and qualifications – a result that is statistically significant in about a third of the countries that participated in the Survey of Adult Skills. This finding lends some support to the hypothesis that under-qualified workers may be well matched to their jobs in terms of their skills but lack the qualifications that would formally certify those skills.

■ Figure 4.29 ■

Under-qualification and over-skilling, by age

Adjusted odds ratios showing the likelihoods of being under-qualified[1] or over-skilled, by age group (reference: 25-44 year-olds)[2]



1. Under-qualification is defined relative to the qualification needed to get the job, as reported by the respondents.

2. From logit regressions including controls for years of education, age, gender and marital status, foreign-born status, establishment size, contract type and hours worked. Statistically (at the 10% level) significant values are shown in darker tones. Estimates based on a sample size less than 30 (odds ratio of 16-24 year-olds with respect to 25-44 year-olds for Spain) are not shown.

3. See notes at the end of this chapter.

Countries are listed in alphabetical order.

Source: Survey of Adults Skills (PIAAC) (2012), Table A4.29.

StatLink http://dx.doi.org/10.1787/888932901866

The effect of mismatch on the use of skills and wages

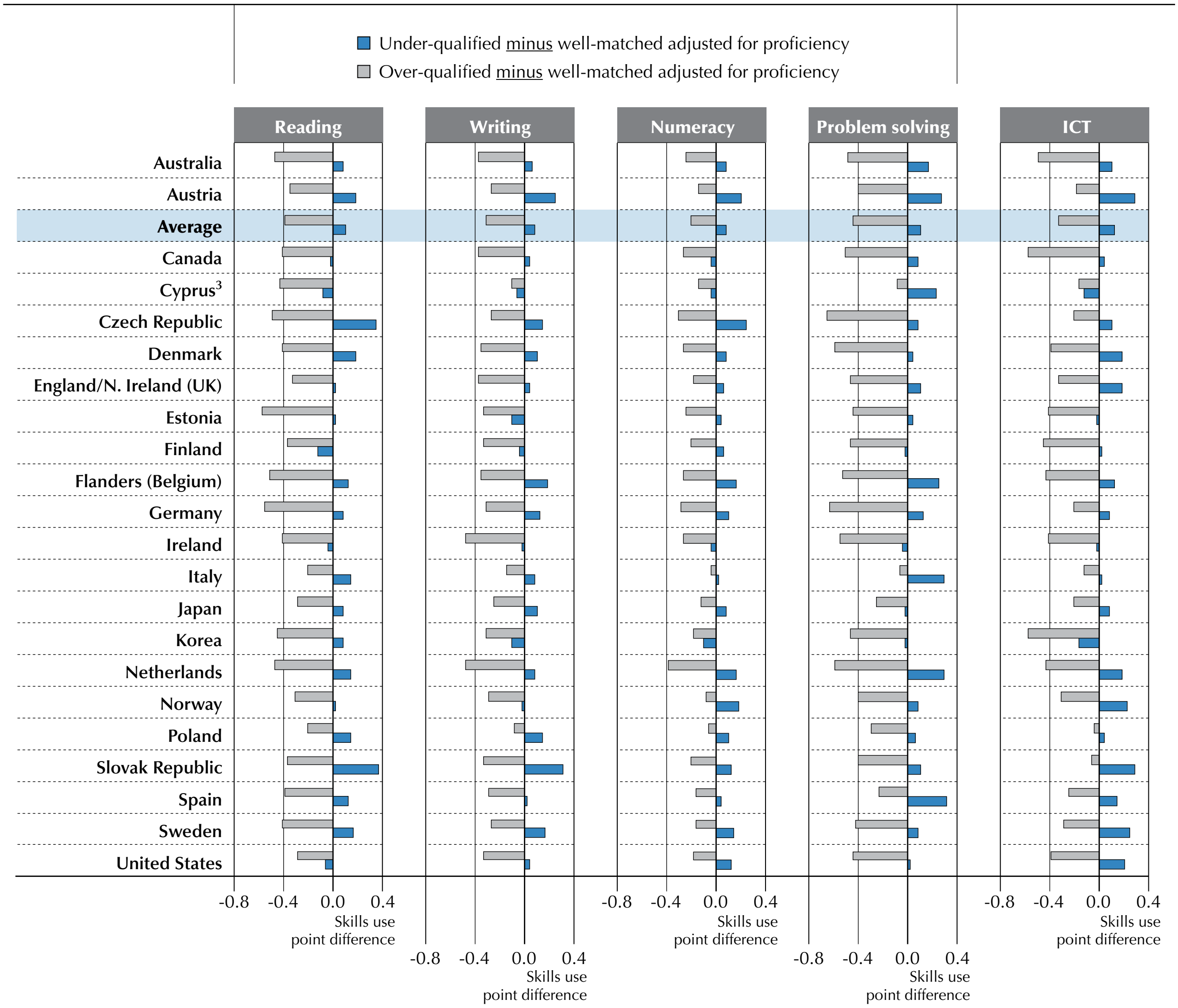
Analysis of data from the Survey of Adult Skills confirms that workers who are over-qualified and over-skilled in literacy use their skills less than their well-matched counterparts with the same level of proficiency (Figures 4.30 and 4.31). The inverse is true for those who are under-skilled in literacy. Workers in the latter group probably have to exert extra effort at work, given their levels of skills, and that can have a negative impact on job satisfaction.

