Job Creation and Local Economic Development 2024

THE GEOGRAPHY OF GENERATIVE AI

OECD

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Preface

Over the last five years, OECD countries have shown remarkable labour market dynamism, with employment rates at or near record-highs. In parallel, gender gaps in labour market participation have narrowed in regions across the OECD.

Strong labour demand has resulted in labour shortages in the most vibrant regions, while other regions continue to have untapped workforce potential. Similar disparities exist regarding labour productivity, with many regions with low employment rates also exhibiting lower levels of productivity.

This edition of Job Creation and Local Economic Development provides new evidence on how the advent of Generative AI can contribute to closing these regional gaps, while continuing to boost economic growth in the most dynamic regions. Generative AI, in addition to automation and other digital breakthroughs, offers significant potential to boost productivity, particularly in urban areas where a third of workers expect to be able to complete many of their tasks twice as quickly. Generative AI can also help to address growing labour shortages, especially in regions with an ageing population or that are experiencing population decline.

Sound policies are needed for all regions to unlock the full potential of generative AI, particularly rural regions that have further potential to boost jobs, productivity and incomes. Targeted programmes should focus on addressing place-specific obstacles, whether they relate to a region's attractiveness to workers and capital, the quality of regional education and training systems, or regulatory frameworks. Adequate investment in digital infrastructure, not least to address existing, and often significant, urban-rural divides in access to high-speed internet, will also be needed.

Through novel estimates for 35 OECD countries that show the degree of exposure of regional labour markets to Generative AI, this edition of Job Creation and Local Economic Development highlights the full potential and impact of Generative AI, as well as opportunities to ensure that all regions are able to benefit.

In doing so, the report aims to provide policy makers at all levels of government, business and civil society with insights into the transformative potential of Generative AI for jobs, and recommendations to leverage AI to drive economic growth, enhance productivity, and create more resilient and inclusive labour markets.

Foreword

Despite the recovery from COVID-19, regional and local economies in OECD countries continue to undergo significant transformations. An ageing workforce, sluggish productivity growth, persistent regional disparities, pervasive labour shortages across even more regions, and the rapid advancement of new technologies will require comprehensive transitions for both individuals and communities. These shifts underscore the need for adaptive strategies that support workforce resilience and help regions remain competitive and resilient.

Employment, education and training systems are not keeping pace with the changing demands for new skills. Technological advancements like artificial intelligence as well as structural shifts such as the decarbonisation of economies imply greater need for new tools to facilitate job transitions and investments in upskilling and reskilling initiatives. Just as people will need to adapt to these changing requirements to find jobs where they live, places must also seize emerging opportunities for local economic development and job creation.

The rapid rise of new AI technologies could offer a strategic tool to OECD regions to address critical economic and labour market challenges, including labour shortages or labour productivity growth. Providing access to AI tools and training can help regions to access untapped talent and raise productivity. However, this requires the right enabling conditions, such as investments and deployment of AI in firms and preparing larger segments of the workforce with the skills to use AI tools effectively to complement their work.

This 6th edition of *Job Creation and Local Economic Development* closely examines the current health and recent evolution of regional labour markets in the OECD. It documents the uneven rise of labour shortages that hold back local economies, especially in jobs that are critical for the green and digital transition. Against this context, the report offers novel insights into the geography of the labour market impact of Generative AI. It explores which jobs and which types of places are already exposed to Generative AI, meaning that AI could be a complement to boost productivity in a job or potentially render some jobs no longer necessary. The report discusses the potential implications of increased adoption of Generative AI for urban and rural communities and workers and zooms in on place-based actions as well as policies to seize the opportunities that these technologies could yield to boost productivity growth and address labour shortages in ageing societies.

This publication contributes to the work of the Co-operative Action Programme on Local Economic and Employment Development (LEED), created in 1982 to provide practical solutions about how to build vibrant communities with more and better jobs for all. It was approved by the Local Economic and Employment Development Directing Committee via written procedure on 13 November 2024 [CFE/LEED(2024)14/REV1].

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Executive summary

While most regions have benefitted from an employment boom, this has not translated into narrowing regional gaps

Employment rates across OECD regions are at record highs but large disparities remain. In 2023, roughly 3 out of 5 (59%) of OECD regions had employment rates over 70%. Within countries, employment is particularly high in metropolitan regions with a high share of employment in tradeable sectors as well as "younger" labour markets. While the majority of regions have recovered from the COVID-19 pandemic, the recovery was faster and larger in metro regions. Overall, significant disparities persist, with little convergence between top- and bottom-performing regions in critical measures such as employment, labour force participation, and labour productivity. On average, regional employment rates differ by up to 10.5 percentage points in OECD countries.

During this employment boom, gender inequalities in regional labour markets have narrowed but age disparities have widened in most regions, to the detriment of younger workers. The gender gap between men and women in labour force participation has fallen in over four out of five (83%) of OECD regions, with two-thirds of OECD regions recording a fall of more than 1.5 percentage points. In contrast, disparities by age group increased in the majority of regions. The gap in labour force participation between youth (15- to 24-year-olds) and prime-age working population (25- to 64-year-olds) increased in three out of five (almost 60%) of regions, growing significantly by over 1.5 percentage points in half of OECD regions. Young people are struggling more to integrate into the labour market, particularly in metropolitan regions.

A troubling slowdown in labour productivity growth and stark differences among regions persist. Labour productivity growth has remained sluggish over the past decade, with half of OECD regions recording growth of less than 0.8% per year. While the least productive regions grew faster than the most productive ones over the last 10 years, it was not sufficient to result in significant regional convergence. As of 2022, the 20% most productive regions still recorded 50% higher labour productivity levels than the 20% least productive regions in the same country. Overall, labour productivity remains considerably higher in capital regions (one-third higher) and regions specialised in tradable sectors (one-fifth higher) than in the rest of a country.

A diversified skills base aligned with labour market needs boosts resilience; however, OECD regions have recorded a noticeable increase in skills polarisation and struggle with large skills mismatches. On average, the share of middle-skilled jobs fell in four out of five OECD regions over the last decade, in many cases being replaced by high-skilled jobs, but also in some cases low-skilled jobs. Skills mismatches (workers that are either under or overqualified for their jobs) persist and vary widely across regions, with one-third of countries exhibiting regional differences in skills mismatch of more than 10 percentage points between the regions with the highest and lowest skills mismatches.

Most OECD regions are struggling with labour shortages

Labour and skills shortages have become one of the most pressing policy concerns in most OECD regions, not only dynamic urban labour markets. Driven by a combination of both cyclical and structural factors, labour markets have become extremely “tight”, as firms struggle to find suitable workers to fill vacancies at different skill levels. The consequences for both firms and local economies can be significant, holding back firm operations and investments, inhibiting local economic growth, and creating obstacles for seizing new economic opportunities offered by technology or meeting environmental objectives.

Regional labour shortages have risen substantially since 2019 and increasingly affect regions with previously low levels of labour shortages. Labour market tightness (defined as vacancies per employed person) increased significantly (e.g. 50% in Germany, 80% in the U.S.) compared to pre-COVID times (2019-2022). While the severity of labour shortages differs between countries, regional disparities are also significant. Within countries, the tightest regional labour markets report on average five times more vacancies per employed person than the least tight regions. Labour shortages are particularly acute in regions focused on tradable services or high-growth industries.

Many regions face significant labour shortages in jobs crucial for the green and digital transitions. In almost all OECD regions (95%), labour shortages in Information and communication technologies (ICT) are higher than for other jobs, with on average twice as high labour market tightness. Labour shortages are also more pronounced for green jobs in nine out of ten (90%) regions. In European regions, labour shortages are on average more than 40% higher for green-task jobs than for other jobs. The scarcity of green and digital “talent” reflects the adjustment of local economies to the twin transition but could also indicate significant skills mismatches, resulting from structural labour market transformation that has not yet been accompanied by the necessary change in education and training systems adapted to regional workforce needs.

Widespread population ageing risks exacerbating labour shortages, especially in the regions with the oldest age structure. More than four in ten OECD regions experienced a shrinking working-age population over the past decade. If current population trends continued, average regional labour market shortages could increase by almost 9% within the next 20 years, and by nearly 16% in the oldest 20% of OECD regions (rising from one vacancy for every 21 working-age persons to one vacancy for every 18 working-age persons). Policies designed to mitigate labour shortages need to reflect place-specific challenges, such as ageing, retaining and attracting (young) talent to remote regions and facilitating job transitions, taking account of the geographic distribution of jobs.

Generative AI will transform many jobs, but its impact will be greatest in regions that have been least exposed to past waves of automation

Generative AI could have a much wider labour market impact than previous technologies that drove automation of tasks, affecting a broader group of people and places. Across the OECD, around a quarter of workers are exposed to Generative AI, meaning 20% (or more) of their job tasks could be done at least 50% faster with the help of Generative AI. Exposure to AI will continue to grow, as new software is developed or integrated with Generative AI technologies, with the share of workers who could be highly exposed (50% of their tasks could be done at least 50% faster with Generative AI) possibly ranging from 16% to more than 70% across OECD regions. In contrast to previous automation technologies, Generative AI excels in doing cognitive, non-routine tasks, shifting regional labour market exposure, with regions concentrating industries such as education, ICT, or finance becoming most exposed to Generative AI.

Regions previously considered to be at comparatively low risk of automation are the most exposed to Generative AI. Technology-led automation, including through other forms of AI, particularly affected non-metropolitan and manufacturing regions. In contrast, Generative AI has the potential to alter a significantly higher share of jobs in metropolitan regions. Exposure to Generative AI is greater for high-skilled workers and women, while previous technology-led automation mainly affected low-skilled workers and men.

While the exact effects of Generative AI on the geography of job creation and displacement remain to be seen, evidence from automation trends show overall net job creation. The share of jobs at high risk of automation, including through forms of AI that predated Generative AI, ranges from around 1% to 29% in OECD regions. However, on average, higher regional risks of automation did not lead to overall reductions in employment over the past decade. Instead, an increase of 10% in the share of jobs at high risk of automation is related to an increase of 5.6% in labour productivity over five years. Yet, in some regions, automation appears to have contributed directly to a loss of overall employment. Moreover, even though new job creation outweighed job losses in most regions, newly created jobs might not have benefitted those workers who lost their jobs due to automation.

New AI technologies could offer a strategic tool for OECD regions to address critical economic and labour market challenges, including labour shortages, and help boost sluggish labour productivity growth. Fostering the adoption of AI technologies could yield a much-needed catalyst for productivity in regional economies. Providing access to AI tools and training can help regions to access untapped talent in low-skilled workers or workers with disabilities for whom many jobs were previously out of reach. In addition, AI technologies can be leveraged to directly supplement workers where feasible, helping to ease labour shortages and the effects of an ageing workforce.

National place-based policies and local actions could foster resilience of regional economies and help seize the benefits of Generative AI

National labour market policies could draw lessons from the uneven recovery from COVID-19 and recent trends in regional labour market performance. By reflecting on the diverse impact and recovery from the pandemic, policy makers could take into consideration the different degrees of resilience to labour market shocks across regions and identify challenges and appropriate policy responses in light of ongoing transformations such as the green-digital twin transition.

In trying to alleviate labour shortages, policy makers need to address their exact, underlying causes, which are often place specific. In some regions, labour shortages might primarily be driven by a lack of available workers, a problem that could be exacerbated by ageing and a shrinking workforce. However, in other contexts, skills mismatches and gaps could be the main driver of labour shortages. Furthermore, some regions struggle with a lack of attractiveness to both attract and retain a skilled workforce. Finally, some regions might rely on employment in jobs that have become less attractive to workers due to lower job quality or work conditions, subsequently creating labour shortages. As such, the right mix of policy responses will need to consider the place-specific factors behind labour shortages.

To seize the opportunities of new technologies and respond to its labour market risks, policy makers could assess regional labour market exposure to different forms of AI. Working with the private sector could foster a better understanding of the job and skills changes that result from the spread of new forms of AI in different regions. This would provide the foundation for more effective up- and re-skilling programmes that are aligned with local labour market needs as well as tailored support for displaced workers. Public-private sector collaboration could help boost the adoption of AI tools, which could raise regional labour productivity, mitigate labour shortages, or offer a new tool to alleviate ageing in regions with significant population decline. Regional policy makers could also consider new opportunities that AI tools could bring such as promoting efficiency gains and enhancing the quality of regional public services or facilitating the labour market inclusion of people with disabilities. Collaboration with social partners to monitor job quality and worker rights should accompany these efforts.

1 The state of regional labour markets

This chapter examines the current state of regional labour markets in the OECD, as well as recent and long-term trends in standard indicators such as employment, inclusion and productivity. It also assesses their resilience to the green, digital and demographic transitions. While most regions have recovered since the COVID-19 crisis, regional convergence in employment and participation rates is limited. Despite record-high employment rates in many regions, the inclusion of certain groups in the labour market remains an issue. Labour productivity growth remains modest, and disparities between the most and least productive regions persist. Skill mismatches and non-traditional work are prevalent, and a lack of sectoral diversification may hamper the ability of regions to adapt. Mass layoffs pose additional challenges, especially given their prevalence and severity in some regions.

In Brief

The landscape of regional labour markets in the OECD over the past decade reveals a mixed picture of recovery and persistent disparities and challenges in productivity and skills.

Healthy regional labour markets promote economic growth, social inclusion, and overall well-being. This chapter examines their evolution in OECD regions over the past decade and in the aftermath of the COVID-19 pandemic, reporting on recent employment trends, productivity growth, skill polarisation and mismatch, non-traditional work, and sectoral diversification. The analysis sheds light on the diversity of regional experiences and their differing abilities to withstand future shocks and transitions. This diversity highlights the need for differentiated actions given the specific labour market challenges of different types of regions.

- **Employment rates across OECD regions are at record highs, but significant regional disparities are widespread in some places.** In 26 OECD countries, employment rates are above 70% in at least three-fourths of regions. In particular, employment is higher in capital-city regions, regions with a high share of employment in green jobs and tradable sectors, and regions with younger working-age profiles. Almost seven in ten regions recovered both employment and participation rates relative to pre-COVID levels, although the recovery was more widespread for employment rates and in metro regions.
- **There is little convergence between top- and bottom-performing regions within countries in employment and participation rates or productivity.** On average in OECD countries, ten percentage points separate the region with the highest and lowest employment. Participation and employment rates remain about 10 to 13% higher, respectively, in the top versus the bottom quintile of regions in a country.
- **Many regions still struggle with the labour market inclusion of different groups.** Age disparities in regional labour markets widened over the past decade, and gender inequalities narrowed, despite fears that COVID-19 would bring a lasting "she-cession". The inclusion gap between youth (15-24 year-olds) and the prime-age working population (25-64 year-olds) grew in almost three in five (58%) regions, and the gender inclusion gap fell in five in six (83%) regions over the past ten years, with 20 countries seeing a rise in the age gap and 31 countries seeing a fall in the gender gap in at least 70% of their regions. Capital-city regions exhibit the greatest age disparities in labour force participation rates, while gender disparities are most prominent in non-capital-city regions, by about seven and four percentage points, respectively.
- **Labour productivity growth remained sluggish over the past decade, with half of OECD regions recording growth rates of less than 0.8% per year.** Within-country gaps between the most- and least-productive regions remain large, despite marginally higher productivity growth in lagging regions. In 2022, in two-thirds of OECD countries, productivity in the most productive region is at least 50% higher than in the least productive region. The quintile of regions with the highest initial productivity, within a country, still has 50% higher productivity than the quintile of regions with the lowest initial productivity. Capital-city regions and regions with a higher share of green jobs or jobs specialised in tradable services record significantly higher labour productivity than the national average.

- **A diversified skills base enhances the quality and resilience of regional labour markets, yet many regions face rising skills polarisation and high skills mismatches.** The share of middle-skilled jobs fell in four-fifths of OECD regions, and the share of low-skilled jobs grew in three-fourths of regions where the share of middle-skilled jobs fell. The falling middle may reflect changing labour market demands, but it has not resulted in a better alignment between workers' skills and those needed by their jobs. Skill mismatches remain an issue for most OECD regions, with significant within-country differences of over ten percentage points in over one-third of countries. Mismatches fell over the past ten years in capital-city regions and in regions with a higher share of green jobs.

Introduction

The past decade has been marked by profound shifts for global economies. These shifts are driven by rapid technological change, the necessity of environmental sustainability, demographic pressures, and heightened geopolitical instability, all against the backdrop of recovery from the shock of the COVID-19 epidemic. Issues such as labour shortages, sluggish productivity and skill mismatches are increasingly relevant in the context of ongoing transformations such as the green and digital transition, specifically the rise of artificial intelligence (AI). In many places too, the pressures of demographic change, with shrinking working-age populations, are further complicating the situation.

Regional labour markets, given their size, specific characteristics, and degree of specialisation, face distinct challenges in adapting to these megatrends. To keep pace, transitions that build upon a regional labour market's strength may be necessary to not only navigate these challenges but to actively transform these challenges into opportunities. This chapter provides an overview of these recent trends in regional labour markets.

Employment rates stand at a record high across OECD countries, even as the regional picture is more uneven. The average employment rate (share of the working-age population in employment) in the OECD reached over 70% in Q2 2024, surpassing this figure in almost two-thirds of OECD countries. These historic employment gains create benefits across demographic groups (OECD, 2024[1]). Most national labour market indicators, such as employment, unemployment, and participation rates, have recovered in most countries following the shock of the COVID-19 pandemic. For example, by Q2 2023, unemployment and inactivity rates were, on average, half a percentage point and one percentage point, respectively, below pre-pandemic levels in OECD countries (OECD, 2023[2]). However, this pattern has not been true for all regions, contributing to persistent or growing regional inequalities in some countries. Employment rates fully recovered or exceeded their pre-pandemic levels by Q2 2022 in less than half of OECD regions across 33 countries (OECD, 2023[3]).The chapter will address the current situation and report on recovery into 2023.

Labour shortages remain a prevalent and persistent issue in this high-employment context. As industries evolve and new technologies emerge, the demand for specific skills can sometimes outpace their supply, making it difficult for firms to fill needed positions. It may also be that available jobs are not attractive enough in terms of pay, working conditions, location, or a combination of these. Even if 2023 saw real wage growth, wage gains remain below pre-pandemic levels (OECD, 2024[4]). This issue is further exacerbated by demographic change, as ageing populations combined with declining birth rates contribute to shrinking working-age populations. Regional labour market tightness increased by around 50% since 2019, affecting regions with high and low prior levels of shortages similarly. At the same time, the average difference between the relatively tightest and least tight regions is almost twice the national average, indicating substantial regional variation in the extent of labour shortages (see Chapter 2).

Labour productivity is an important driver for reducing income inequality, yet regional differences remain large: levels in the most productive region are almost twice as high as the least productive region, on average within OECD countries (OECD, 2023[3]). The trend of stagnating labour productivity adds to the challenge of widening regional inequalities in GDP per capita in more than half of OECD countries with available data. This is especially a challenge where large differences in productivity levels exist even where there were declines in GDP per capita inequality (OECD, 2023[3]).

Active innovation and the diffusion of new technologies, for example, artificial intelligence, across regions, coupled with targeted investments in infrastructure such as digital technologies may be avenues for boosting productivity (OECD, 2023[3]). Yet, whether artificial intelligence will support or replace workers depends on the "task-based" nature of jobs and the ability of AI to perform those tasks more efficiently (Nedelkoska and Quintini, 2018[5]). The issue is addressed in Chapter 3 through new estimates on occupational exposure to AI, such as large-language models. The regional-level analysis presents within-country disparities in AI exposure, affecting a broader group of people and places. It discusses the potential double-edged sword of the integration of AI in the workforce: whether it is productivity-boosting or leads to job displacement.

Overall, the rapid pace of technological change and the shift towards greener economies creates a growing need for new skills and competencies and regions have different capacities to adapt. For example, while 18% of workers in the OECD have jobs with a significant share of green tasks that promote environmental sustainability, the share of these “green-task” jobs shows a considerable range across regions, from 7% to more than 35%, and are especially concentrated in capital-city regions (OECD, 2023[6]).

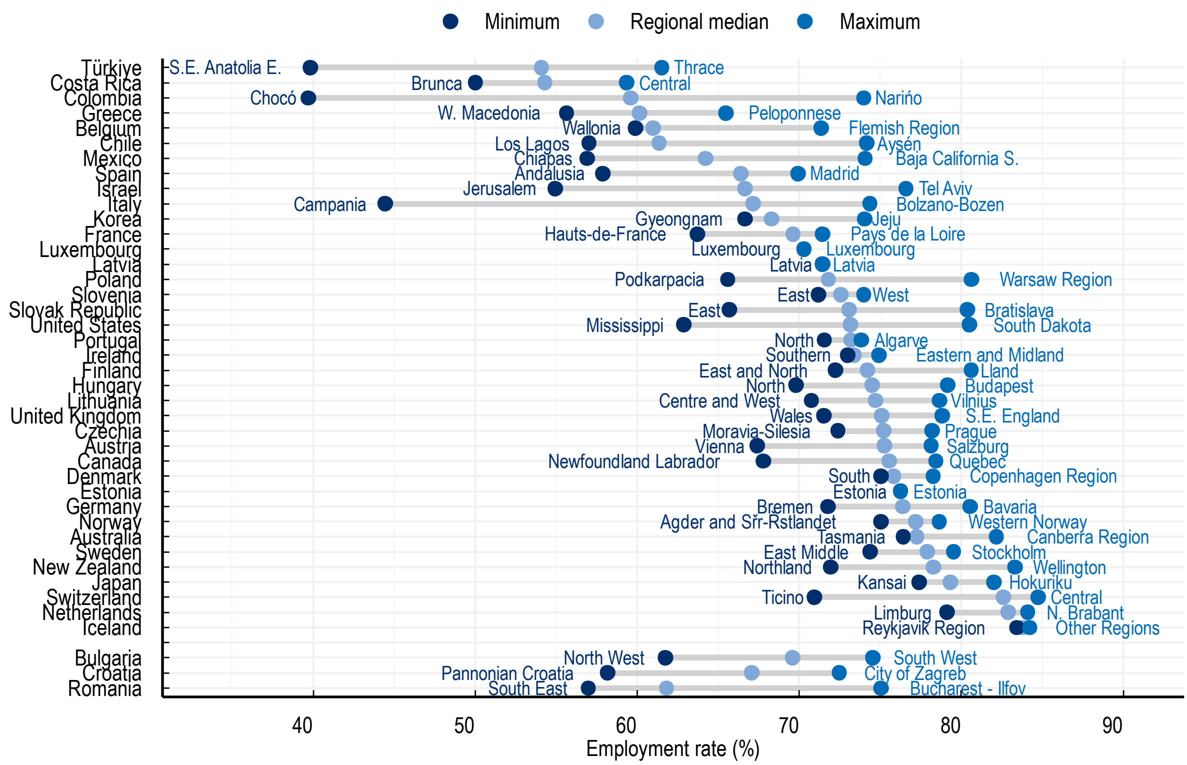
In light of these trends, this chapter examines the current state of regional labour markets and their resilience to major transitions. The first section explores regional labour market dynamics over the past decade, touching upon the recovery from the COVID-19 crisis, and regional convergence. It considers recent developments and implications for employment, labour productivity and inclusion. The second section delves into different indicators linked to the ability of regional labour markets to adapt and benefit from the full potential of both workers and firms. For example, it investigates recent trends in the take-up of non-traditional work, skills polarisation and skills mismatch, as well as the sectoral concentration of employment and the incidence of mass layoffs.

Regional disparities persist, highlighting the absence of regional convergence despite a strong recovery from the COVID-19 shock

Across OECD regions, employment rates have reached record highs (Figure 1.1). In 26 OECD countries, employment rates are above 70% in at least three in four regions, and in 20 countries, in all regions. In almost three in five regions (59%), employment stands at over 70% of the labour force and over 80% in almost one in ten regions (8%). Employment is particularly high in Iceland, Switzerland, and the Netherlands, which all boast at least two regions in the top ten of employment rates across OECD regions. Four out of the top ten regions are in the Netherlands, which can likely be attributed to the high take-up of part-time work. On the other hand, the employment rate is lagging and below 60% in at least one-third of their regions for seven OECD countries. This is also the case in about one in seven (14%) OECD regions. This is a particular challenge for Türkiye and Italy, which have six (out of 26) and three (out of 21) regions, respectively, in the bottom ten of employment rates across OECD regions. The lowest employment rate is in Chocó (Colombia), likely due to its geographical isolation and lack of infrastructure. This is similar to the challenges faced by the Italian regions, which are all located in the south. While in Türkiye, low female labour market participation rates, which range from 24% to 49%, limit employment rates.

Within-country regional differences are widespread. In 16 out of the 35 countries with more than one region, the difference between the top and bottom regions in employment rates is over ten percentage points. In Colombia, the difference exceeds 34 percentage points; in Italy, it is almost 30 percentage points and in Türkiye and Israel, almost 22 percentage points, highlighting particularly large disparities in these countries. Portugal has the smallest dispersion, among countries with at least five regions, at about two percentage points. This is followed by Denmark and Norway, where the difference is about 3 and 3.6 percentage points, respectively. As many regions experience all-time high employment, the focus is shifting towards widespread labour shortages (see Chapter 2).

Figure 1.1. Employment rates are high, and regional differences exist across OECD countries

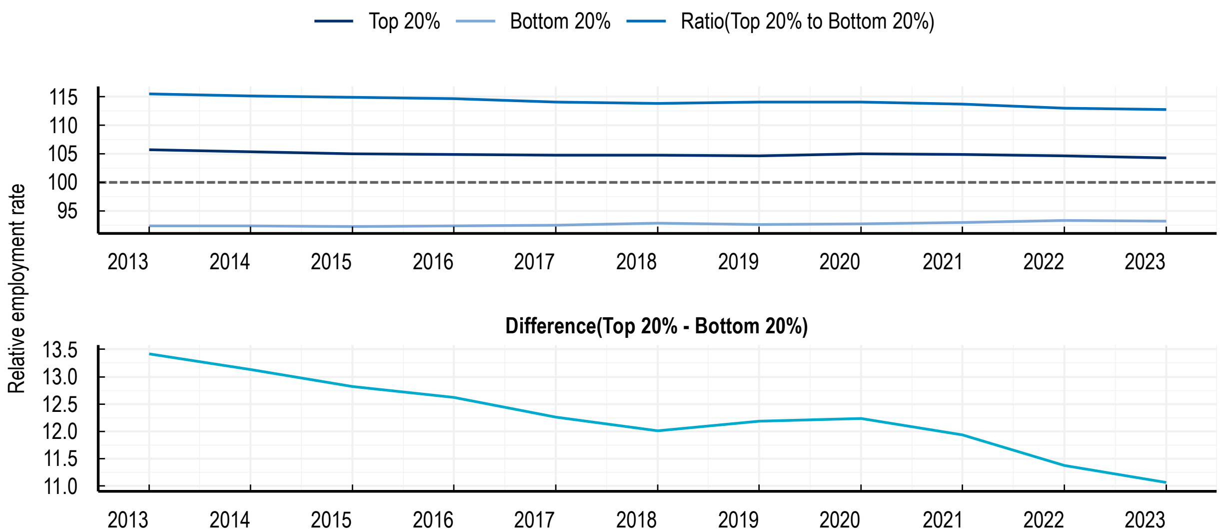


Note: The figure shows the regional dispersion (highest, lowest and median value) in the employment rate for 15-64 year-olds in 2023. For Colombia, the data refers to 2022 due to data availability. The sample is all TL-2 regions in countries (including the OECD accession countries of Bulgaria, Croatia and Romania) with available data. The employment rate is defined as the number of working-age employed persons out of the working-age population, where the working-age is defined as 15-64 year-olds.
Source: OECD calculations based on the OECD Regional databases.

Over the past decade, there has been minimal progress towards regional convergence in employment rates. In 2023, employment rates in the top quintile of regions in a country were more than 4% above the national median versus almost 6% in 2013 (Figure 1.2). In contrast, employment in the bottom quintile of regions is almost 7% below the national median, versus almost 8% in 2013. Thus, there have been small decreases in within-country disparities over the past ten years. In 2013, the top quintile of regions had employment rates almost 16% higher than the bottom quintile, with the gap falling to 13% by 2023. Overall, the within-country difference in employment rates between top and bottom regions fell by about 2.5% of the national average over the past ten years.

Figure 1.2. As employment rates reach a record high, there has been minimal regional convergence over the last decade

Evolution of the employment rate relative to the national median, 2013 to 2023

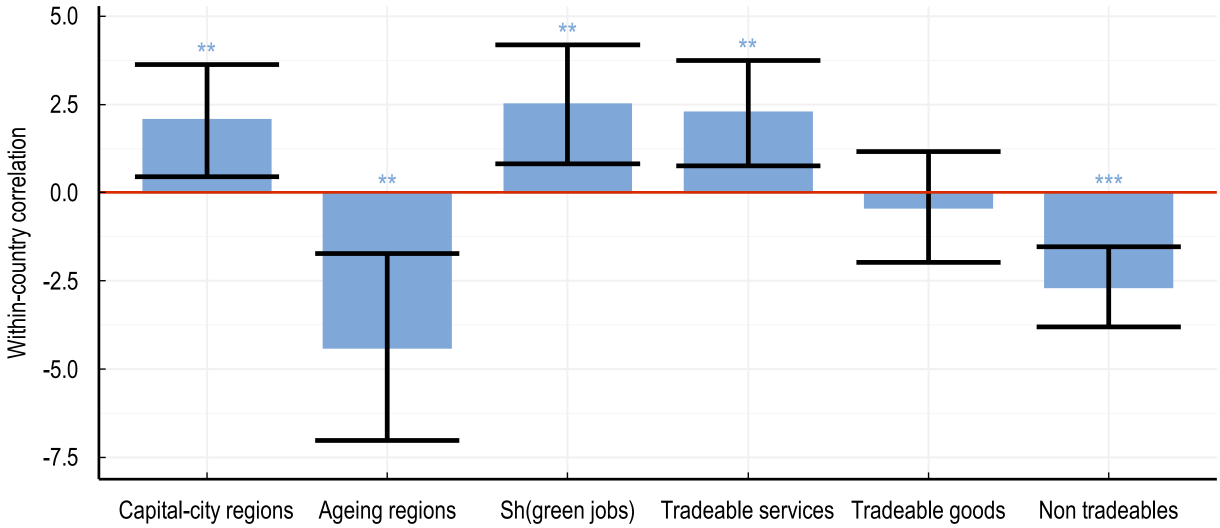


Note: The figure shows the evolution of the employment rate for the working-age population (15-64 year-olds), relative to the national median (which corresponds to 100 on the top graph), for the top and bottom 20% of regions which account for at least 20% of the population in a country. The sample is all TL-2 regions in OECD countries with at least five regions and with data available over the entire period. The employment rate is defined as the number of working-age employed persons out of the working-age population, where the working-age is defined as 15-64 year-olds.
Source: OECD calculations based on the OECD Regional databases.

Regions with younger age profiles (non-ageing regions), capital-city regions and regions where employment is specialised in green jobs or tradeable sectors lead employment rates (Figure 1.3). The strongest predictor of high employment rates is the absence of an increase in the old-age dependency ratio: within-country employment levels are close to 4.5 percentage points higher, on average, in those regions than regions where the old-age dependency ratio rose. This is followed by the regional employment structure. In regions with an above-country-median employment share in green jobs or in tradeable goods or services, the employment rate is about 2.5 percentage points higher, on average, than in regions with a below-median share of green jobs or specialised in non-tradeable sectors. Finally, capital-city regions have employment rates that are two percentage points higher than non-capital-city regions. These regional differences in employment rates exist regardless of national characteristics or population size and account for country-level shocks. In contrast, none of these regional characteristics is correlated with within-country employment *growth* over the past ten years (Annex Figure 1.B.1). Regional characteristics in the same country, such as demographics, location or industry structure, are thus important for understanding current employment rates.

