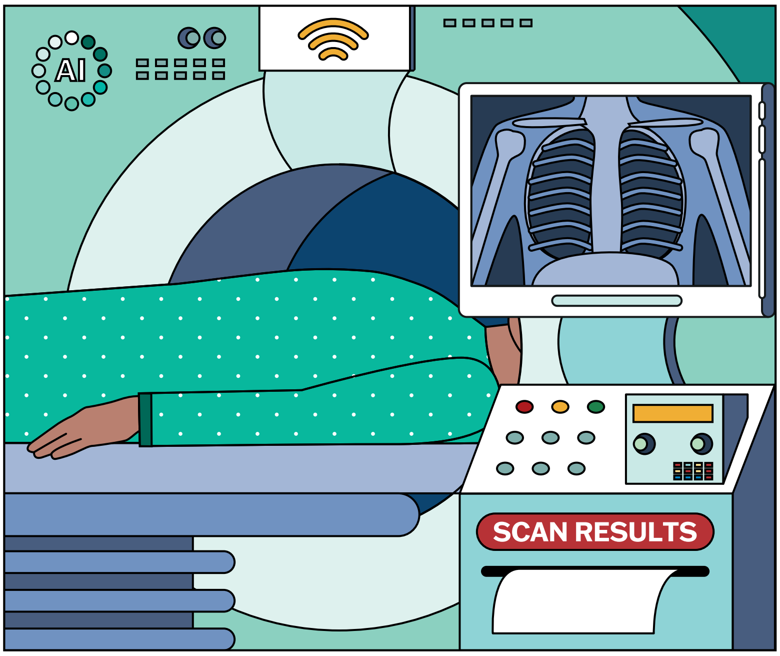
3 TELEWORKING, AI AND THE LABOUR FORCE

This chapter provides an overview of "teleworkability" – the extent to which all tasks relating to an occupation can be performed remotely – and people's changing attitudes towards working from home. There is considerable variation in teleworkability, both across and within the EBRD regions, with young people and women more likely to have teleworkable occupations than older cohorts and men. On average, workers plan to work from home two days a week after the Covid-19 pandemic, with many people feeling that they work more efficiently at home. This chapter also explores the impact that artificial intelligence is having on the labour market, showing that, while the effect is limited, occupations which are more exposed to automation have seen greater job losses.



Introduction

Digitalisation of the workplace has taken a leap forward during the Covid-19 pandemic and is changing the ways in which people work and the jobs that they do. In particular, use of digital technologies that are complementary to human effort (especially when working from home) has increased. Cloud computing, online contracting and digital payment systems are all prime examples of this. Evidence from advanced economies indicates that highly skilled, high-income workers tend to benefit most from remote-working arrangements.[1] This chapter starts, therefore, by looking at how "teleworkability" – a measure capturing the extent to which all tasks relating to an occupation can be performed remotely – is distributed in terms of geography, gender, age and educational attainment in the EBRD regions (see Box 3.1 for details of the construction of that measure).[2] While the measure in question does not indicate whether tasks are *actually* performed remotely, this chapter complements that teleworkability analysis by looking at de facto remote-working patterns.

The analysis reveals that teleworkability is spread unevenly across the EBRD regions. Young people and women are more likely to have teleworkable occupations than older cohorts and men, while people with a tertiary qualification are up to three times more likely to have a teleworkable occupation than those with lower levels of education.

There is also substantial variation across countries in terms of actual remote-working patterns. Overall, there is only a weak correlation between teleworkability and actual remote working. This chapter finds that, beyond the availability of digital infrastructure necessary for working from home, the extent to which the former translates into the latter also depends on other factors, such as the degree of trust.

The second section of the chapter examines changing attitudes towards remote working, using data from a novel household survey conducted in 15 countries in 2021. Recent shifts in attitudes towards remote working could be an indication of more permanent changes.[3] The survey shows that workers across the EBRD regions prefer more flexible approaches to work and generally feel more efficient when working from home. However, they believe that employers will not embrace frequent remote working. If that is borne out in reality, it may point to a slower digital transformation of the workforce in the EBRD regions relative to more advanced economies (see also Box 3.3 on the way in which digitalisation shapes intentions to migrate).

[1] See Adams-Prassl et al. (2020) and Angelucci et al. (2020).
[2] See also Dingel and Neiman (2020).
[3] See also Barrero et al. (2021) on the United States of America.

A third section explores the impact that advances in artificial intelligence are having on employment.[4] AI technologies are computer programs that solve problems and achieve goals that normally require human intelligence. Unlike the routine manual tasks that robots replace, AI technologies can perform routine cognitive tasks, such as the categorisation of images. The Covid-19 pandemic could accelerate the adoption of such technologies. Many firms have struggled to operate remotely during lockdowns as a result of non-teleworkable processes, and such firms may now seek to replace human workers with AI-based machines that are not susceptible to illness. While the effect that large-scale adoption of AI will have on overall employment is unknown at present, highly skilled workers specialising in non-routine cognitive tasks are likely to benefit most.

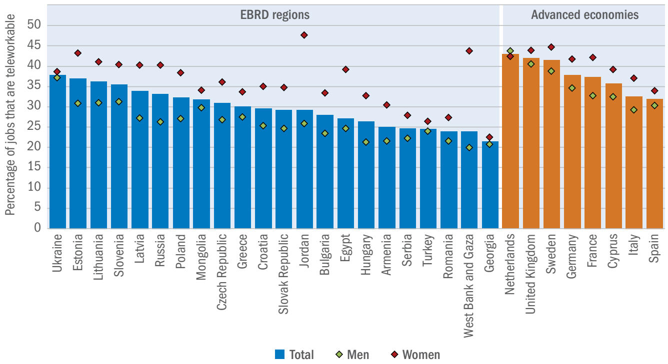
In order to explore these issues in the EBRD regions, this chapter analyses the extent to which AI technologies can perform occupational tasks as well as – or better than – humans (which is referred to as "AI exposure"). AI exposure does not capture actual adoption of specific AI technologies, but instead captures the technical *potential* for adoption. The analysis finds that, over the last decade, AI exposure has had a very limited impact on employment growth for individual occupations, as very few jobs have high levels of AI exposure at present. The effect that AI exposure has on employment growth will, however, probably increase in the future.

Teleworkability: transforming how people work

People's recent experience with teleworking, the associated investments made and the protracted nature of the pandemic will probably mean that remote working remains popular in many economies in the near future, potentially increasing further over time. Increased teleworking could have a considerable impact on labour markets in the EBRD regions.

First, well-managed teleworking has the potential to benefit both firms and workers. Pre-pandemic evidence from China, Italy and the United States of America shows that remote working can increase productivity across industries and skill levels.[5] Firms can gain from the reduced need for full-time desks, helping them to save on office space and related expenditure (such as the cost of electricity). While these costs are instead shifted onto workers, who may end up paying for production inputs such as working space, heating and electricity, many workers may find such costs are outweighed by the benefits of working from home, such as reduced commuting time.[6]

CHART 3.1. Teleworkability is typically higher for women than for men



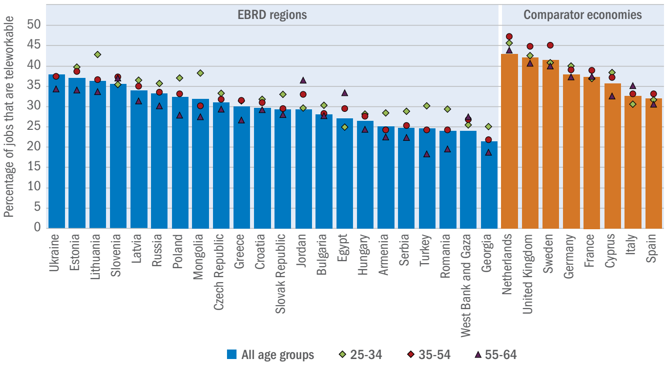
Source: Dingel and Neiman (2020), labour force surveys (2016-19) and authors' calculations.

Second, detaching workers from the office has important implications for cities. Labour demand is generally a more important driver of urban migration than urban amenities.[7] Because teleworking reduces the need to live in cities, people who have less of a preference for urban living or are seeking more affordable housing may decide to leave. This could boost the economies of smaller population centres. Indeed, recent research estimates that cities with high levels of inward commuting will see a 5-10 per cent drop in local spending.[8] While peripheral areas may benefit from some reallocation of spending, higher demand for housing, goods and services may increase the cost of living there. Moreover, de-urbanisation may also weaken economies of agglomeration. And while recent developments in online labour markets and videoconferencing have created opportunities for digital labour market pooling and knowledge spillovers, it remains to be seen whether these can truly replace physical proximity in practice.[9]

Third, increased teleworking may also affect labour markets beyond national borders. In particular, detaching workers from the office may increase offshoring from more advanced economies. Teleworking relies on digital communication and coordination and may therefore make it easier for firms to maintain a globally distributed workforce. Here, economies in the EBRD regions may stand to gain from offshored teleworking jobs, given their highly skilled labour forces and relatively reliable legal environments. Such shifts may also alter demand for skills in those host countries: on the positive side, they could encourage upskilling; however, they could also increase the take-up of jobs that will eventually be lost to automation.

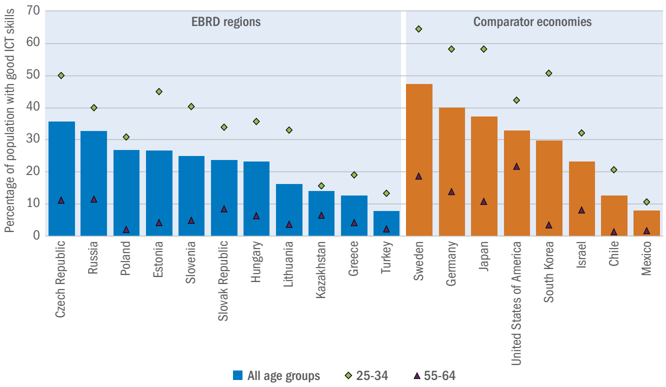
[4] The Oxford Living Dictionary defines AI as "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages".
[5] See Angelici and Profeta (2020), Bloom et al. (2015) and Choudhury et al. (2021).
[6] See Mas and Pallais (2017).
[7] See Moretti (2013).
[8] See Barrero et al. (2021).
[9] See Rosenthal and Strange (2020) and Wheaton and Lewis (2002).