Overall, numeracy skills appear to be better used at work, while problem-solving skills appear to be most often and most extensively ill-used. Across countries and skills, the largest "waste" of human capital resulting from over-qualification in information-processing skills is observed in Canada, Ireland, Flanders (Belgium) and the Netherlands (Figure 4.30). By contrast, over-skilling has more negative consequences for the use of skills in Australia, the Netherlands and the United States (Figure 4.31).

■ Figure 4.30 ■

Skills use and qualification mismatch

Difference in the use of information-processing skills between under/over-qualified[1] and well-matched workers, adjusted for literacy and numeracy proficiency scores[2]



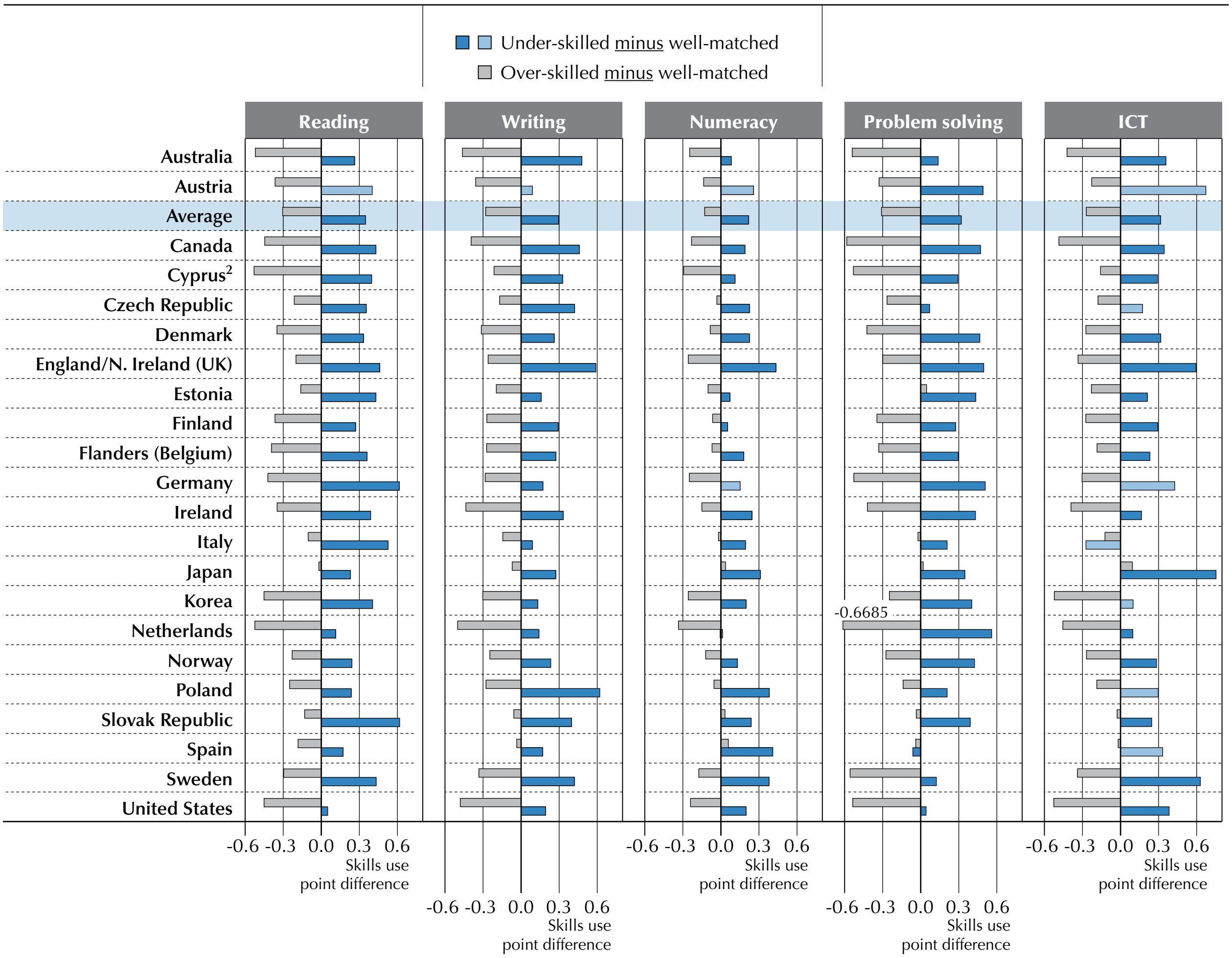
1. Over- and under-qualification are defined relative to the qualification needed to get the job, as reported by the respondents.
2. OLS regressions including literacy and numeracy proficiency scores as controls.
3. See notes at the end of this chapter.
Countries are listed in alphabetical order.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.30.
StatLink http://dx.doi.org/10.1787/888932901885

Over-qualification has a stronger negative effect on real hourly wages than over-skilling, when workers are compared with equally-qualified and equally-proficient well-matched counterparts (Figure 4.32a). On average, across countries, over-qualified workers earn about 13% less than well-matched workers with the same qualification and proficiency levels. The largest differences – at or exceeding 18% – are observed in Estonia, Korea, Poland and the United States. These results remain unchanged when controls for skills mismatch are removed.

■ Figure 4.31 ■

Skills use and skills mismatch

Difference in the use of information-processing skills between workers under/over-skilled in literacy and well-matched workers, adjusted by literacy and numeracy proficiency scores¹



1. OLS regressions including literacy and numeracy proficiency scores as controls. Estimates based on a sample size less than 30 are shown in lighter tones.
2. See notes at the end of this chapter.
Countries are listed in alphabetical order.
Source: Survey of Adults Skills (PIAAC) (2012), Table A4.31.
StatLink http://dx.doi.org/10.1787/888932901904

The effect of over-skilling on wages is small and often not statistically significant, and remains so even when the controls for qualification mismatch are removed. The largest and statistically significant differences are observed in Poland and the United States, where over-skilled workers earn about 10% less than their equally skilled, well-matched counterparts. In both countries, this relatively large negative effect is in addition to the sizeable adverse effect of over-qualification on wages.

Both under-skilling and under-qualification are associated with higher wages compared to the wages of workers who are well-matched and equally qualified and skilled, although the effect of under-skilling is usually not statistically significant and is negative in Ireland (Figure 4.32b).