Figure 1.3. Employment rates are higher in capital-city regions, non-ageing regions, regions with a high share of green jobs and jobs in tradeable service sectors

Within-country correlation of the employment rate to selected characteristics, 2023 or latest available year

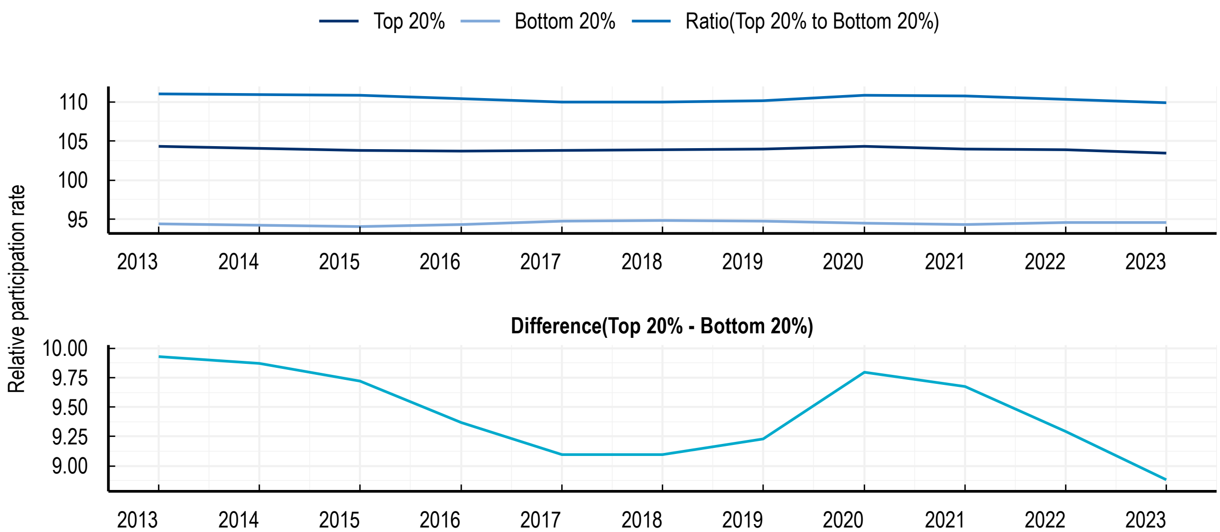


Note: ***p-value<0.01, **p-value<0.05, *p-value<0.1. The graph shows the coefficient and 90% confidence intervals of separate multivariate regressions of the employment rate in 2023 (for Colombia, the latest available year is 2022) on a dummy for capital-city regions, ageing regions (defined as those that experienced an increase in the elder-dependency rate over the past five years), for an above national median employment share in green jobs in 2021, in tradeable services (ISIC broad sectors G to N), tradeable goods (ISIC sectors B, D, E) or neither tradeable goods nor services. The coefficient (`within-country correlation') presents the within-county percentage point difference in employment rates based on the characteristic on the x-axis. Each regression also controls for the log of population in 2023 or latest available year and country fixed effects. The level of observation is the TL-2 region. The sample of countries includes all OECD countries. Robust standard errors are clustered at the country level. The employment rate is defined as the number of working-age employed persons out of the working-age population, where the working-age is defined as 15-64 year-olds.
Source: OECD elaboration based on the OECD Regional databases.

Despite concerns that COVID-19 would exacerbate regional inequalities through substantial and sustained workforce dropout in more affected regions, within-country differences in participation rates have been stable (Figure 1.4). Participation rates refer to the share of people employed or looking for work out of the working-age population. A fall in participation rates implies that people are dropping out of the workforce into economic inactivity, i.e. they are no longer employed or looking for work. There was a particular risk of this during the COVID-19 crisis due to its specific nature, characterised by lockdowns, challenges to specific industries, risks to older workers, and an increased burden of home care. Thus, it is notable that the ratio of participation rates in the top compared to the bottom quintile of regions in a country is at its lowest level over the past ten years: about 9.9%, which is a modest decrease from 11% in 2013. This is despite the small (0.6 percentage points) increase in the ratio during 2020. Overall, in 2023, the top quintile of regions had participation rates 3.5% higher than the national median, while the bottom quintile of regions trails the national median by 5.5%.

Figure 1.4. Participation rates remain 10% higher in the top versus the bottom quintile of regions within a country, a difference of almost 9% of the national median

Evolution of the participation rate relative to the national median, 2013 to 2023

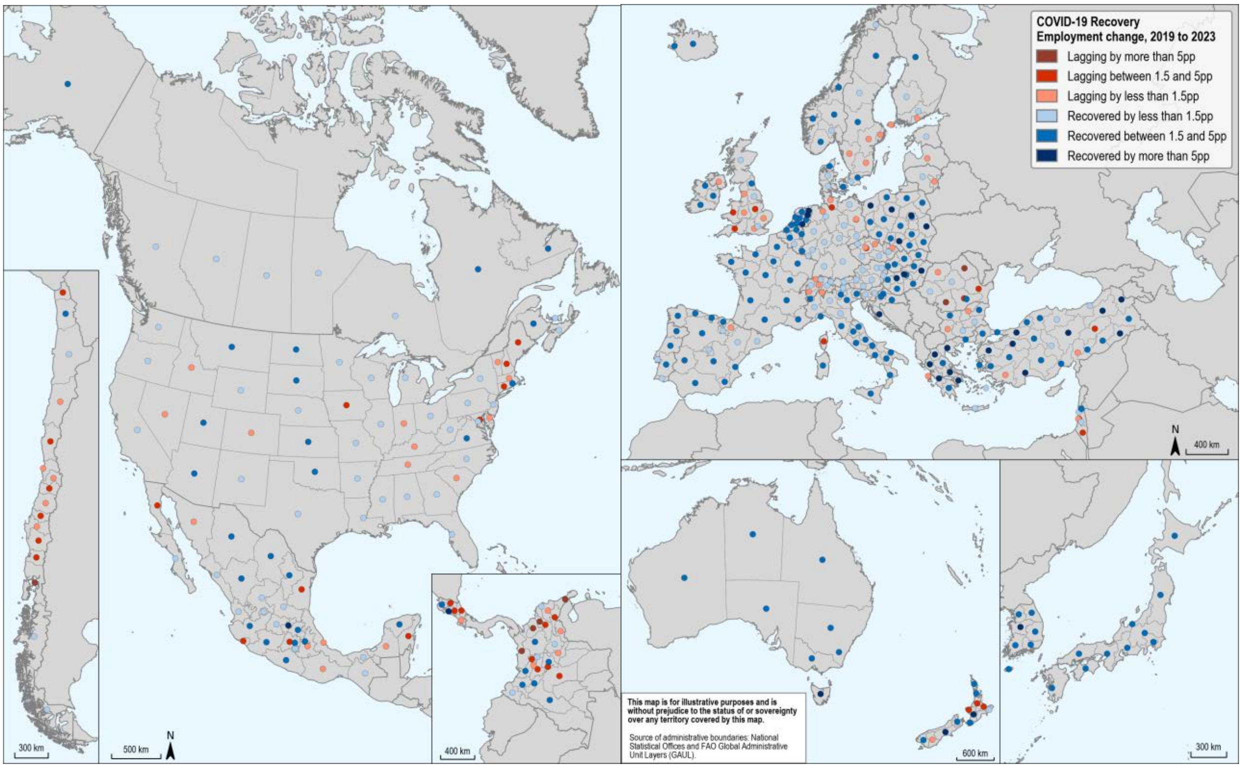


Note: The figure shows the evolution of the participation rate for the working-age population (15-64 year-olds), relative to the national median (which corresponds to 100 on the top graph), for the top and bottom 20% of regions which account for at least 20% of the population in a country. The sample is all TL-2 regions in OECD countries with at least five regions and with data available over the entire period. The participation rate is defined as the number of working-age employed persons or persons looking for work out of the working-age population, where the working-age is defined as 15-64 year-olds.
Source: OECD calculations based on the OECD Regional databases.

Employment and participation rebounded strongly after the COVID-19 shock

By 2023, half of OECD countries (19 out of 38 countries) saw all regions recover their employment levels to at least pre-pandemic levels (Figure 1.5). In ten countries, employment rates surpassed pre-pandemic levels by more than 1.5 percentage points in all regions, while in eight OECD countries, employment recovery is limited, and no region rebounded by more than 1.5 percentage points. In only one country (Latvia), all regions have yet to recover to their pre-crisis employment rate; in all other countries, regional employment recovery is uneven with some regions recovering while others lag. Overall, more than three-fourths (76%) of OECD regions recovered their pre-pandemic employment rates, with almost half (49%) of regions recovering by at least 1.5 percentage points, and almost one in ten (8%) regions by over 5 percentage points. In contrast, for one in ten OECD regions, employment rates are still more than 1.5 percentage points below pre-crisis levels, and for a little over one in a hundred (1.2%) OECD regions, rates lag by more than 5 percentage points. While the vast majority of OECD regions showed strong employment recovery after the COVID-19 shock, some still face challenges in regaining their pre-pandemic employment levels.

Figure 1.5. Regional employment recovery is uneven in half of OECD countries

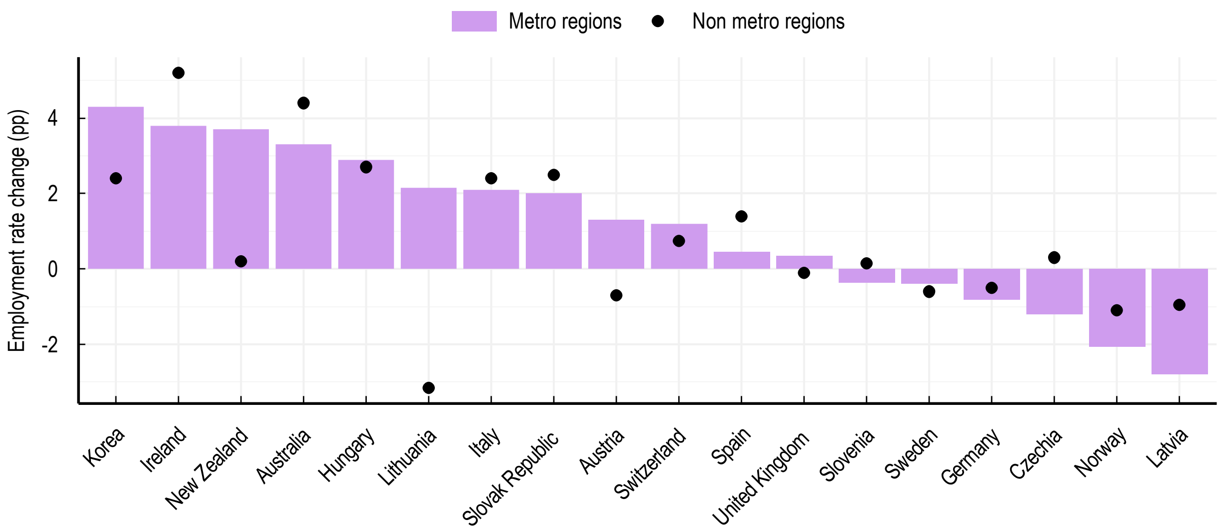


Note: The figure shows the regional difference between the employment rate in 2019 and the employment rate in 2023, except for Colombia where the latest available year is 2022. The sample is all TL-2 regions (including the OECD accession countries of Bulgaria, Croatia and Romania) with available data. The employment rate is defined as the number of working-age employed persons out of the working-age population, where the working-age is defined as 15-64 year-olds.
Source: OECD calculations based on the OECD Regional databases.

Employment rates returned to pre-crisis levels for metropolitan regions in 12 countries and for non-metropolitan regions in 11 countries, out of the 18 countries with available data (Figure 1.6). Yet, employment in metropolitan regions rebounded by 0.3 percentage points more than in non-metropolitan regions on average, ranging from -3.2 percentage points in Lithuania (since non-metropolitan regions recovered the quickest) to over 5 percentage points in Ireland. Furthermore, although the average employment change is similar across metropolitan and non-metropolitan regions (about 1.1 and 0.9 percentage points, respectively), non-metropolitan regions showed much greater volatility with greater employment gains and employment declines than metropolitan regions. Thus, despite the increased severity of the COVID-19 epidemic in cities and metropolitan areas, metropolitan regions proved to be more resilient and stable in responding to the pandemic-related labour market shock.

Figure 1.6. Metro and non-metro regions recovered congruently, despite greater COVID-19 incidence in the former

Median employment rate change, 2019 to 2023 or latest available year

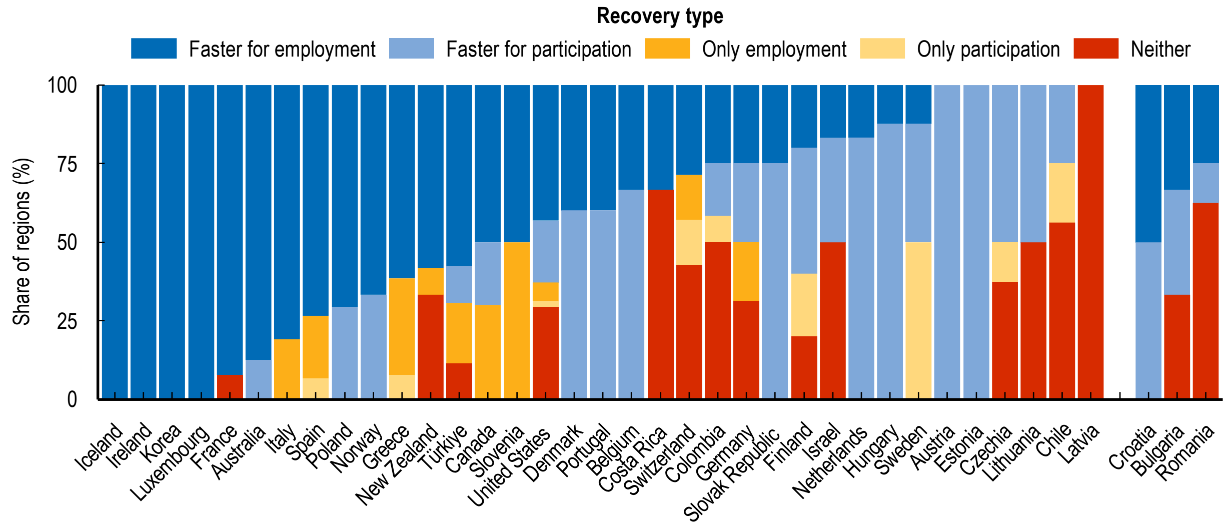


Note: The figure shows the change in the employment rate from 2019 to 2023 (or the latest available year after 2020), in metropolitan regions and non-metropolitan regions, defined at the TL-3 level, for each country. For Germany, the latest available year refers to 2021, and for Czechia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom, to 2022. The employment rate is defined as the number of working-age employed persons out of the working-age population, where the working-age is defined as 15-64 year-olds.
Source: OECD calculations based on the OECD Regional databases.

Most regions recovered strongly from the COVID-19 pandemic both in employment and labour market participation. Compared to pre-COVID levels, almost seven in ten (69%) OECD regions reached at least pre-crisis levels in both dimensions, with over one-third (36%) of regions displaying improvements in both rates by over 1.5 percentage points (Figure 1.7). Yet, regional disparities exist. More than one-third of OECD countries have regions that recovered in only one dimension. And in one in nine (11%) OECD regions, both participation and employment rates are at least 1.5 percentage points below their pre-Covid values. The average employment change since the pandemic across all OECD regions is 1.5 percentage points, while for participation rates, the change is 1.1 percentage points.

In general, regional employment rates recovered more widely than participation rates. This suggests that employment rates, if viewed in isolation, may paint a slightly more positive picture since they obscure the presence of economic inactivity, i.e. the working-age population that is neither employed nor looking for work. Particularly, in almost half (45%) of OECD regions, employment rates recovered by more than participation rates; and in one in twelve (9%) regions, only employment rates recovered, more than double the regions where only participation rates recovered. Among regions that have yet to recover, the average gap (the extent to which the current rate is below the pre-crisis value) is similar: about 1.6 percentage points for both participation and employment rates. The policy response of countries to COVID-19, particularly through employment support programmes, was without precedent, matching the novel nature of the shock (OECD, 2022[7]). Yet, given that labour market participation rates lagged employment rate recovery, additional efforts may be required to bring back workers who left the labour market during COVID-19.

Figure 1.7. Regional employment recovered more widely than participation rates



Note: The figure shows the share of regions in each country which belong to each of the five categories comparing the change in employment and participation rates from 2019 to 2023, except for Colombia where the latest available year is 2022. `Faster for employment' means that the employment and participation rate are at or above their 2019 rate, but employment recovered by more. `Faster for participation' means that both the employment and participation rates are at or above their 2019 rate, but participation recovered by more. `Only employment' means that the employment rate is at or above the 2019 rate, but not the participation rate. `Only participation' means that the participation rate is at or above the 2019 rate, but not the employment rate. `Neither' means that both the employment and participation rates are below their 2019 rate. The sample is all TL-2 regions in all OECD countries (including the OECD accession countries of Bulgaria, Croatia and Romania) with available data. The employment rate is defined as the number of working-age employed persons out of the working-age population, where the working-age is defined as 15-64 year-olds. The participation rate is defined as the number of working-age employed persons or persons looking for work out of the working-age population, where the working-age is defined as 15-64 year-olds.
Source: OECD calculations based on the OECD Regional databases.

Government action likely played a key role in the post-pandemic recovery patterns of employment and participation, but no particular scheme stands out for explaining regional recovery. These policies included job retention schemes such as short-term work (STW) schemes, wage subsidies, and cash transfers (see Box 1.1 for an overview). Furthermore, government action, particularly furlough schemes, likely avoided large negative shocks to employment (Calligaris et al., 2023[8]). Yet, some workers who are more represented in certain regions, for example, the self-employed, were often not eligible to benefit from these schemes in many countries. Differences in accounting techniques, particularly whether furloughed workers were counted as unemployed, as in North America, or employed, as in Europe, also obscure the ability to comment on their efficiency. It is also important to note that regions may have been exposed to other shocks in the same period, which are not considered here. For example, the energy crisis triggered by Russia's war of aggression against Ukraine likely affected the recovery of European regions to different degrees, depending on their reliance on Russian gas supplies (OECD, 2022[9]; OECD, 2022[10]).

Regions experienced narrowing gender inequalities and widening age inequalities over the past ten years

Box 1.1.From crisis to recovery: Employment support policies during COVID-19

In response to the unprecedented shock of the global pandemic in 2020, countries implemented or expanded employment support policies to sustain economies and workers. These policies include the use of job retention schemes in the form of short-term work (STW), wage subsidies, and cash transfers to mitigate the economic impact of the shock. Both existing and temporary policies were expanded during the pandemic to allow for increased access, coverage, and generosity (OECD, 2020[11]). These policies aimed to mitigate the effects of the crisis, prevent mass layoffs, maintain attachment to the workforce, and support a quick recovery after public health restrictions were lifted.

Most OECD countries had pre-existing job retention schemes (JRS), while others implemented temporary policies. Examples include job retention schemes such as STW and expanded benefits, while others introduced temporary wage subsidies and direct cash transfers to cover independent workers. The STW schemes are temporary partial or full suspensions of work contracts that directly subsidise hours not worked. Wage subsidy schemes do not necessarily reduce the working hours of workers but rather subsidise hours worked and can also supplement the earnings of workers on reduced hours. Most also provided cash transfers to help workers not covered by traditional job retention schemes (OECD, 2020[11]).

STW schemes existed in most OECD countries and were expanded during the crisis, with some regional differences in take-up rates. This was the case in Belgium, France, Germany, the United Kingdom and the United States. Otherwise, other OECD countries, such as Australia, Canada and Colombia, used temporary wage subsidies instead of STW schemes to maintain employer-employee relationships.

Countries also rolled out innovative cash transfers to aid workers, adapting these support measures dependent on earnings, or offering cash transfers at a flat rate or value to the entire eligible population. These countries include Austria, Canada, Italy, Japan, Korea, the United States and the United Kingdom.

Across the OECD, JRS supported over 50 million jobs, ten times as many as during the global financial crisis of 2008-10 (OECD, 2020[12]). However, there are significant regional disparities within countries in the participation rates in these programmes. These are likely the result of local economic structures as well as geographically targeted containment measures. Unfortunately, the lack of comprehensive data on the regional take-up of these schemes prevents any analysis of whether regional take-up explains why some regions performed better during the crisis. It is also important to note that while most EU countries had pre-existing JRS, many other OECD countries such as Australia, Canada, and the United Kingdom, had to quickly implement a temporary JRS, often in the form of wage subsidies.

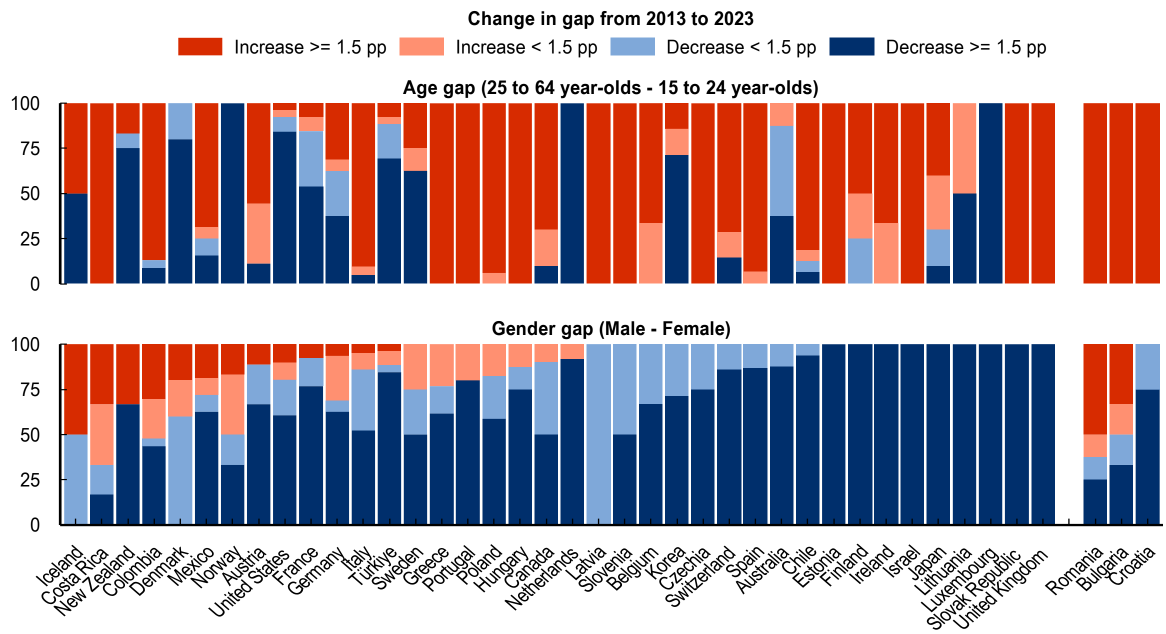
The labour market experience of workers during the past decade has varied depending on their demographics, with distinct challenges and responses shaping their paths (OECD, 2022[7])**.** The recovery from the recent pandemic is especially pertinent in this regard. For example, older workers, given the health risks during the COVID-19 crisis, may have chosen to permanently exit the labour force, such as taking early retirement. For the cohort of young workers who entered the labour market during the crisis, the shock could have had a lasting impact on their labour market integration and career progression. Lastly, lockdown restrictions put further pressure on child and home care activities, the brunt of which tends to fall on women, bringing down their participation rates (Djankov et al., 2021[13]; OECD, 2021[14]; Alon et al., 2020[15]). The aggregate picture of the post-crisis recovery of labour force participation masks the diversity of these experiences. Consequently, analysis of differences in labour market outcomes by gender and age warrants specific attention.

The past decade in OECD regions witnessed a narrowing of gender inequalities in many labour markets. In five out of six (83%) OECD regions, the gender gap in participation rates, which reflects the difference between male and female labour market participation rates, fell from 2013 to 2023 (Figure 1.8). In more than two-thirds (67%) of regions, the gap fell by more than 1.5 percentage points. In 31 countries, gender gaps fell in at least 70% of their regions. And, in 18 OECD countries, the gender inclusion gap fell in all regions. While no OECD countries saw the gender participation gap increase in all regions, some countries (Chile, Colombia, Costa Rica, Greece, Mexico, New Zealand, Türkiye and the United States) show significant regional disparities in the change in the gender gap of over ten percentage points. For example, in Türkiye and New Zealand, over 21 and 17 percentage points separate the region with the greatest reduction in the gender gap (Western Black Sea Middle and East in Türkiye and Gisborne Region in New Zealand) and the greatest increase (Eastern Anatolia - West in Türkiye and Tasman-Nelson-Marlborough in New Zealand). On average, the gender inclusion gap fell by 2.7 percentage points across OECD regions.

Over the same period, age disparities increased by 0.9 percentage points, on average, across OECD regions. The age inclusion gap, or the difference between participation rates of the prime-age (25-64 year-olds) working population and youth (15-24 year-olds), grew in almost three in five (59%) of regions, growing significantly by over 1.5 percentage points in more than half (53%) of regions (Figure 1.8). In 23 OECD countries, age gaps grew in at least 70% of their regions. All regions in 13 OECD countries saw increases in the age inclusion gap. In four countries, all regions decreased their age inclusion gap. Of the remaining countries where the change in the age inclusion gap did not change in the same direction for all regions, in Chile, France, Mexico, New Zealand, Slovak Republic, and the United States, the difference between the region with the greatest increase and the region with the greatest reduction is over twenty percentage points. It is important to caveat these findings as the labour force participation rates of youth are not adjusted to account for the general trend of young people deciding to remain longer in higher education.

Figure 1.8. Age inequalities, but not gender, exacerbated over the last decade

Share of regions given change in the gap in the participation rate by age and gender, 2013 to 2023 or latest available year

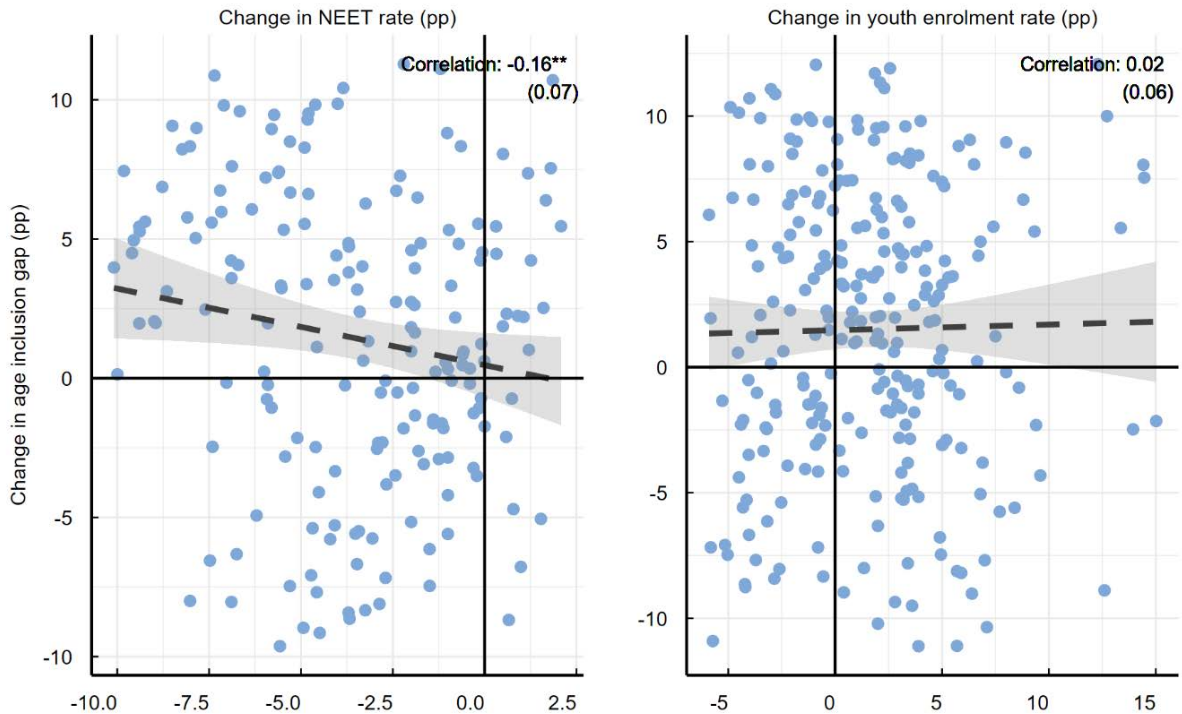


Note: The figure shows the share of regions in each country which belong to each of the four categories representing the difference between the age gap between the prime-age working population (25-64 year-olds) and youth (15-24 year-olds) (top panel) and gender gap between male and women (bottom panel) in the participation rate in 2013 and the gap in the participation rate in 2023. For Colombia (except for Chocó where the data refers to 2010 to 2020), Korea and the United Kingdom (except for North where the data refers to 2011 to 2021); for Mexico (except for Nayarit where the data refers to 2009 to 2019) the last year is 2020. The sample includes all TL-2 regions in countries with available data, including the OECD accession countries of Bulgaria, Croatia and Romania. The participation rate is defined as the number of working-age employed persons or persons looking for work out of the working-age population in the same subgroup, where the working-age is defined as 15-64 year-olds.
Source: OECD calculations based on the OECD Regional databases.

Rising age disparities cannot solely be attributed to rising educational enrolment rates; they are also not associated with increases in the NEET rates (Figure 1.9). While a positive correlation between rising youth enrolment rates and increases in the age gap in participation rates exists across regions, the association is small (0.02) and weak (not statistically different from zero). Thus, widening age disparities cannot be entirely attributed to a general trend of staying longer in education. At the same time, the share of youth not in employment or education (NEET) fell over the past ten years in almost nine in ten (88%) OECD regions with available data, even as age disparities widened.[1] Furthermore, a time-series analysis of the evolution of the age and gender gap in employment and participation rates suggests that age disparities grew during the pandemic, while men and women were similarly affected (Annex Figure 1.B.2).[2] These pieces of evidence suggest that, despite the rise in the age gap in participation rates, there is likely a limited risk of further labour market scarring, whereby youth who graduate during a recession or shock suffer long-term negative effects on their earnings and career opportunities over time (Tomlinson and Tholen, 2023[16]; Schwandt and von Wachter, 2019[17]). Yet, it is important to continue to monitor the situation. These evolving patterns underscore the need for targeted policies to address age inequalities where they persist while supporting the gains achieved in gender balance (for selected examples, see Annex Box 1.A.1. in Annex 1.A).

Figure 1.9. Regions with large increases in the age inclusion gap saw NEET rates fall, and there is little link with changes to youth enrolment rates

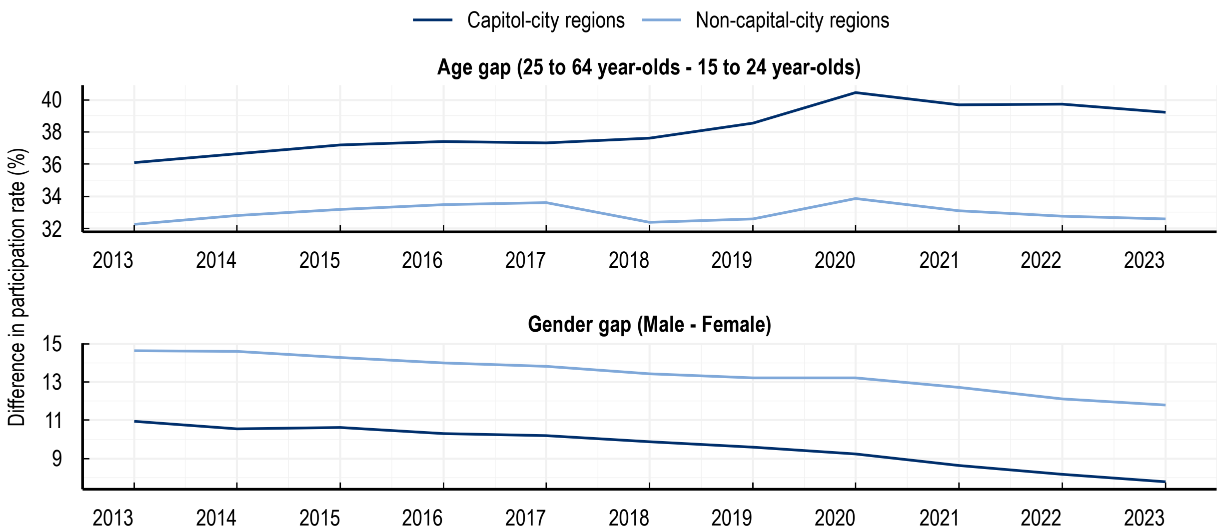
Correlation between the ten-year change in the NEET rate (left) or the youth enrolment rate (right) and the age inclusion gap, 2013 to 2023 or closest available years



Note: The figure shows the ten-year change in the difference in the participation rate for the prime-age working population (25-64 year-olds) and youth (15-24 year-olds) on the y-axis, and the ten-year change in the youth not in employment, education or training rate (18-24 year-olds) on the x-axis on the left graph and the ten-year change in the educational enrolment rate for youth (20-29 year-olds) on the x-axis on the right graph, over the years 2013 to 2023, or the closest available years for OECD TL-2 regions with available data. For the age inclusion gap, the last available year is 2022 for regions in Colombia (except for Chocó where the data refers to 2010 to 2020), Korea, and the United Kingdom (except for North where the data refers to 2011 to 2021); for Mexico (except for Nayarit where the data refers to 2009 to 2019) the last year is 2020. For youth enrolment rates, the ten-year period is 2012 to 2022 for Colombia, Latvia, New Zealand, and the United States; the initial year is 2014 for Estonia and Poland, and 2016 for Chile and Korea; for Austria, Australia, Belgium, Czechia, Denmark, Germany, Greece, Spain, Finland, France, Hungary, Italy, the Netherlands, Norway, Poland, Portugal, Sweden, Slovak Republic, Switzerland, Türkiye, and the United Kingdom, the last available year is 2022. For NEET rates, the ten-year period refers to 2011 to 2021 for Sweden, to 2012 to 2022 for Australia, Belgium, Israel, Japan, Mexico, Slovak Republic, Spain, Switzerland, the United Kingdom and the United States. The dotted line represents the correlation line, and the grey-shaded area represents the 95% confidence intervals between the two measures. The estimate of the correlation is listed on the top right of each graph with standard error in paratheses. Each dot represents a TL-2 region. Outliers, defined as regions with values in the top or bottom 8% of the distribution, are not included. The participation rate is defined as the number of working-age employed persons or persons looking for work out of the working-age population in the same subgroup, where the working-age is defined as 15-64 year-olds. The NEET rate is defined as the share of youth not in employment, education or training) out of the youth working-age population (15- 24 year-olds). The educational enrolment rate is the share of individuals aged 15-29 year-olds enrolled in all types of schools and education institutions, including public, private and all other institutions that provide organised educational programmes according to the ISCED 2011 classification, regardless of education level, out of all individuals aged 15-29 year-olds.
Source: OECD calculations based on the OECD Regional databases.