CHART 3.2. In the EBRD regions, young people are most likely to have a teleworkable job



Source: Dingel and Neiman (2020), labour force surveys (2014-19) and authors' calculations.

CHART 3.3. Young people have better ICT skills than older cohorts



Source: PIAAC and authors' calculations.
Note: "Good ICT skills" refers to an average score of more than 290 across the 10 plausible values for problem solving in a technology-rich environment. See also Chapter 2 of EBRD (2018).

IN MOST ECONOMIES IN THE EBRD REGIONS, YOUNG ARE MOST LIKELY TO HAVE TELEWORKABLE JOBS, FOLLOWED BY THE MIDDLE-AGED AND OLDER WORKERS

Who is most likely to have a teleworkable job?

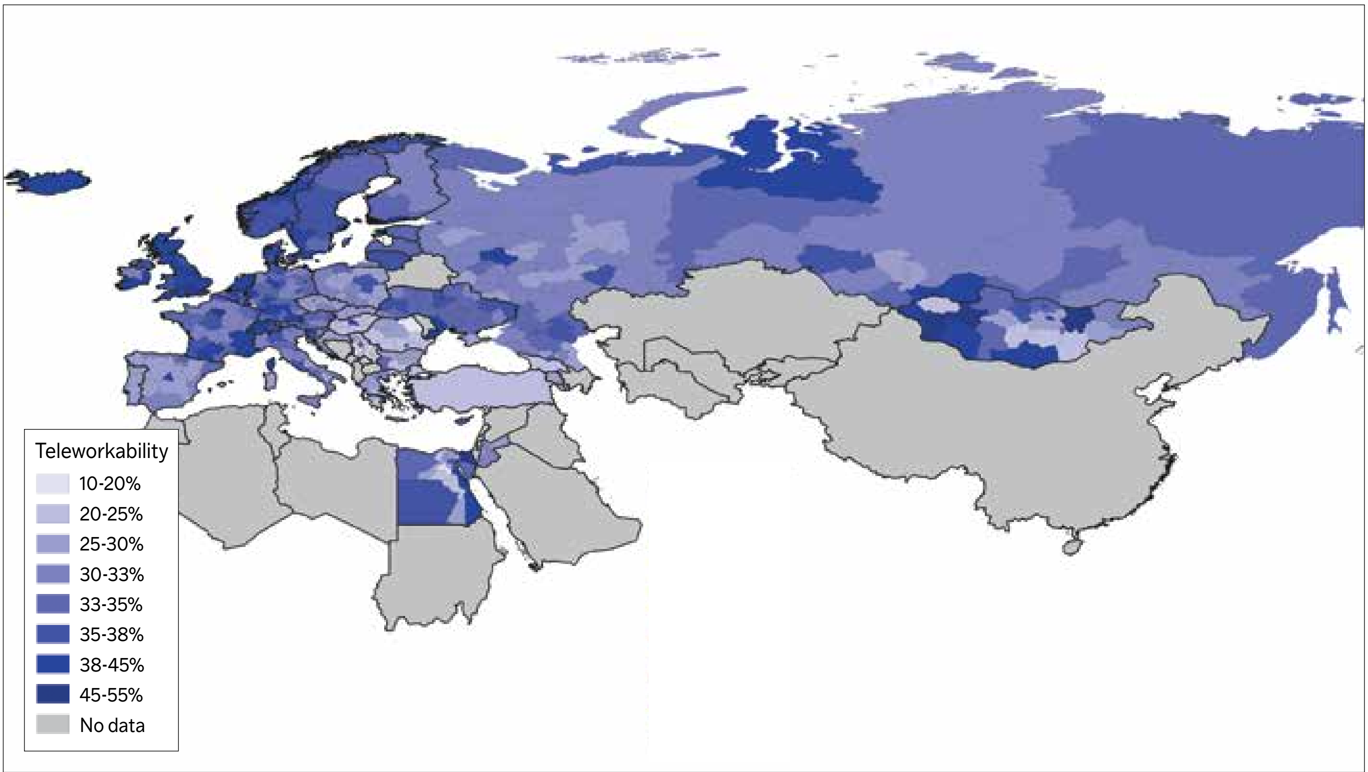
While the pandemic has led to unprecedented adoption of new technologies and processes in order to accommodate remote working, it has also reinforced pre-existing trends.[10] In order to better understand the ways in which digitalisation may transform labour markets across the EBRD regions, this chapter first analyses the pre-Covid-19 status quo in terms of both teleworkability (as a measure of *potential* remote working) and *actual* remote working. It does so by looking at various labour force surveys covering the European Union (including 14 economies in the EBRD regions), Armenia, Egypt, Georgia, Jordan, Mongolia, Russia, Serbia, Ukraine, and the West Bank and Gaza.

We can see from those data that women are more likely to have teleworkable jobs than men (see Chart 3.1). Furthermore, that female-male teleworkability gap is typically larger in the EBRD regions than in advanced comparator economies. This is driven mainly by women's greater representation in the service sector (although women are, in fact, under-represented in the *most* teleworkable occupations, such as management positions). In contrast, men are clustered in industries in the lowest quintile of the teleworkability distribution (such as agriculture, construction, manufacturing and mining).

In most economies in the EBRD regions, young people (aged 25-34) are most likely to have teleworkable jobs, followed by the middle-aged (35-54) and then older workers (55-64; see Chart 3.2). In more advanced economies, by contrast, middle-aged people are most likely to have teleworkable jobs, with no clear pattern for younger and older workers. In some EBRD regions, this could be explained by a combination of fast-growing digital-intensive sectors and weak ICT skills among older workers (see also Chapter 1). Between 2006 and 2016, for example, 40 per cent of all new jobs in OECD countries were created in highly digital-intensive sectors.[11] Meanwhile, data from the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) – an assessment of adult skills – show that the percentage of older people in EBRD economies who have good ICT skills is between 5 and 14 percentage points lower than the average for advanced economies (see Chart 3.3). ICT skills are generally stronger among the young, although even younger cohorts in the EBRD regions lag behind their counterparts in advanced economies.

[10] See Mas and Pallais (2020).
[11] See OECD (2020). Digital intensity is measured as a combined average of sector-specific rankings for five indicators: ICT investment as a percentage of total investment; purchases of intermediate ICT goods and services relative to output; the stock of robots per employee; ICT specialists as a percentage of total employment; and propensity to engage in e-commerce sales. "Low", "medium" and "high" digital intensity refer to the bottom 25 per cent, the middle 50 per cent and the top 25 per cent of the distribution of average scores respectively (see Calvino et al., 2018).

CHART 3.4. Some economies have significant regional variation in the percentage of jobs that are teleworkable



Source: Dingel and Neiman (2020), labour force surveys (2016-19) and authors' calculations.
Note: This map is used for data visualisation purposes only and does not imply any position on the legal status of any territory.

Cities typically have a higher percentage of teleworkable jobs than rural areas. However, this pattern is more pronounced in some economies than others (see Chart 3.4). A number of economies (including most advanced European economies, as well as Ukraine) have relatively high average teleworkability, with limited variation across subnational regions.[12] In contrast, many others (including most economies in the EBRD regions) are characterised by significant intra-economy variation, with up to 55 per cent of jobs being teleworkable in a single metropolitan area, compared with only around 10 to 30 per cent in most other regions. This imbalance is suggestive of strong economies of agglomeration – and, conversely, limited economic development in more peripheral regions. (Turkey, where detailed regional data are unavailable, has low overall teleworkability – fewer than 30 per cent of people have teleworkable occupations.)[13]

IN MANY ECONOMIES, UP TO 55% OF JOBS ARE TELEWORKABLE IN A SINGLE METROPOLITAN AREA, COMPARED WITH AROUND 10-30% IN MOST OTHER REGIONS

[12] Comparator economies include Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Sweden, Switzerland and the United Kingdom.
[13] All figures for Armenia and Turkey in this chapter have been calculated using one-digit ISCO codes.

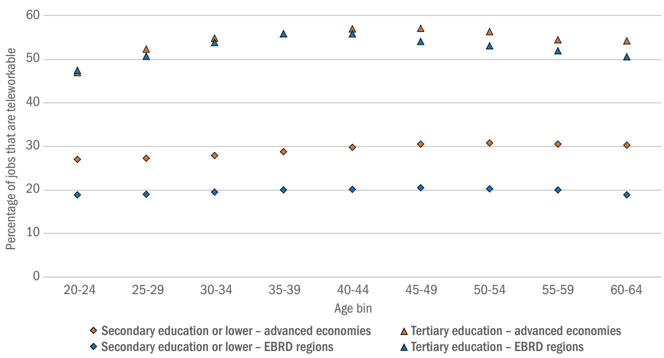
In the EBRD regions, workers with lower levels of education are the least likely to have teleworkable jobs. They are also much less likely to have teleworkable jobs than peers in the same age cohort in advanced economies (see Chart 3.5). In contrast, the EBRD regions are very similar to advanced economies when it comes to the percentage of highly educated workers with teleworkable jobs. The more pronounced differences among the less educated are probably partly due to occupational structures and partly due to a skills gap. For example, in economies outside the EBRD regions, people without tertiary qualifications do medium-skill and even high-skill jobs: in those economies, around 10 per cent of people without such qualifications are managers or professionals, compared with 5 per cent in the EBRD regions.[14]

Teleworkability among young, highly educated workers in the EBRD regions is similar to that of their peers in other economies. This is in stark contrast with the situation observed for older highly educated workers, where economies in the EBRD regions are lagging behind (see also Chapter 1). The difference between the two could reflect the long-term impact of transition. Middle-aged and older workers will have received their tertiary qualifications prior to 1990 and may have struggled to transfer their skills to jobs in the new market economy. This could have resulted in highly educated workers ending up in low-skill careers. In the EBRD regions, for example, 5 per cent of people with a tertiary education are employed in elementary occupations, with another 5 per cent working as plant and machine operators.