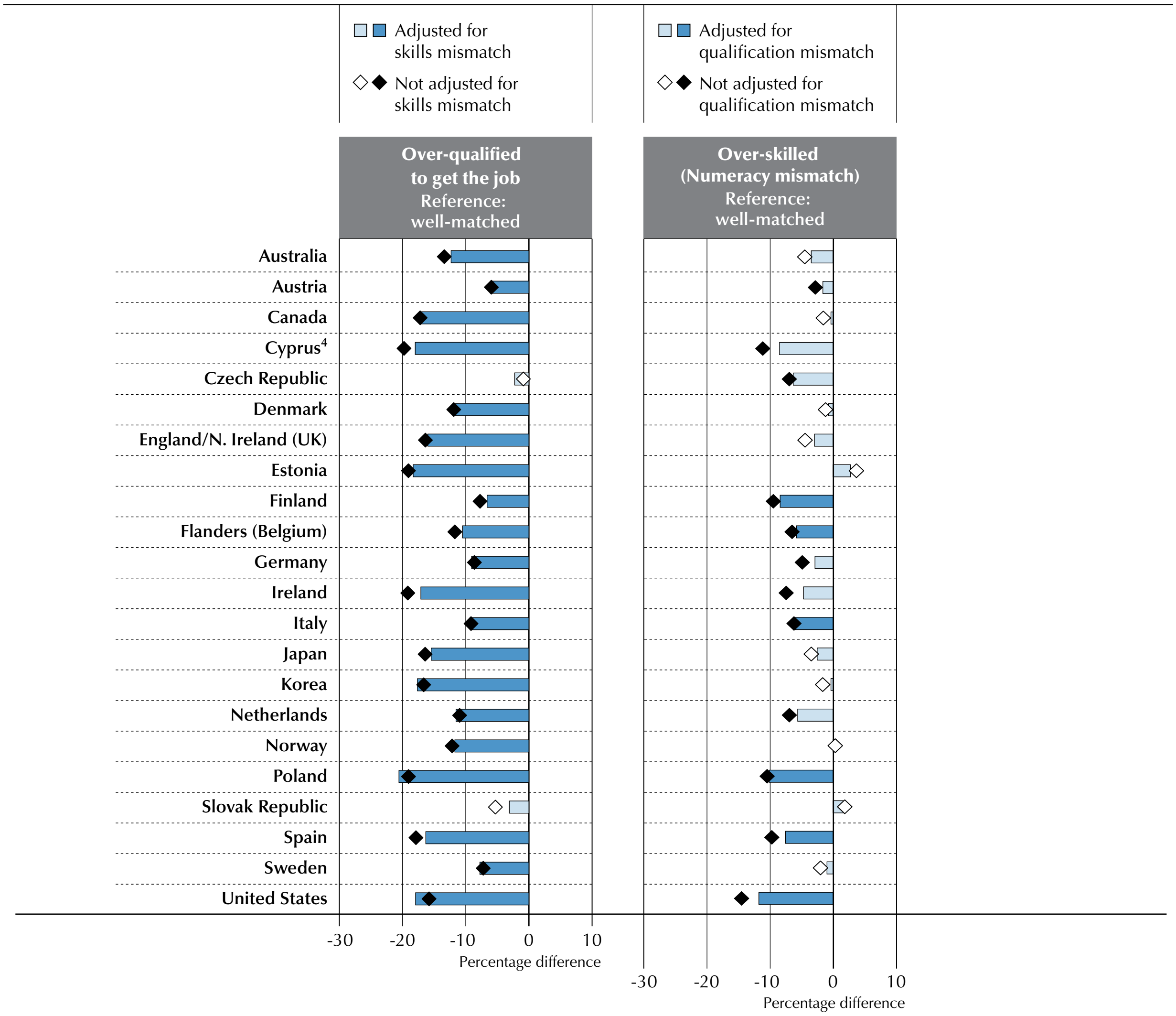
This evidence should not be interpreted as suggesting that having qualifications in excess of those required at work is not valued at all on the labour market. On average across countries, over-qualified workers earn about 4% more than well-matched workers in similar jobs. In other words, a tertiary graduate who holds a job requiring only an upper secondary qualification will earn *less* than if he were in a job requiring a tertiary qualification, but *more* than an upper secondary graduate in a job requiring upper secondary qualifications. Similarly, on average, an under-qualified individual earns about 17% *less* than workers who are well-matched in similar jobs. Hence, an upper secondary graduate in a job requiring tertiary qualifications will earn *more* than an upper secondary graduate in a job requiring upper secondary qualifications but *less* than a tertiary graduate in a job requiring tertiary qualifications.