Age disparities in labour force participation rates are highest for capital-city regions, while gender disparities are most prominent in non-capital-city regions (Figure 1.10). In 2023, capital-city regions had a gender inclusion gap that was almost four percentage points below that of non-capital-city regions. In contrast, the age gap in participation rates was almost seven percentage points higher in capital-city regions. Both types of regions exhibit the same general trend over the past years in the evolution of the age and gender gap in participation rates: the age gap is increasing over the decade while the gender gap is decreasing. Yet, in both cases, disparities between capital and non-capital-city regions are widening. From 2013 to 2023, they increased marginally by 0.3 percentage points for the gender inclusion gap and by 2.8 percentage points for the age inclusion gap. Universities, and thus, a higher share of students, tend to be located in capital-city regions, which likely explains a part of the increase, as previously discussed.

Figure 1.10. Capital-city regions contribute most to the age gap in participation rates while the gender gap is highest in non-capital-city regions



Note: The figure shows the evolution of the difference in the participation rate for youth (aged 15 to 24) and the prime-age population (top panel) and the gender difference for males and females (bottom panel) for the working-age population (15-64 year-olds) for capital-city regions vs non-capital-city regions. The sample is all TL-2 regions in OECD countries with data available over the entire time period. The participation rate is defined as the number of working-age employed persons or persons looking for work out of the working-age population in the same subgroup, where the working-age is defined as 15-64 year-olds.
Source: OECD calculations based on the OECD Regional databases.

Most regions face persistently low productivity growth, with little progress in closing regional gaps in labour productivity

Labour productivity, defined as output per worker, is often cited as a primary driver of growth, well-being, and competitiveness in the global economy (see Box 1.2). It plays a role in enabling higher wages, improved living standards, and increased investments in public services and infrastructure. As economies globally face the challenges of technological adaptation and demographic shifts, understanding the dynamics of their productivity allows regions to adapt to these challenges. Factors such as technological innovation, human capital, regulatory environments, and infrastructure development play significant roles in shaping productivity trends. However, recent years have witnessed a troubling slowdown in productivity growth across various advanced economies, accompanied by a disconnect between productivity gains and real wage increases. This scenario underscores the need for insightful policy interventions that can revive productivity while aiming for benefits that extend to workers and enhance the economic well-being of regions.

Box 1.2. Navigating the productivity puzzle: Factors, trends, and challenges facing OECD regions

Labour productivity, measured here as the output per worker, is a fundamental indicator of economic efficiency and a key driver of economic growth and well-being.[3] Higher labour productivity allows for increased wages and living standards since it implies more value is generated per worker or hour worked. This, in turn, can support higher income levels and greater investments in public services and infrastructure (Abiad, Furceri and Topalova, 2015[18]). On a global scale, productivity improvements allow regions to maintain their competitiveness, as they reflect an economy's ability to innovate and adapt to technological advancements (OECD, 2018[19]; Schwab and Zahidi, 2020[20]). Consequently, a focus on labour productivity growth is vital for driving local economic development and improving the quality of life in OECD regions.

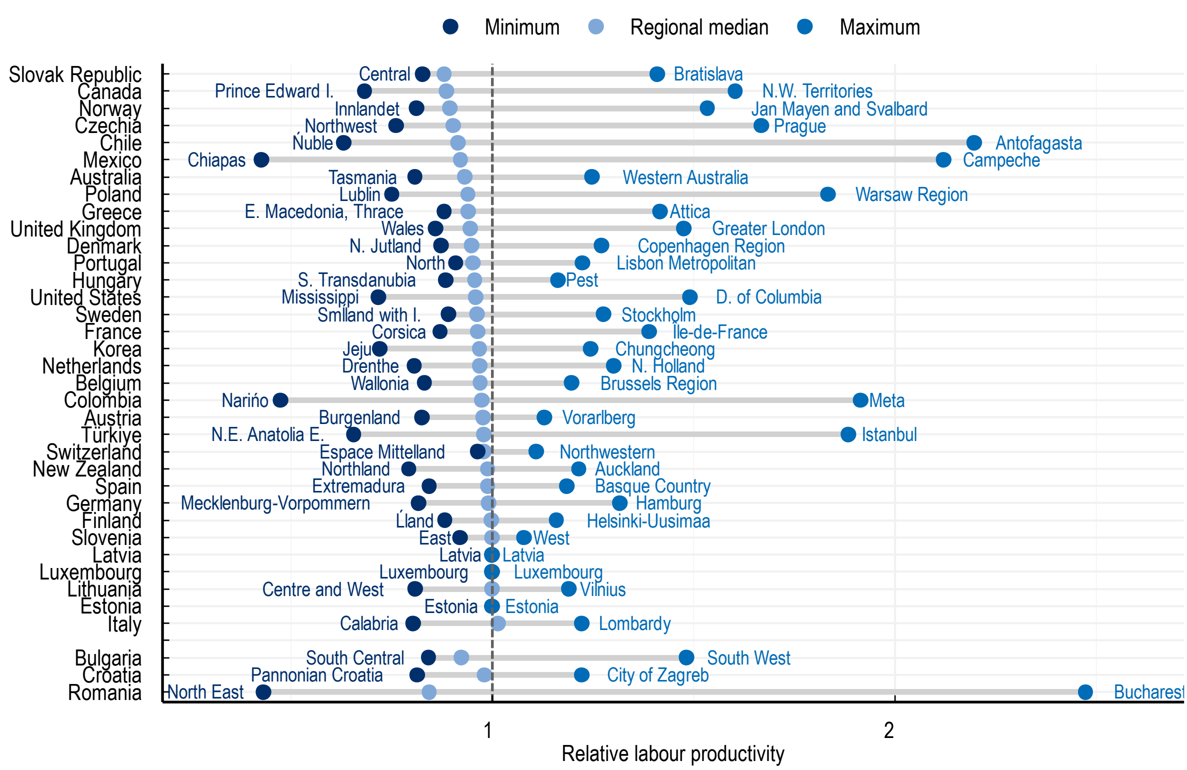
Productivity growth is driven by a confluence of factors, including technological advancements, human capital development, regulatory environments and infrastructure improvements (Syverson, 2011[21]). Technological innovation, particularly in the digital and manufacturing sectors, has been identified as a key enhancer of productivity by enabling more efficient production processes and fostering new business models (OECD, 2024[22]; OECD, 2023[23]). For example, there is early micro-evidence that artificial intelligence, such as large language models, may be productivity-enhancing, although long-run aggregate effects are not yet evident (Filippucci et al., 2024[24]). Its impact on workers and occupations is also not yet clear (see Chapter 3). Human capital also plays a role: better-educated workforces adapt more swiftly to new technologies and processes, thereby increasing output (OECD, 2019[25]). In addition, regulatory frameworks that encourage competition and facilitate fair market conditions can significantly boost productivity by promoting efficiency among businesses (Nicoletti and Scarpetta, 2003[26]; Rubens, 2023[27]). Lastly, investments in infrastructure not only improve efficiency but also connect markets more effectively, enhancing productivity at both national and regional levels (OECD, 2023[3]).

Despite its central role in driving economic growth and well-being, productivity growth slowed down significantly in recent years, turning negative in the European Union, the United States and the OECD in 2022 (OECD, 2024[28]). Several potential, and likely inter-linked, explanations lie behind this productivity slowdown rooted in macroeconomic, societal and technological shifts. For example, one theory relates to the slowdown in technological progress given the increasing difficulty of generating new ideas and fewer groundbreaking innovations (such as electricity and the internal combustion engine) versus advances in software and information technology (Bloom et al., 2020[29]; Gordon, 2017[30]). Structural factors, such as ageing populations, the slowdown in trade and lower growth of allocative efficiency, also play a role (Goldin et al., 2024[31]; Maestas, Mullen and Powell, 2023[32]; Daniele, Honiden and Lembcke, 2019[33]). Skills mismatches and inadequate investment in education and training, depressing the contribution of human capital, may have also hindered productivity improvements across various industries (World Bank Group, 2021[34]). Finally, difficulties in measuring labour productivity may also be a factor, albeit a small one that cannot fully explain the widespread phenomenon (Ahmad, Ribarsky and Reinsdorf, 2017[35]).

An important caveat is the documented trend of the decoupling of productivity and real wage growth, which casts doubt on the ability of productivity gains to translate into improvements in well-being. A study across 24 OECD countries found that productivity increases decoupled from gains in real wages over the period 1995 to 2015, given declines in total-economy labour shares and a partial measure of wage inequality (the ratio of median wages to average wages) (Schwellnus, Kappeler and Pionnier, 2017[36]). Increase in knowledge-based capital, technological change, and the rise of global value chains and income inequality are all cited as potential drivers of this phenomenon (Autor and Salomons, 2018[37]; Berlingieri, Blanchenay and Criscuolo, 2017[38]). Policies that call for higher minimum wages, unionisation, employer protection laws and reduced wage inequality may contribute to a positive link between productivity and wages over time, as well as to encourage upskilling of workers to reduce capital-labour substitution (Berlingieri, Blanchenay and Criscuolo, 2017[38]; OECD, 2018[39]). Many of these factors are likely to depend on regional characteristics; for example, gains from knowledge-based capital are likely to accrue in metropolitan regions.

Within-country productivity differences are widespread, driven by a few top-performing regions. The most productive region is twice as productive as the least productive, on average (Figure 1.11). Labour productivity in the most productive region is more than three times higher than in the least productive regions in 3 out of 33 (9%) OECD countries and twice as high in 20 out of 33 (60%) OECD countries with available data. This is mainly driven by a few regions that lead productivity within a country. In 30 out of 33 OECD countries, the median relative productivity level is below the national average, which is normalised to one. Overall, almost two-thirds (62%) of OECD regions have productivity levels below the national average.

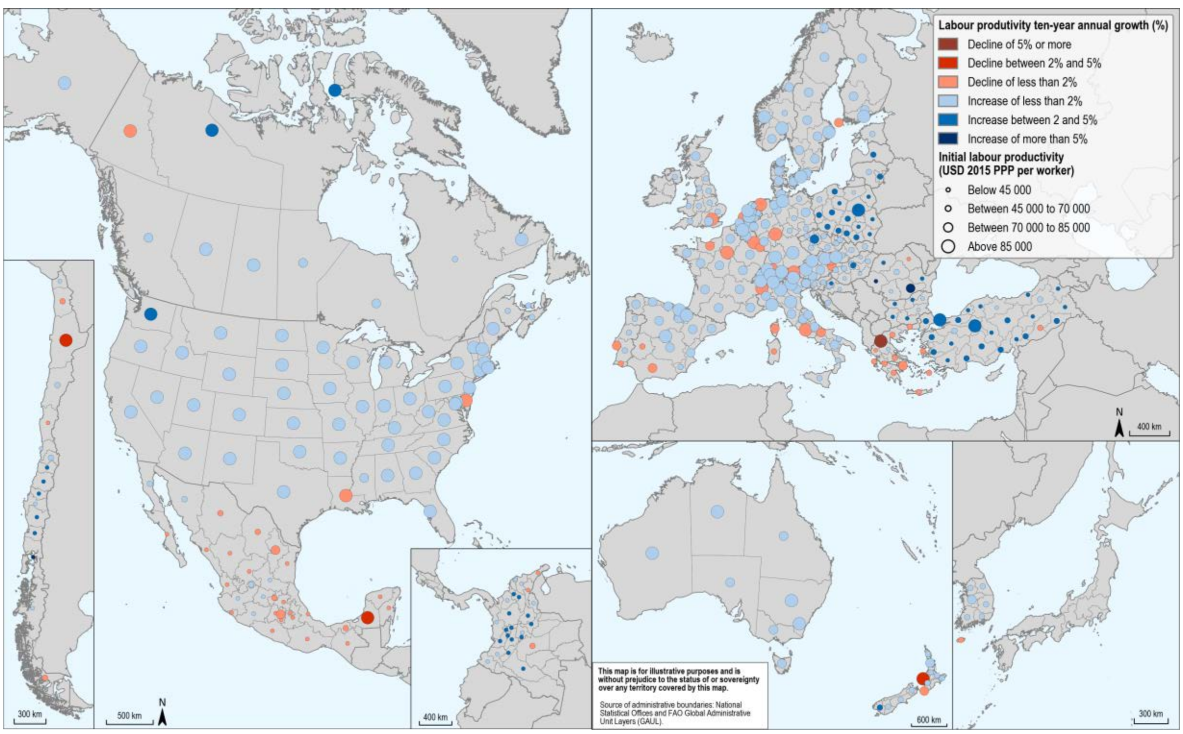
Figure 1.11. Within OECD countries, the leading region's productivity is, on average, double that of the least productive region



Note: The figure shows the regional dispersion (highest, and lowest value) for labour productivity, relative to the regional median in the country for 2022 or the latest available year. The vertical line represents the national average, normalised to one. The data refers to 2021 for New Zealand, Norway, Switzerland and the United Kingdom; to 2020 for Australia and Alaska (United States); and to 2018 for Nunavut, N.W. Territories, and Yukon regions in Canada. The sample is all TL-2 regions in countries (including the OECD accession countries of Bulgaria, Croatia and Romania) with available data, excluding Ireland.
Source: OECD calculations based on the OECD Regional databases.

In half of OECD regions, labour productivity growth over the past decade was below 0.8% per year (Figure 1.12). Labour productivity growth, nonetheless, varies widely across OECD regions, ranging from a decrease of about 5% in Greece's Western Macedonia region to increases of almost 6% in Chile's Los Lagos region and almost 5% in several regions in Turkey (Southern Aegean; Western Black Sea – West; and Northeastern Anatolia - East). Within-country differences are also significant among OECD countries. The median regional dispersion, i.e. the difference between the top and bottom region, in annual productivity growth over the past ten years is about 1.4 percentage points. The highest dispersions were observed in Chile (8 percentage points), and Greece (6 percentage points). The lowest dispersions were observed in Belgium (0.5 percentage points) and Sweden (0.8 percentage points). In more than half of the countries with available data and with more than three regions, regional dispersion is above two percentage points.

Figure 1.12. Most regions experienced only modest productivity growth over the past decade

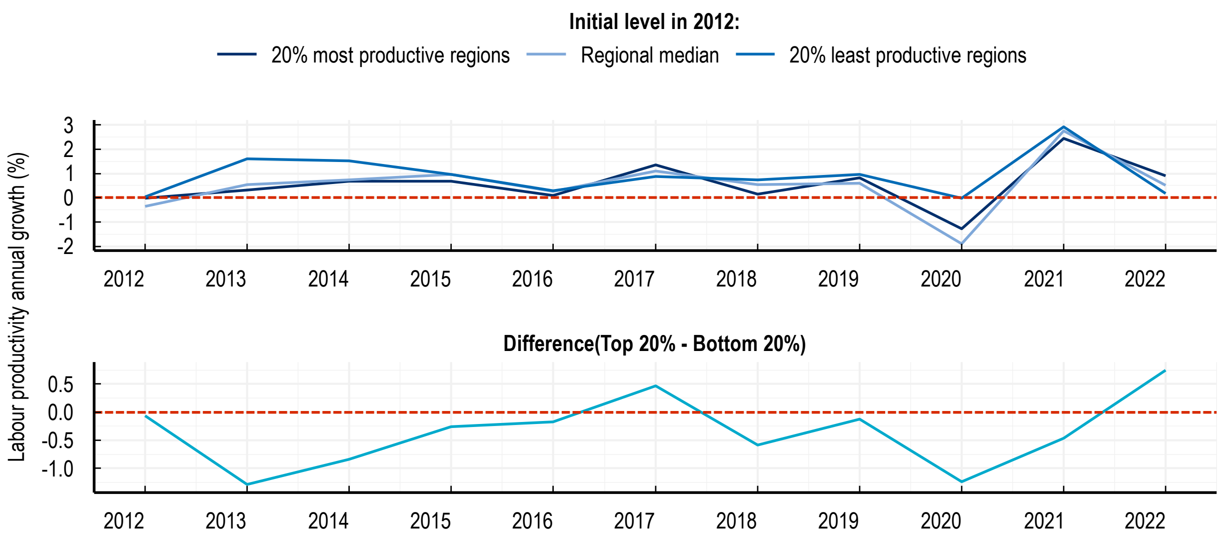


Note: The map shows the initial labour productivity in 2012 and the annual rate of labour productivity growth over the past ten years, from 2012 to 2022 or the closest available years. The initial year refers to 2013 for Chile. The last year refers to 2021 for New Zealand, Norway, Switzerland and the United Kingdom; to 2020 for Australia and Alaska (United States); and to 2018 for Nunavut, N.W. Territories, and Yukon regions in Canada. Initial productivity levels are shown through the size of the circles and the change in labour productivity is shown through the colour scale. Labour productivity is measured as GDP (in USD 2015 PPP) per worker, using regional deflators. The sample is all TL-2 regions (including the OECD accession countries of Bulgaria, Croatia and Romania) with available data, excluding Ireland.
Source: OECD calculations based on the OECD Regional databases.

Annual labour productivity growth, within countries, evolved similarly over the past decade (2012 to 2022) for regions with higher and lower levels of productivity, even if the least productive regions grew marginally faster (Figure 1.13). Between 2012 and 2022, productivity growth in the least productive regions grew faster than the least productive in all but two years. For most of the decade, the least productive regions grew, on average, at an annual rate of about 0.9%. During this time, the most productive regions experienced slightly more sluggish growth of 0.6%, on average, or even negative growth, as in the years 2012 and 2020. Indeed, in 2020 in the aftermath of the onset of the COVID-19 pandemic, both groups of regions experienced negative annual productivity growth, with the most productive regions seeing a downtick of almost 1.3 percentage points more than the least productive regions. Productivity growth in the most and least productive regions grew sharply and converged in 2021, with a less than 0.5 percentage point difference in annual growth rates. This may be due to the shifting composition of employment during the crisis, where smaller firms and lower-skilled workers dropped out of the labour market, mechanically raising the average (Kapsos, 2021[40]). In the most recent year, 2022, the most productive regions overtook the least productive regions in terms of growth. The gap in labour productivity growth reached 0.7 percentage points, mostly due to a decline in labour productivity growth in the least productive regions of almost 2.8 percentage points. This shift may represent a temporary fluctuation as the economy stabilised from the COVID-19 shock and distortions caused by furloughed workers are no longer as prevalent, or it may represent a longer-term trend that should be monitored.

Figure 1.13. Within OECD countries, annual productivity growth kept in step for both the most and least productive regions

Annual labour productivity growth given initial productivity level, 2012 to 2022

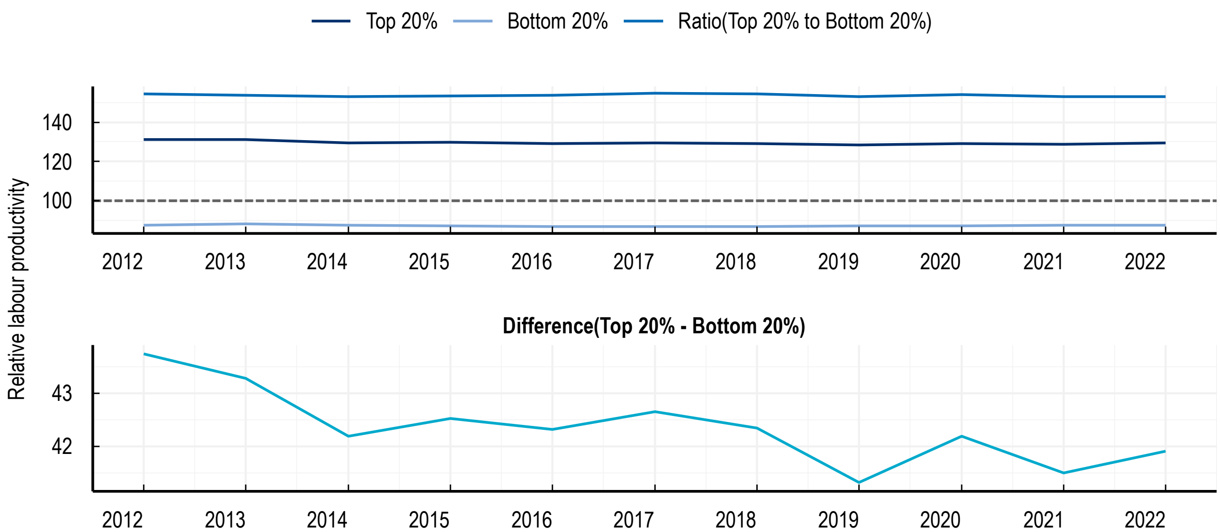


Note: The figure shows the evolution of the annual growth rate of labour productivity for the top and bottom 20% of regions within a country from 2012 to 2022 based on initial productivity levels in 2012 which account for at least 20% of the population. The sample is all regions in countries with at least five regions and with data available over the entire time period, excluding Ireland.
Source: OECD calculations based on the OECD Regional databases.

Productivity gains among the least productive regions were not enough to significantly narrow the gap between the top and bottom-performing regions. By 2022, productivity levels are almost 53% higher in regions in the top quintile of productivity than regions in the bottom quintile, compared to almost 56% in 2012, a decrease of less than two percentage points (Figure 1.14). Thus, although the least productive regions have marginally higher annual productivity growth, these gains do not show up in terms of relative productivity gains. The most productive regions have productivity levels almost 30% above the national median, on average, while the least productive regions have productivity levels that are almost 13% below the national median in 2022. This represents a difference of 41% of the national median, on average. The gap in productivity levels between the best- and worst-performing regions within a country highlights persistent regional inequalities within the OECD. While some regions are thriving with high productivity levels, others are struggling significantly, which could exacerbate socio-economic disparities.

Figure 1.14. Productivity in the top quintile of regions remains over 50% higher than in the bottom quintile of regions

Evolution of the labour productivity relative to the national median, 2012 to 2022

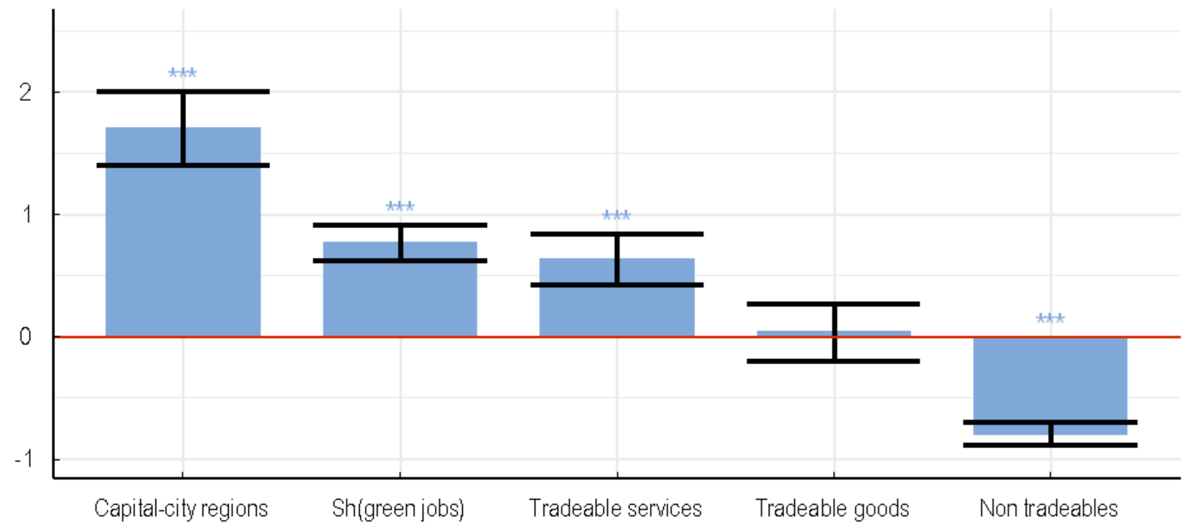


Note: The figure shows the evolution of labour productivity, relative to the national median (which corresponds to 100 on the top graph), for the top and bottom 20% of regions which account for at least 20% of the population in a country. The sample is all TL-2 regions in OECD countries with at least five regions and with data available over the entire period, excluding Ireland.
Source: OECD calculations based on the OECD Regional databases.

Productivity levels are higher in capital-city regions and regions with a higher share of green jobs or specialising in tradeable services (Figure 1.15). Regions that contain the capital city have higher productivity, far above non-capital-city regions, by over 1.7 standard deviations from the national mean. The industrial composition of employment also plays a role. In regions with an above-median share of green jobs or where employment is specialised in tradeable sectors, labour productivity is higher by almost 0.8 standard deviations from the national mean. In contrast, none of these characteristics are correlated with higher *labour productivity growth* (Annex Figure 1.B.5).

Figure 1.15. Capital-city regions and regions with a higher share of green jobs or specialised in tradeable services lead productivity levels

Within-country standardised correlation of labour productivity to selected characteristics, 2022 or latest available year

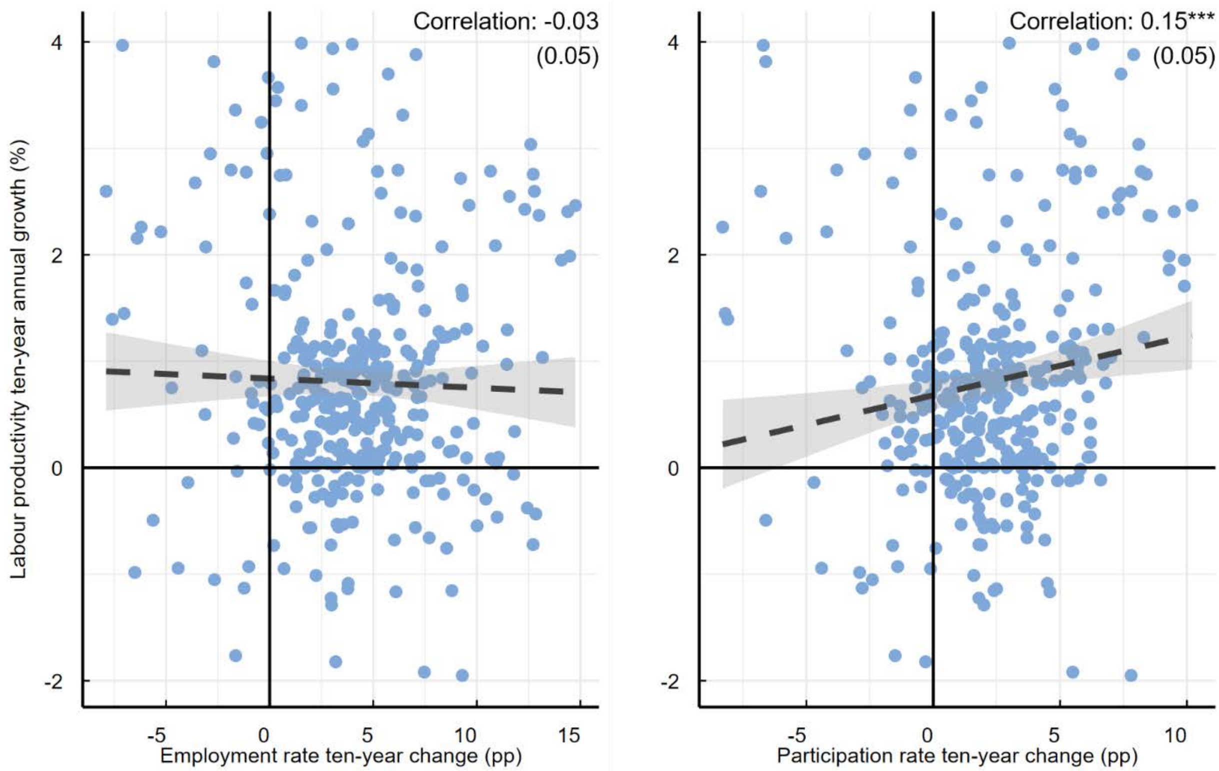


Note: ***p-value<0.01, **p-value<0.05, *p-value<0.1. The graph shows the coefficient and 90% confidence intervals of separate multivariate regressions of labour productivity, standardised within each country, in the latest available year on a dummy for capital-city regions (large regions that include the capital city), regions with an above national median employment share in green jobs in 2021, in tradeable services (ISIC broad sectors G to N), tradeable goods (ISIC sectors B, D, E) or neither tradeable goods nor services. The coefficient represents the change in productivity, measured in standard deviations from the national mean, for regions with the specified characteristic on the x-axis. Each regression also controls for the log of population in the latest available year, a dummy for the latest available year, and country fixed effects. The level of observation is the TL-2 region. The sample of countries includes all OECD countries with available data, excluding Ireland. The data refers to 2021 for New Zealand, Norway, Switzerland and the United Kingdom; to 2020 for Australia and Alaska (United States); and to 2018 for Nunavut, N.W. Territories, and Yukon regions in Canada. Robust standard errors are clustered at the country level.
Source: OECD elaboration based on the OECD Region and Cities databases.

Productivity growth over the past decade complemented gains in labour market participation but not employment across OECD regions (Figure 1.16). There is a positive correlation between labour productivity growth and the change in labour force participation rates. For employment, this correlation is null. Indeed, productivity gains can lead to job losses, for example, in the case of labour-saving technological change. Furthermore, job losses can mechanically raise labour productivity if output does not fall at the same rate as the number of workers. Nonetheless, productivity gains did go hand-in-hand with gains in participation rates: over four-fifths (83%) of regions where participation rates increased also exhibited overall productivity growth at the same time. Furthermore, about two-thirds (64%) of OECD regions are situated in the upper right quadrant of both graphs, indicating positive labour productivity gains with increases in both employment and participation rates over the past ten years. Additionally, almost three-fourths (74%) of regions experienced positive labour productivity growth, with an increase in either employment or participation, but not both. Yet, in almost one in twelve (8%) regions, productivity gains did not accompany either employment or participation gains.

Figure 1.16. Over the past ten years, labour productivity growth accompanied gains in participation but not employment

Correlation between labour productivity growth and employment (left) or participation growth (right), 2012 to 2022 or the closest available years



Note: The figure shows the ten-year change in the employment rate (left) or the participation rate (right) on the x-axis, and the ten-year compound growth rate in labour productivity on the y-axis using the years 2012 to 2022, or the closest available years, for OECD regions with available data. For labour productivity, the first year refers to 2013 for Chile and the last year refers to 2021 for New Zealand, Norway, Switzerland and the United Kingdom; to 2020 for Australia and Alaska (United States); and to 2018 for Nunavut, N.W. Territories, and Yukon regions in Canada. The dotted line represents the correlation, and the grey shaded area represents the 95% confidence intervals between the two measures. Each dot represents a TL-2 region. Outliers are not shown. The employment rate is defined as the number of working-age employed persons out of the working-age population, where the working-age is defined as 15-64 year-olds. The participation rate is defined as the number of working-age employed persons or persons looking for work out of the working-age population, where the working-age is defined as 15-64 year-olds.
Source: OECD calculations based on the OECD Regional databases.