As one might expect, working from home is indeed more prevalent in more teleworkable occupations. However, the relationship between the two is weak in the EBRD regions (see Chart 3.6). The percentage of jobs that are teleworkable in theory ranges from 23 per cent in Romania to 36 per cent in Lithuania. These levels are comparable to those seen in advanced economies such as Austria and France (though a long way short of the 49 per cent seen in the economy with the highest rate – Luxembourg). However, the EBRD regions have much smaller percentages of people who actually report working from home. Indeed, in all but three of the EBRD economies in the sample, less than 10 per cent of the labour force sometimes work from home. And even in the other three – Estonia, Poland and Slovenia – less than 20 per cent of people sometimes work from home.

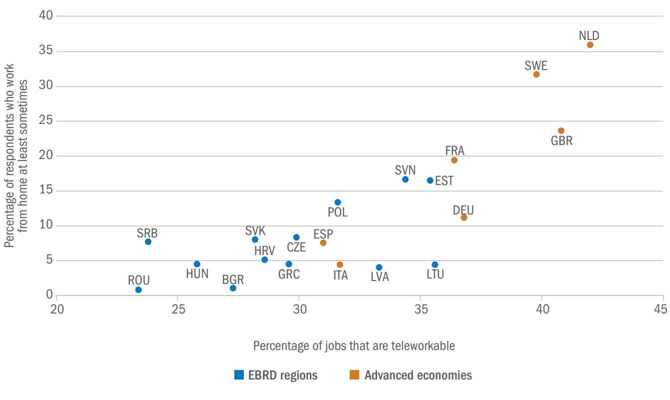
5%
OF TERTIARY-EDUCATED WORKERS IN THE EBRD REGIONS HAVE ELEMENTARY OCCUPATIONS, WITH ANOTHER
5%
WORKING AS PLANT AND MACHINE OPERATORS

CHART 3.5. The difference between the EBRD regions and advanced economies in terms of teleworkability is driven by people with lower levels of education



Source: Dingel and Neiman (2020), labour force surveys (2016-19) and authors' calculations.

CHART 3.6. Teleworkability is a predictor of actual remote working, but this correlation is weaker in the EBRD regions



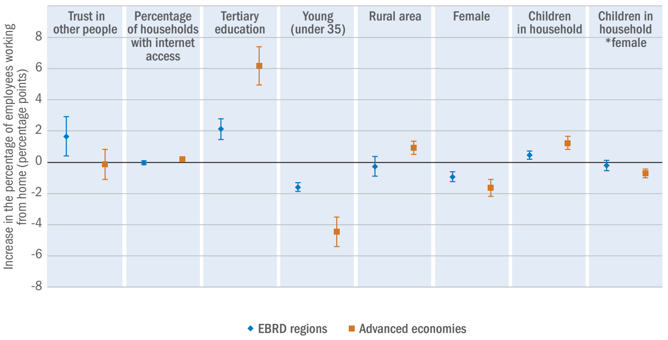
Source: Dingel and Neiman (2020), labour force surveys (2016-19) and authors' calculations.

[14] In this analysis, "high-skill" occupations comprise managers, professionals, technicians and associate professionals. "Medium skill" occupations comprise clerical support workers, service and sales workers, skilled agricultural, forestry and fishery workers, and crafts and related trades. "Low-skill" occupations comprise plant and machine operators, assemblers and elementary occupations.

CHART 3.7. Levels of remote working are low in the EBRD regions, even taking into account differences in countries' occupational structures

Source: Dingel and Neiman (2020), labour force surveys (2016-19) and authors' calculations.

CHART 3.8. Interpersonal trust is strongly associated with working from home in the EBRD regions



Source: European Social Survey (2008-16), labour force surveys (2016-19) and authors' calculations.
Note: This chart plots the marginal increase in the percentage of employees working from home "at least sometimes" that is associated with a one unit increase in the different variables. The trust variable is standardised, so the point estimate gives the marginal increase in the percentage of people working from home that is associated with a 1 standard deviation improvement in trust in other people. Square brackets indicate 95 per cent confidence intervals. See Box 3.2 for further details.

Even in economies where a high percentage of jobs could potentially be done from home, actual remote working is limited in the EBRD regions. This remains the case even when taking account of differences in countries' occupational structures (see Chart 3.7, which shows the same correlation as Chart 3.6, but disaggregated by occupation). As in advanced economies, there is substantial variation in the teleworkability of country-occupation pairs in the EBRD regions. However, while some economies in the EBRD regions have teleworkability rates similar to those seen in advanced economies, actual use of that capacity is consistently low.

Low levels of remote working may reflect factors beyond the availability of the necessary digital infrastructure. Thus, the following analysis looks at whether trust – which, through its link with social capital, is associated with better-functioning local governments and stronger economic growth[15] – could also influence levels of remote working.[16] Low trust can inhibit teleworkability if it prevents employers from giving (or employees from accepting) permission to work with less supervision. Recent research also shows that interpersonal trust is relatively low in the EBRD regions.[17]

Regression analysis indicates that living in a subnational region with high levels of interpersonal trust is indeed important in explaining remote working in the EBRD regions, even when controlling for the availability of internet infrastructure (see Chart 3.8 and Box 3.2). The identified effects also control for individual demographic characteristics (gender, level of education and whether there are children in the home) and both country and occupation-industry fixed effects.

An individual living in a region where trust is 1 standard deviation higher is 1.7 percentage points more likely to work from home at least sometimes. This is a sizeable effect, as the average percentage of people working from home at least sometimes was just 5.7 per cent in the EBRD regions prior to the pandemic. Thus, trust barriers may limit the gains from teleworkability relative to more advanced economies.

In advanced economies, there is a significant correlation between internet coverage and working from home. In regions with high-quality digital infrastructure, even rural residents with teleworkable jobs can work from home,

PRE-PANDEMIC, THE AVERAGE PERCENTAGE OF PEOPLE WORKING FROM HOME AT LEAST SOMETIMES WAS JUST
5.7%
IN THE EBRD REGIONS

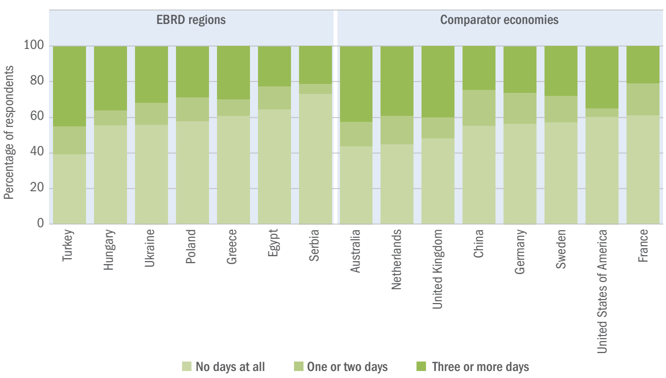
[15] See Beugelsdijk et al. (2004) and Putnam (1993).
[16] See De Leede and Kraijenbrink (2014).
[17] See EBRD (2011).

saving on commuting time. In the EBRD regions, by contrast, there is no significant correlation between internet coverage and working from home once regional development indicators have been controlled for, suggesting that workers may not be able to work from home even in regions that have high-quality digital infrastructure.

People with a tertiary education are more likely to work from home than people with lower levels of education. This probably reflects both (i) the fact that they are more likely to choose occupations that are teleworkable in theory and (ii) the fact that they are more likely to have good digital skills. However, the correlation is significantly higher in advanced economies. Since this analysis controls for income and place of residence, the differences between the effects of tertiary education in the EBRD regions and advanced economies are likely to be driven by skill mismatches. For example, the percentage of tertiary-educated employees holding jobs in manufacturing or mining is higher in the EBRD regions than it is in advanced economies.

The analysis also shows that, within occupations, women and young people are the least likely to work from home. Parents are more likely to work from home, and in the EBRD regions mothers are no more likely to work from home than fathers. This could mask a selection effect, whereby women who would prefer to work remotely opt out of the labour force when such options are limited. Thus, new trends in teleworking may open up new opportunities for mothers to work full time. This also underlines the importance of childcare and early childhood development programmes in terms of supporting working parents.

CHART 3.9. A substantial proportion of respondents worked from home in August 2021



Source: EBRD-ifo survey (2021) and authors' calculations.
Note: This chart shows the percentage of respondents aged 20-59 who worked from home (i) one or two days, (ii) three or more days, or (iii) no days at all in the survey week, broken down by country. The survey question was: "How many full paid working days are you working from home this week?"

Working from home: attitudes and expectations

The sudden closure of workplaces during the pandemic ushered in a new era of remote working for millions of employees and triggered a significant shift in the attitudes and expectations surrounding remote working. This section draws on the results of a new large-scale online survey that the EBRD and the ifo Institute recently conducted in 15 countries (including 7 economies in the EBRD regions), the respondents for which were representative of the working-age population in terms of age, gender and educational attainment. The purpose of the survey was to understand employees' experiences with working from home (in terms of time allocation, efficiency and future preferences) and employers' post-pandemic plans as regards remote working. While the survey provides early insights into such patterns and preferences, the limitations of online surveys should be borne in mind when considering the analysis that follows. In particular, online surveys may suffer from sampling bias, as certain sections of the population (such as elderly and rural residents) are less likely to have internet access and respond to online questionnaires, whereas the young, those living in cities, and those with higher levels of education and better digital skills are more likely to respond.