Qualification mismatch and skills mismatch may both have distinct effects on wages, even after adjusting for both qualification level and proficiency scores, because jobs with similar qualification requirements may have different skill requirements. This may happen because employers can evaluate qualifications but they cannot measure skills directly. In addition, the kinds of mismatch in skills captured by the two indicators are different: the survey's indicators of skills mismatch are based on numeracy, literacy and problem solving, while skills mismatch captured by qualification-based indicators may be interpreted as more general and may be based, for example, on the level of job-specific skills.

■ Figure 4.32a ■

Effect of over-qualification and over-skilling on wages

Percentage difference[1] in wages[2] between over-qualified[3]/skilled and well-matched employees



1. From OLS regressions including controls for years of education, age groups, gender, marital status, working experience, tenure, foreign-born status, establishment size, contract type, hours worked, public sector dummy, proficiency in numeracy and use of skills at work. The sample includes only employees. Statistically (at the 10% level) significant values are shown in darker tones.

2. Hourly wages. The wage distribution was trimmed to eliminate the 1st and 99th percentiles.

3. Over-qualification is defined relative to the qualification needed to get the job, as reported by the respondents.

4. See notes at the end of this chapter.

Countries are listed in alphabetical order.

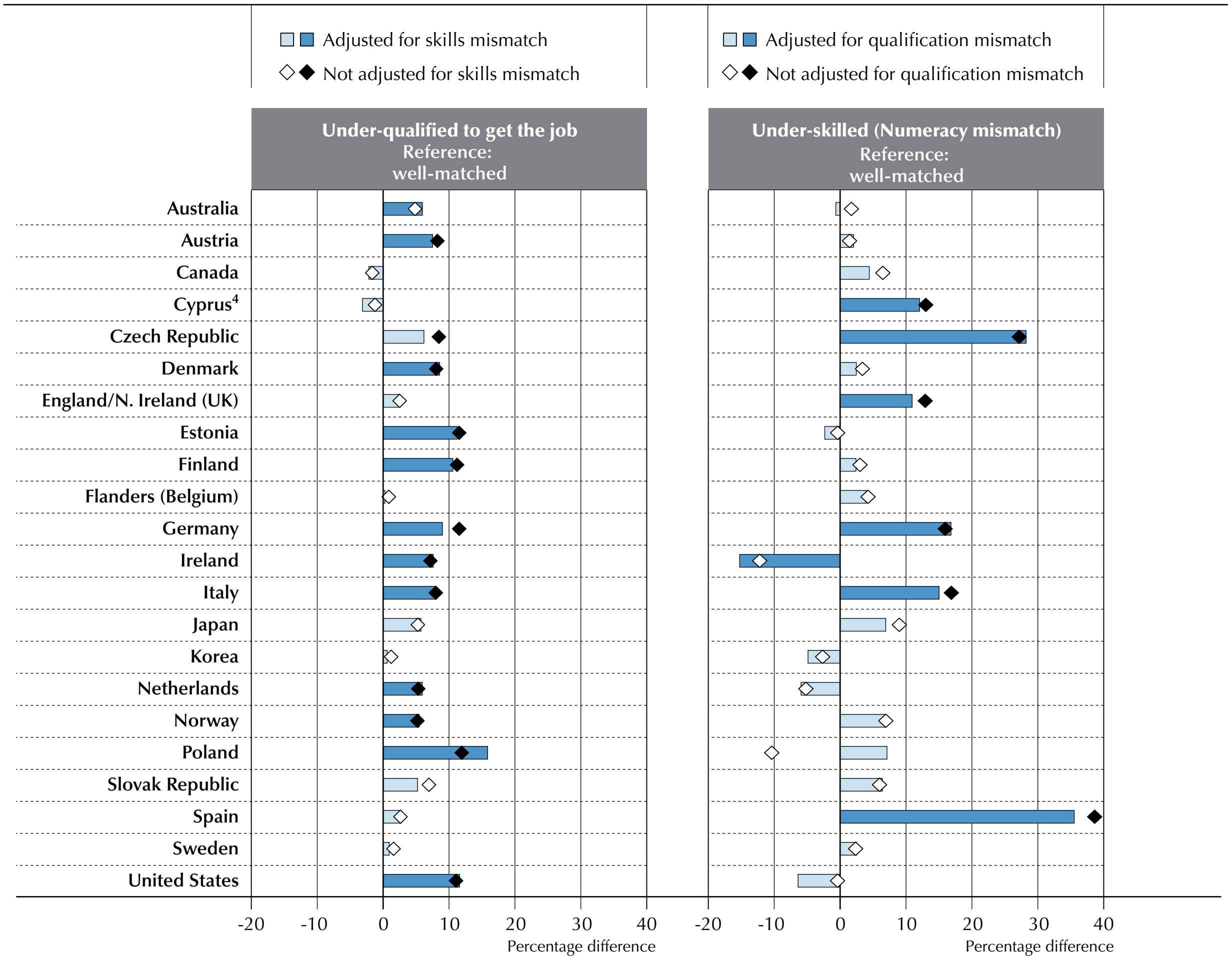
Source: Survey of Adults Skills (PIAAC) (2012), Tables A4.32a, A4.32b and A4.32c.