Building resilient regional labour markets: the role of workers and firms

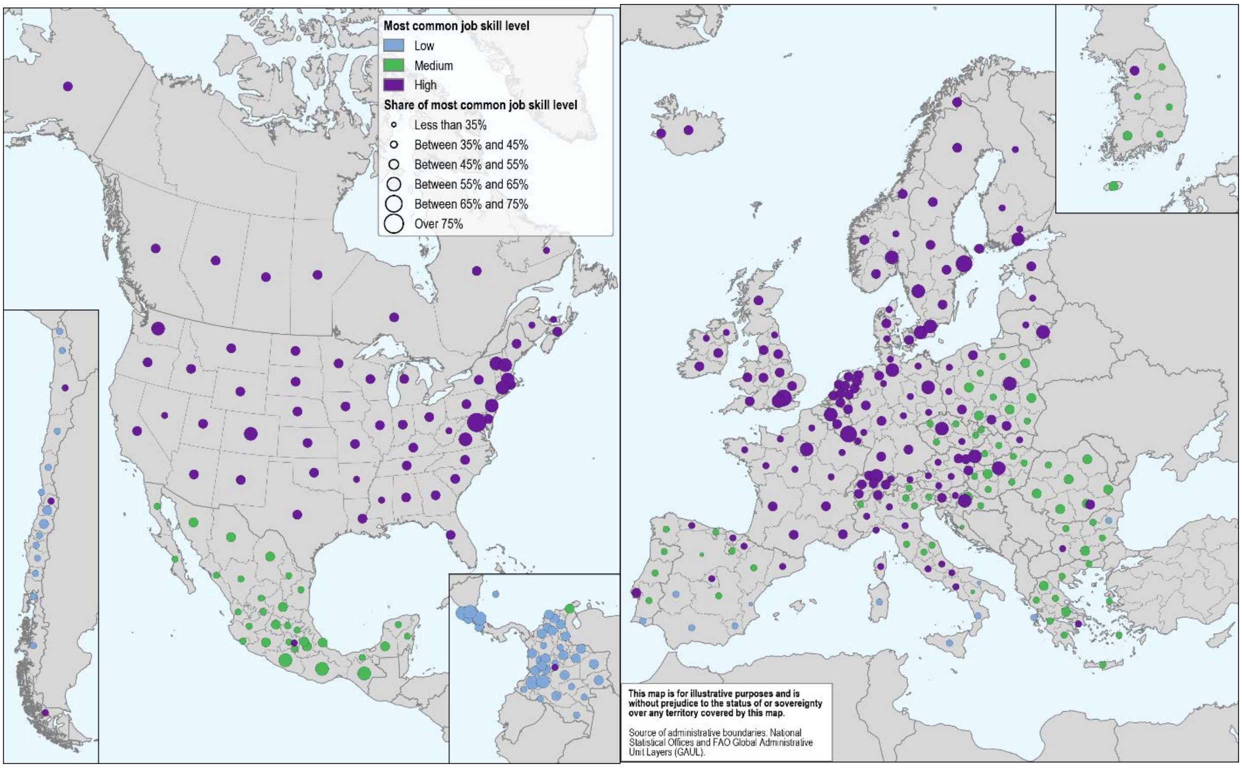
Regional resilience involves the ability of a local economy to weather and recover from shocks through adaptative changes in economic structures and social arrangements (Martin and Sunley, 2014[41]). These shocks include economic recession, natural disasters, and structural changes accelerated by megatrends such as the green, digital and demographic transitions. Policies that support a dynamic business environment, diversified sectoral base and local skills development are key to regional labour market quality, while at the same time, to building resilience in the face of external shocks. For example, targeted economic support measures, like maintaining employer-employee relationships and short-term business support schemes, can aid recovery without compromising efficiency but must be balanced to promote flexible labour markets. Active labour market policies, such as job-seeker support and skills development programmes, enhance regional resilience by improving employability and cushioning against unemployment during economic crises (Vermeulen, 2022[42]). Lastly, supporting vulnerable groups through in-work benefits, partial unemployment aid, and skills subsidies helps to build more equitable resilience. This section considers several indicators covering skill levels and mismatch, the take-up of non-traditional work on the worker side, and sectoral diversification and the case of mass layoffs on the firm side, to comment on the resilience of regional labour markets.

High-skilled jobs dominate regional employment, as the share of middle-skilled jobs shrinks

A diversified skills base in the regional labour force can help to enhance the quality and resilience of regional labour markets. Skills diversity not only supports adaptability to changing economic conditions but also fosters innovation and productivity growth (Aghion and Howitt, 2008[43]; Acemoglu and Autor, 2011[44]). Effective skills development programmes, including vocational training and lifelong learning initiatives, play a pivotal role in equipping workers with the necessary competencies to thrive in evolving industries (European Commission, 2020[45]; Winthrop, Mcgivney and Fellow, 2016[46]). This is in addition to investments in high-quality education and training, which can enhance workforce flexibility and reduce vulnerability to economic shocks, thereby bolstering regional resilience (Heckman and Kautz, 2012[47]; World Bank Group, 2019[48]). Lastly, policies that promote skills matching, such as job placement services and apprenticeship programmes, facilitate smoother transitions for workers and contribute to overall labour market efficiency (European Commission, 2020[49]; Autor, 2014[50]; OECD, 2018[51]). By prioritising a diverse skills agenda, regions can better withstand disruptions and position themselves for sustained economic growth in an increasingly competitive global landscape.

Occupations that require a high level of skills account for the largest proportion of jobs in OECD regions. In more than half (55%) of OECD regions, most workers are employed in high-skilled jobs, followed by three in eleven (27%) regions where most workers are in medium-skilled jobs (Figure 1.17). This highlights a trend towards more advanced, professional, and technical occupations in the overall distribution of jobs within OECD regions. Yet, this distribution varies significantly across countries, and in some cases within countries, likely reflecting differences in education systems, labour market policies, and economic structures. Within-country differences tend to be driven by the capital-city region, where high-skilled jobs dominate. This is the case in Colombia, Greece, Korea, Mexico, and Portugal, where only the capital-city region has the high-skilled as the most common occupational skill level. In 5 out of 28 OECD countries with available data, there is at least one region where each of the skill levels dominates, reflecting significant within-country differences in the skill levels demanded by the labour market.

Figure 1.17. High-skilled jobs represent the highest share across OECD regions

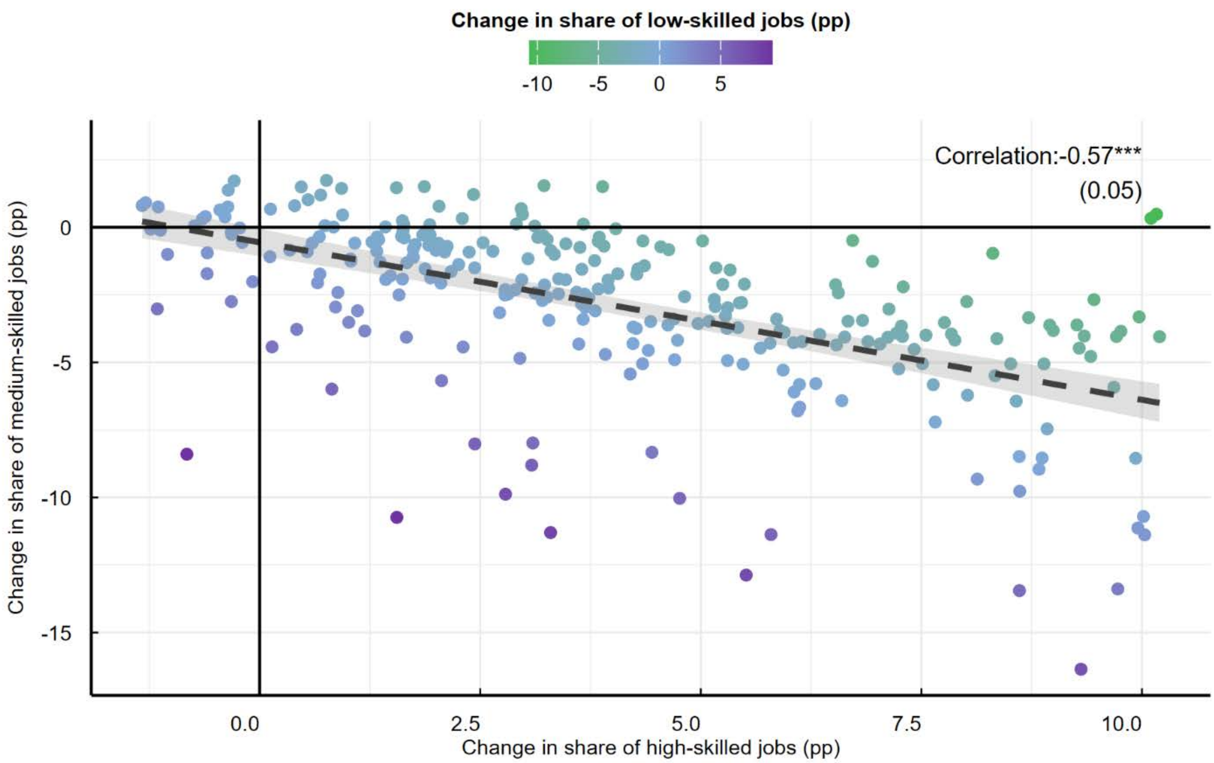


Note: The figure shows the most common job skill level and its share for OECD regions in 2023 or latest available year. For European Union countries, the data refers to 2022 and for Korea, to 2021. Job skill is defined using ISCO occupational categories. Low-skilled corresponds to jobs in sales and services and un-skilled occupations (ISCO 5 and 9), medium-skilled workers hold jobs as clerks, craft workers, plant and machine operators and assemblers (ISCO 4, 7 and 8), and high-skilled workers are those who have jobs in managerial, professional, technical and associated professional occupations (ISCO 1, 2 and 3). The definition of skill is based on the educational level thought to be required of an occupation and does not consider skills not related to educational level. The sample is all TL-2 regions with available data.
Source: OECD calculations based on national labour force surveys for the European Union (including the OECD accession countries of Bulgaria, Croatia and Romania), Canada, Chile, Colombia, Costa Rica, Korea, Mexico, the United States and the United Kingdom.

Over the past decade, the share of middle-skilled jobs contracted in OECD regions, as the share of high-skilled jobs increased. In four in five (80%) OECD regions with available data, the share of middle-skilled jobs fell over 2013 to 2023, falling significantly by over five percentage points in almost two in eleven (22%) regions (Figure 1.18). To a large extent, increasing demand for high-skilled jobs compensated for the falling share of middle-skilled jobs. The share of high-skilled jobs grew in three-fourths (75%) of regions where the share of middle-skilled jobs fell. In contrast, in a majority (63%) of OECD regions, the share of low-skilled jobs changed by less than three percentage points. In one in eleven (11%) regions, the share of low-skilled jobs grew by over three percentage points and in tandem with the share of high-skilled jobs. While in more than half (53%) of regions, low-skilled and middle-skilled jobs fell together, as high-skilled jobs grew. Similar to the skill distribution across countries, this trend indicates a shift towards more managerial, professional, technical, and associated professional occupations at the cost of a decline in clerks, craft workers, plant and machine operators and assemblers. This may reflect a shifting skills demand, driven by changes in technology, automation, and the global economic landscape. In contrast, there is a consistent demand for low-skilled jobs in sales, services and unskilled occupations, despite these advancements in technology and economic shifts.

Figure 1.18. High-skilled jobs are replacing middle-skilled job

Correlation between the ten-year change in the regional skill distribution, 2013 to 2023 or closest available years



Note: The figure shows the ten-year change in the share of high-skilled jobs on the x-axis and the ten-year change in the share of medium-skilled jobs on the y-axis. The colour of the point refers to the ten-year change in the share of low-skilled jobs. The ten-year period is 2013 to 2023, or closest available years. The time period refers to 2013 to 2022 for European Union countries, to 2015 to 2023 for the United Kingdom; and 2013 to 2021 for Korea. The dotted line represents the correlation line, and the grey shaded area represents the 95% confidence intervals between the two measures. The estimate of the correlation is listed on the top right of each graph with standard error in paratheses. Each dot represents a TL-2 region. Outliers, defined as regions with values in the top or bottom 5% of the distribution, are not included. Job skill is defined using ISCO occupational categories. Low-skilled corresponds to jobs in sales and services and un-skilled occupations (ISCO 5 and 9), medium-skilled workers hold jobs as clerks, craft workers, plant and machine operators and assemblers (ISCO 4, 7 and 8), and high-skilled workers are those who have jobs in managerial, professional, technical and associated professional occupations (ISCO 1, 2 and 3). The definition of skill is based on the educational level thought to be required of an occupation and does not consider skills not related to educational level. The sample is all TL-2 regions in OECD countries with available data.

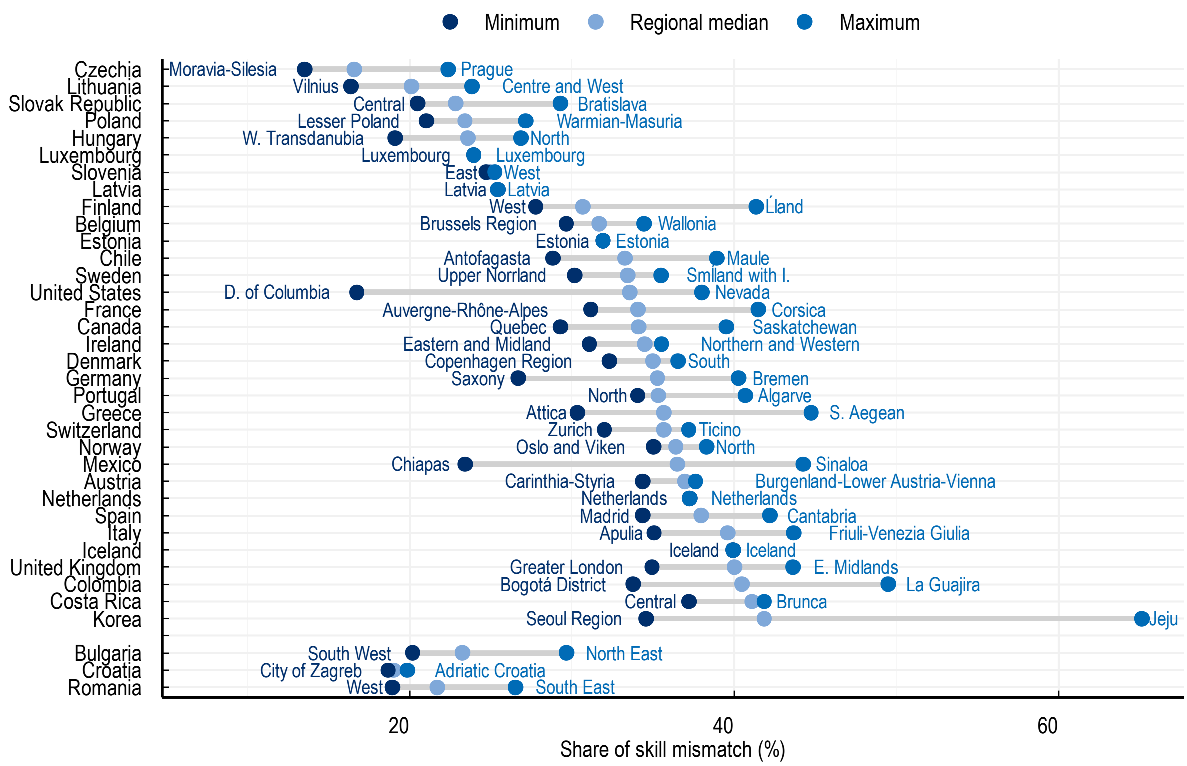
Source: OECD calculations based on national labour force surveys for the European Union, Canada, Chile, Colombia, Costa Rica, Korea, Mexico, the United States and the United Kingdom.

Regional disparities in over- and under-skilling highlight challenges in labour market alignment

Skills mismatches, defined as discrepancies between the skills of workers and those demanded by employers, pose challenges for aligning labour market needs with available talent.[4] These mismatches can result in underemployment—where individuals work in jobs that do not fully utilise their skills—, in in workers underqualified for the jobs they are employed in, or in job vacancies that remain unfilled due to a lack of qualified candidates. This friction can influence the economic performance of regions, weighing on growth and the capacity to respond to market changes effectively. As regions strive to enhance their economic resilience, understanding and addressing skill mismatches becomes increasingly important.

Skill mismatches are prevalent across OECD regions with almost one in three employed individuals working in jobs that do not match their skill level, regardless of whether they are over- or under-qualified (Figure 1.19)**.** Countries such as Czechia, Lithuania, and Slovakia exhibit relatively low regional median skill mismatches, around 16.5% to 23%. Conversely, the top four OECD countries experiencing the greatest degree of mismatch, are Korea (41.8%), Costa Rica (41.1%), Colombia (40.5%), and the United Kingdom (40%). Low mismatch suggests effective alignment in most regions, given equally low regional dispersion of around 7.5 to 9 percentage points difference between the region with the highest and lowest mismatch. Conversely, 10 out of the 33 OECD countries with available data indicate large regional dispersion with a difference of over ten percentage points. The largest dispersions are present in high mismatch countries, such as Korea, Mexico and Colombia, where the difference is over 30 percentage points, 20 percentage points and over 15 percentage points, respectively. The difference between the region with the highest and lowest mismatch is also large in the United States (21 percentage points), despite having a lower-than-average regional mismatch.

Figure 1.19. On average, more than 9 percentage points (a third of the OECD regional median) separate the region with the highest and lowest share of mismatched jobs within OECD countries



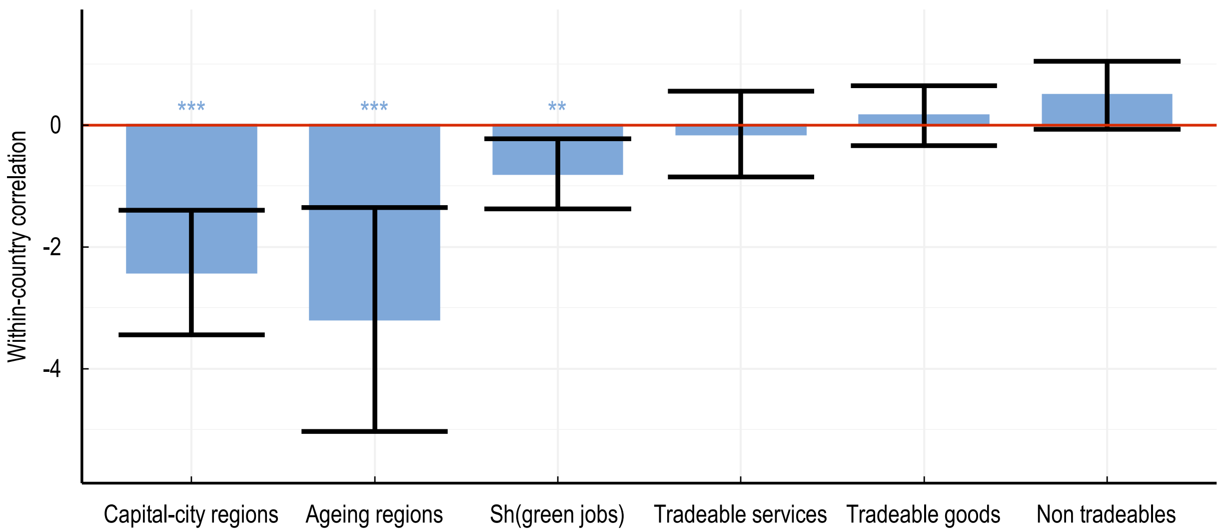
Note: The figure shows the regional dispersion (highest, lowest and median value) in the share of workers in mismatched jobs in 2023 or the latest available year. For European Union countries, the data refers to 2022, and for Korea, to 2021. Skill mismatch is calculated following the methodology of the Skills for Jobs Indicators of the OECD's Directorate for Employment, Labour and Social Affairs, whereby a worker is in a mismatched job when their educational skill level does not match the most common skill level of workers in that occupational group in that country. The sample is all TL-2 regions with available data.

Source: OECD calculations based on national labour force surveys for the European Union (including the OECD accession countries of Bulgaria, Croatia and Romania), Canada, Chile, Colombia, Costa Rica, Korea, Mexico, the United States and the United Kingdom.

Capital-city regions, ageing regions and regions with a higher share of green jobs saw the share of mismatched workers fall over the past ten years (Figure 1.20). Ageing regions, or regions where the old-age dependency ratio increased over the past five years, are correlated with a 3.2 percentage point decrease in the share of mismatch. This is likely driven by both the exit of older workers with less education and an overall demand shift toward a more educated labour force. Job mismatch also fell by 1.4 percentage points in capital-city regions, and marginally by 0.2 percentage points in regions with a higher share of green jobs, compared to regions in the same country. The share of mismatched workers is lower in capital-city regions, compared to other regions in the same country (Annex Figure 1.B.6). In contrast, other demographic (such as an ageing population), or economic (such as the sectoral employment composition) characteristic is not correlated with within-country differences in the share of mismatch.

Figure 1.20. Over the past ten years, the share of mismatch fell in capital-city regions, ageing regions and regions with a high relative share of green jobs

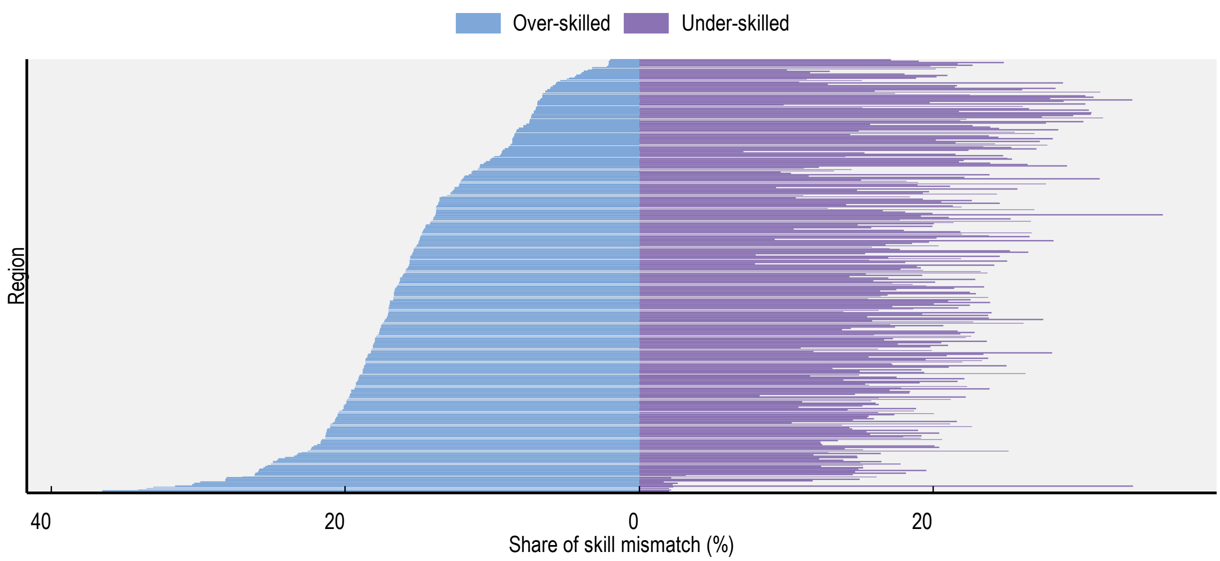
Within-country correlation of the ten-year change in the share of mismatch (pp) to selected characteristics, 2023 or latest available year



Note: ***p-value<0.01, **p-value<0.05, *p-value<0.1. The graph shows the coefficient and 90% confidence intervals of separate multivariate regressions of the ten-year change in the share of job mismatch from 2013 to 2023 (or closest available years) on a dummy for capital-city regions, ageing regions (defined as those that experienced an increase in the elder-dependency rate over the past five years), for an above national median employment share in green jobs in 2021, in tradeable services (ISIC broad sectors G to N), tradeable goods (ISIC sectors B, D, E) or neither tradeable goods nor services. The coefficient (`within-country correlation') presents the within-county percentage point difference in the share of mismatch based on the characteristic on the x-axis. Skill mismatch is calculated following the methodology of the Skills for Jobs Indicators of the OECD's Directorate for Employment, Labour and Social Affairs, whereby a worker is in a mismatched job when their educational skill level does not match the most common educational skill level of workers in that occupational group in that country. Each regression also controls for the log of population in 2023 or latest available year and country fixed effects. For European Union countries, the data refers to 2013 to 2022, for Korea, to 2013 to 2021, and for the United Kingdom, to 2015 to 2023. The level of observation is the TL-2 region. The sample of countries includes all OECD countries. Robust standard errors are clustered at the country level.
Source: OECD elaboration based on the OECD Regional databases.

Regions with a higher prevalence of over-skilled workers generally exhibit lower levels of under-skilling (Figure 1.21). The mean difference between the share of underqualified and overqualified workers is around nine percentage points across OECD regions. The top five regions with the greatest difference are all in Canada, with over 30% of over-skilled workers and 1.5% to 2.3% of under-skilled workers. In contrast, the regions with the smallest differences between the share of over-skilled and under-skilled workers are in three different countries (Italy, Poland, Spain and the United States), with a difference of under 0.3 percentage points. Regions with a high share of either over- or under-skilled workers may be experiencing a high- or low-skill equilibrium, whereby the skills demand of jobs adapts to match the skills supply of the population. This can be a particular issue in a low-skill equilibrium when employers adopt a price-based competition strategy that relies on low-skilled and standardised production (OECD, 2014[52]). Jeju region (Korea) stands out with a high share of both under- and over-skilled workers at over 30% each, likely due to its economy specialised in agriculture, fishing and tourism, which differs from the rest of Korea, which is more industrialised. As such, workers in the same occupation in Jeju likely require different skills than their counterparts in the rest of Korea. The regional economic structure, industrial composition and educational system are likely to all contribute to this distinct distribution of skill mismatches.

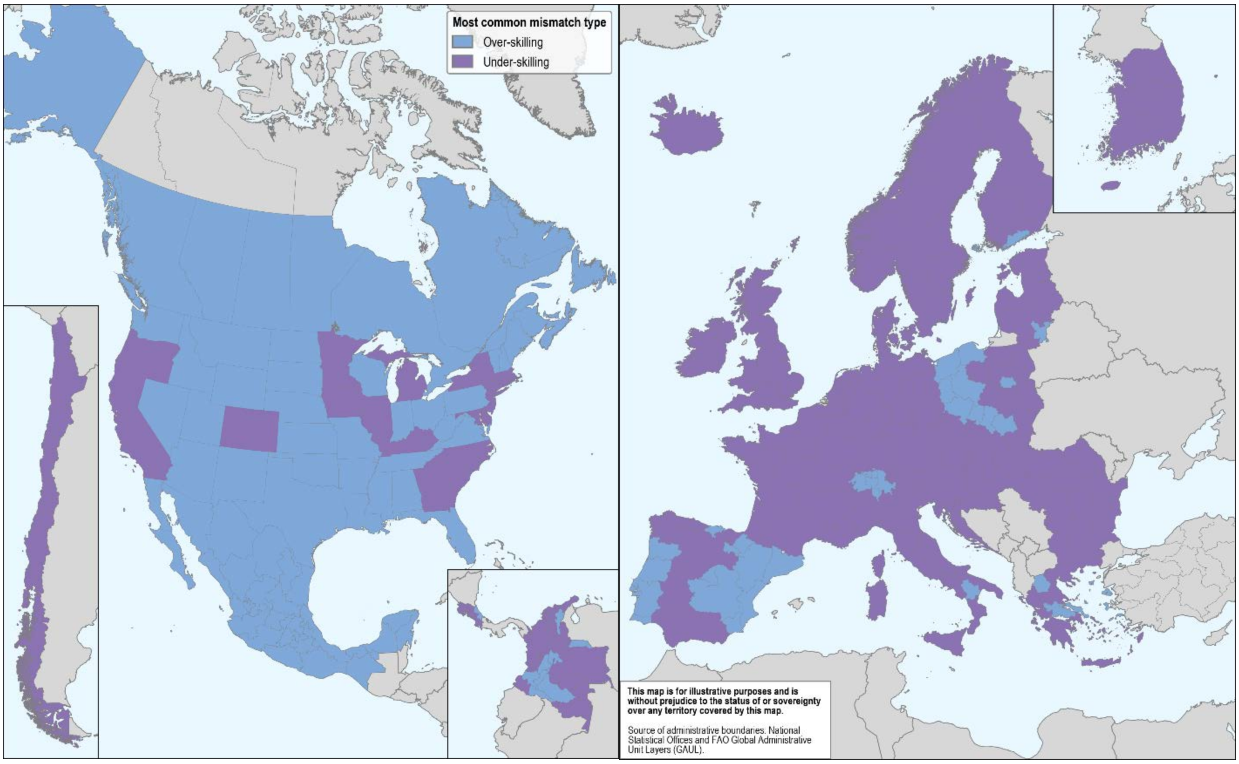
Figure 1.21. Regions specialise in a type of skill mismatch: those with more over-skilled workers tend to have fewer under-skilled workers



Note: The figure shows the share of over- and under-skilled workers for each OECD TL-2 region in 2023 or the latest available year. For European Union countries, the data refers to 2022, and for Korea, to 2021. Skill mismatch is calculated following the methodology of the Skills for Jobs Indicators of the OECD's Directorate for Employment, Labour and Social Affairs, whereby a worker is in a mismatched job when their educational skill level does not match the most common educational skill level of workers in that occupational group in that country. `Over-skilled' means that the worker has an educational skill level above the most common educational skill level of their occupation. `Under-skilled' means that the worker has an educational skill level below the most common educational skill level of their occupation.
Source: OECD calculations based on national labour force surveys for the OECD countries in the European Union, Canada, Chile, Colombia, Costa Rica, Korea, Mexico, the United States and the United Kingdom.

Spatial variation in the incidence of over- and under-skill across regions highlights distinct patterns in how educational qualifications align with labour market demands. There exist opportunities in some countries to leverage complementarities between types of skill mismatch. For example, Illinois (United States) has 18% of under-skilled workers, while its neighbouring regions, such as Indiana and Wisconsin, have 16% of over-skilled workers (Figure 1.22). Overall, for half of OECD regions with available data, there exists a region in the same country with a complementary type of mismatch. In contrast, in 10 out of the 33 OECD countries with available data, all regions display the same type of mismatch, whether it is over-skilling or under-skilling. In these countries, skill mismatch is likely driven by national trends. Vocational education and training systems (VET) can be leveraged to bridge skill gaps by providing skills training in alignment with industry needs. At the same time, these systems should be flexible with recognised credentials, to respond to evolving skills needs and labour market transitions such as in Germany, Austria and Switzerland (OECD, 2023[53]).

Figure 1.22. Within-country complementarity in the type of mismatch exists for half of OECD regions



Note: The map shows the most common type of mismatch, workers in jobs below their skill level ("under-skilling") or workers in jobs above their skill level ("over-skilling") in 2023 or latest available year. For European Union countries, the data refers to 2022, and for Korea, to 2021. Skill mismatch is calculated following the methodology of the *Skills for Jobs Indicators* of the OECD's Directorate for Employment, Labour and Social Affairs, whereby a worker is in a mismatched job when their educational skill level does not match the most common skill level of workers in that occupational group in that country. The sample is all TL-2 regions with available data.
Source: OECD calculations based on national labour force surveys for the European Union (including the OECD accession countries of Bulgaria, Croatia and Romania), Canada, Chile, Colombia, Costa Rica, Korea, Mexico, the United States and the United Kingdom.

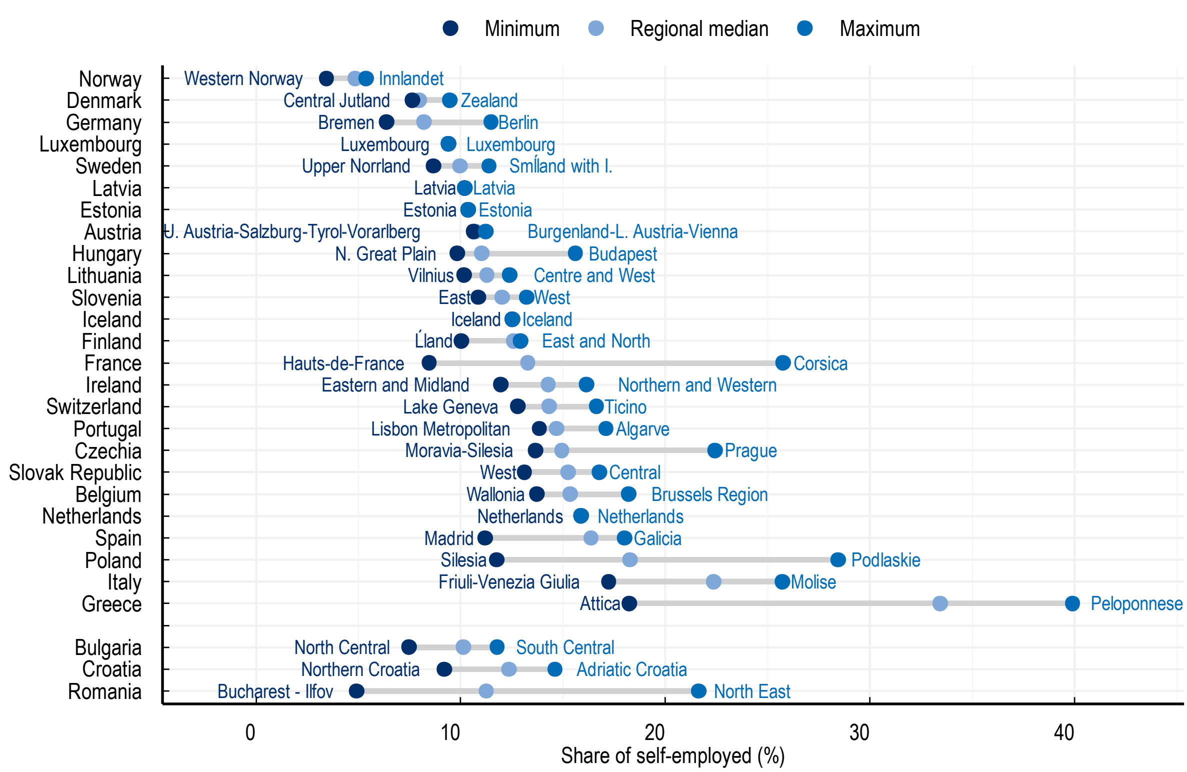
Across regions, self-employment is higher where more traditional jobs are lacking

Non-traditional forms of employment, such as self-employment, as well as part-time and temporary work, play an important role in today's labour markets, reflecting broader shifts in work arrangements across OECD countries. Self-employment, defined by individuals owning and operating their businesses, provides independence and can encourage labour market engagement among those desiring more control over their work, exploring entrepreneurial ventures, or adapting to unique personal circumstances. Part-time employment, characterised by fewer working hours per week than full-time jobs, provides flexibility and can facilitate increased labour market participation among students, caregivers, and older adults. Similarly, temporary work, including fixed-term contracts and seasonal employment, offers both employers and employees greater adaptability in response to fluctuating economic conditions and personal circumstances. Take-up of the latter two forms of non-traditional forms of work is mainly driven by structural national policies, implying few regional dimensions. See Annex Figure 1.B.8 to Annex Figure 1.B.11 in Annex 1.B for more information about the regional take-up of part-time and temporary work.