This survey points to a considerable Covid-induced shift towards remote working across the EBRD regions. The percentage of people who work remotely at least sometimes has increased from 8 to 44 per cent in Hungary, from 14 to 41 per cent in Poland, from 5 to 39 per cent in Greece and from 8 to 27 per cent in Serbia. More than 44 per cent of respondents spent at least one day working from home in the survey week (42 per cent in the EBRD regions, 47 per cent in high-income countries and 44 per cent in China; see Chart 3.9). In the EBRD regions, Turkey, Hungary and Ukraine had the highest levels of remote working, with 60, 45 and 44 per cent of respondents respectively saying that they worked from home at least one day that week. Levels of remote working in the EBRD regions are generally somewhat lower than in advanced European economies, but similar to China.

Respondents were also asked about their preferences as regards remote working after the pandemic. In order to inform possible future trends, respondents were asked the following questions:

- "After Covid, in 2022 and later, how often would you like to work from home (that is, have paid workdays at home)?"
- "After Covid, in 2022 and later, how often is your employer planning for you to work full days at home?"

Respondents with a tertiary education, those who previously commuted long distances (in 2019), those who use computers at work and those with children in the household all reported stronger preferences for working from home.

More generally, however, there is a gap between what employees desire and what they believe their employer is planning for the future (see Chart 3.10). Employees, for example, have a very strong preference for working from home in all countries: on average, they would like to do about two full working days per week at home once the pandemic is over.

Respondents generally reported favourable experiences with working from home. In the EBRD regions, 40 per cent of respondents reported that working from home had turned out better than they had expected pre-Covid, whereas only 14 per cent reported that it had turned out worse than expected. Indeed, respondents would, on average, even be willing to forgo 5 to 10 per cent of their monthly income in exchange for the option of working from home two or three days per week after the pandemic.

In contrast, employers plan, on average, to allow one full day of remote working per employee per week. That is consistent with recent research in this area, which has found that business leaders often mention concerns around workplace culture, motivation and innovation as important reasons for bringing workers onsite three or more days per week.[18]

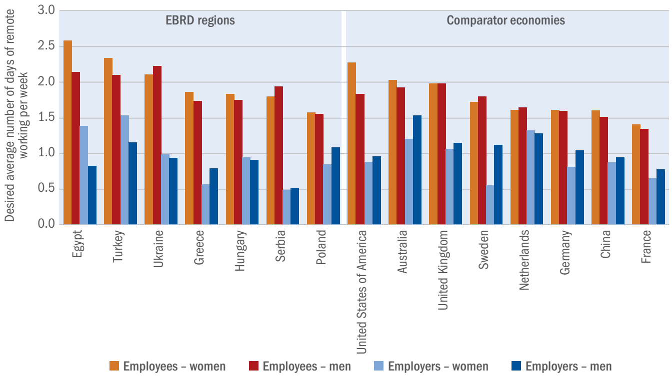
There are notable gender-based differences in preferences for remote working. In Egypt, Turkey and Ukraine, for example, preferences for remote working are considerably higher among women. In Greece and Poland, meanwhile, women have a stronger desire to work from home than men, but are less likely than men to believe that their employer will allow it. More generally, regression analysis controlling for earnings, the industry in question and the composition of the occupation shows that women are 5 percentage points less likely than men to believe that their employer plans to allow them to work from home at least one day a week after the pandemic.

In line with previous research, the results of this survey also suggest that the pandemic-induced shift towards working from home might increase efficiency.[19] About a third of respondents report that they have been more efficient working from home during the pandemic than they were working on the firm's premises before the pandemic (see Chart 3.11). On average, workers in the banking, finance, insurance and ICT service sectors report that they are over 7 per cent more efficient, whereas people working in education report efficiency gains of less than 1 per cent. In the EBRD regions, Turkey has the highest percentage of respondents perceiving themselves to be more efficient (more than 40 per cent), followed by Greece and Poland. At the other end of the spectrum, the lowest percentage of respondents experiencing efficiency gains is in Ukraine (25 per cent). Additional analysis indicates that while 39 per cent of respondents aged 45 to 59 in comparator economies report increased efficiency, the same is true of only 26 per cent of respondents in that age group in the EBRD regions. For respondents below the age of 45, the equivalent figures are 42 and 36 per cent respectively. Overall, self-reported efficiency gains in the EBRD regions are lower than in advanced economies, but higher than in China.

The pandemic has also improved attitudes towards working from home in all countries (see Chart 3.12). About 65 per cent of respondents report improvements in this regard, ranging from 78 per cent in Turkey to 49 per cent in Poland. Less than 10 per cent report a deterioration.

Improved perceptions about remote working, coupled with lingering fears about being around other people, are likely to sustain people's desire to work from home. Only about a third of respondents say that they will fully return to pre-Covid-19 activities once most of the population has been vaccinated. The vast majority of respondents report that they will continue to avoid crowded lifts, travelling on underground trains and dining indoors at restaurants.

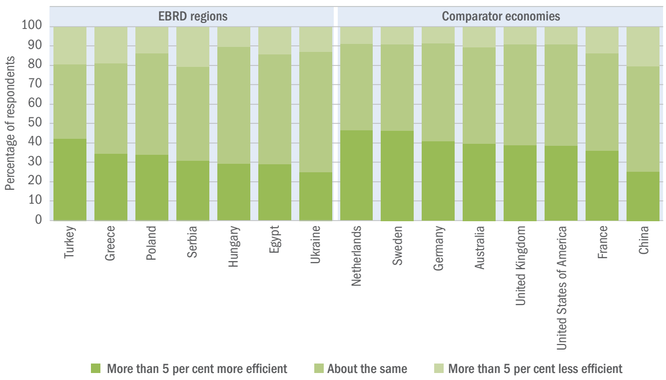
CHART 3.10. There is a gap between the views of employees and employers as regards working from home



Source: EBRD-ifo survey (2021) and authors' calculations.
Note: Respondents who were unaware of their employer's plans (19 per cent of respondents) and those who did not have an employer at the time of the survey (4 per cent) have been omitted from this analysis.

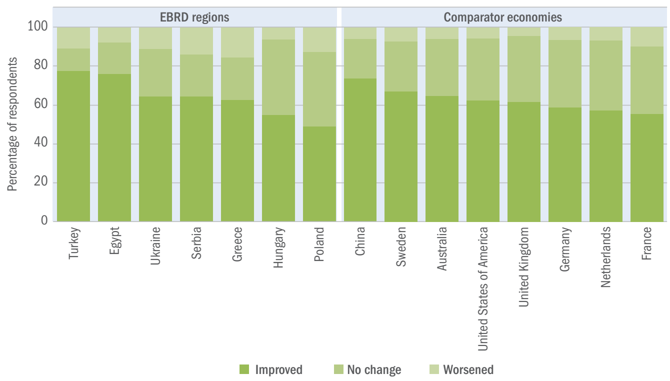
[18] See Barrero et al. (2021) and Altig et al. (2020).
[19] See Barrero et al. (2021).

CHART 3.11. About a third of respondents believe they are more efficient when working from home



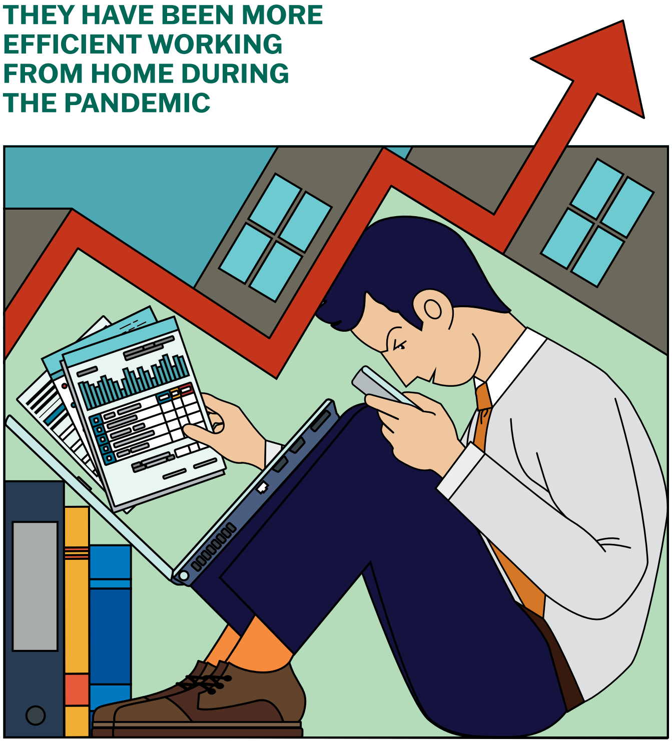
Source: EBRD-ifo survey (2021) and authors' calculations.
Note: The survey question was: "How does your efficiency working from home during the Covid-19 pandemic compare to your efficiency working on business premises before the pandemic?"

CHART 3.12. Perceptions about working from home have improved in most economies



Source: EBRD-ifo survey (2021) and authors' calculations.
Note: The survey question was: "Since the Covid pandemic began, how have perceptions about working from home changed among people you know?"

ABOUT A THIRD OF WORKERS SAY THAT THEY HAVE BEEN MORE EFFICIENT WORKING FROM HOME DURING THE PANDEMIC



Advances in AI: transforming the jobs that people do

AI technologies can perform tasks that humans would otherwise do. Such tools can be both labour saving and labour-augmenting, so they have the potential to both displace and create jobs.

On the one hand, AI technologies can generate digital dividends through increases in the marginal productivity of labour. This, in turn, can increase labour demand, for both pre-existing and previously non existent occupations. As with the first wave of digitalisation (which was characterised by widespread adoption of the personal computer) and with robotisation, one can expect labour productivity to increase as a result of the adoption of AI.[20] This will happen in occupations where AI is complementary to human effort. Such occupations tend to be non-manual and include a combination of both routine and non-routine work. Rather than complete routine tasks themselves, workers can use AI. Already, advances in AI have delivered impressive results in the fields of translation, text generation and legal research. The time saved can then be used for more creative or interpersonal aspects of production.[21]

On the other hand, AI can also be used to replace human workers. Such job displacement occurs when the new technology performs tasks just as well as – or better than – humans, such that the technology can be substituted for human labour. AI is advancing rapidly in this regard. For example, machine learning models are now better at detecting lung cancer from CT scans than experienced radiologists.[22]

[20] See Cardona et al. (2013), Brynjolfsson and Hitt (2003) and Graetz and Michaels (2018).
[21] See Damioli et al. (2021) for evidence of increases in productivity at firms patenting AI.
[22] See Ardila et al. (2019).