StatLink http://dx.doi.org/10.1787/888932901923

■ Figure 4.32b ■

Effect of under-qualification and under-skilling on wages

Percentage difference[a] in wages[b] between under-qualified[c]/skilled and well-matched employees



1. From OLS regressions including controls for years of education, age groups, gender, marital status, working experience, tenure, foreign-born status, establishment size, contract type, hours worked, public sector dummy, proficiency in numeracy and use of skills at work. The sample includes only employees. Statistically (at the 10% level) significant values are shown in darker tones.
2. Hourly wages. The wage distribution was trimmed to eliminate the 1st and 99th percentiles.
3. Under-qualification is defined relative to the qualification needed to get the job, as reported by the respondents.
4. See notes at the end of this chapter.
Countries are listed in alphabetical order.
Source: Survey of Adults Skills (PIAAC) (2012), Tables A4.32a, A4.32b and A4.32c.
StatLink http://dx.doi.org/10.1787/888932901942

SUMMARY

Analysis of results from the Survey of Adult Skills shows that the use of skills in the workplace influences a number of labour market phenomena, including productivity and the wage gap between temporary and permanent workers. The distribution of workers across occupations is found to be the single most important factor shaping the distribution of skills use. In addition, skills-use indicators are found to correlate only weakly with measures of skills proficiency, with the distributions of skills use among workers at different levels of proficiency overlapping substantially. As a result, it is not uncommon that more proficient workers use their skills at work less intensively than less proficient workers do. This latter finding points to the existence of significant mismatch between skills and their use at work, particularly for some socio-demographic groups. Data show that over-qualification is particularly common among foreign-born workers and those employed in small establishments, in part-time jobs or on fixed-term contracts. Over-qualification has a significant impact on wages, even after adjusting for proficiency. It also implies a "waste" of human capital, since over-qualified workers tend to under-use their skills. However, part of this type of mismatch is due to the fact that some workers have lower skills proficiency than would be expected at their qualification level, either because they performed poorly in initial education or because their skills have depreciated over time. By contrast, under-qualified workers are likely to have the skills required at work, but not the qualifications to show for them. Mismatches in skills proficiency have a weaker impact on wages than qualification mismatch. This suggests either that labour market mismatch may be more often related to job-specific or generic skills than to those measured in the three domains covered by the survey; and/or that employers succeed in identifying their employees' real skills, irrespective of their formal qualifications, and adapt job content accordingly.