Non-traditional work arrangements also present challenges, such as lower job security, reduced career progression opportunities, and often limited access to benefits compared to permanent, full-time roles (OECD, 2018[54]; OECD, 2019[55]). In particular, self-employment can raise specific challenges, such as income instability, difficulty in accessing credit and financing, and the burden of managing administrative tasks and regulatory compliance (OECD, 2019[55]; OECD/European Union, 2017[56]). Rather than a deliberate choice for greater work autonomy, workers may engage in self-employed work due to a lack of other options. In addition, it tends to be under-represented among women, youth, the elderly, immigrants, and the unemployed (OECD/European Commission, 2023[57]).[5] Consequently, understanding the dynamics in the take-up of non-traditional employment allows for the development of comprehensive policies that promote equitable work conditions and protection for all workers, regardless of their employment status.

Median within-country regional dispersion in self-employment rates stands at over 6 percentage points (Figure 1.23). Yet, this difference between the regions with the most and least self-employed ranges from about 0.5 percentage points in Austria to over 21 percentage points in Greece. Countries with a high overall share of self-employed tend to also have high regional dispersion. For example, in Greece, Italy and Poland, the median share of self-employed across all regions is over 18%, with regional dispersion at over eight percentage points. France is an exception, as the overall share of self-employed resembles the OECD average, yet it has high regional dispersion at over 17 percentage points. In contrast, regional self-employment rates are limited in Austria, Norway and Denmark, where the difference between the region with the highest and lowest share of the self-employed is under two percentage points. Regions, where the tourism and agriculture sectors dominate, such as in Peloponnese (Greece), Podlaskie (Poland), Corsica (France), and Molise (Italy), tend to have the highest self-employment rates.

Figure 1.23. There is considerable within-country range of over 5 percentage points between the region with the highest rate of self-employed vs. the lowest for almost half of OECD countries

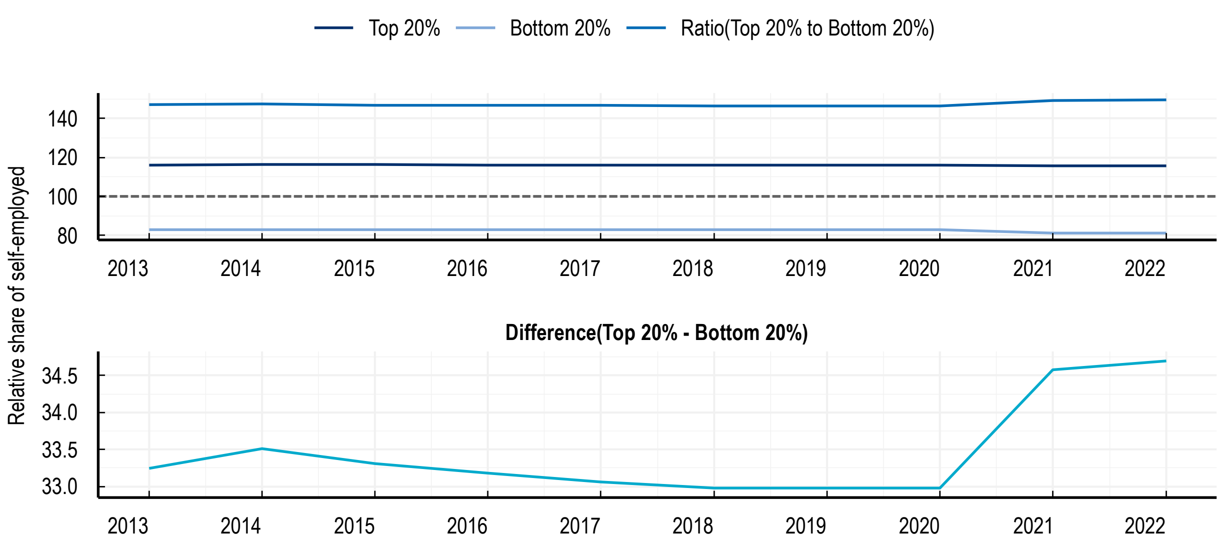


Note: The figure shows the regional dispersion (highest, lowest and median value) in the share of self-employed among all working-age employed persons in 2022. The working-age population is defined as 15-64 year olds. The sample is all TL-2 regions with available data.
Source: OECD calculations based on national labour force surveys for the European Union (including the OECD accession countries of Bulgaria, Croatia and Romania).

Regional disparities in the rates of self-employment between regions with the highest and lowest rates increased by three percentage points following the COVID-19 shock (Figure 1.24). In 2013, high self-employment regions had rates of self-employment almost 47% higher than regions with low-self-employment, in the same country. By 2022, this ratio rose to almost 50% higher. The difference between the top and bottom quintile of regions, based on self-employment rates, increased from about 33% of the national median to almost 35%. The increase is mostly driven by falling self-employment rates in regions in the bottom quintile of self-employment, relative to the national median.

Figure 1.24. Increase in post-pandemic within-country disparities between the regions with the highest and least share of the self-employed

Evolution of the self-employment rate relative to the national median, 2013 to 2022

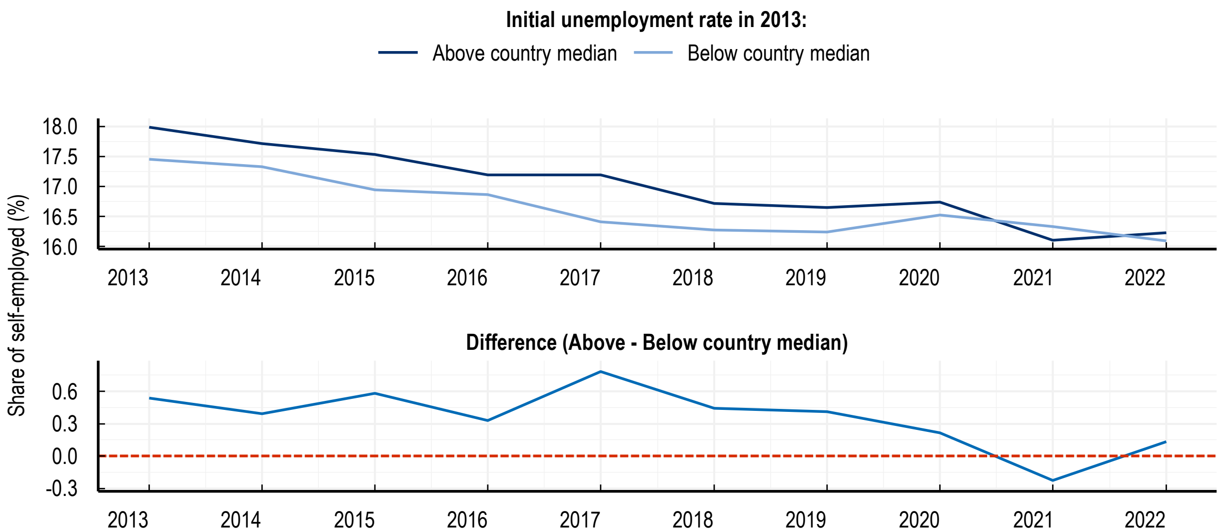


Note: The figure shows the evolution of the share of self-employed among the employed in the working age population (15-64 year-olds), relative to the national median (which corresponds to 100 on the top graph), for the top and bottom 20% of regions which account for at least 20% of the population. The sample is all TL-2 regions in OECD countries with at least five regions and with data available over the entire period.
Source: OECD calculations based on national labour force surveys for the OECD countries in the European Union.

Self-employment is marginally most prevalent in regions facing higher unemployment rates (Figure 1.25). In regions with unemployment rates below the national median, about 17% of workers are self-employed at the start of the period. For regions facing unemployment rates above the national median, the self-employed represented almost 18% of workers. The difference in the share of self-employed between higher and lower unemployment regions, in the same country, remained relatively stable at about 0.5 percentage points, up until 2020. In 2021, the trend briefly reversed so that regions with unemployment rates below the national median had marginally higher rates of self-employment. By 2022, the difference in the share of self-employed for regions above and below the national median narrowed to about 0.1 percentage points. This may be linked to overall falling unemployment rates, especially in high-unemployment regions (Annex Figure 1.B.7). High unemployment rates suggest that jobs are scarce so more traditional types of work are difficult to find. Thus, rather than solely representing a voluntary shift to a more autonomous working environment, self-employment take-up is also likely a recourse from a difficult labour market situation.

Figure 1.25. Take-up of self-employment is greatest in regions facing higher unemployment rates, although the difference is narrowing

Evolution of the self-employment rate given initial unemployment rate, 2013 to 2022



Note: The figure shows the evolution of the share of self-employed among the employed in the working-age population for the regions above and below the national-specific median of unemployment rates in 2013. The unemployment rate is defined as the share of persons looking for work as a percentage of the labour force (employed or looking for work) in the working-age population (15-64 year-olds). The sample is all regions in OECD countries with data available over the entire time period.
Source: OECD calculations based on national labour force surveys for the OECD countries in the European Union.

Sectoral diversity and mass layoffs: The role of firms in regional resilience

The adaptability and competitiveness of firms are pivotal in determining a region's capacity to withstand economic shocks and capitalise on new opportunities for innovation, job creation and productivity gains. As regions navigate the challenges posed by globalisation, technological advancements, and changing market demands, the strength and diversity of local businesses and sectors become instrumental in promoting sustainable development and long-term economic stability. Therefore, a deep understanding of the firm and sectoral structure of regions is essential for policymakers to design informed and effective strategies that enhance regional resilience.

The composition of sectoral employment represents an important feature of regional economies with implications for economic diversity and resilience. Regions dominated by a limited number of industries often face increased vulnerability to economic fluctuations and external shocks, such as technological changes or global market shifts, even if regions concentrated in trade-exposed sectors tend to be relatively more resistant (OECD, 2018[19]). Conversely, regions with a diversified employment base tend to exhibit greater economic stability and adaptability (Audretsch and Feldman, 1996[58]; Giannakis, Bruggeman and Mamuneas, 2024[59]; Delgado, Porter and Stern, 2014[60]). This sectoral diversification also influences labour market dynamics, affecting everything from wage levels to employment opportunities and workforce skills development (Autor, Katz and Kearney, 2008[61]; Boeri et al., 2019[62]; Greenstone, Hornbeck and Moretti, 2010[63]). It is important to understand these dynamics to mitigate the risk associated with economic specialisation.

In over two-thirds of OECD regions, the sectoral composition of employment shows moderately-low or low diversification (Figure 1.26). Diversification is measured using the Herfindahl-Hirschman Index (HHI) (See Box 1.3 for details). This is driven mainly by a high share of regions with moderately-low diversified labour markets: only 13% of OECD regions with available data (57 out of 419 regions) display a low sectoral diversification of employment (mean HHI index of 2 822), while in ten regions, sectoral employment diversification is especially low (over 3 000). While the region with the highest index score (and lowest diversification) is Nunavut in Canada (likely due to its remoteness and low population density), other top regions include three regions in Czechia, two in Mexico and Türkiye, and one in Romania and Greece. Then, 142 out of 419 regions (34%) are in moderately-high diversified labour markets. In contrast, no regions fall into the category of high diversification, likely due to the low total number of available sectors. The five regions with the highest diversification are Luxembourg, Central (Costa Rica), Prague (Czechia), Warsaw (Poland), and Tel Aviv (Israel) (HHI ranging from 1 615 to 1 661). '

Box 1.3. Defining sectoral diversification

The Herfindahl-Hirschman Index (HHI) is a standard measure of market concentration, usually used to consider firm power in a certain product market, sector or economy (Antitrust Division, 2024[64]). When considering labour markets, this measure can be adapted to look at firms' share of vacancies, new hires, or employment within a market (OECD, 2022[7]). To consider sectoral diversification, this chapter takes the share of workers employed in each sector in a subnational region.

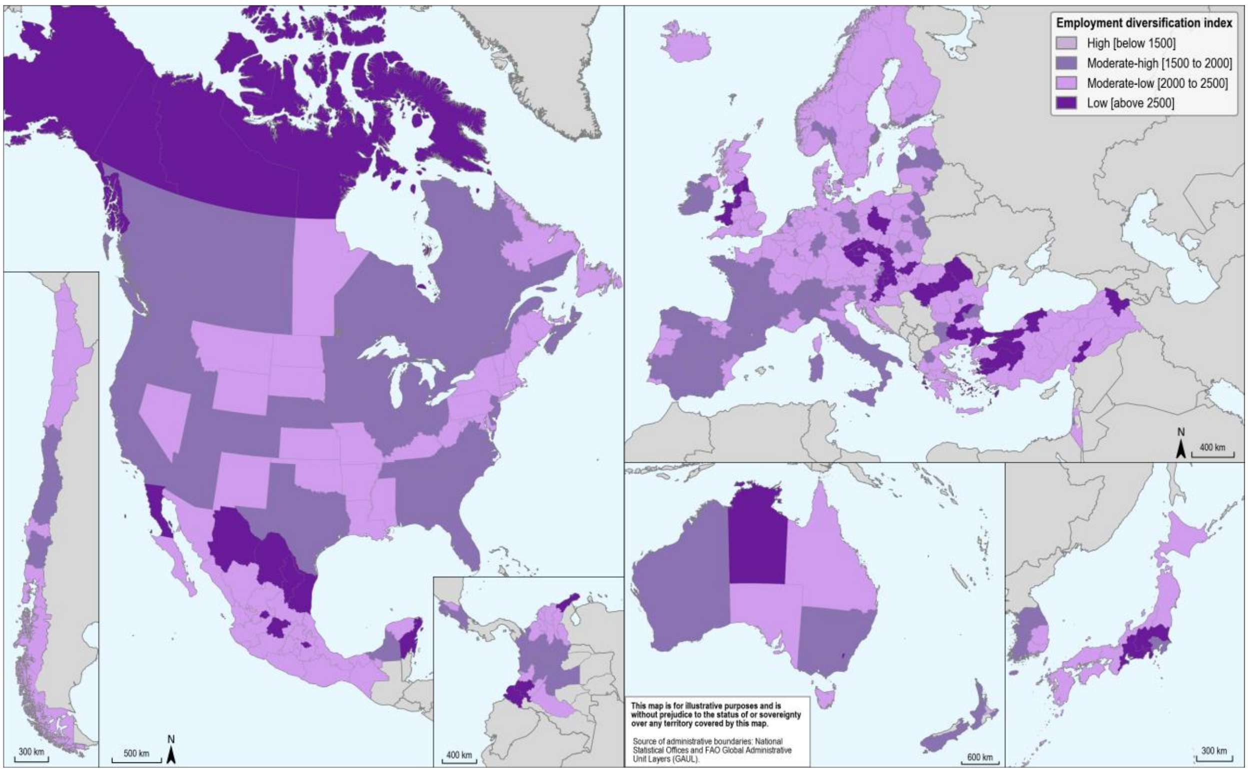
The measure is thus defined as the sum of the squared percentage shares of each sector in the economy. In this way, the index accounts for the relative size distribution of firms in the regional economy. Given data availability, sectors are classified into ten broad categories*: "Agriculture, Forestry & Fishing", "Industry", "Manufacturing", "Construction", "Trade, Repair, Transport, Accommodation", "Information and communication", "Financial and insurance activities", "Real estate activities", "Professional, scientific and technical activities; administrative and support service activities", "Public admin., Defence, Edu., Health, Social", and "Arts, Entertainment, Recreation".* It ranges from 1 000 when a labour market is occupied by an equal share of employment in each of the ten sectors, and a maximum of 10 000 if all employment is concentrated in one sector.

Given the high level of aggregation of the sectors considered, the measure presented in this chapter should not be taken to be an indicator of the concentration of a regional labour market. Instead, the purpose is to give a sense of the sectoral diversity of the distribution of employment and to comment on sub-regional differences.

Conventionally, a market is considered concentrated (or less diverse) if it has an HHI of 2 500 or above, a threshold usually considered conservative (Nocke and Whinston, 2022[65]; Affeldt et al., 2021[66]). A moderately concentrated (or moderately less diverse) market is between 1 500 and 2 500, which can be further broken down into moderately-low (HHI of 1 500 to 2 000), moderately-high (HHI of 2 000 to 2 500) and a low concentrated market is an HHI below 1 500 (US Department of Justice and Federal Trade Commission, 2010[67]).

Recent work found pervasive labour market concentration in OECD countries using harmonised data on job postings: 16% of business-sector workers in 15 OECD countries are in national labour markets that are at least moderately concentrated and 10% in highly concentrated markets. Exploiting harmonised linked employer-employee databases, it also finds evidence of monopsony power, i.e. firm discretion in setting wages and working conditions in contrast to competitive markets where firms must pay workers the "market rate" aligned with their productivity: 10% of workers employed in the most concentrated labour markets experience a wage penalty of at least 5% compared to a worker in a median-concentrated market. Job quality is also affected, as evident in the increased use of flexible and temporary contracts, as well as higher skill requirements (OECD, 2022[7]). Reintroducing competition into labour markets requires policies that increase the relative bargaining power of workers and promote fair wage-setting mechanisms in the face of power imbalances, towards the goal of improved labour market efficiency.

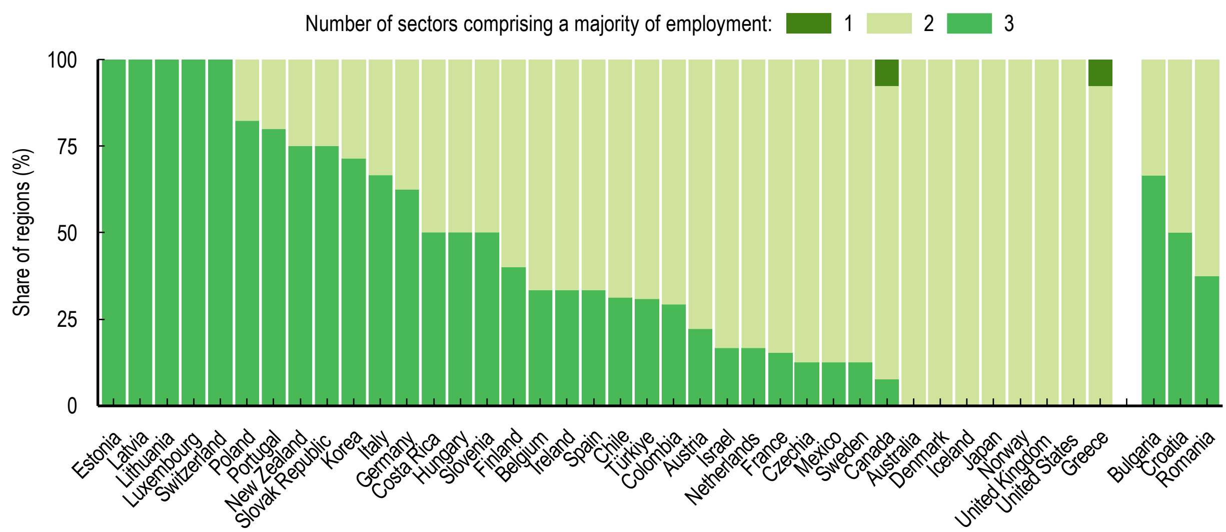
Figure 1.26. Employment is moderately diversified in a few sectors across OECD regions



Note: The map shows the regional distribution of the degree of diversification of employment in 2023 or the last available year. The data refers to 2022 for Belgium, Colombia, Czechia, Denmark, Estonia, France, Hungary, Luxembourg, Malta, Mexico, Slovenia and Spain; to 2021 for Austria, Bulgaria, Croatia, Finland, Germany, Greece, Ireland, Italy, Japan, Latvia, Lithuania, the Netherlands, Poland, Portugal, Romania, Slovak Republic, Sweden, Switzerland, and the United Kingdom; to 2020 for the United States; and to 2014 for Iceland. The colour represents the value of the employment diversification index, measured through the Herfindahl-Hirschman Index, which is the sum of the squared shares of employment of ten broad industries*: "Agriculture, Forestry & Fishing", "Industry", "Manufacturing", "Construction", "Trade, Repair, Transport, Accommodation", "Information and communication", "Financial and insurance activities", "Real estate activities", "Professional, scientific and technical activities; administrative and support service activities", "Public admin., Defence, Edu., Health, Social", and "Arts, Entertainment, Recreation"*. High diversification is values below 1 500, moderate-high diversification is values between 1 500 and 2 000, moderate-low diversification is values between 2 000 and 2 500, and values above 2 500 represent a low degree of diversification. The thresholds are adapted from the definition of concentration by the U.S. Department of Justice and Federal Trade Commission (US Department of Justice and Federal Trade Commission, 2010[67]). The sample is all TL-2 regions (including the OECD accession countries of Bulgaria, Croatia and Romania) with available data.
Source: OECD calculations based on the OECD Regional databases.

Industry is the dominant sector (i.e. the sector with the highest employment share) in the least diversified labour markets, leading in 24 regions. *"Trade, Repair, Transport and Accommodation"*, *"Public services"* and *"Agriculture"* are the dominant sector in 12, 13, and 8 regions, respectively. Industry is the most common sector due to the complementary between the *"Industry"* sector and the *"Manufacturing"* sector. In almost 92% (22 out of 24) of regions with low diversification driven by the *"Industry"* sector, *"Manufacturing"* represents the second highest sectoral share of employment. The findings highlight interdependencies between these sectors which drive economic specialisation of the region, but also potentially limiting the scope for further diversification.

Figure 1.27. A majority of workers are employed by up to three sectors across OECD regions



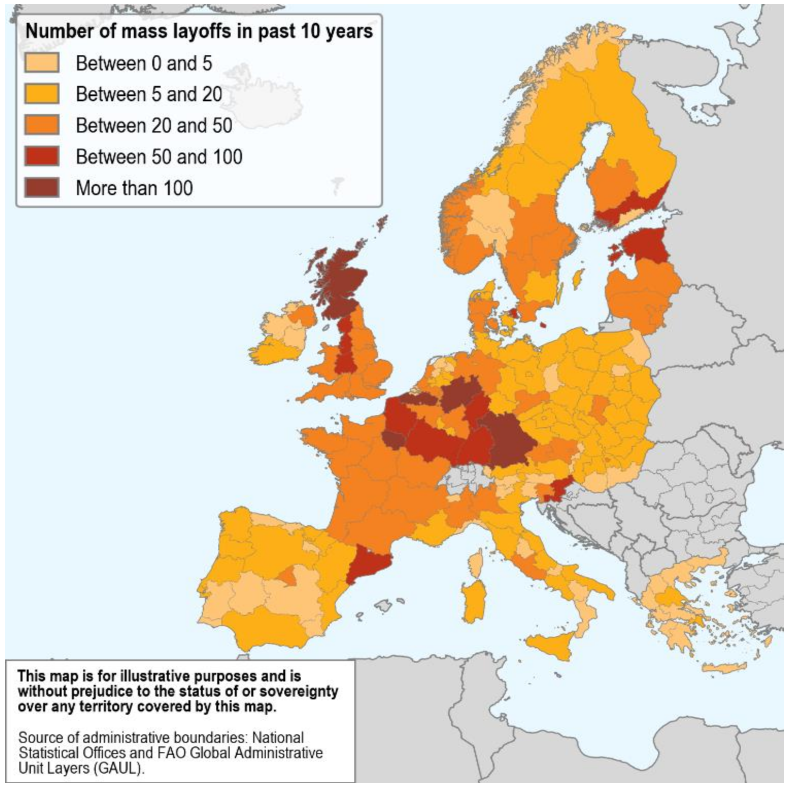
Note: The figure shows the share of regions in each country that belong to each category which represents the number of sectors that cumulatively represent a majority (50% or higher) of employment in that region for the year 2023 or the latest available year. The data refers to 2022 for Belgium, Colombia, Czechia, Denmark, Estonia, France, Hungary, Luxembourg, Malta, Mexico, Slovenia and Spain; to 2021 for Austria, Bulgaria, Croatia, Finland, Germany, Greece, Ireland, Italy, Japan, Latvia, Lithuania, the Netherlands, Poland, Portugal, Romania, Slovak Republic, Sweden, Switzerland, and the United Kingdom; to 2020 for the United States; and to 2014 for Iceland. The sectors considered are ten broad groups based on NACE-REV2 categories: *"Agriculture, Forestry & Fishing", "Industry", "Manufacturing", "Construction", "Trade, Repair, Transport, Accommodation", "Information and communication", "Financial and insurance activities", "Real estate activities", "Professional, scientific and technical activities; administrative and support service activities", "Public admin., Defence, Edu., Health, Social", and "Arts, Entertainment, Recreation"*. The sample is all TL-2 regions (including the OECD accession countries of Bulgaria, Croatia and Romania) with available data.
Source: OECD calculations based on the OECD Regional databases.

Two sectors or fewer are responsible for employing at least half of all workers in the region in almost two-thirds of OECD regions with available data (Figure 1.27). In three OECD regions, one industry accounts for more than half of employment, indicating a high level of specialisation in that sector. In contrast, a majority of employment is spread across three sectors in all regions of Estonia, Latvia, Lithuania, Luxembourg, and Switzerland. This is the case for only two sectors in all regions of Australia, Denmark, Iceland, Japan, the United Kingdom and the United States. Thus, in many OECD regions, few industries account for the majority of employment, highlighting the limited degree of economic diversification across OECD regions.

Industry-specific downturns can contribute to mass layoffs, which can destabilise regional economies given the relative size of the shock. Mass layoffs are defined as the separation of a significant number of employees from a single establishment over a short period. These events often occur for many reasons, for example, in response to economic downturns, industry restructuring, or technological advancements (Silva et al., 2019[68]; Chhinzer, 2023[69]). The occurrence of mass layoffs can significantly disrupt regional labour markets, leading to sudden increases in unemployment, persistent wage losses, reductions in consumer spending, and broader economic downturns within affected regions (Vermeulen and Braakmann, 2023[70]; Foote, Grosz and Stevens, 2018[71]; Cederlöf, 2021[72]; Flaaen, Shapiro and Sorkin, 2017[73]; Arquié and Grjebine, 2024[74]). For example, job losses are recorded not only in the directly affected establishments but also in nearby businesses and regions, indicating sizeable spillover effects on regional economies (Gathmann, Helm and Schönberg, 2018[75]). Thus, while the direct consequences are often severe, leading to substantial job losses, the indirect effects can also profoundly alter the economic stability of the affected regions. This is particularly true for regional labour markets as these events affect a larger proportion of workers than at the national level.

Mass layoffs are prevalent among OECD regions although there is considerable range in their occurrence over the past decade. Figure 1.28 presents the spatial variation in the instance of mass layoffs over the past ten years in European regions.[6] In almost one-tenth (9%) of OECD regions in the European Union with available data, no mass layoffs are reported, while in the same proportion of regions, over 50 mass layoff events occurred. Five regions experienced one hundred or more of these events, with the most mass layoffs occurring in North Rhine-Westphalia (Germany) with over 130 events. Despite this, the majority of regions with available data experienced a modest number of mass layoffs in the past ten years: two in five (41%) regions had less than 10 mass layoff events, and almost three in five (60%), had less than 15 mass layoffs. There is a noted spatial dimension to the occurrence of mass layoff events linked to the bias in the data towards medium and large firms, especially in the manufacturing sector. Mass layoffs are notably most prevalent in current or historical industrial and manufacturing hubs, such as central Germany, northern United Kingdom, eastern France, and others. Lastly, apart from a brief increase during the COVID-19 pandemic, the frequency of mass layoffs has remained relatively constant over the past decade.

Figure 1.28. Large disparities in the instance of mass layoffs across regions



Note: The map presents the number of mass layoffs that occurred in the region over the past 10 years. A mass layoff is defined as the announced destruction of (1) at least 100 jobs or (2) affects at least 10% of the workforce at sites (i.e. workplaces) employing more than 250 people. This means that the lower bound of job loss for a mass layoff event is at least 25 workers. The information on mass layoffs comes from a database of large restructuring events reported in the principal national media and company websites, collected by Eurofound. Importantly, this database is not representative of mass layoff events as the size requirement leads to a bias towards medium and large firms, especially in the manufacturing sector. The sample is TL-2 regions in OECD countries with available data.
Source: OECD calculations based on the European Restructuring Monitor (Eurofound, 2024[76]).

Conclusion

This chapter provides an analysis of the current state and evolution as well as the resilience of regional labour markets in the aftermath of major shocks, reflecting on the recovery process and the capacity of regions to handle significant transitions. It assesses recovery from the COVID-19 pandemic, implications for employment and productivity, and explores various indicators that highlight the adaptability of regional labour markets to leverage the full potential of both workers and firms.

While employment rates across OECD regions have reached record highs, the decade-long view reveals persistent regional disparities in employment and participation rates. However, the recovery has come at the cost of labour market exclusion for specific groups, such as young workers, who have experienced widening age disparities. This trend will likely aggravate the current context of tight labour markets where firms report difficulty in recruitment. Chapter 2 examines the issue of labour market shortages by zooming in on the places, sectors and occupations facing greater difficulties in finding workers. Identifying these trends allows for the design of well-informed policy to address the bottleneck caused by labour market shortages and its impact on employment and local development.

Labour productivity growth has been lagging in many OECD regions, with little progress in closing the gap between the top and bottom performers. Notably, in half of OECD regions, labour productivity growth over the past decade was below 0.8% per year, indicating that gains in labour market outcomes have not necessarily been accompanied by proportional productivity increases. Population ageing contributes to declines in per capita income and limits productivity growth, but it may also incentivise the adoption of labour-enhancing or labour-saving technologies like AI, depending on its efficiency in job-specific tasks (Nedelkoska and Quintini, 2018[5]; André, Gal and Schief, 2024[77]). Chapter 3, through new estimates on occupational exposure to AI, discusses the double-edged sword of the integration of AI in the workforce. In order for AI to support rather than undermine productivity growth, policymakers may want to consider the pace and nature of AI adoption, the ability of workers to adapt, and the need for transitional support policies.

A flexible and diversified skills base in the regional labour force contributes to the increased quality and resilience of regional labour markets. However, skill mismatches are prevalent across OECD regions, and non-traditional forms of employment, such as self-employment, play an important role in today's labour markets. Furthermore, in over two-thirds of OECD regions, labour markets exhibit moderately low or low employment diversification. Amid accelerating green, digital, and demographic transitions, policy measures that contribute to building resilience through labour markets that encourage flexibility and integrate regional labour market demands to establish realistic career pathways across different regions are needed.

In conclusion, the diversity of regional experiences across OECD countries highlights both achievements and ongoing challenges. Valuable lessons can be drawn from these experiences, including the importance of enhancing the quality and diversity of the regional labour force, effectively managing sectoral employment diversification and potential vulnerabilities like mass layoffs, leveraging technological advancements, such as artificial intelligence, to address lagging productivity growth, and prioritising skills and job development. In light of past trends and in anticipation of future challenges, it is essential to adopt proactive place-based strategies that foster more inclusive and resilient labour markets in the future.

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Notes

[1] For more data on NEET rates, see Annex Figure 1.B.3 and Annex Figure 1.B.4.

[2] This is despite the worries that the gendered impact of lockdowns, as described above, contributed to an initial worry of a “she-cession” especially as initial indicators saw a disproportionate drop in female labour market participation at the onset of the crisis (Landivar et al., 2020[87]).

[3] Labour productivity can also be defined as output (real gross domestic product (GDP)) per hour worked. This would account for the overall trend of falling working hours across OECD countries, although there are some exceptions, for example, in Turkey, Mexico and Colombia. Over the past two decades, the average annual hours worked per worker decreased, due to changes in work patterns, increased part-time work and shifts towards service industries (OECD, 2021[88]). Nonetheless, the same general pattern of sluggish labour productivity growth is observed also with this definition (OECD, 2024[28]).

[4] Measuring skill mismatches poses several challenges as it requires quantifying both the skills of workers and the demands of their jobs, neither of which are observable. Thus, to quantify skill mismatch, this chapter proxies a workers’ skill level through their level of education, using the ISCED classification. The skill demands of the job are calculated as the most common skill level of workers in that occupation-

country-year. Skill mismatch is thus present when the skill level of an individual worker does not match the skill level of their occupation. Over-(under-) skill mismatch is when the worker's skill level is above (below) their occupation's skill level. The advantage of this approach is that it only requires information on the educational level and occupation of workers, both of which are readily available in most labour force surveys. Furthermore, by defining the occupational skill level relative to the country and year, the approach takes into account cross-country differences and changing skill demands of an occupation.

[5] Note that it is not possible to look at the demographics of self-employment take-up, i.e. the share of women, male, youth, elderly, immigrants, natives, etc. engaged in self-employment due to issues of small sample sizes in labour force surveys. The Chapter focuses only on overall rates of self-employment among the employed.