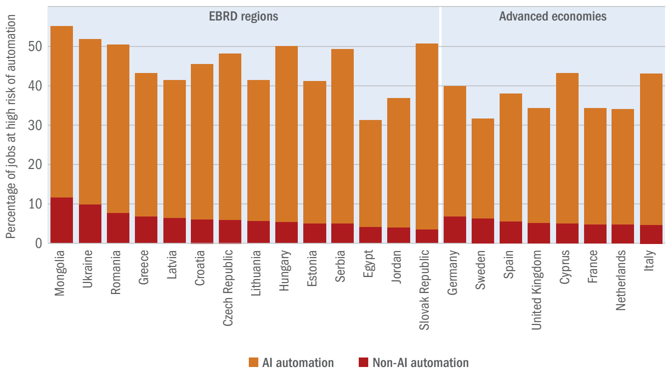
This section assesses AI exposure, looking at how it is distributed across countries, regions, gender and age cohorts (see also Box 3.4 on the ways in which industrial robots affect the gender pay gap). AI exposure is measured as a weighted share of the abilities that AI technologies can perform in a given occupation (see Box 3.1 for details).[23] While greater AI exposure does not automatically mean greater displacement (as automation may not be profitable), jobs with very high levels of AI exposure will be more vulnerable to displacement.

This section also compares the percentages of jobs that are at risk of displacement by AI and non-AI automation.[24] Non-AI automation involves the use of computer controlled equipment such as industrial robots, which has been at the heart of recent debates about digitalisation and job losses.

Lastly, this section estimates changes in employment that are due to advances in AI (see Box 3.6 for a discussion of the wider implications for the labour market). A decline in employment in highly exposed occupations would point to a net displacement of labour, while an increase would be indicative of a net productivity effect. Employment effects for tertiary and non-tertiary-educated workers are evaluated separately. This analysis of changes in employment does not seek to predict productivity growth or job creation. Nonetheless, assessing the net impact of AI so far, and the areas that are vulnerable to displacement, can provide an indication of the ways in which AI may affect labour markets.

THE 10% OF OCCUPATIONS WITH THE HIGHEST AI EXPOSURE ACCOUNT FOR JUST 6.3% OF JOBS IN THE EBRD REGIONS (RANGING FROM 3.6% IN THE SLOVAK REPUBLIC TO 11.8% IN MONGOLIA)

CHART 3.13. Fewer jobs are at high risk of displacement by AI automation than non-AI automation



Source: Felten et al. (2018), Frey and Osborne (2017), labour force surveys (2016-19) and authors' calculations.
Note: An occupation has a high level of exposure to non-AI automation if the probability of computerisation, as defined by Frey and Osborne (2017), exceeds 0.7. Similarly, an occupation has high exposure to AI automation if its normalised AI exposure exceeds 0.7. See Box 3.1 for details.

Jobs that can be done by AI

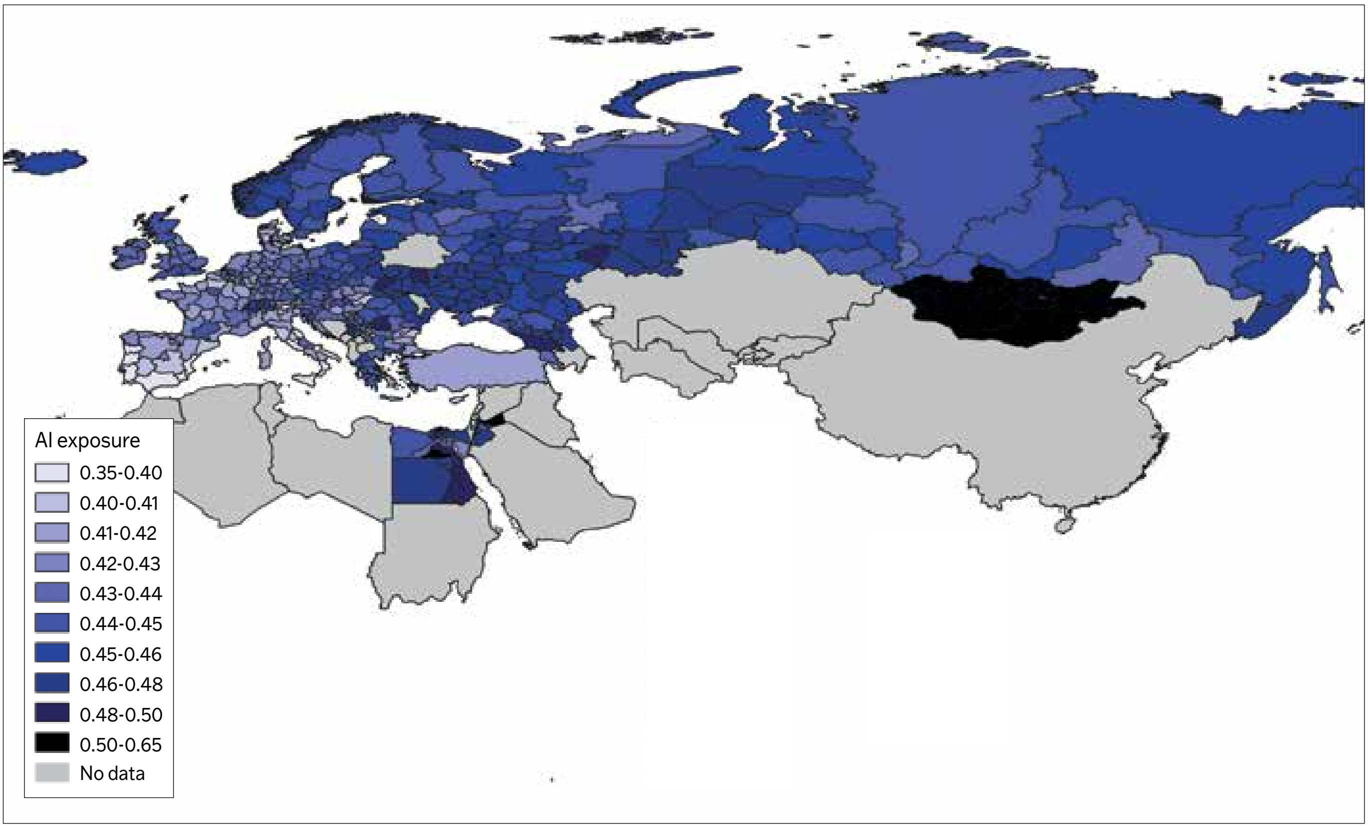
The 10 per cent of occupations with the highest AI exposure scores account for only 6.3 per cent of jobs in the EBRD regions (with that percentage ranging from 3.6 per cent in the Slovak Republic to 11.8 per cent in Mongolia; see Chart 3.13). Thus, AI technologies threaten substantially fewer jobs than non-AI automation.

Many economies in the EBRD regions have higher levels of AI exposure than advanced European economies (see Chart 3.14). Previously, demand for AI-related skills was confined almost exclusively to the ICT sector, but that is no longer the case.[25] For instance, Mongolia's high AI exposure is driven by the fact that agricultural workers – an occupation with a high level of exposure to AI – make up a large percentage of the country's labour force. In advanced European economies, by contrast, many such jobs with high exposure to AI are already in decline as a result of new production technologies (including AI-based methods).[26]

AI exposure varies more across occupations than across countries. Highly exposed occupations typically involve a variety of abilities that AI technologies can perform reasonably well, such as vision related, communication and cognitive abilities. In contrast, occupations that rely mostly on manual dexterity have low levels of AI exposure. The people with the least exposed occupations are cleaners and domestic helpers, while health professionals (including both

[23] See also Felten et al. (2018).
[24] See Frey and Osborne (2017).
[25] See Alekseeva et al. (2021) and Chapter 1 of this report.
[26] See also Cedefop (2016).

CHART 3.14. The EBRD regions have higher levels of AI exposure than advanced European economies

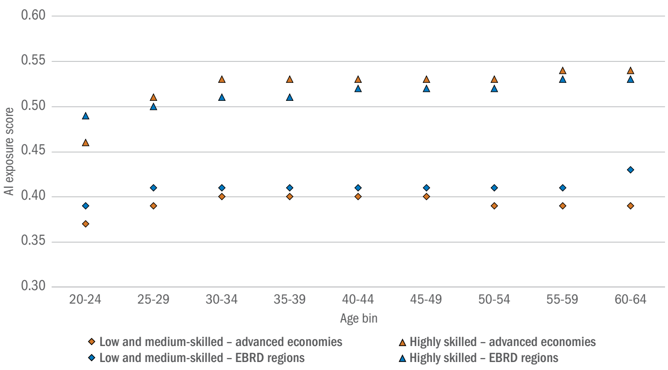


Source: Felten et al. (2018), labour force surveys (2016-19) and authors' calculations.
Note: This map is used for data visualisation purposes only and does not imply any position on the legal status of any territory.

nurses and surgeons) are among the most highly exposed since AI is adept at performing vision-related tasks and can quickly combine and organise information. High-skill jobs in the field of science, such as physicists, also have high levels of AI exposure owing to AI's proficiency in inferring rules from information and combining information to deduce formal rules.

While the occupations of highly skilled workers are 25 to 40 per cent more exposed to AI than those of low-skilled workers (see Chart 3.15), highly skilled workers may still benefit more from advances in AI in the long run (see also Box 3.5 for a discussion on promoting equal opportunities in the context of digitalisation). One reason for this is that high-skill jobs often require a combination of tasks, involving both pattern-recognition tasks (which are very well suited to AI) and interpersonal tasks (which are less suitable for AI).