Notes

1. Although there is some parallel between the skills included in the direct assessment exercise – literacy, numeracy and problem solving in technology-rich environments – and the use of reading, numeracy, problem solving and ICT at work (and at home), there are important differences. The skills use variables are derived by aggregating background questions on tasks carried out at work (or at home). For instance, these questions cover both reading and writing at work but two separate indices are created to maintain, to the extent possible, consistency with the direct assessment module which only tests reading skills in the literacy module. Similarly, the use of problem solving and ICT skills at work are not to be confused with the assessment of proficiency in problem solving in technology-rich environments. Finally, it should be kept in mind that even when there is a parallel between skills use and skills proficiency concepts – notably between reading use and literacy proficiency and between numeracy use and proficiency – there is no correspondence between the questions concerning the tasks performed at work (or at home) and those asked in the direct assessment modules. These issues should be kept in mind when comparing skills proficiency to skills use.

2. The labels *information-processing* and *generic skills* serve a mere presentational purpose and should not be over-interpreted.

3. It should be borne in mind that these data are self-reported by respondents, and that cross-country variations may be partly due to cultural differences in response behaviours.

4. Specifically, the figure shows the fraction of workers whose indices of skills use lay in the top 25% of the overall distribution of each skills-use index. The top 25% threshold is chosen to get a sense of how many people use each skill most intensively at work. It is computed using all the observations in the Survey of Adult Skills (PIAAC), i.e. pooling all the countries together using the appropriate sampling weights.

5. No cluster of skills use is identified for Poland.

6. Only proficiency in literacy and numeracy is considered in this analysis, as the average score in the problem-solving section of the assessment does not take into account the relatively large and variable proportion of respondents who did not take that part of the assessment, either because they refused to or because they could not use a personal computer.

7. The adjustment is based on multivariate regression analysis. First, both labour productivity and the average use of reading at work are separately regressed on average proficiency scores in literacy and numeracy, i.e. they are adjusted to control for the effect of literacy and numeracy proficiency. Then, the residuals of such two regressions are, in turn, regressed on one another. The adjusted results displayed in Figure 4.4 come from such a regression. This is a rather standard econometric procedure, commonly known as *partitioned regression*.

8. In fact, the average levels of proficiency in literacy and numeracy are only weakly correlated with productivity: in a simple linear regression, they jointly capture less than 2% of the cross-country variation.

9. For instance, women may sort themselves into jobs that require less investment in human capital during the period of childrearing.

10. The adjusted differences are produced from the individual data by running one OLS regression for each country and for each skill, with skill-use indicators as dependent variables, a gender dummy as the main independent variable of interest, and adding skills proficiency scores, a dummy for part-time jobs and occupational dummies (ISCO 1 digit). The estimated coefficient on the gender dummy can be directly interpreted as the adjusted difference in skills use between men and women. The same procedure is used for the other figures in this section, appropriately changing the dependent variables and the control set.

11. Differences in the use of skills between part-time and full-time workers should be interpreted with caution, as they may simply relate to the fact that part-time workers are less often at work than full-time workers.

12. In the absence of panel data, this interpretation cannot be tested against the alternative possibility that there is a trend towards less-intensive use of certain skills over time. However, given the evolution of technology and labour demand towards more skill-intensive work, as discussed in Chapter 1, this latter explanation does not seem particularly plausible.

13. Further adjusting for occupation and industry does not change the main findings.

14. The populations over which the averages of the skills-use indicators are taken are the same for both ICT use at home and ICT use at work in all countries.

15. Less than upper secondary = ISCED 0, 1, 2 and 3C short; completed upper secondary education = ISCED 3A, 3B, 3C long or 4A, B, C; tertiary education = ISCED 5A, B or 6.

16. Self-employed workers are excluded from these calculations.

17. In the Survey of Adult Skills (PIAAC), approximately 12% of the employees report being employed under a fixed-term contract.

18. However, there are likely to be significant differences in the characteristics of temporary employment across countries as well as in the characteristics of temporary jobs under different types of contracts – e.g. temporary-work agency contracts compared to fixed-term contracts.