[6] The information on mass layoffs comes from a database on large restructuring events reported in the principal national media and company websites, collected by Eurofound. It provides information on the instance of mass layoffs, defined as the announced destruction of at least 100 jobs or that affects at least 10% of the workforce at sites employing more than 250 people. Importantly, this database is not representative of mass layoff events as the size requirement leads to a bias towards medium and large firms, especially in the manufacturing sector. Nonetheless, it is a useful resource to get an overall idea of their instance across OECD regions.

Annex 1.A. Additional background on policy

Annex Box 1.A.1. Examples: policies for inclusive labour market participation

Youth

- **The EU Youth Guarantee** was reinforced by member states in 2020 by committing that people under 30 receive quality employment, continued education, or a traineeship within four months of becoming unemployed or leaving education (European Commission, 2020[78]). Since its establishment in 2013, the European Union improved and expanded employment services for youth such as continued education, traineeship or connecting them with employment opportunities, resulting in a record-low drop in youth unemployment of 14.9% in 2020 and 1.7 million fewer youth in neither employment, education or training (NEETs) (European Commission, 2020[78]). The reinforced programme has a broader target group of 15-to 29-year-olds at risk of unemployment or unable to enter the labour market and offers individualised approaches; providing youth with the appropriate guidance and helping them find courses or boot camps for upskilling (European Commission, 2020[78]).
- The Municipality of **Rotterdam,** in the **Netherlands** gave training vouchers to residents facing economic and labour market challenges due to the pandemic. The vouchers paid for courses and training in professional areas in high demand, to adjust to the changes produced by the pandemic. The programme was successful in improving the labour market and continued beyond the pandemic as an active and integral part of the youth labour market activation. The municipality will expand the programme to over 20 000 vouchers by 2024 (OECD, 2023[79]).

Women

- **Canada** promoted a CAD 10-a-day **child care framework**, which was implemented through bilateral agreements with provinces and territories. The objective is to get more women into the labour force. Since this investment in the federal budget of 2021 and the culmination of the regional agreement negotiation, labour force participation among working age mothers with young children is at a record high of 79.7% (Employment and Social Development Canada, 2024[80]). The government is now making more progress by increasing inclusive access to child care, with funding focused on underserved communities (Employment and Social Development Canada, 2024[80]).
- **Donegal,** in **Ireland** implemented the **Women's Integration Skills and Employment Project (WISE),** which provides services to support women entering and re-entering the labour market. Over 70% of women in WISE have found a job and sustained employment in the long-term (OECD, 2022[81]). WISE worked by assigning participants to a personal advisor who supports training in writing CVs, improving interview skills, and understanding employment contracts. In addition, it matched women with local employer opportunities and assisted with access to public funding for training and childcare (European Commission, 2019[82]).

Elderly

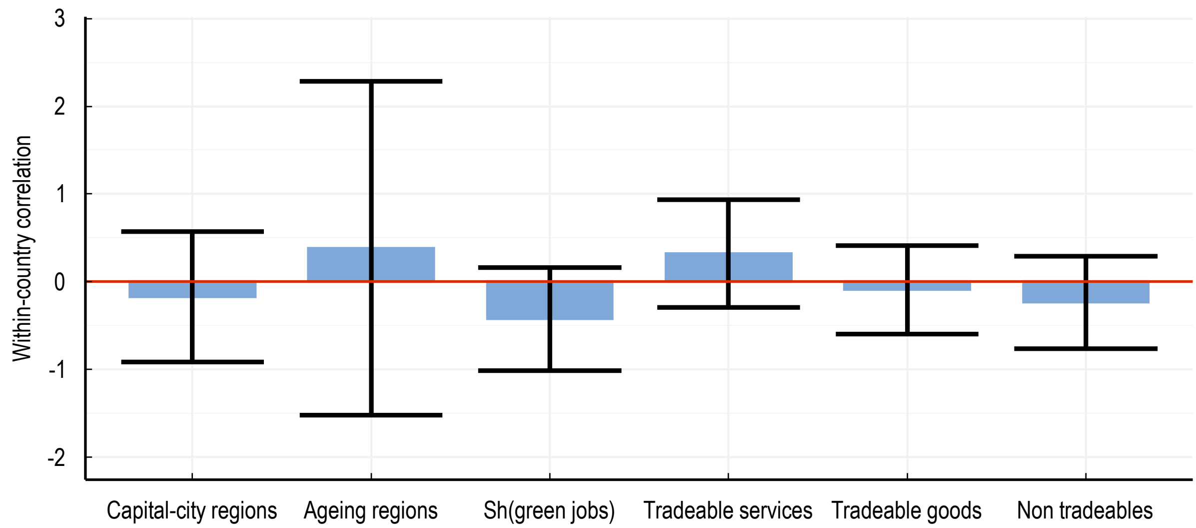
- In **Kamikatsu, Japan**, more than half of the 1 415 population is 65 and older. The waning agriculture industry resulted in economic decline and depopulation. In response, the public-private Irodori Corporation brought together local farmers and the town government to sell *tsumamono*, a leaf used in Japanese gastronomy. Almost 200 farmers are aged 70 on average, 90% being women (OECD, 2024[83]). The programme impacted well-being as the region has the lowest per capita costs of medical care in the prefecture, despite having a large proportion of older individuals (OECD, 2024[83]).

- **Suwon, in South Korea**, established nearly 600 lifelong learning centres to help residents improve career prospects and participate in adult learning (OECD, 2020[84]). The initiative aims to support disadvantaged groups, such as the elderly, by increasing access to learning spaces. The city also offers subsidies for citizen-developed learning programmes, involves NGOs in running lifelong learning initiatives, and supports the certification of lifelong learning teachers (OECD, 2020[84]). This certification requires mandatory training and has been introduced by the Government of Korea, for people who want to become lifelong learning teachers (UNESCO, 2023[85]). This bottom-up approach to adult learning helps the elderly to actively engage in society, offering opportunities to continue learning and contributing (OECD, 2020[84]).

Annex 1.B. Additional results

Annex Figure 1.B.1. Employment did not increase faster over the past ten years depending on demographics or employment structure

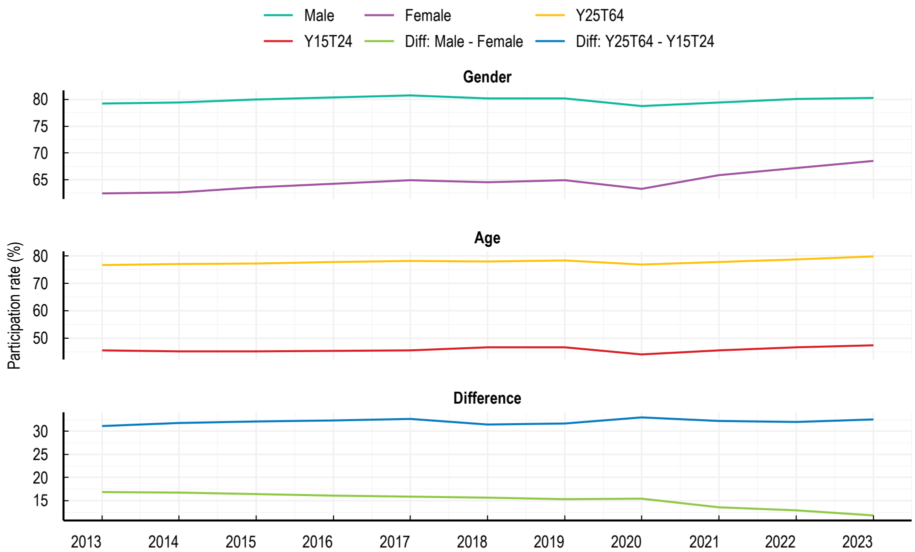
Within-country correlation of ten-year employment change (pp) to selected characteristics, 2013 to 2023 or closest available years



Note: ***p-value<0.01, **p-value<0.05, *p-value<0.1. The graph shows the coefficient and 90% confidence intervals of separate multivariate regressions of the ten-year change in employment rates (2013 to 2023) on a dummy for capital-city regions, ageing regions (defined as those that experienced an increase in the elder-dependency rate over the past five years), for an above national median employment share in green jobs in 2021, in tradeable services (ISIC broad sectors G to N), tradeable goods (ISIC sectors B, D, E) or neither tradeable goods nor services. Each regression also controls for the log of population in 2023, or latest available year, and country fixed effects. The level of observation is the TL-2 regions. The sample of countries includes all OECD countries. Robust standard errors are clustered at the country level.
Source: OECD elaboration based on the OECD Region and Cities databases.

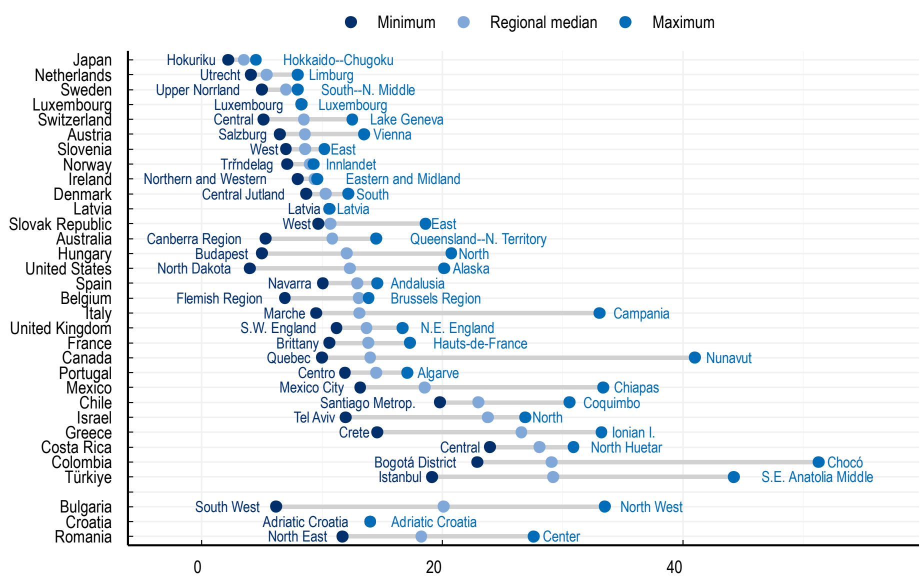
Annex Figure 1.B.2. COVID-19 exacerbated regional inequalities along age, but not gender

Average participation rate of OECD regions by gender and age and their differences, 2013 to 2023



Note: The figure shows the mean participation rate for OECD regions in the years 2013 to 2023, by demographic group. The mean participation rate for men and women is presented in the first panel, for workers aged 15 to 24 and workers aged 25 to 64 in the second panel, and the difference in the participation rate between men and women and older and younger workers in the bottom panel.
Source: OECD calculations based on the OECD Regional databases.

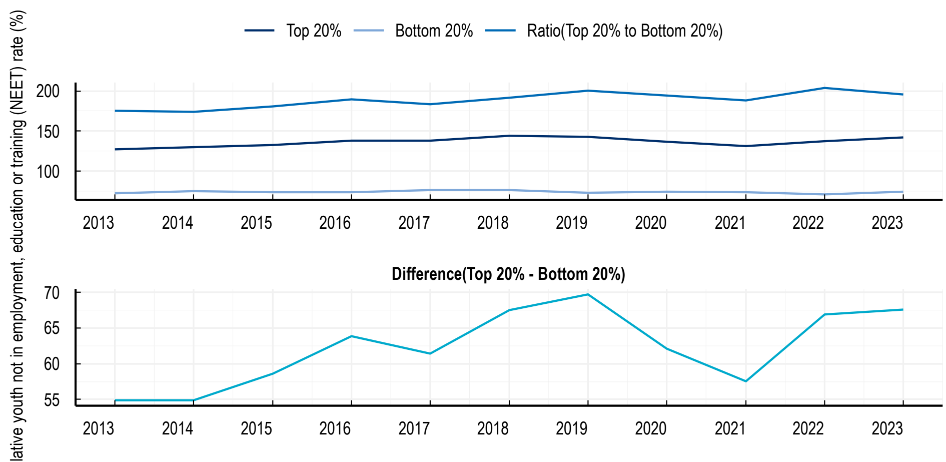
Annex Figure 1.B.3. Half of countries show significant regional dispersion in youth inactivity rates



Note: The figure shows the regional dispersion (highest, lowest and median value) in the NEET rate (not in employment, education or training) for the youth working-age population (15-24 year-olds) in 2023 or latest available year. The last year refers to 2022 for Australia, Belgium, Colombia, Israel, Japan, Mexico, Slovak Republic (except for Bratislava where the data refers to 2017), Spain, Switzerland, the United Kingdom and the United States; to 2021 for Sweden; to 2019 for Bulgaria, Croatia, Denmark, France, Luxembourg, Malta, the Netherlands (except for Zealand where the data refers to 2016), and Romania; to 2017 for Chile; and to 2016 for Norway. The sample is all TL-2 regions in countries with available data, including the OECD accession countries of Bulgaria, Croatia and Romania.
Source: OECD calculations based on the OECD Regional databases.

Annex Figure 1.B.4. Within-country differences between regions with the highest and lowest NEET rates are growing

Evolution of the NEET rate relative to the national median, 2013 to 2023

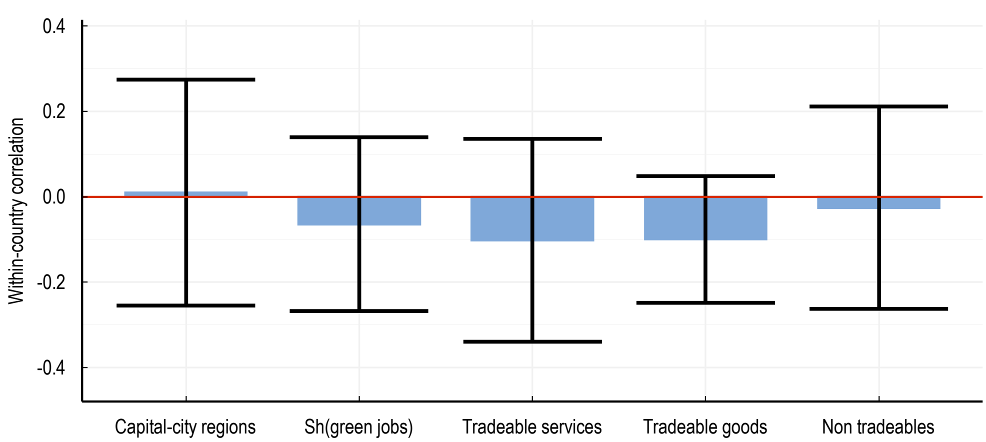


Note: The figure shows the evolution of the NEET rate (not in employment, education or training) for the youth working-age population (15-24 year-olds), relative to the national median (which corresponds to 100 on the top graph), for the top and bottom 20% of regions which account for at least 20% of the population in a country. The sample is all TL-2 regions in OECD countries with at least five regions and with data available over the entire period

Source: OECD calculations based on the OECD Regional databases.

Annex Figure 1.B.5. Neither demographic nor economic structure is correlated with higher productivity growth

Within-country correlation of ten-year annual labour productivity growth (pp) to selected characteristics, 2012 to 2022 or closest available years

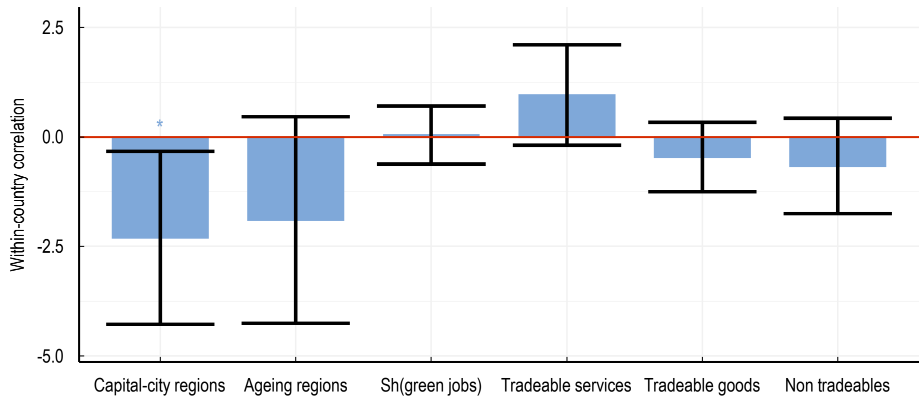


Note: ***p-value<0.01, **p-value<0.05, *p-value<0.1. The graph shows the coefficient and 90% confidence intervals of separate multivariate regressions of annual labour productivity growth in the latest available year on a dummy for capital-city regions (large regions that include the capital city), regions with an above national median employment share in green jobs in 2021, in tradeable services (ISIC broad sectors G to N), tradeable goods (ISIC sectors B, D, E) or neither tradeable goods nor services. The coefficient (`within-country correlation') presents the within-country percentage point difference in productivity growth rates based on the characteristic on the x-axis. Each regression also controls for the log of population in the latest available year, a dummy for the latest available year, and country fixed effects. The level of observation is the TL-2 region. The sample of countries includes all OECD countries with available data, excluding Ireland. Robust standard errors are clustered at the country level.

Source: OECD elaboration based on the OECD Region and Cities databases.

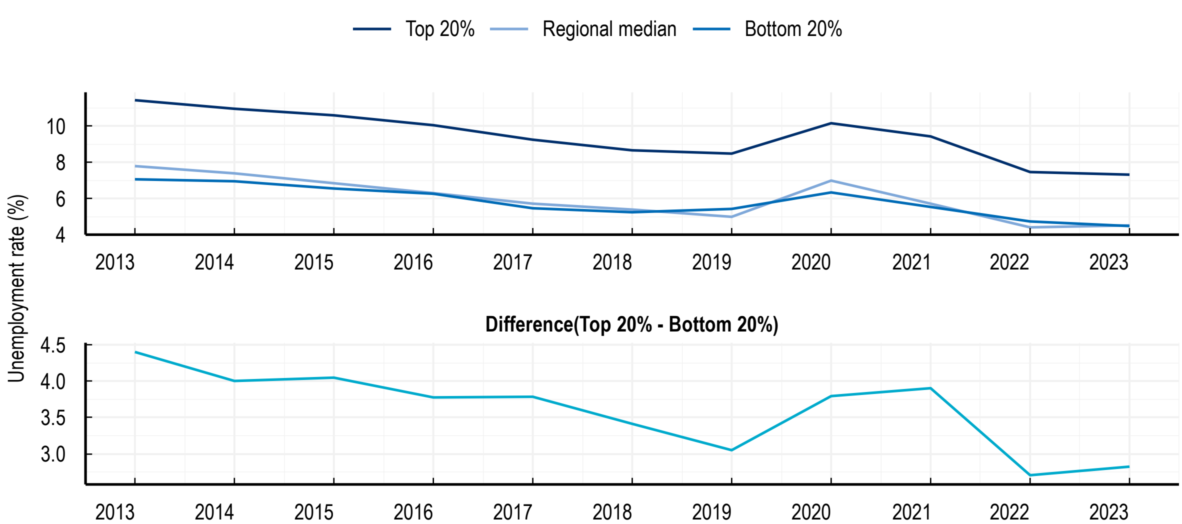
Annex Figure 1.B.6. Mismatch is lower in capital-city regions

Within-country correlation of the share of mismatch to selected characteristics, 2023 or latest available year



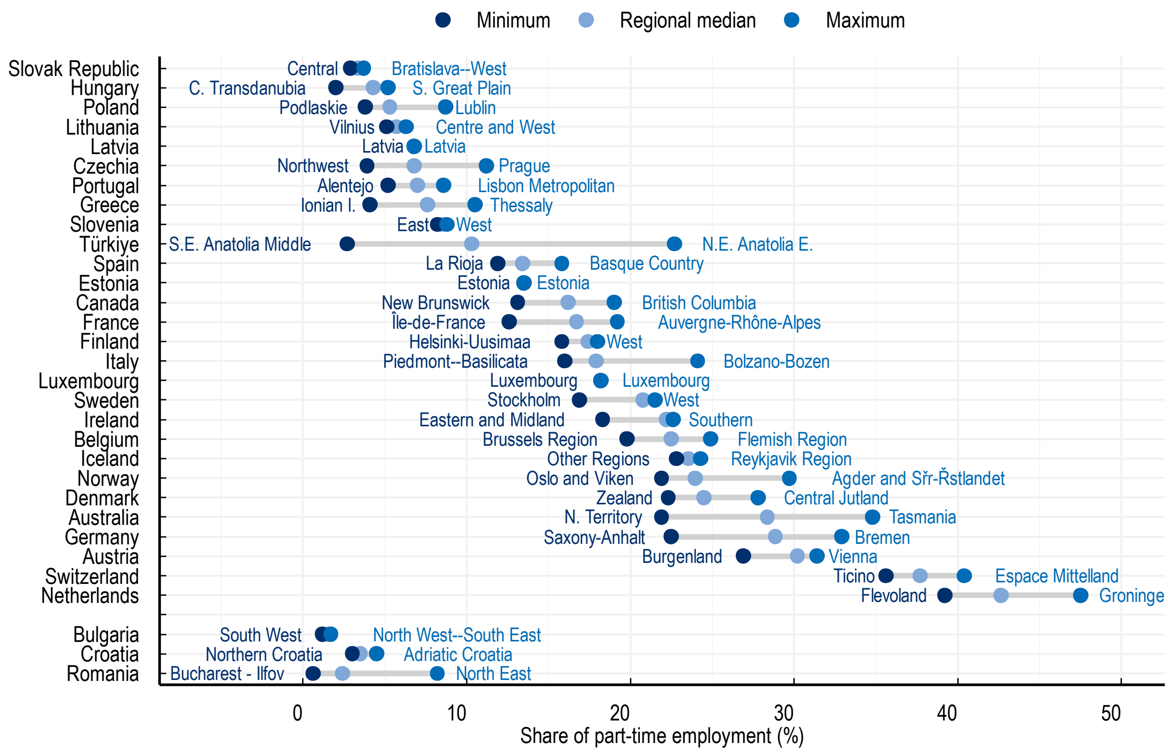
Note: ***p-value<0.01, **p-value<0.05, *p-value<0.1. The graph shows the coefficient and 90% confidence intervals of separate multivariate regressions of the share of job mismatch in 2023 (or latest available year) on a dummy for capital-city regions, ageing regions (defined as those that experienced an increase in the elder-dependency rate over the past five years), for an above national median employment share in green jobs in 2021, in tradeable services (ISIC broad sectors G to N), tradeable goods (ISIC sectors B, D, E) or neither tradeable goods nor services. The coefficient (`within-country correlation') presents the within-county percentage point difference in the share of mismatch based on the characteristic on the x-axis. Skill mismatch is calculated following the methodology of the Skills for Jobs Indicators of the OECD's Directorate for Employment, Labour and Social Affairs, whereby a worker is in a mismatched job when their educational skill level does not match the most common educational skill level of workers in that occupational group in that country. Each regression also controls for the log of population in 2023 or latest available year and country fixed effects. For European Union countries, the data refers to 2022, and for Korea, to 2021. The level of observation is the TL-2 region. The sample of countries includes all OECD countries. Robust standard errors are clustered at the country level.
Source: OECD elaboration based on the OECD Regional databases.

Annex Figure 1.B.7. Record-low unemployment rates, with convergence continuing past Covid-19 recovery



Note: The figure shows the evolution of the unemployment rate for the working-age population (15-64 year-olds) for the top and bottom 20% of regions in a country, which account for at least 20% of the population. The sample is all TL-2 regions in OECD countries with at least five regions and with data available over the entire period.
Source: OECD calculations based on the OECD Regional databases.

Annex Figure 1.B.8. Across OECD regions, about 16% of workers are engaged in part-time work, with little regional dispersion in most countries

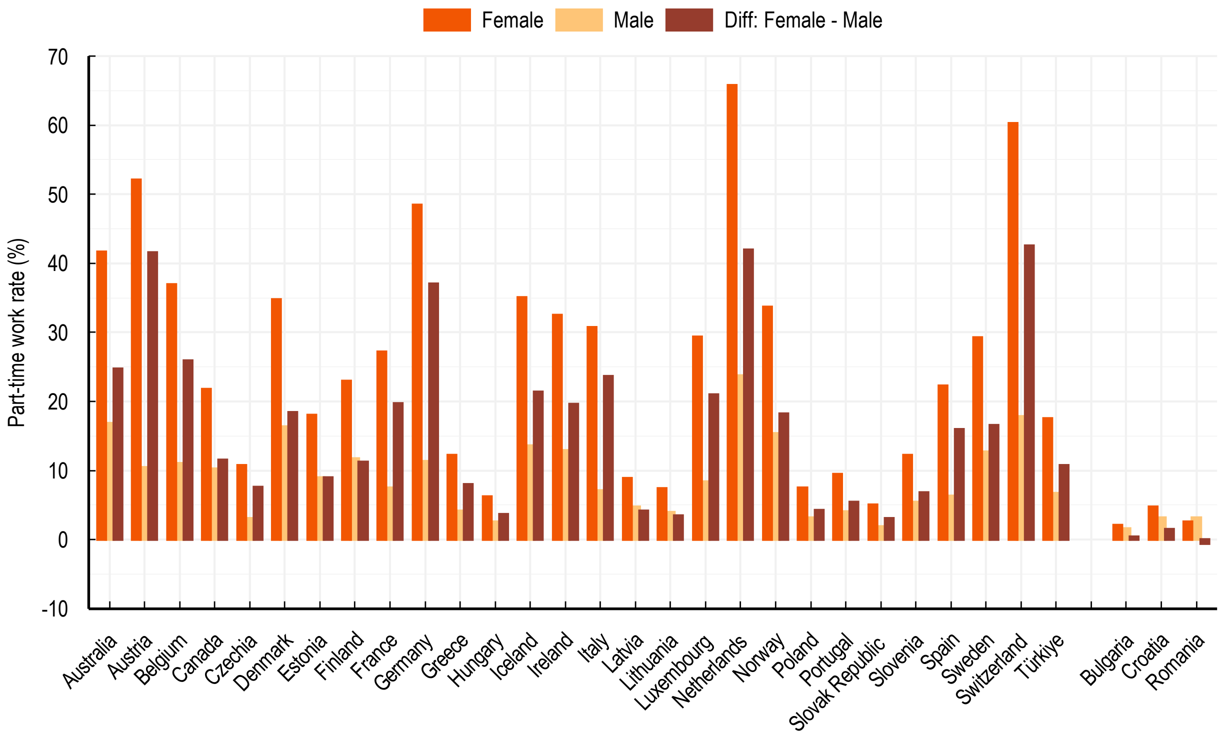


Note: The figure shows the regional dispersion (highest, lowest and median value) in the part-time employment rate for employed individuals, 15-64 year-olds in 2023 or the latest available year. The data refers to 2022 for Finland and Iceland; and to 2021 for Romania. When the region name is double-hyphenated, it signifies two regions with the same value. The sample is all TL-2 regions (including the OECD accession countries of Bulgaria, Croatia and Romania) with available data.
Source: OECD calculations based on the OECD Regional databases.

On average across OECD regions, take-up of part-time work is higher than the OECD average, representing around 16% of employment versus 14.7% for the OECD as a whole (Annex Figure 1.B.8) (OECD, 2024[86])**.** Within-country variance is low. The mean difference between the region with the largest vs. lowest take-up of part-time work stands at around 4 percentage points. The exceptions are Türkiye and Australia, where this difference is around 17 and 12 percentage points, respectively. However, there is large variance in the take-up of part-time work across OECD countries and regions. The regional median region of the share of employment in part-time contracts varies widely from under 2% in Bulgaria, with the lowest regional share in North East and South Central at around 1% of employment, to over 42% in the Netherlands, with close to one in two workers engaged in part-time work in Groningen.

Yet, this aggregate picture conceals that women are almost 15 percentage points more likely to be employed in part-time contracts than men across OECD countries (Annex Figure 1.B.9). The gender difference in part-time work ranges from -0.55 percentage points in Romania to over 42 percentage points in the Netherlands and Switzerland, largely driven by high overall take-up of part-time work among women at over 60% in both countries. The ratio of women to men employed in part-time work is above two in all but six out of the thirty-one OECD countries with available data, reaching over 4 women for each man in Germany, Italy and Austria.

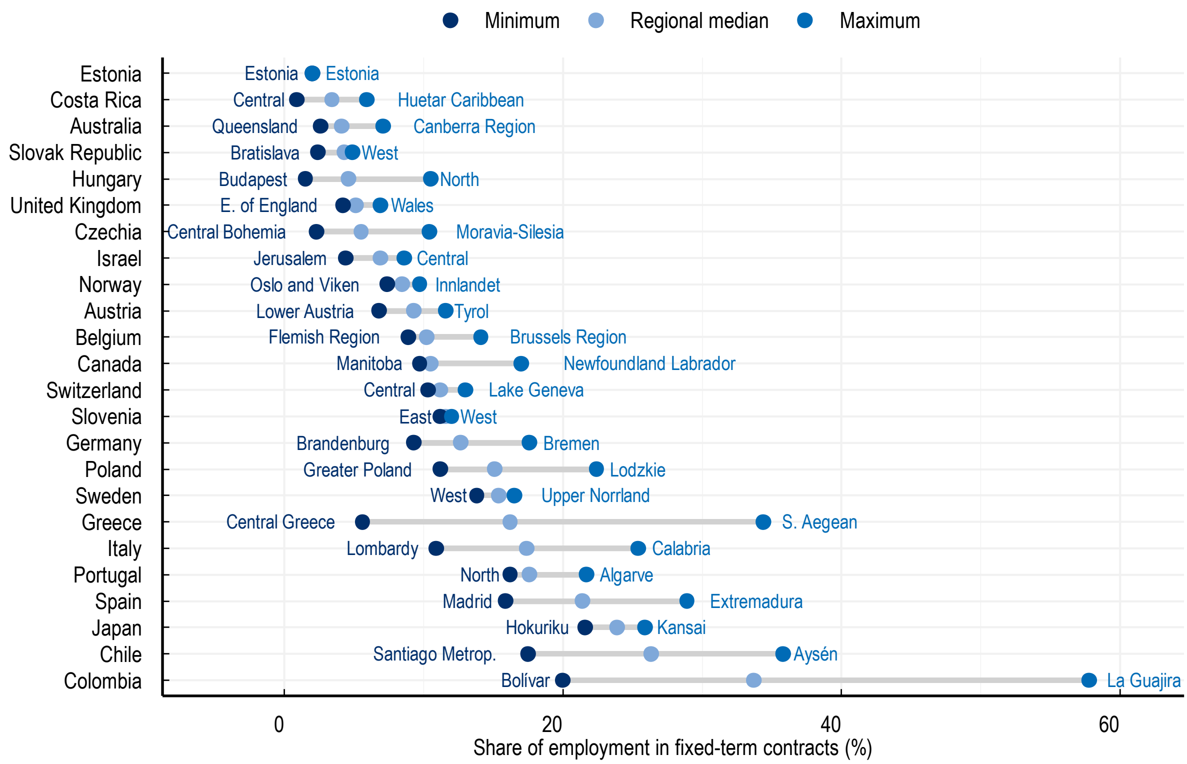
Annex Figure 1.B.9. Stark gender divides in the take-up of part-time work



Note: The figure shows the gender distribution and difference in the regional median for each country for part-time employment rate for employed individuals, 15-64 year-olds in 2023 or the latest available year. The data refers to 2022 for Finland and Iceland; and to 2021 for Romania. The sample is all TL-2 regions (including the OECD accession countries of Bulgaria, Croatia and Romania) with available data.
Source: OECD calculations based on the OECD Regional databases.

The instance of temporary employment is slightly below part-time employment across OECD regions: about 12% of employed individuals are employed through fixed-term contracts (Annex Figure 1.B.10). Regional dispersion is also limited: the mean country difference between minimum and maximum regions in a country stands at about 4.5 percentage points, once the three countries with the greatest difference are excluded: Colombia (38.8 percentage points), Greece (21.2 percentage points) and Chile (18.2 percentage points). La Guajira in Colombia leads in the use of temporary work contracts, with over half of its workforce employed through these fixed-term arrangements. Following significantly behind is Aysén in Chile, where the share of employment in fixed-term contracts stands at about 37%—over 20 percentage points lower than La Guajira. In contrast, the lowest use of temporary contracts, less than 1%, is in the Central region of Costa Rica. In Estonia, Costa Rica, Australia, Slovak Republic, and Hungary, the take-up of temporary work is particularly low: less than 5% of workers are employed by these contracts.