CHART 3.15. Differences in AI exposure on the basis of skill levels are smaller in the EBRD regions than in advanced economies



Source: Felten et al. (2018), labour force surveys (2016-19) and authors' calculations.

MEN ARE MORE LIKELY TO HAVE OCCUPATIONS WITH A HIGH LEVEL OF AI EXPOSURE

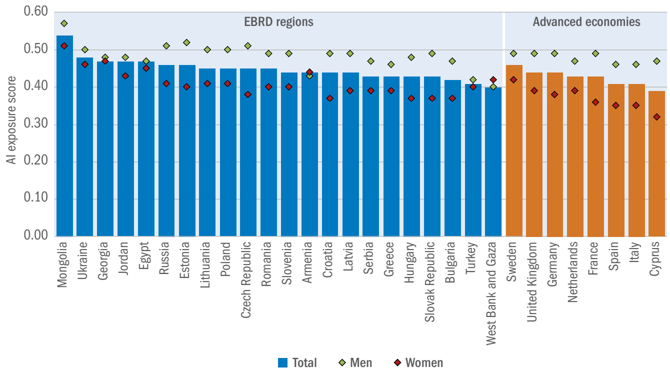
The highly exposed jobs performed by highly skilled workers (such as medical doctors, physical and earth science professionals, engineering professionals and life science professionals) have high levels of AI exposure because of their pattern-recognition tasks, which AI does well. Thus, while it may be unwise to completely automate patient-facing healthcare occupations, for example, it is entirely possible for AI to perform large percentages of the diagnostic tasks associated with such jobs.

Men are more likely to have occupations with a high level of AI exposure (see Chart 3.16). Highly exposed occupations commonly held by men include jobs in the electrical and electronic sector and jobs in the protective services sector.

In order to assess the net effect that advances in AI have on employment, this chapter analyses changes in each occupation's share of national employment between 2011 and 2019 that could be linked to AI exposure (controlling for factors that could influence both AI exposure and employment growth). The ICT industry is omitted (see Box 3.2 for details). The results indicate that, although the effect is not statistically significant, occupations with higher levels of AI exposure have seen a decline in their share of national employment. The effect is larger for highly skilled workers (see Chart 3.17). At industry level, however, the correlation is positive and statistically significant. A 1 standard deviation increase in an industry's AI exposure is associated with a 3 per cent increase in its share of employment, with an additional 4.6 per cent increase for tertiary-educated workers. By way of comparison, tertiary educated workers' share of overall employment rose by over 30 per cent more than that of non-tertiary-educated workers in the same period.

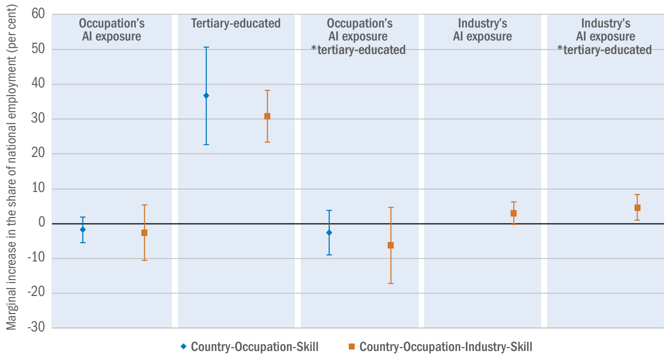
Thus far, advances in AI have not yet had a strong impact on employment,[27] but as AI becomes more sophisticated, the level of AI exposure will increase for many occupations. This analysis does not seek to predict which new jobs will be created as a result of future AI technologies or which jobs will be made redundant. Indeed, the measure of exposure does not capture the most recent advances in AI, such as those seen in the field of natural language processing. Nonetheless, the analysis presented here points to a complex impact on the labour market, with highly educated people benefiting relative to less-educated workers.

CHART 3.16. In almost all economies, men's jobs have higher levels of AI exposure



Source: Felten et al. (2018), labour force surveys (2016-19) and authors' calculations.

CHART 3.17. Exposure to AI is associated with a limited decline in the share of employment at occupation level



Source: Dingel and Neiman (2020), EU labour force surveys (2011 and 2019), Felten et al. (2018), Goos et al. (2014), Webb (2019) and authors' calculations.
Note: This chart plots the marginal increase in the share of national employment that is associated with a 1 standard deviation increase in the different variables, broken down by industry and occupation. Square brackets indicate 95 per cent confidence intervals. See Box 3.2 for details of the regression.

[27] A separate analysis using the European Social Survey fails to find any impact on wages over the period 2010-14 as a result of exposure to AI. Thus, any productivity effects are not reflected in wages.

Conclusion

The digitalisation of the workforce is changing the ways in which people work and the jobs that they do. Covid-19 has accelerated pre-existing trends, particularly by bringing forward some workers' geographical separation from the office. Across the EBRD regions, women are more likely to have teleworkable occupations than men. However, they are also less likely to work from home in practice. And while highly educated workers in the EBRD regions are up to three times more likely to have a teleworkable occupation than workers with lower levels of education, the rate at which they work from home is far lower than that of their peers in more advanced economies. Some of that is to do with trust, since people in regions with lower levels of interpersonal trust are less likely to work from home, even after controlling for occupational characteristics.

Low levels of digital skills are probably also a barrier to increases in remote working, especially among older workers. Unlike in advanced economies, older cohorts in the EBRD regions are less likely to have teleworkable occupations. However, even young people in the EBRD regions have weaker ICT skills than their peers in more advanced economies.

When it comes to actual remote working, workers have proven that they can be productive outside of the workplace, and acceptance of remote working has increased. Survey respondents have indicated that they want to keep working from home after the pandemic ends, planning to work about two full days per week from home. These results suggest that, broadly speaking, working from home is likely to become more acceptable in the longer term.

The pandemic may also be accelerating firms' adoption of AI technologies. Workers who perform routine cognitive tasks may start to see many of those tasks being executed by AI. While occupations with the highest exposure to AI account for only a small percentage of overall employment, some sectors may be dramatically affected, including sectors not traditionally thought of as digital-intensive. The impact of AI can be expected to increase over time. Thus far, the effect of high AI exposure on employment growth at occupation level has been negative but not statistically significant. Meanwhile, the impact has been marginally greater for highly skilled workers in highly exposed industries, pointing to possible productivity effects.

These findings have several policy implications. First, increases in teleworking may lead to de-urbanisation.[28] Regions with high levels of teleworkability may then lose low and medium-skill jobs that serve the commuting population. The resulting reduction in the tax base could also weigh on local spending on infrastructure, maintenance and other public goods. Monetary support for cities undergoing such a transition will be important – for example, so that local governments can help to match remaining residents to appropriate jobs.

Second, the upgrading of skills will be essential for economies in the EBRD regions. Private sector-led digital training programmes can send clear signals about demand for skills, while also increasing supply. Moreover, closing the gap in terms of ICT-related skills will help the EBRD regions to leverage the benefits of future technological change while minimising any disruptive impact that digitalisation has on the labour market. At the same time, this may potentially make economies in the EBRD regions more attractive as destinations for teleworkable jobs offshored from advanced economies.

Third, although AI technologies have not yet had a significant impact on employment at occupation level, job vacancies advertised by highly exposed firms are showing increased demand for skills that complement AI, implying an intention to make greater use of AI moving forward.[29] This suggests that policymakers should be aware of the potential for job displacement – not only for low and medium-skill occupations, but also for some highly exposed, high-skill occupations. Specific suggestions in this regard include: (i) providing child support payments to displaced parents, in order to mitigate the intergenerational impact of job losses; (ii) encouraging collaboration among private-sector partners with a view to helping workers to find new employment; (iii) helping people to deal with the psychological impact of job displacement, for example by raising awareness of and increasing support for displaced people within their communities; and (iv) broadening eligibility for wage support payments, for instance by making them available to part-time employees.

[28] See also Federal Reserve Bank of Dallas (2020).
[29] See Acemoğlu et al. (2020a).

BOX 3.1.

Constructing measures of teleworkability and exposure to AI

This box explains the measures of teleworkability and AI exposure that are used in this chapter, which are constructed in line with Dingel and Neiman (2020) and Felten et al. (2018) respectively. In this analysis, each occupation is defined as a finite collection of core tasks, which require specific skills. For example, a chief executive carries out a broad range of tasks, such as "making decisions and solving problems" and "developing and building teams".

Teleworkability

An occupation is considered to be teleworkable if all of the relevant tasks can be performed remotely. Occupations that are not teleworkable involve at least one task that cannot be carried out remotely. The task content of occupations is sourced from the "work content" and "work activities" modules of the O*NET database. That database contains data on 1,000 occupations in the United States of America (disaggregated at the level of six-digit SOC codes). Data are collected by surveying randomly sampled workers, as well as occupation experts. A median of 25 workers are surveyed per occupation.

All occupations are assessed on the basis of the same 15 tasks. For example, if the majority of survey respondents spend the majority of their time at work walking or running, the occupation as a whole is not considered to be teleworkable. Teleworkability scores for six-digit SOC codes are mapped to two and three-digit ISCO occupational codes using employment weights. However, a number of caveats apply. Partially teleworkable occupations (which account for around 10 per cent of workers) are considered to be non-teleworkable in this analysis. Moreover, estimates based on a US survey may not be an entirely accurate reflection of an occupation's task content at a global level (although they should provide a useful approximation).

AI exposure

The measure of AI exposure relies on data on the ability requirements of each occupation, based on 52 distinct abilities recorded in O*NET. Examples of abilities include spatial orientation, fluency of ideas and reaction time. In addition, each AI technology is characterised by the speed of its progress between 2010 and 2015, using data from the Electronic Frontier Foundation (EFF) and the methodology in Felten et al. (2018).