19. See also Green and James (2003) for evidence of a high correlation between employees' and employers' views of skills requirements at work, suggesting that self-reported information on skills use provided by employees is a good proxy for the skills required at work.

20. Evidence on the link between mismatch and productivity is mixed. Because of the difficulty of measuring the relationship directly, studies infer the consequences of mismatch on productivity either by relying on human capital theory, equating wages to productivity, or by studying the effect of mismatch on job satisfaction. Using these approaches, most studies conclude that mismatch has a negative impact on productivity. However, some researchers have cast doubts on these findings. Notably, Kampelman and Rycx (2012) find evidence of a positive link between mismatch and productivity which they attribute to positive effects associated with a pool of higher skills, as more educated individuals can positively shape not only the nature of their own job tasks but also those of their colleagues.

21. Most often, this term is employed with reference to apparent over-qualification. See for example, Chevalier (2003).

22. While this is complicated by the fact that some jobs may not have an obvious requirement in terms of qualifications or workers may not be fully aware of it, survey experts have found that both workers and employers tend to find it easier to define jobs in terms of required qualifications than in terms of individual skills.

23. Because Figures 4.25 and 4.26 are based on workers' views of what qualification is required to get their job the results may be affected by respondent's bias – i.e. the tendency to over- or under- value the content of one's work – or by qualification inflation – i.e. whereby employers raise minimum job requirements as a result of an increase in the number of tertiary-qualified candidates without upgrading job content. The latter would tend to reduce the incidence of over-qualification when the self-reported measure is used, while the former may bias the results in either direction.

24. To limit the potential impact of outliers on these measurements, the 5th and the 95th percentiles instead of the actual minimum and maximum are used for computing skill mismatch.

25. The comparison of skills proficiency and skills use rests on the assumption that the two can be measured on the same scale, an assumption that is very difficult to defend for concepts that are so clearly distinct theoretically and that cannot be represented along the same metrics. In addition, the measures of skills proficiency and skills use are based on structurally different pieces of information: indicators of skills use normally exploit survey questions about the frequency (and/or the importance) with which specific tasks are carried out in the respondents' work activities, whereas skills proficiency is measured through information-processing tests. See the *Reader's Companion* to this report (OECD, 2013) for more details.

26. Similar results are obtained when using skills mismatch in numeracy.

27. These differences in skills proficiency within a qualification level are not necessarily related to performance in initial education. Some graduates may lack the generic skills, such as communication, team-work and negotiation skills, that the education system can foster, but that are better learned in the workplace. In addition, some workers may have the skills expected of their qualification level at graduation, but these skills may atrophy or become obsolete over time, particularly if they are not used or upgraded.

28. These personal characteristics are likely to influence both the level of proficiency and the likelihood of mismatch.

29. Similar results are obtained when using scores in numeracy or problem solving in technology-rich environments.

30. This is consistent with the mixed results, found in other studies, concerning the role played by gender and family status in explaining qualification mismatch (Quintini, 2011a). Husbands tend to optimise their job search, while their wives' job search is considered – by both the husband and the wife – to be of secondary importance. Also, some researchers have argued that women with children may be more likely to be over-qualified because of the constraints on job choice imposed by child-rearing. However, there is no empirical evidence to support these claims.

Notes regarding Cyprus

Note by Turkey: The information in this document with reference to "Cyprus" relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Turkey recognises the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of the United Nations, Turkey shall preserve its position concerning the "Cyprus issue".

Note by all the European Union Member States of the OECD and the European Union: The Republic of Cyprus is recognised by all members of the United Nations with the exception of Turkey. The information in this document relates to the area under the effective control of the Government of the Republic of Cyprus.

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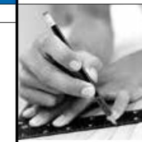

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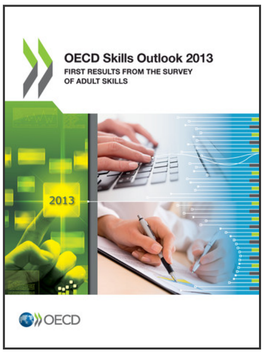

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