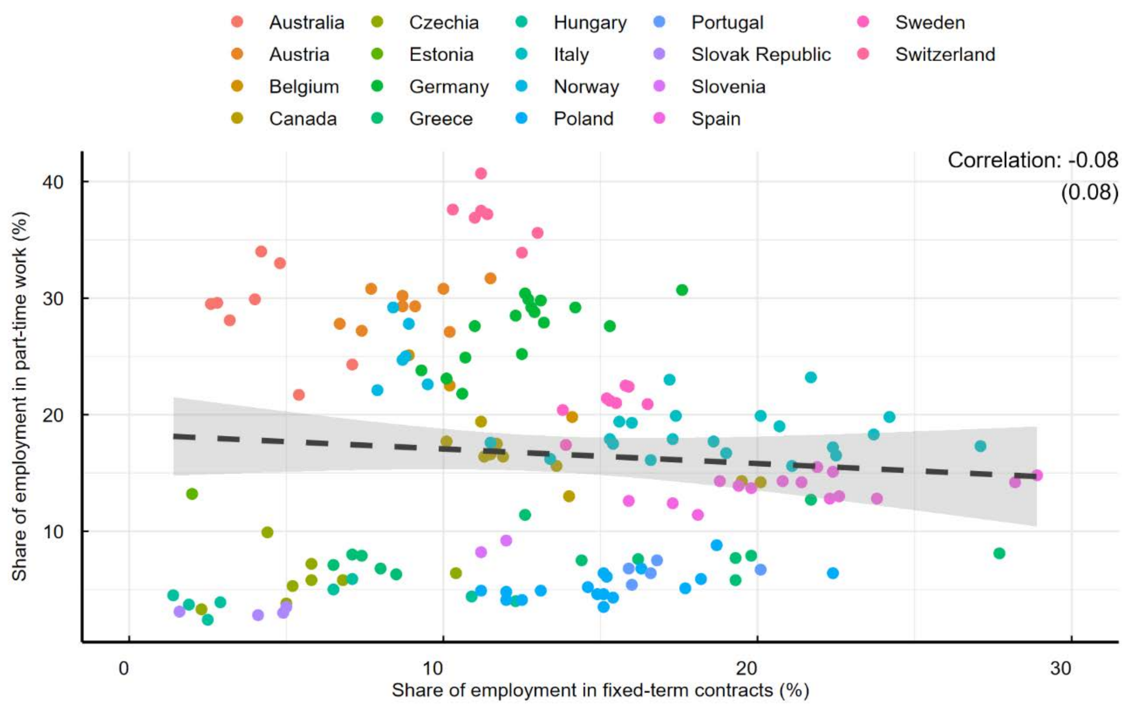
Annex Figure 1.B.10. Little regional dispersion in the incidence of temporary employment, apart from in some Latin American countries



Note: The figure shows the regional dispersion (highest, lowest and median value) in the share of employment on fixed-term contracts (15-64 year-olds) in 2023 or the latest available year. The data refers to 2022 for Australia, Belgium, Colombia, Costa Rica, Czechia, Estonia, Germany, Japan, Poland, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom. The sample is all TL-2 regions with available data.
Source: OECD calculations based on the OECD Regional databases.

Regions with a high degree of take-up in part-time work do not necessarily also have more workers employed in short-term contracts, pointing to substitutability between part-time and short-term work. Annex Figure 1.B.11 plots the regional share of workers in part-time work contracts versus the regional share of workers in temporary employment. The correlation of these two variables, accounting for country-specificities, reveals a lack of relationship between the two. Furthermore, there are clear clusters of regions in the same country, which indicates that structural national policies likely shape employment practices in the take-up of different types of non-traditional work.

Annex Figure 1.B.11. There is little within-country variation in temporary and part-time employment, reflecting that take-up is driven by structural national policies



Note: The figure shows the share of employment in fixed-term contracts on the x-axis and the share of employment in part-time work on the y-axis in the year 2023 or latest available year for OECD regions with available data. For part-time work, the data refers to 2022 for Finland and Iceland; and to 2021 for Romania. For the temporary work rate, the data refers to 2022 for Australia, Belgium, Colombia, Costa Rica, Czechia, Estonia, Germany, Japan, Poland, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom. The dotted line represents the correlation line, and the grey shaded area is 95% confidence intervals between the two measures. Each dot represents a region.
Source: OECD calculations based on the OECD Regional databases.

2 Labour shortages across regional labour markets

Many OECD regions struggle with significant labour shortages that hold back economic growth. This chapter presents new data and analysis on labour market tightness across OECD regions. It examines some of the drivers of labour shortages and explores which sectors and jobs face the greatest labour shortages in different regions. It also considers the shortages for green and Information and communication technologies (ICT) jobs, which could hold back progress in the twin transition for many regions. Finally, this chapter analyses how and where current population trends of demographic change could intensify regional labour shortages.

In Brief

Driven by record-high employment rates, population ageing, new skills requirements, and changing worker preferences, most OECD regions are struggling with labour and skills shortages.

Labour markets across OECD regions have more than bounced back from the COVID-19 pandemic. Employment levels are record high in many countries. There are also increasing demands for new types of skills across many sectors, including those for advanced AI and “green-task” jobs. As a result, firms now face increasing difficulties in finding and hiring the right workers to fill vacancies. The resulting labour and skills shortages are a potential drag on firm operations, productivity, and economic growth, as well as producing flow-on consequences for the supply of critical public services.

- **Regional labour shortages have risen substantially since 2019 and increasingly also affect regions with previously low levels of labour shortages.** Regional labour market tightness, defined as vacancies per employed person, has increased substantially since 2019. Data from the United States and Germany show that regional labour market tightness has increased by 50% and 80%, respectively, between 2019 and 2022, affecting all types of regions.
- **The severity of rising labour shortages differs a lot across regions. In the United States, for example, tightness grew by 29% and 105% in the 10% of regions with the lowest and the highest increases on average.** While the growth in labour shortages seems to have slowed in most OECD regions since 2021, shortages remain at a high level relative to pre-COVID-19 levels (e.g. 50% higher in the United States), highlighting that the drivers of labour shortages go beyond the temporary post-COVID-19 recovery.
- **Regional disparities in labour shortages are significant across the OECD.** Within countries, the tightest regional labour market reports on average five times higher labour market tightness than the least tight region. Regions with a large population and high employment rates (relative to the national average) experience 14% and 26% higher shortages relative to low-population and low-employment places, respectively. Labour shortages are also more acute in regions that rely more on tradable services or that have benefitted from the presence of high-growth industries.
- **In 95% of regions, labour shortages in ICT are higher than for other jobs, with on average over twice as high labour market tightness.** Similarly, labour shortages are more pronounced for green jobs in 89% of regions. On average, labour shortages are between 40% (European regions) and 15% (Australian regions) higher for green than non-green jobs. Greater shortages in green and digital jobs partly reflect the transformation of regional economies in the twin transition but could also indicate skills mismatches, as education and training systems have not yet fully adapted to new labour market demand. Furthermore, regions with a 10% higher green jobs tightness also show an 18% higher ICT job tightness, suggesting that the digital and green transitions impact many places simultaneously.
- **Population ageing risks exacerbating labour shortages to varying degrees across regions.** If current population trends continue, regional labour shortages could increase by almost 9% by 2042, and almost twice as much (16%) in the oldest 20% of OECD regions. Consequently, tightness is projected to increase from one vacancy for every 21 working age persons to one vacancy for every 18 working age persons in the oldest 20% of regions.

- **Policies designed to mitigate labour shortages need to reflect place-specific challenges, which include retaining and attracting (young) talent to remote regions and facilitating job transitions, taking into account the geographic distribution of jobs.** Labour market intelligence tools can inform the design of such place-based policies, which requires more detailed employment data, for example at the geographic and occupational level.

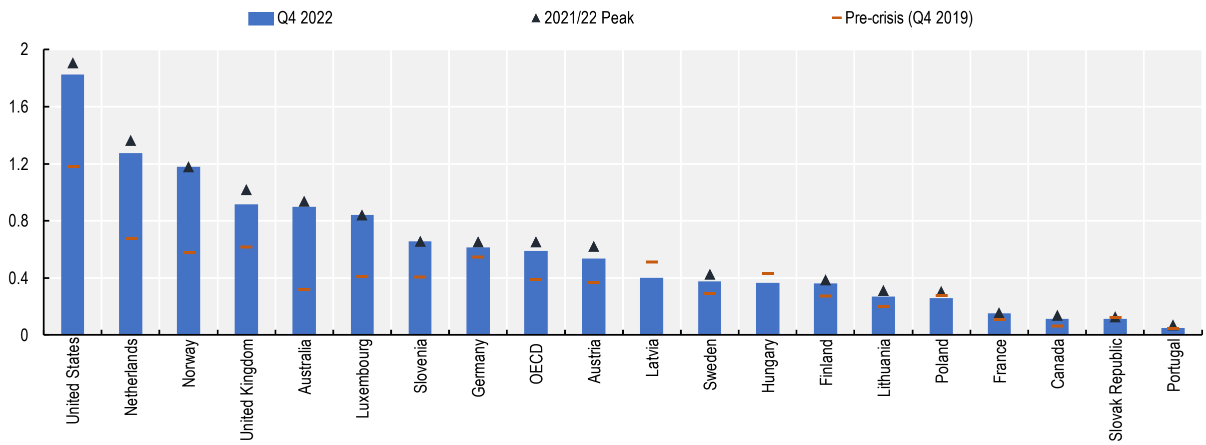
Introduction

Labour shortages are a major challenge for firms and for economic development more broadly across the OECD. More than half (54%) of all SMEs in the European Union report difficulties in finding employees with the right skills – the most commonly nominated among a range of business problems (European Commission, 2023[1]). Although difficult to quantify, this lack of adequately skilled employees represents a drag on firm operations, negatively impacting innovation, productivity and economic growth. While labour shortages have somewhat attenuated since the post-COVID recovery (OECD, 2024[2]), a substantial skills mismatch persists in the labour market (Chapter 1). Tensions are particularly significant in occupations that are crucial for the green and digital transitions, representing bottlenecks on the path to achieving net-zero emission goals. Regions will need to revisit policies and tools they have at their disposal, including their skills training systems, support for the economically inactive, (im)migration policies, and labour market intelligence to address these labour and skills shortages.

While labour shortages have eased after the marked increase due to COVID-19, national labour markets remain tight (Figure 2.1)**.** By the end of 2022, there were about 0.6 vacancies per unemployed person on average for OECD countries with available data, down from its peak of 0.65 in 2021 but still significantly above the pre-crisis average of 0.4. The United States stands out with the greatest labour market tightness of about 1.8 vacancies per unemployed person, down from almost two vacancies per unemployed person at its peak. Still, labour market tightness is 55% higher than before the COVID-19 crisis, indicating that labour shortages persist. The latest increase in labour market tightness is especially pronounced in some countries. In Australia, for example, vacancies per unemployed persons tripled compared to pre-crisis levels. For Luxembourg and Norway, that figure doubled.

Figure 2.1. Labour markets are tight in many countries, despite some signs of easing post-2020

Number of vacancies per unemployed person. National definitions, seasonally adjusted.



Note: This figure is taken from (OECD, 2023[3]). OECD is an unweighted average of the countries shown above. In Panel A, the definition of vacancies is not harmonised across countries. See figure 1.7 in (OECD, 2023[3]) for details.
Source: OECD (2020), "Labour: Registered unemployed and job vacancies (Edition 2019)", Main Economic Indicators (database), https://doi.org/10.1787/190bb5bc-en (accessed on 23 June 2023) for Australia, Austria, Germany, Hungary, Portugal, the United Kingdom, Job vacancy statistics by NACE Rev.2 activity for Finland, Luxembourg, Latvia, Lithuania, the Netherlands, Norway, Poland, the Slovak Republic, Slovenia and Sweden (Eurostat), Job vacancies, payroll employees, and job vacancy rate (Statistics Canada), Les demandeurs d'emploi inscrits à Pôle emploi (Dares, France), Posti vacanti (Italian National Institute of Statistics), Job Openings and Labor Turnover Survey (U.S. Bureau of Labor Statistics, retrieved from FRED); Online job posting on Indeed.

Labour shortages are widespread, and the main drivers are a combination of cyclical and structural factors, with the latter being the larger driver in European countries. Cyclical factors reflect the reprise of economic activity after downturns to which the supply of workers does not adjust quickly enough. Structural factors arise from longstanding mismatches in terms of skills and preferences (e.g. working conditions) between jobseekers and employers. The decline in the working-age population and an insufficient supply of workers with highly specialist skills, such as STEM, are important contributing factors. Furthermore, the ongoing green and digital transitions are placing additional pressure on shortages (European Labour Authority, 2022[4]). This is in line with evidence that firms with higher skill requirements and fast-growing innovative firms are more likely to experience labour shortages (Groiss and Sondermann, 2023[5]).

While labour shortages were mostly limited to high-skilled occupations over the past decades, previous research found that they affect both high-skilled and lower-skilled, contact-intensive occupations since the COVID-19 pandemic (Causa et al., 2022[6]). This is due in part to workers shifting away from jobs with poor working conditions, such as low-paying and contact-intensive ones (Zwysen, 2023[7]). However, country-specific factors exist, as this shift is observed in the US and the UK but not in Germany (OECD, 2024[2]). Another reason for shortages spreading to different types of occupations is the relatively small pool of unemployed persons seeking employment (due to high employment rates) during the post-COVID recovery. A strong labour market is likely to further aggravate shortages by encouraging workers to quit their jobs as a tight labour market facilitates the job search (OECD, 2024[2]). Additionally, labour hoarding, which occurs when companies retain workers without fully utilising their capacity, contributed to the resilience of the European labour market despite weak economic growth throughout 2022 and 2023 (Gayer et al., 2024[8]). Yet, it can also aggravate labour shortages, by preventing workers from moving to recruiting firms (Doornik, Igan and Kharroubi, 2023[9]).

This chapter aims to fill the knowledge gap on labour market tightness in regional labour markets, as well as at the occupational and industry level. Country-level estimates mask regional differences and effective policy measures depend on a local labour market perspective. Therefore, this chapter zooms in on OECD regions and analyses the geography of labour market tightness. Additionally, it presents new estimates on labour market tightness for different sectors and occupations, which helps to shed light on which regional economies are driving labour shortages and therefore most in need of policy support. The possible additional impact of ageing populations on labour shortages is also explored. The chapter concludes with a discussion of potential policy levers to alleviate labour shortages, such as the increased use of technology, increasing participation of hard-to-reach groups, labour market intelligence tools, skills training, and (im)migration policies.

Workers' geographic mobility is more likely to impact estimates of regional (compared to national) labour market tightness and, consequently, their interpretation. Measures of labour market tightness implicitly assume that vacancies can only be filled by jobseekers within the same geographic unit, making the geographic level of analysis an important methodological choice. Ideally, the geographic level would coincide with functional labour markets, within which workers commute between their place of residence and their workplace (i.e., no mobility between regions). However, due to data limitations, this chapter uses the first administrative tier of subnational governance (i.e., TL2, corresponding to states in the United States), whenever subnational employment data are available. While TL2 regions are relatively large such that, in many cases, workers stay within the same TL2 region, labour markets can span multiple TL2 regions and multiple labour markets may exist in one TL2 region, resulting in an inaccurate picture of labour market tightness. This caveat, particularly relevant for TL2 regions with high inter-region mobility, needs to be kept in mind when interpreting regional tightness estimates. More detailed geographic employment data would mitigate this shortcoming by enabling the analysis at the level of functional labour markets.

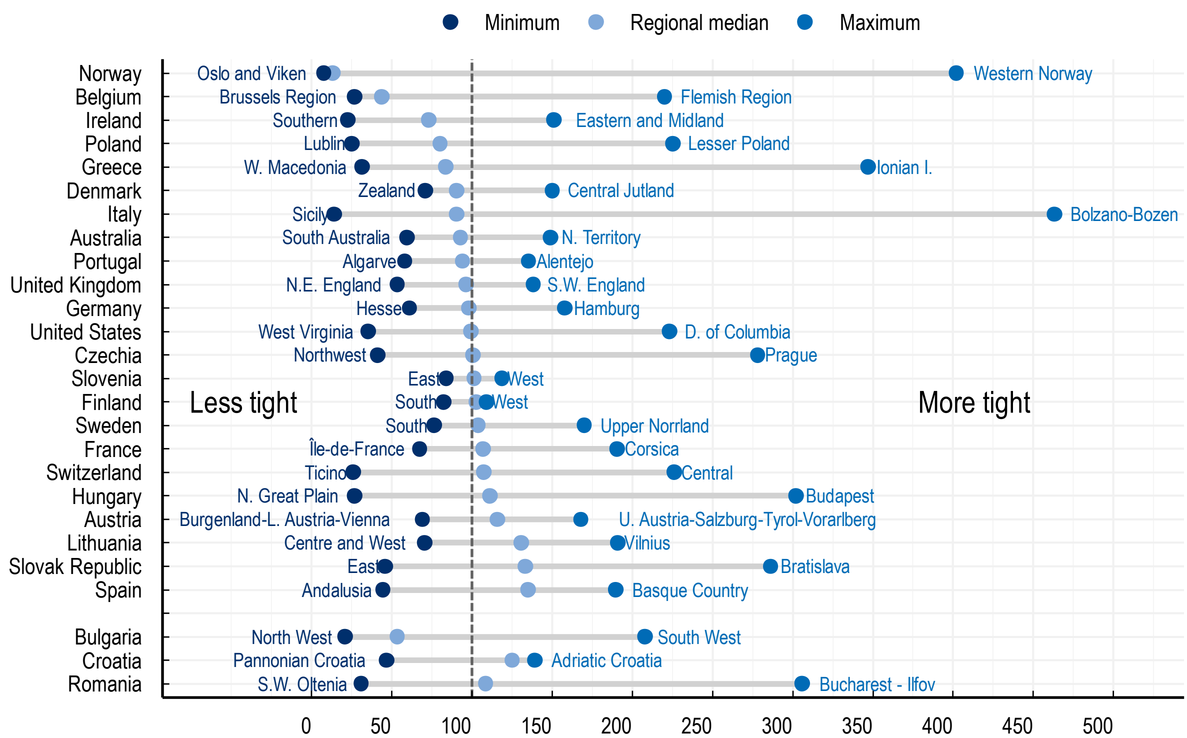
This chapter's tightness estimates do not allow for comparisons across regions in different countries due to data limitations in online job postings data (Box 2.3 and Box 2.4). Online job postings provide detailed and timely data on labour demand. However, there exist differences across countries in terms of their overall coverage, as well as the representation of specific industries, occupations and regions (Box 2.4). Therefore, this chapter presents tightness measures relative to the country average for aggregate regional estimates, and relative to the regional average for occupational (or industry) breakdowns.

Disparities in labour market tightness across regions remain large despite widespread increases in recent years

In the vast majority of OECD countries, regions face substantially different degrees of labour shortages. Based on the relative labour market tightness indicator (see Box 2.3 for methodology), the tightest region is on average more than five times tighter than the least tight region within a country (Figure 2.2). The country with the greatest regional dispersion is Italy, where the greatest relative tightness observed in the Bolzano-Bozen Province is over four times the national average and the region with the lowest tightness is less than one-seventh of the national average. Norway also displays high dispersion: Western Norway (the tightest region) shows tightness of almost four times the national average, while the lowest tightness is evident in Oslo and Viken at 0.07 times the national average. These regions with high relative tightness potentially reflect low unemployment rates as in Bolzano-Bozen Province (2.3% in 2022) or the concentrated nature of each regional economy: offshore oil in Western Norway and tourism in the Ionian Islands. The lowest regional dispersion is found in Finland.

Figure 2.2. Labour markets are tight across OECD regions, with large dispersion in over half of countries

Regional labour market tightness relative to national average, 2022.



Note: Relative labour market tightness at the regional level is the number of vacancies over unemployment for a given region, divided by the national labour market tightness average. The horizontal axis shows the average relative labour market tightness across regions. Regions with a population below 10 000 are dropped. The sample includes all OECD countries with available data, including the OECD accession countries of Bulgaria, Croatia and Romania.
Source: OECD elaboration based on OECD regional database for unemployment data, and Lightcast data for vacancies.

Labour shortages are often concentrated in specific communities that drive a high labour market tightness in OECD countries. In 10 out of 26 countries, the median of regional relative labour market tightness is below the national average, which is normalised to one. In these countries, most regions display low tightness and so, there are few regions with high labour market tightness within the country. In addition, capital regions do not stand out in terms of tightness: they are the tightest region only in five out of the 26 countries with data. This may partly be because in some countries urban regions are, surprisingly, underrepresented in online job vacancy data (Box 2.4).

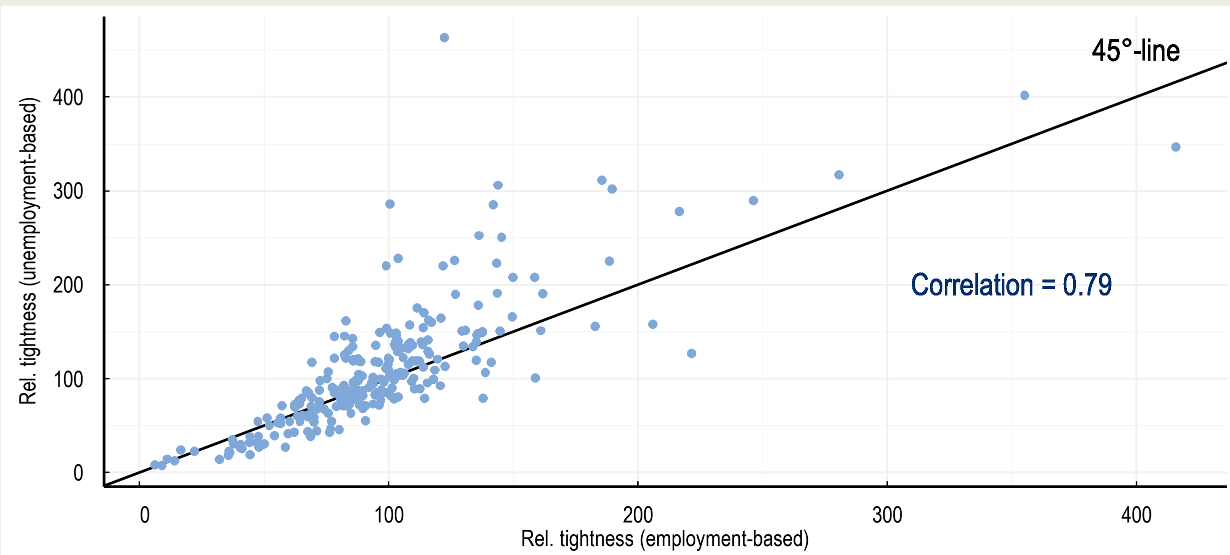
To estimate labour market tightness at a detailed occupational and industry level, the remainder of this chapter measures tightness as the ratio of online job vacancies to employment, rather than unemployment. The reason for this is that most countries do not provide information on the unemployed persons' last occupation, which would be required to construct occupation-level tightness estimates using the standard tightness measure. Nevertheless, Box 2.1 shows that both labour market tightness measures, namely the one using the standard unemployment-based definition and this chapter's employment-based definition, align well across regions.

Box 2.1. How well do different measures of labour market tightness align?

Standard measures of labour market tightness divide vacancies by unemployment. To provide tightness estimates at the occupational level, this chapter uses employment instead of unemployment, as information on unemployed individuals' last occupation is not available for most countries. This box assesses the degree of alignment between the two measures, one based on unemployment and the other on employment.

Figure 2.3. Employment and unemployment-based measures lead to similar tightness results

Regional tightness relative to the national level (=100) using employment (horizontal axis) and unemployment (vertical axis) in the denominator, 2022.



Note: labour market tightness on the horizontal axis is computed by dividing online vacancies by employment at the regional level, while the vertical axis reports tightness based on a measure that uses unemployment in the denominator. The 45°-line indicates where both measures produce identical results.
Source: Own elaboration based on Lightcast, OECD regional unemployment statistics, and labour force surveys: EU-LFS, UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics.

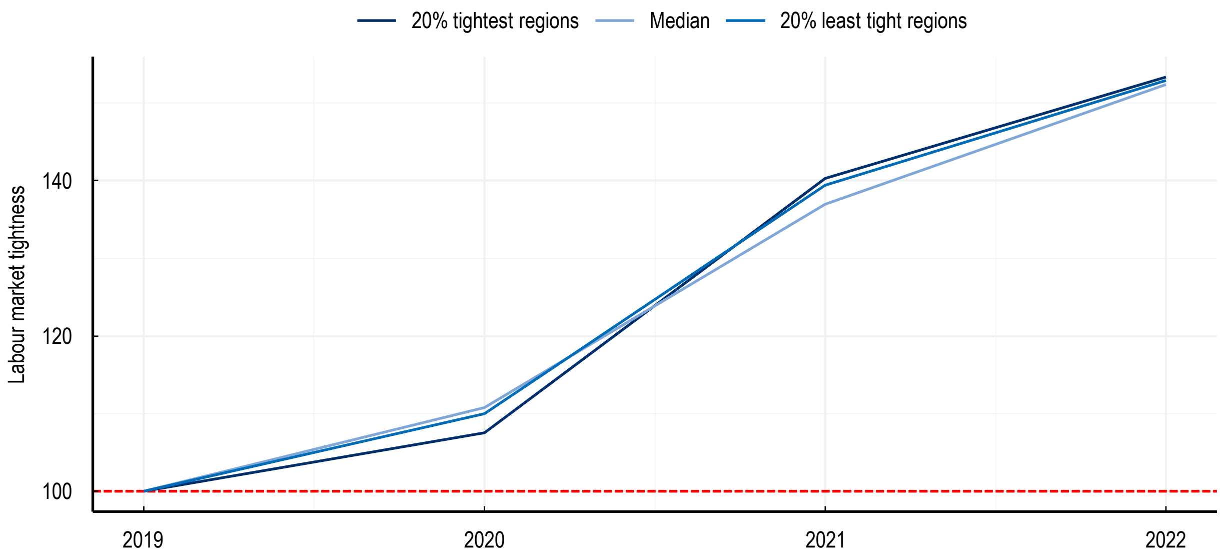
Both the unemployment-based (vertical axis) and the employment-based (horizontal axis) relative tightness measures provide similar results (Figure 2.3). In most cases regional tightness, relative to the national average, falls close to the 45°-line, on which both measures are identical. The similarity of the two measures is confirmed by a high correlation of 0.79. This suggests that this chapter's employment-based tightness measure is also an appropriate proxy for labour shortages.

Regional labour markets have witnessed a notable increase in tightness since 2019, a trend especially exacerbated by the COVID-19 crisis. Figure 2.4 presents an illustrative example using regions in the United States, where Lightcast data is best comparable since 2019, but similar trends are observed across OECD countries (OECD, 2023[3]). Between 2019 and 2022, regional labour market tightness in the United States increased by over 50%. The increase is especially pronounced during the COVID-19 crisis. Between 2020 and 2021, the regional median increased by an additional thirty percentage points, relative to 2019, in contrast to the approximately 10 percentage point increases observed in the preceding and subsequent years.

While regions still face widespread labour shortages, the growth of labour market tightness is showing signs of slowing down after the initial effect of the COVID-19 pandemic. Both regions with the most and the least severe shortages show a slower increase in labour market tightness since 2021. However, by the end of 2022, tightness was still increasing at a relatively high rate across all regions, standing at more than 10 percentage points.

Figure 2.4. Labour markets have become tighter — across all regions

Evolution of relative labour market tightness in US regions indexed to 2019 (= 100), 2019 to 2022.



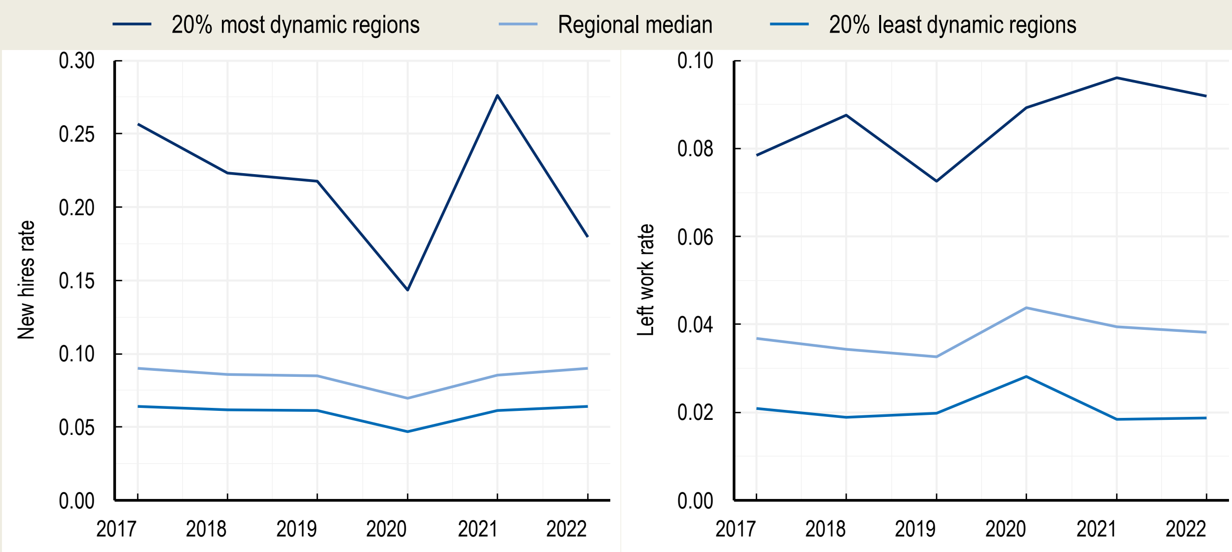
Note: Illustration based on the United States. Absolute tightness is indexed to the year 2019 (=100). The figure shows the evolution of absolute labour market tightness for US regions in the top 20%, bottom 20% and the regional median of absolute tightness. The group of regions in the top and bottom 20% each account for at least 20% of the employed population in the region.
Source: Own elaboration based on Lightcast vacancies and Bureau of Labour Statistics (USA).

Box 2.2. Shortages vs. dynamism: disentangling drivers of labour market tightness

Rising labour market tightness cannot be explained through increasingly dynamic labour markets. If workers are entering and leaving their jobs at a more frequent rate, it is a sign of a vibrant labour market, since workers can quickly transition to new jobs. Figure 2.5 plots the rate at which workers start new jobs and leave their jobs in European regions. Based on this evidence, labour markets have not become more dynamic: besides the dip in new hires and rise in separations in 2020, the trend is flat. This contrasts with labour market tightness, which increased sharply in 2021 and continues to increase into 2022 (Figure 2.4). Therefore, the measure of labour market tightness presented in this chapter is more likely to capture actual labour shortages than dynamic labour markets, and the two terms are used interchangeably throughout this note.

Figure 2.5. Job switches do not explain increasing labour market tightness

New hires and job separation rates over all employed persons, 2017 to 2022.



Note: Illustration based on European countries. New hires rate is defined as the number of people who stated they started a new job in that year over the employed population. The turnover rate is defined as the number of people who stated they left their job that year over the employed population. The figure shows the evolution of the new hires (left) and turnover rate (right) for regions in the top 20%, bottom 20% and the regional median of absolute tightness. The group of regions in the top and bottom 20% each account for at least 20% of the employed population in the region.
Source: OECD elaboration based on EU-LFS, including the OECD accession countries of Bulgaria, Croatia and Romania.

The extent of labour shortages depends on the characteristics of the regional economy

This section examines to what extent labour shortages depend on the regions' demographic composition, labour market conditions and economic structure. To do this, it analyses the relation between labour market tightness (relative to the national level) and regional characteristics in linear regression models (Figure 2.6).

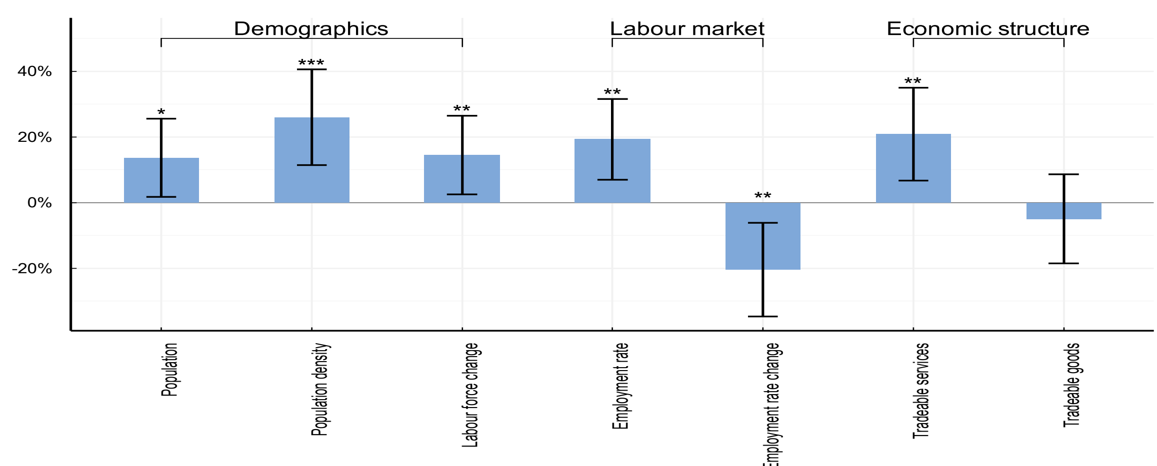
Tightness differs by regional demographic and employment characteristics

More populous and urban regions face more intense labour shortages. The 50% of regions with the highest population in a country (i.e. those above the population median) have 14% higher tightness levels than those below the median (Figure 2.6). Similarly, regions with above-median population density and projected labour force growth have on average 26% and 15% higher tightness levels, respectively, compared to those below the median. Labour demand is likely strongest in more urban areas, to which the labour force adapts by relocating to such high labour demand areas.