Each technology is mapped to 16 categories of AI (such as image recognition, speech recognition or machine translation), and they, in turn, are mapped to the abilities in O*NET. This generates a weighted measure of AI performance for each ability. The AI exposure score for an occupation aggregates the AI performance scores of the relevant abilities. AI exposure scores at six digit SOC level are then mapped to two and three-digit ISCO occupations. The final score is normalised such that it lies between 0 and 1.

The main caveat with this measure is that it relies on published data on the progress of AI, which could exclude private development efforts and understate actual progress for some technologies. A second caveat is that the abilities which are needed to carry out more complex tasks may be harder to quantify. Lastly, the relationship between advances in AI and their commercial use may be non-linear. Whereas some tasks, such as autonomous driving, require very robust levels of performance, for other tasks (such as recognition of handwritten addresses) the bar may be much lower.

BOX 3.2.

Regression analysis

Trust and propensity to work from home

In the analysis of the importance of trust for the propensity to work from home, working from home for at least one hour per week is linked to the average level of trust in a person's region of residence, the percentage of households with broadband internet and individual level characteristics (including occupation (at three-digit level), industry of employment (at one digit level) and country of residence).

The average level of trust in other people is measured at NUTS-2 level using an average of waves 4 to 8 of the European Social Survey. The percentage of households with broadband internet at NUTS-2 level is obtained from Eurostat.

NUTS-2-level control variables include the European Quality of Government Index produced by the University of Gothenburg, trust in police (derived from the European Social Survey) and population density (taken from Eurostat). In addition, several individual-level variables are included in the analysis: dummy variables indicating whether a person is tertiary-educated, lives in a rural administrative unit, is male or female, is under 35 years of age, has children in their household (for men and women separately) or works part time. The analysis also includes occupation-industry fixed effects. The sample includes all respondents participating in EU labour force surveys in the period 2016-19 who were aged between 18 and 64 and part of the workforce. Bulgaria, Malta, Poland and Slovenia are excluded, since detailed data on occupations are not available. The regressions are run separately for the EBRD regions and comparator economies.

Changes in employment and exposure to AI

Linear probability model regressions relate (i) relative changes in employment between 2011 and 2019 in a bin comprising a given occupation, level of educational attainment and country (as a percentage of total employment) to (ii) the measure of AI exposure for a given occupation. A similar specification is used to relate (i) changes in employment at country-industry-occupation-education level to (ii) AI exposure at both industry and occupation level. Another key coefficient of interest is that of a binary dummy for tertiary education. Interaction terms combining AI exposure and tertiary education are included to assess the differential impact that AI has on low and high-skilled workers.

Additional control variables include measures of exposure to software and exposure to robotisation derived from Webb (2019), a measure of the ease with which production can be moved offshore – which is calculated for the same occupations and industries as AI exposure, building on Goos et al. (2014) – and country fixed effects. Occupations are at three-digit ISCO level, industries are at one-digit NACE level, and educational attainment indicates whether or not people are tertiary-educated.

Changes in employment shares are calculated on the basis of responses to labour force surveys conducted in 2011 and 2019, using the associated weights. (As before, Bulgaria, Malta, Poland and Slovenia are excluded.) ICT-related sectors are omitted, in order to focus on the effects in industries not closely involved in the development of AI. Standard errors are clustered at the level of measures of AI exposure.

BOX 3.3.

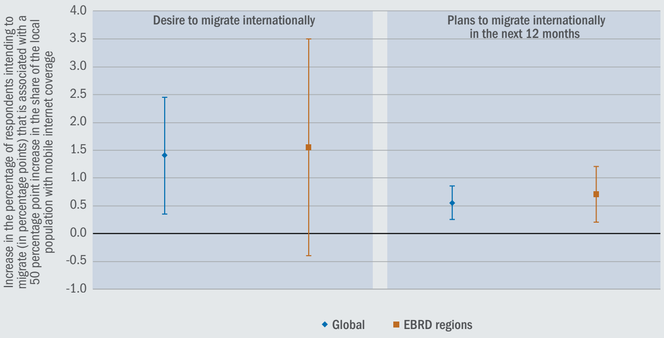
The expansion of mobile internet and increases in the desire to migrate

Digital technologies – particularly broadband internet, mobile phones and other means of sharing information digitally – have profoundly changed the ways in which people connect, meet and exchange information. This rapid technological progress has also led to increased interest in the socio-economic and political impact of widespread access to the internet, with the number of internet users worldwide rising from 413 million in 2000 to nearly 4.1 billion in 2019.[30]

The rapid expansion of mobile internet around the world means that people are increasingly gaining access to detailed information about living standards in other countries. Indeed, progress in terms of digital technologies has coincided with increases in cross-border migration: in 2017, almost 10 per cent of people living in the EBRD regions were not in their country of birth or citizenship – up from 8 per cent in 1990.[31]

This box looks at how the roll-out of mobile (3G) internet is shaping intentions to migrate abroad, both globally and in the EBRD regions. It combines data on intentions to migrate (as reported by more than 600,000 respondents surveyed as part of the Gallup World Polls across 2,105 subnational regions in 110 countries in the period 2006-18) with data on the roll-out of mobile internet derived from Collins Bartholomew's Mobile Coverage Explorer.

CHART 3.3.1. The expansion of 3G internet coverage is associated with increases in people's desire to migrate



Source: Gallup World Poll and authors' calculations.
Note: This chart reports estimated coefficients from a linear probability model regressing stated intentions to migrate on the percentage of the local population that has access to mobile internet. Controls include (i) gender, (ii) age, (iii) age squared, (iv) marital status, (v) the presence of children in the household, (vi) whether the respondent lives in an urban area, (vii) educational attainment, (viii) whether the respondent was born in the country, (ix) satisfaction with housing, health care, education, roads, transport, the city and life in general, (x) other attitudes, experiences and beliefs, (xi) the log of average per capita income in the region, (xii) the log of per capita income in the respondent's household, (xiii) the Polity 2 score and (xiv) the percentage of respondents under the age of 30. The 95 per cent confidence intervals shown are based on standard errors with two-way clustering at country-year and region level. The unit of analysis is at individual level.

The regression analysis relates intentions to migrate to the penetration of 3G mobile internet in a subnational region in a given year, while accounting for subnational region and year fixed effects, linear region-level time trends, and various characteristics at individual, region and country level.[32]

The results of the analysis indicate that increasing 3G coverage in a given locality in the EBRD regions from 0 to 50 per cent of the local population is associated with an increase of 1.5 percentage points in the likelihood of having a desire to migrate, and an increase of 0.7 percentage points in the likelihood of having plans to migrate in the next 12 months. These are sizeable effects, given that an average of 21 per cent of respondents report a desire to migrate in principle and an average of 1.3 per cent report having plans to do so in the near future. These effects are similar to those estimated for the global sample – and, if anything, somewhat larger (see Chart 3.3.1).

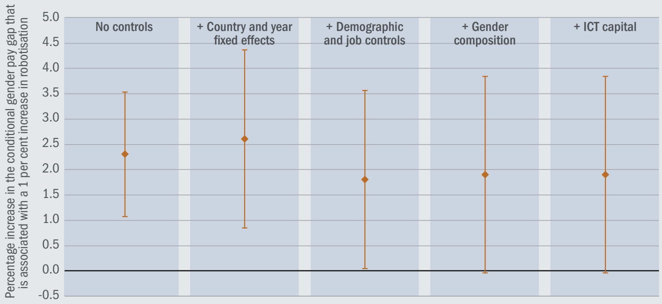
Additional analysis reveals that the effects are stronger for unemployed respondents and those with less than tertiary education. What is more, the results are driven mainly by middle and higher income countries. As migration tends, at first, to increase as incomes rise (only falling at much higher income levels),[33] digitalisation can further accelerate this trend by increasing the quality of information about life abroad. In order to address the resulting labour shortages in their domestic economies, governments can work with firms to establish training programmes with a view to fostering skills that are widely sought after in domestic labour markets. Policies aimed at attracting highly qualified migrants from abroad can also help to address specific labour market shortages in the short term.

[30] See Guriev et al. (2021) and ITU (2019).
[31] See EBRD (2018).
[32] See Adema et al. (2021) for details.
[33] See Clemens and Mendola (2020).

BOX 3.4.

Could automation exacerbate the gender pay gap?

CHART 3.4.1. Robotisation is associated with a larger gender pay gap



Source: Structure of Earnings Survey, International Federation of Robotics, EU KLEMS and authors' calculations.
Note: This chart reports coefficients from instrumental variable regressions of the conditional gender gap in median monthly earnings in a given country-sector pair on the level of robotisation (inverse hyperbolic sine transformation of changes in the number of robots per 10,000 workers). The instrumental variable is replaceable hours, which measures the percentage of each industry's hours in 1980 (before robotisation) that were performed by occupations and later became susceptible to replacement by robots. The analysis is performed at "demographic cell" level (whereby data are collapsed by country, industry, year, age group, occupation and firm size). All regressions include a constant, the age group, the occupational group, the percentage of full-time workers, a dummy for firms employing more than 250 workers, the percentage of female workers, and the change in the percentage of female workers for a given country-sector pair. The calculation is based on Bellemare and Wichman (2020). The 95 per cent confidence intervals shown are based on robust standard errors with two-way clustering by country and industry.

Building on Aksoy et al. (2021), this box provides large-scale evidence on the impact that the adoption of robots has on the gender pay gap, studying 20 European countries over the period 2006-14. Specifically, the box looks at how robotisation (as measured by increases in the number of robots per 10,000 workers between survey years) affects the gender gap in the monthly earnings of workers in sectors that commonly employ robots (manufacturing of vehicles, plastics and chemicals, metals, food and beverages, electrical equipment, wood and paper, and textiles, as well as other manufacturing, mining, education and research, construction and utilities).

The analysis is motivated by the fast-moving changes seen in the frontier between activities performed by humans and activities performed by machines, which have been transforming the world of work.[34] The impact of automation is likely to be different for men and women. For instance, Brussevich et al. (2019) construct a gender-specific index of routine task intensity (RTI) using the OECD's PIAAC database. The RTI index quantifies the extent to which tasks performed as part of a job can be codified, indicating that a worker is engaged in more routine activities. In occupations with higher levels of RTI (such as hand packing), workers are easier to replace with machines.

Using the RTI index, Brussevich et al. (2019) find that female workers are, on average, more exposed to automation risk. The gender gap in RTI is driven by female workers performing fewer tasks that require analytical or interpersonal skills or physical labour, and more tasks that are characterised by a lack of flexibility, little on-the-job learning and higher levels of repetition. The analysis in this box complements that study by looking at the evolution of wages by gender in response to robotisation.

Findings

This box estimates a conditional gender pay gap – defined as the difference between the earnings of men and women of a similar age residing in the same country who work within the same occupational category and industry and in firms of a similar size – which is calculated on the basis of data from Eurostat's Structure of Earnings Survey. Thus, the conditional pay gap takes account of many factors that may account for differences between men's and women's earnings and is closely related to the principle of "equal pay for equal work". The analysis links the conditional gender pay gap to the rate of increase seen in the use of robots in a specific sector and country (as obtained from the International Federation of Robotics), as well as a number of other characteristics (such as the industry and country in question).

The results suggest that robotisation increases the gender pay gap, with a 10 per cent increase in robotisation leading to a 1.8 per cent increase in the conditional gender pay gap across the sample as a whole (see Chart 3.4.1).

Mechanisms

The results probably reflect the fact that men's productivity has increased more in response to robotisation, especially in medium and high-skill occupations. In other words, women tend to be under represented in medium and high-skill occupations in industries where workers' productivity is enhanced by robotisation. This exacerbates the gender pay gap, especially in countries where gender inequality was already severe. Since this analysis is based on a conditional gender pay gap, the results cannot be explained by changes in the gender composition of the workforce, either across the economy as a whole or in specific sectors.

Implications

In order to lean against this trend, governments need to ensure that education and vocational training systems provide all people – irrespective of their gender and other characteristics – with the skills they need to take advantage of technological progress. People in sectors affected by automation could, for example, benefit from targeted reskilling programmes. Dedicated funding for education providers that is tied to gender equality in training programmes or targeted support for childcare can also help to mitigate the unequal impact of automation across genders.

[34] See Grigoli et al. (2020).

BOX 3.5.

Promoting equal opportunities when demand for skills changes

Digitalisation is changing the ways in which people work, learn and earn across the EBRD regions, creating new opportunities for some while threatening to marginalise others. Remote-working possibilities, for example, can unlock new economic opportunities for workers with the right digital skills who are less mobile than others.

Process automation and machine learning are supplanting demand for manual and routine work, stranding workers' human capital in the absence of adequate retraining opportunities. Meanwhile, digital technologies can also boost demand for low-skilled workers in occupations that are difficult to automate (such as cleaning or construction), as well as increase labour demand in high-skill occupations which involve non-routine, creative tasks that leverage the use of digital technologies. The analysis below looks at such polarisation of jobs in the EBRD regions using employment data broken down by occupation.

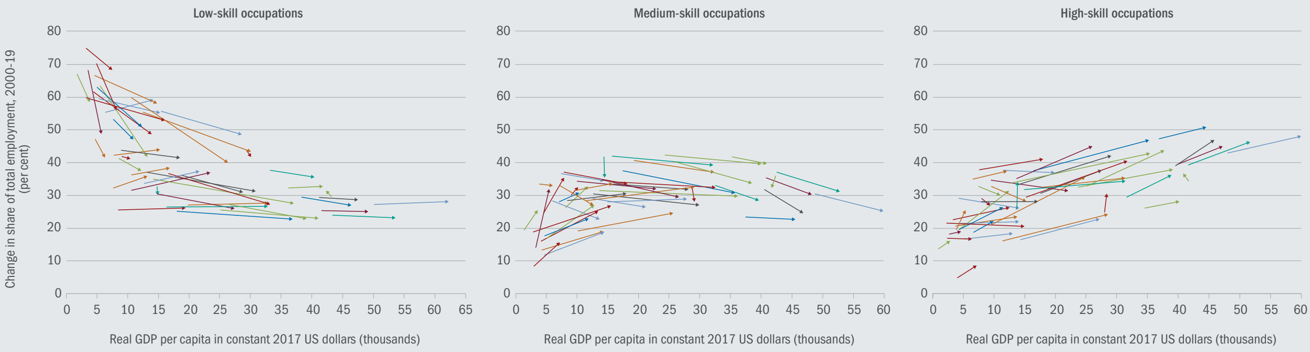
Skills profiles have shifted dramatically across the labour markets of the EBRD regions over the last two decades (see Chart 3.5.1). Low-skill occupations have been in decline, particularly in lower income economies that previously had large numbers of low-skilled workers as a percentage of total employment (such as Armenia, the Kyrgyz Republic, Moldova and Morocco). The percentages of low skilled workers in those economies have tended to slowly move towards the 25-30 per cent mark – the average across the G 7, where the percentage of low-skilled workers has been stable over the last two decades.

Demand for medium-skill occupations intensifies as economies develop, before falling away again. As economies in the EBRD regions have grown richer, many workers in traditional sectors with lower levels of value added have switched to more productive medium-skill work. In the Kyrgyz Republic, for instance, the percentage of workers with medium-skill occupations has increased by 19 percentage points since 2000. In contrast, that percentage has waned in more technologically advanced countries on the back of the automation of production (with declines of 6-7 percentage points being seen in Estonia and Slovenia, for example – equivalent to the rates of decline observed in Germany and the United States of America).

High-skill occupations, meanwhile, continue to expand in both lower and higher-income countries. For example, highly skilled workers' share of total employment has risen by 12 percentage points in Moldova and 11 percentage points in Poland since 2000. This is a welcome trend, insofar as workers with such occupations typically enjoy better working conditions, career opportunities and pay.

Analysis suggests that digitalisation has, on balance, been accompanied by upgrading of occupations in the EBRD regions. Policymakers can take a number of steps to help sustain such upskilling going forward. The first area of focus is equality of opportunity at the point of entry into the labour market. Second, policymakers should leverage partnerships between industry and providers of vocational training, as well as seeking private-sector input when developing sectoral skills standards to ensure a better match between the supply of skills in the economy and employers' demand for skills. In this context, the EBRD has been supporting a number of industry-specific training programmes, from ICT and agribusiness in Serbia to the automotive sector in Morocco. Third, equal access to the internet across urban and rural areas is a key feature of equality of opportunity in the digital era, as discussed in Chapters 1 and 4 of the report. And fourth, specific training programmes and more inclusive user interfaces may be needed in order to support people with disabilities, older workers and other people facing barriers to accessibility.

CHART 3.5.1. The shares of medium-skill occupations rise as economies develop, before falling away again on the back of automation



Source: ILOSTAT database, IMF and authors' calculations based on modelled ILO estimates.
Note: Low-skill occupations comprise ISCO-88 groups 5, 6 and 9 (service workers and shop and market sales workers; skilled agricultural and fishery workers; and elementary occupations). Medium-skill occupations comprise groups 4, 7 and 8 (clerks; craft and related trades workers; and plant and machine operators and assemblers). High-skill occupations comprise groups 1, 2 and 3 (legislators, senior officials and managers; professionals; and technicians and associate professionals).

BOX 3.6.

Is there too much automation?

There is enormous potential for digitalisation to improve the productivity of human effort. However, achieving a socially optimal level of digitalisation may be difficult. On the one hand, to the extent that new technologies such as software are costly to develop but easy to copy, their supply is sometimes lower than would be socially optimal. Tax systems often attempt to correct this by providing incentives to invest in R&D, which helps to create new, more productive jobs.

On the other hand, light taxation of capital and heavy taxation of labour can give rise to "excessive" digitalisation. Capital tends to be substantially more mobile across borders than labour, and international competition for investment in physical capital can drive down effective rates of taxation on capital relative to labour.[35] Large US technology companies, for instance, are estimated to pay an effective tax rate of around 5 per cent on their foreign profits.[36]

Taxes that favour capital incentivise firms to adopt more labour-saving technologies than would be socially optimal. If the tax wedge is large enough, firms may even use digital technologies that fail to perform as well as humans.[37] The wedge between the socially optimal level of tax on capital relative to labour and the actual level of tax is estimated to have increased since 2000 in the United States of America, as global competition for capital has intensified.[38] The wedge is largest when it comes to investment in software.

Job displacement owing to technological change is a necessary driver of economic development. Technological change tends to create new, productive jobs while destroying others, with net job creation estimated to be close to zero.[39] However, excessive job displacement caused by policy distortions can have considerable costs in terms of increased inequality and lower social cohesion. Those costs can be particularly high in economies where large numbers of people have occupations involving routine cognitive tasks. Automation is affecting a growing number of occupations, with AI performing increasingly complex tasks, from identifying fraudulent loan applications to finding errors in legal documents. What is more, job losses caused by such displacement have lasting effects on workers. Wages rarely recover relative to peers who leave their jobs by choice. Displacement can also impair health, increase mortality and have a negative impact on children.[40]

Labour market frictions such as job search costs or the cost of firing workers amplify the costs of under-taxation of capital by acting as an additional tax on labour. Indeed, it may be socially optimal to reduce taxes on labour to compensate for pronounced labour market frictions. In addition, flexible labour market policies, standardised professional accreditation and large-scale online job markets can all help to ease labour market frictions.

Rebalancing the taxation of labour and capital requires international cooperation. Discussions are under way on setting a global minimum tax rate for capital, which may pave the way for a broader rebalancing of tax systems.

[35] See Winner (2005).
[36] See Toplensky (2018).
[37] See Acemoğlu and Restrepo (2019).
[38] See Acemoğlu et al. (2020b).
[39] See Acemoğlu and Restrepo (2020) and Graetz and Michaels (2018).
[40] See Lachowska et al. (2020), Schaller and Stevens (2015), Sullivan and von Wachter (2009) and Oreopoulos et al. (2008).

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