Regions with high employment rates face more severe labour shortages. Labour market tightness is on average 19% higher in regions with employment rates above the national median, relative to those with below-median employment rates. This aligns with the interpretation of high employment rates being a driver of labour shortages, as the pool of job seekers is relatively small. Additionally, labour shortages are 20% lower in regions with above-median employment growth over the past five years, potentially because employment growth is more likely to be observed in regions with relatively low employment rates and low levels of tightness. The negative association between employment growth and tightness is also intuitive as firms in regions with a growing labour market are able to fill vacancies and therefore experience lower labour shortages. An important caveat is that the association between labour market tightness and employment rate growth is partially mechanical since a higher number of filled positions decreases labour market tightness according to this chapter's definition.

Figure 2.6. Labour shortages are higher in regions that are more urban, have high employment rates, and rely more on tradable services

Average difference in labour market tightness (relative to the national level) between regions with high levels (i.e. above median) and low levels (i.e. below median) of the characteristics reported on the horizontal axis.



Note: ***p-value<0.01, **p-value<0.05, *p-value<0.1. Each bar corresponds to the coefficient of a univariate, regional-level regression of labour market tightness (relative to the national average) on the respective characteristic on the horizontal axis. In each regression, the covariate takes the form of a binary variable indicating that a region is above the country-specific median value of the respective characteristic (e.g. population). Thus, the vertical axis reports the mean difference in labour market tightness between regions above the country-specific average (e.g. in population) relative to those below the country-specific average. The characteristics are defined (from left to right) as a region's working-age population, population density, its projected labour force change over the future 10 years, the level and the 5-year change in its employment to working-age population rate, the employment share in tradeable services (ISIC broad sectors G to N) and tradeable goods (ISIC sectors B, D, E). Standard errors are clustered at the country level. The regressions include all regions in countries with at least two subnational regions with available data, namely Australia, Belgium, Switzerland, Czechia, Germany, Denmark, Greece, Spain, Finland, France, Hungary, Ireland, Italy, Lithuania, Norway, Poland, Portugal, Sweden, Slovenia, Slovakia, the United Kingdom and the United States.
Source: OECD elaboration based on Lightcast, the OECD Region and Cities databases and labour force surveys: EU-LFS, UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics.

The regional economic structure also matters for the extent of shortages

Regions that are more specialised in tradeable services experience higher labour shortages. Regions with an above-median employment share in tradeable services industries (i.e. ISIC broad groups G to N) experience 21% higher tightness levels compared to those below median.[1] A likely explanation is that some tradeable services industries have seen particularly high and growing demand, for example ICT as a central industry to the twin transition or accommodation and food service activities in the post-COVID recovery. Additionally, it is important to note that office-based jobs – many of which are part of tradeable services industries – are overrepresented in online vacancy data in many countries (Box 2.4), which might overstate the statistical relation between labour market tightness and tradeable services to some degree. Regions with a high share of employment in tradeable goods industries do not show tighter labour markets than those with low employment shares in these industries.

Box 2.3. Labour market tightness as a proxy for labour shortages

Labour market shortages occur when firms are not able to fill open positions. As firms cannot hire the desired employees, labour shortages may impede economic growth and productivity, both for individual firms and the economy as a whole. Despite its importance for the monitoring of a region's economic health, labour market shortages are difficult to measure since standard labour market statistics do not typically track job vacancies (and whether these are filled) in a consistent manner across time and countries. Throughout this note, labour market tightness is used as a proxy for labour shortages.

Methodology

Labour market tightness is calculated as the number of job vacancies over the number of employed persons in a given region and year. The measure is calculated for different occupations and industries in a given region as:

$$labour\ market\ tightness_{r,t} = \frac{Online\ job\ postings_{r,t}}{Employment_{r,t}} \quad \text{for region } r \text{ and year } t.$$

The number of job vacancies comes from online job postings collected by Lightcast while employment data are derived from labour force surveys and national statistics (see notes). This indicator differs from other approaches in that it divides the number of job vacancies by employment (rather than unemployment) (OECD, 2023[3]). However, using employment in the denominator allows for a more accurate disaggregation by occupation and industry, as employed individuals can be attributed to a specific occupation and industry. This results in more detailed information on which sectors or occupations experience greater labour market shortages. Figure 2.3 shows that the standard unemployment-based and the employment-based measure used in this chapter align well across regions.

This chapter presents labour market tightness over time (i.e. 2019-2022), for subnational regions (mostly TL2), as well as by occupation and industry. Since the data quality of online job postings (i.e. how accurately it tracks all job openings in an economy) varies by country and over time, this note reports *relative* measures of tightness. Specifically, the results report occupation- and industry-level estimates relative to the region's average level of tightness, while regional estimates (i.e. for all occupations and industries) are presented relative to the national tightness level. Thus, this approach only allows for comparisons of tightness levels between regions relative to their country's average, rather than in absolute terms. Similarly, occupation- and industry-level tightness estimates can only be compared across regions in relation to their regional tightness average. Additionally, the evolution over time is only reported for the United States (Figure 2.4), as its data is the most reliable across time.

However, some challenges arise when proxying labour shortages with labour market tightness. First, the labour market tightness measure does not account for whether a vacancy is filled. Theoretically, both actual labour shortages and a dynamic labour market (with many vacancies that are filled) could lead to high labour market tightness index. Second, the regional, occupational, and sectoral representativeness of online job postings data varies by country (Box 2.4). This chapter mitigates these shortcomings by restricting the results to where the data are reliable and by reporting results in relative terms.

Notes: Job vacancies are provided by Lightcast; employment data come from EU-LFS, UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics.

High-skilled occupations mainly drive regional labour shortages

Within regions, labour market tightness varies to a large degree by occupation. The tightest ten occupations in Europe and the United States have between two and almost five times more job openings per employed person in that occupation than the average job in that region (Figure 2.7). Furthermore, the tightest occupation in Europe (Sales Marketing and Development Managers) is among the five tightest occupations in 42% of regions, highlighting that many regions face shortages in that occupation. The same is true for 42% of regions when it comes to software and applications developers and analysts, and 35% of regions in the case of transport and storage labourers.

Box 2.4. How representative are online job postings data?

Vacancy data from online job postings (OJPs) provide timely and detailed information. However, they also come with differences in terms of representativeness across countries, regions within countries, occupations and industries. This box provides a brief overview of the representativeness of OJP data from Lightcast (LC) in countries included in this chapter. Existing work in this area compares LC data to official data from national statistical offices and labour agencies, which come with their own limitations (e.g. if firms report vacancies voluntarily). Thus, these comparisons provide a measure of similarity between available sources, rather than an absolute measure of representativeness.

For Anglophone countries, namely the United States, the United Kingdom, and Australia, LC data match official statistics relatively well when considering the *distribution* of vacancies (e.g. the share of vacancies in a specific region, occupation or industry) (Tsvetkova et al., 2024[10]). Since the *total numbe*r of vacancies in LC data is consistently below the one in national statistics, this chapter refrains from reporting absolute levels of tightness (i.e. the number of OJPs per filled position). Nevertheless, differences in the distribution of vacancies do exist. Overrepresentation is highest for the education and health sectors, whose share is between 12 and 15 percentage points higher in LC than in official statistics. Evidence of occupational representation is limited to Canada, where management and professional occupations are overrepresented and lower skilled occupations are underrepresented. Importantly, these sectoral and occupational patterns remain relatively stable between 2015 and 2022. The regional representation is in general high for Anglophone countries, showing differences of one percentage point at most between LC data and official records with very few exceptions.

The representativeness of LC data varies strongly across European countries (Vermeulen and Gutierrez Amaros, 2024[11]). In 2020, the ratio of OJPs to those reported in official statistics ranged from 6.8 in Ireland to 0.4 in Czechia. Between 2019 and 2022, the coverage of OJPs increased substantially such that in 2022 the number of OJPs exceeds the ones from official statistics in all countries except Luxembourg. Consequently, this chapter does not report time trends for European countries. Subnational regions are not equally represented in most countries, with the exception of Sweden and the Netherlands. Surprisingly, urban areas are not always overrepresented, as capital regions are underrepresented in Belgium, Hungary and Romania. Regarding industries, manufacturing, utilities, ICT, and finance and insurance activities are in general overrepresented. Furthermore, professional and administrative occupations tend to be overrepresented, potentially because office-based job vacancies are more likely to be posted online. It is important to take these results into account when interpreting this chapter's findings.

Source: (Vermeulen and Gutierrez Amaros, 2024[11]); (Tsvetkova et al., 2024[10])

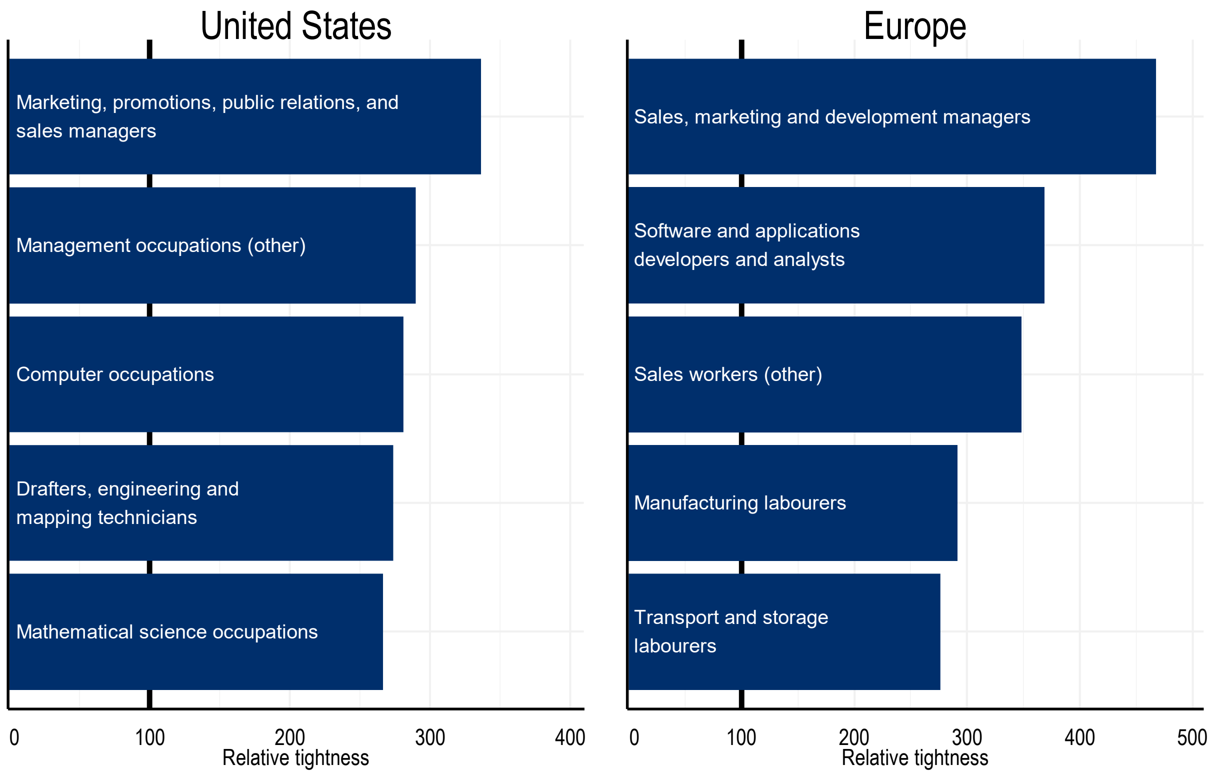
High-skilled occupations are in demand across OECD regions

Labour shortages in OECD regions affect high-skilled occupations more than low- and medium-skilled occupations. In two-thirds of European regions and all regions in the United States, high-skilled jobs, namely managers and professionals (i.e. defined at the 1-digit level of the European occupational classification ISCO), are the tightest occupational group. Their average tightness is 25% and 41% higher than the average job in the labour market in Europe and the United States, respectively. Low-skilled jobs, for example, service and sales workers, are the second tightest skilled group, with 2% and 32% lower-than-average tightness levels in Europe and the United States, followed by medium-skilled jobs (22% and 34% lower-than-average tightness). These findings contrast evidence on increased labour shortages among low-and medium-skilled occupations, which may partly be explained by office jobs, many of which are high-skilled, being overrepresented in the underlying online job postings data (Box 2.4).

However, occupations of all skills groups and in a variety of industries count among the tightest occupations. In Europe, both high-skilled occupations (e.g. Software and Applications Developers and Analysts) and lower-skilled occupations (e.g. manufacturing, transport, and storage labourers) are among the tightest occupations on average across regions. In the United States, the tightest occupations include mostly high-skilled occupations (e.g. management occupations or computer occupations), with few exceptions (e.g. physical therapist assistants). Additionally, jobs in a wide range of industries show high labour market tightness in the United States, namely the ICT, wholesale, arts and healthcare industries, and in Europe, namely the ICT, manufacturing and logistics industries.

Figure 2.7. Labour market tightness is up to four times higher-than-average for the most affected occupations

Labour market tightness by occupation relative to the regional average (=100) for the ten tightest occupations, 2022.



Note: Relative labour market tightness by occupation is calculated at the regional level as the number of vacancies over employment for a given occupation and region, divided by the regional labour market tightness average. The horizontal axis shows the average relative labour market tightness across regions (weighted by employment) in the US and the EU. The figure shows the ten tightest occupations in the US and the EU. Occupations are classified according "minor" occupational SOC codes (4 digit) in the US and 3-digit ISCO codes in the EU.
Source: Own elaboration (see Box 2.3); Lightcast; EU-LFS, UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics.

Missing green and digital talent hold back many OECD regions

Tightness estimates at the occupational level allow for aggregations by relevant occupational groups, such as green and ICT jobs, and can provide valuable evidence for policies to target shortages effectively. This chapter uses the task-based definition of green jobs established in previous LEED work, according to which occupations with at least 10% green tasks are classified as green (OECD, 2023[12]). In this definition, tasks that contribute to environmental objectives, such as preserving the environment and reducing greenhouse gas emissions, are considered green. For ICT jobs, this chapter adopts Eurostat's classification of ICT specialists which are defined as "workers who have the ability to develop, operate and maintain ICT systems, and for whom ICT constitute the main part of their job" (Eurostat, 2024[13]). Since Eurostat defines ICT specialists at the 4-digit ISCO level, this classification is further converted to the 3-digit level based on employment shares and adapted to other occupational taxonomies (e.g. SOC) used in this chapter.

Jobs that are crucial for the digital transition experience high labour shortages in almost all OECD regions. ICT jobs show 156% more vacancies per filled position than the regional labour market on average. Although ICT are tighter than the average job in 97% of OECD regions with available data large regional disparities exist within countries (Figure 2.8). On average, ICT jobs show more than twice (126%)

more vacancies per filled position in the region with the highest compared to the one with the lowest ICT shortages.[2] This difference can reach up to 700% (Thessaly region in Greece). On average across countries, ICT jobs are tightest in Greece, Portugal and Poland, which have around 4 times more vacancies per filled position in ICT jobs compared to the average job. Nordic European countries, namely Finland, Sweden and Denmark, experience the lowest ICT shortages as ICT jobs are approximately as tight as the regional labour market on average. Apart from job-specific skills, other factors, such as generally higher educational requirements among digital (and green) jobs compared to the average job, likely contribute to these tightness differences.

For green jobs, this gap in relative tightness is smaller than for ICT jobs, but still substantial. Similarly to ICT jobs, green jobs show more vacancies per filled position than the average job in more than nine out of ten OECD regions (91%) (Figure 2.9). With 37% more vacancies per filled position than the average job, the magnitude of this tightness difference for green jobs is substantial, but smaller than for ICT jobs (156%). Regions vary in their tightness of green jobs, as green jobs are 44% tighter in the region with the most relative to those with the least severe green jobs shortages. Yet these regional disparities are smaller than in the case of ICT jobs. Greece experiences the strongest green jobs shortages both at the national level, where green jobs are 95% tighter, and at the regional level, with green jobs in Eastern Macedonia showing more than twice as many vacancies than the average job. The three countries with the lowest green jobs shortages on average are Norway, Sweden and Finland, where green jobs are about as tight as the average job. These Nordic countries also experience relatively little variation across regions, with the exception of Norway where green jobs are almost 57% less tight than the average job in Trøndelag.

Box 2.5. How does labour market tightness affect wages?

Theoretically, occupations and industries that experience labour shortages should see an increase in their real wages. The reason for this is that firms need to improve job conditions (including but not restricted to wages) to attract the relatively few job candidates. Past and current economic projections have repeatedly highlighted that this mechanism could lead to additional upward pressure on wages, potentially exacerbating a wage-price spiral, in the current context of high inflation (OECD, 2024[14]).

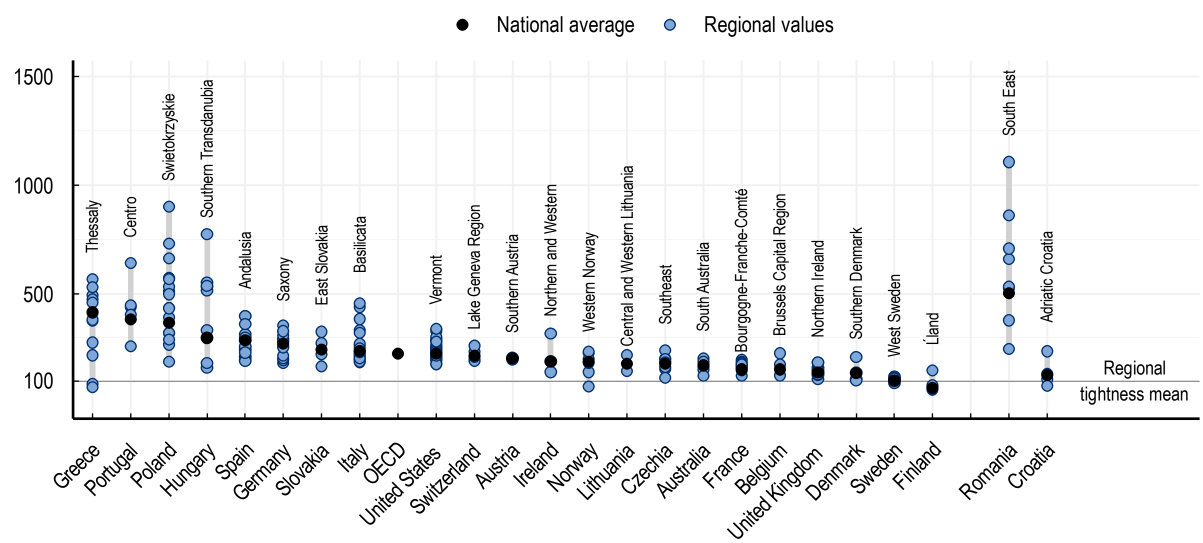
In practice, despite widespread labour shortages, real wages have declined across the OECD by 2.2% on average between Q4 2019 and the end of 2022 as nominal wages have not kept pace with inflation in recent years. Although nominal wages grew by 14.3% over the same period, high inflation rates overshadowed the (likely) labour shortages-induced upward pressure on real wages. Real wages performed better (i.e. fell by less) in low- than in medium- or high-paying industries, as a result of stronger nominal wage growth in lower-wage industries (OECD, 2023[3]). This aligns with evidence that labour shortages have increased strongly in lower-paid and lower-quality occupations over this period (Zwysen, 2023[7]).

As inflation fades, labour shortages could lead to higher real wages in affected occupations and industries. Supporting this hypothesis, tentative evidence suggests that industries that faced higher increases in labour market tightness also experienced higher nominal wage growth (OECD, 2023[3]). More specifically, industries that experienced a 1% increase in tightness saw their nominal wages rise by 0.03%. Indeed, evidence from 2023 shows that real wage growth has turned positive in most OECD countries (29 out of 35), standing at 3.5% across the OECD on average (OECD, 2024[2]). However, more detailed regional analysis is not feasible due to the lack of regional and occupational wage data, which represents a major limitation to offer valuable policy options to address the issue of stagnating wages across OECD regions.

Regions with more severe labour shortages for green jobs also experience higher ICT job tightness (and vice versa), highlighting that the digital and green transitions are intertwined. Regions with a 10% higher green jobs tightness level also have a 18% higher tightness of ICT jobs on average (relative to the average regional tightness) (Figure 2.10). This positive relationship likely stems from the fact that the green and the digital transitions – and their associated job profiles – complement each other, as both the innovation and the implementation of green technologies often require an adequate ICT infrastructure and a digitally-skilled workforce. For example, digital technologies, such as “smart” meters can help make industrial processes more energy-efficient, including in the most emissions-intensive industries, such as cement, steel and chemical industries (European Commission, 2022[15]). However, the positive association between tightness of green and digital jobs at the regional level can partly also arise from some occupations being classified as both green and digital.

Figure 2.8. ICT jobs experience particularly severe shortages across OECD regions

Labour market tightness of ICT jobs relative to the regional average (= 100), 2022.

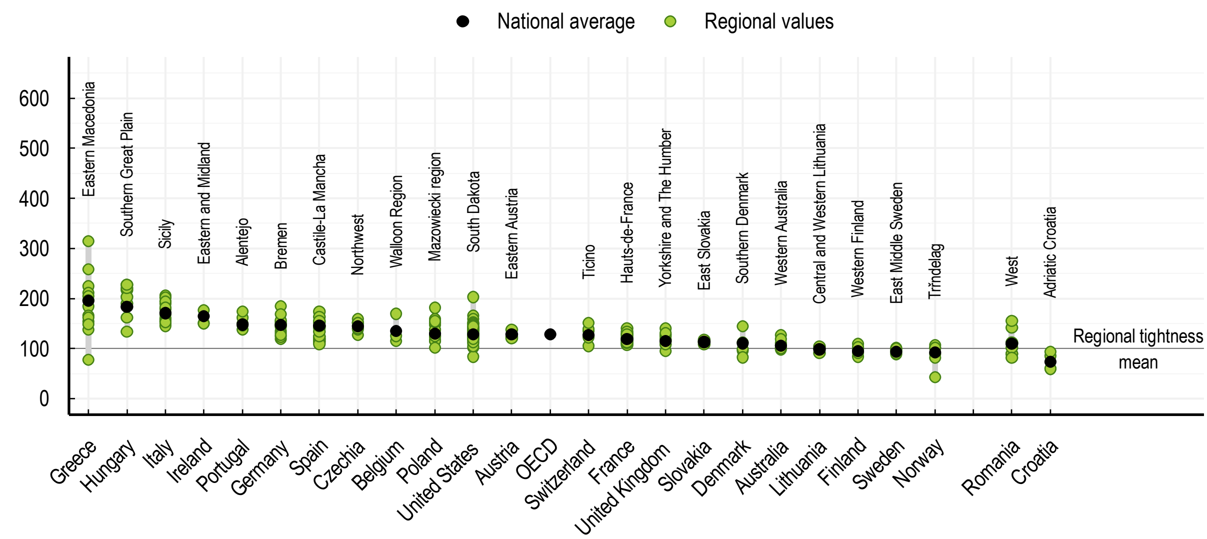


Note: The relative labour market tightness of ICT jobs is based on the relative tightness estimates by occupation, which are aggregated at the regional level using Eurostat’s definition of ICT specialists.[3] Since Eurostat’s ICT specialists classification is defined at a lower occupational level (4 digits) than the available employment data (mostly 3 digits), the classification is aggregated to the 3-digit level assuming equal employment shares among the 4-digit occupations. The vertical axis shows the average relative labour market tightness of ICT jobs relative to the average job in the region’s labour market. Hence, a value above 1 indicates higher-than-average tightness of ICT jobs in that region.
Source: Own elaboration (see Box 2.3); Lightcast; EU-LFS, UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics; (Eurostat, 2024[13]).

Shortages of workers with green and digital skills are an obstacle to firm investments and inhibit local economic growth (OECD, 2023[12]). In Europe, for example, more than 80% of firms report skills shortages, especially for green and digital skills, which limits the implementation of climate change projects and progress on the green transition (EIB, 2023[16]). This reflects the high demand for workers with green and digital skills as economies adjust to the twin transition and could be a result of a skills mismatch as labour markets undergo a process of structural transformation that is not yet complemented through adaptations in education and training systems.

Figure 2.9. Green jobs are tighter than the average job in the vast majority of OECD regions

Labour market tightness of green jobs relative to the regional average (= 100), 2022.

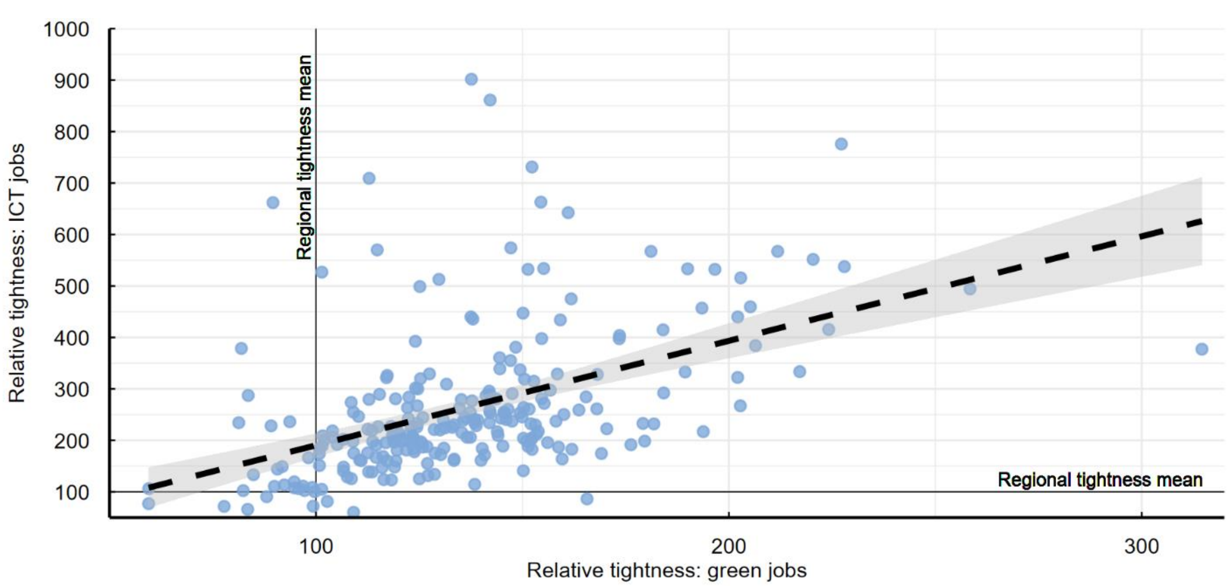


Note: The relative labour market tightness of green jobs is based on the relative tightness estimates by occupation, which are aggregated at the regional level using the green jobs classification established in (OECD, 2023[12]). The vertical axis shows the average relative labour market tightness of green jobs relative to the average job in the region's labour market. Hence, a value above 1 indicates higher-than-average tightness of green jobs in that region.

Source: Own elaboration (see Box 2.3); Lightcast; EU-LFS, UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics; (OECD, 2023[12]).

Figure 2.10. Shortages in green and ICT jobs tend to co-occur in OECD regions

Labour market tightness of green jobs (horizontal axis) and ICT jobs (vertical axis) relative to the regional average (=100), 2022.



Note: The figure shows the labour market tightness of green jobs (horizontal axis) and ICT jobs (vertical axis) relative to the regional average in 2022 for all OECD regions with available (subnational) data. The dashed line represents the regression line of a linear model with a 95% confidence interval.

Source: Own elaboration (see Box 2.3); Lightcast; EU-LFS, UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics; (OECD, 2023[12]); (Eurostat, 2024[13]).

High-productivity and contact-intensive industries experience the strongest labour shortages

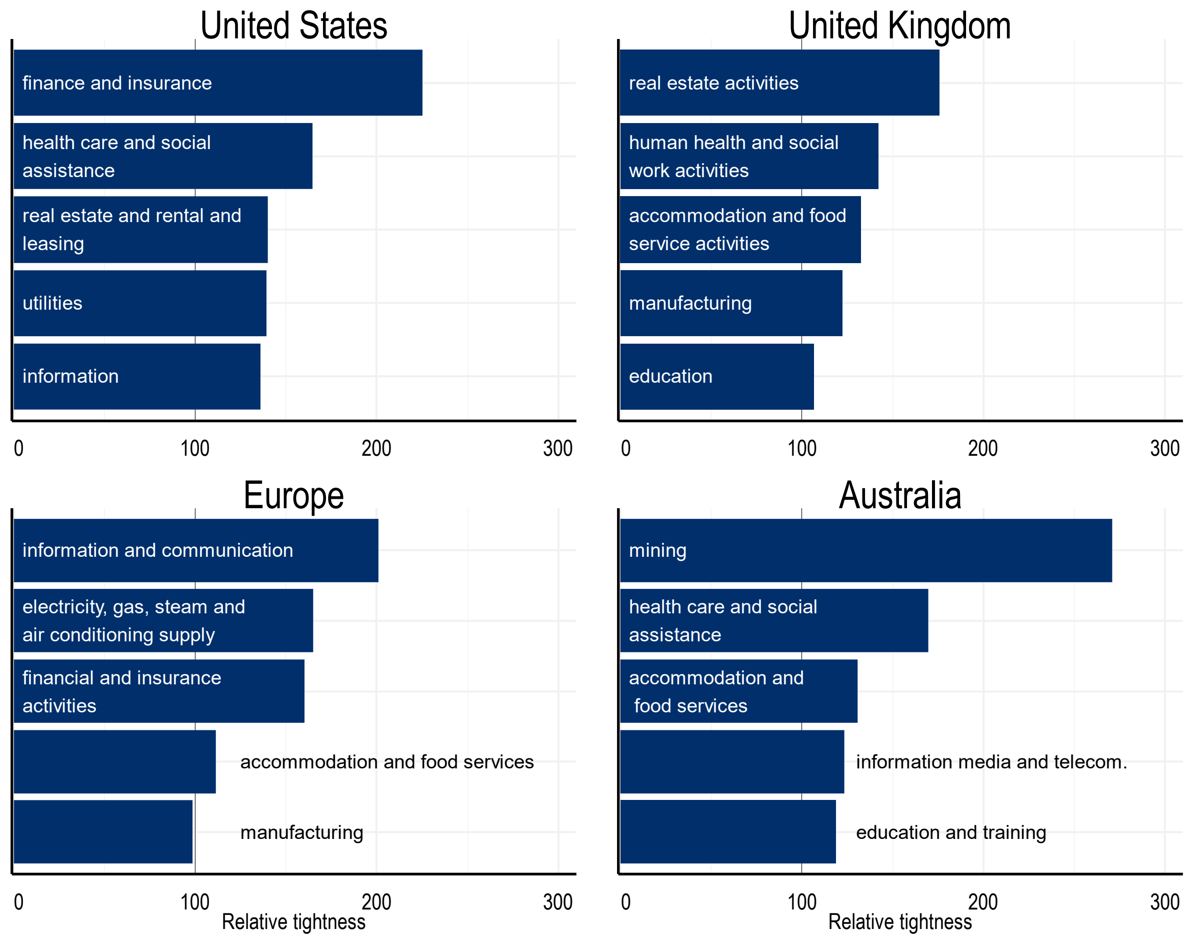
Industries differ substantially in terms of labour market tightness, yet the magnitude depends on the geographic area. While jobs in the tightest industry are 2.7 times tighter than the regional average in Australia (mining), the tightest industry in the United Kingdom (real estate activities) stands at 1.8 times the average regional tightness level (Figure 2.11).

High-productivity industries, such as ICT and finance and insurance, tend to be among the tightest industries. Mirroring the ongoing digital transition in many regions, the ICT industry ranks among the five tightest industries in three out of four geographical areas analysed (Figure 2.11). Jobs in the ICT industry display between 1.2 times (Australia) and two times (European regions) more vacancies per filled position than the average job in a region. Moreover, ICT is the tightest industry in 33% of European regions and in 24% of US regions. This aligns with ICT specialist occupations showing particularly high levels of tightness (Figure 2.8). Furthermore, financial and insurance activities and utilities are particularly tight in the United States and Europe. In fact, the finance and insurance industry is the tightest industry in the United States, with 2.5 times more vacancies per filled position than the regional average (1.6 times in the European Union).

Contact-intensive industries, namely health care, and accommodation and food services also show strong signs of labour shortages. In line with reports of widespread shortages of health care workers – a lack of 15 million health workers in 2022 worldwide (Boniol et al., 2022[17]) – the health care industry ranks among the five tightest industries in the United States, the United Kingdom and Australia, with values ranging from 1.4 to 1.6 times the average regional tightness level. Similarly, accommodation and food services are among the five tightest industries in the United Kingdom and Australia (both 1.3 times the regional average), and Europe (1.1 times tighter), reflecting the post-COVID-19 surge in labour shortages in contact-intensive industries (Causa et al., 2022[6]).

Figure 2.11. Industries differ substantially in terms of labour market tightness

Labour market tightness of the five tightest broad industries relative to the regional average (=100), 2022.



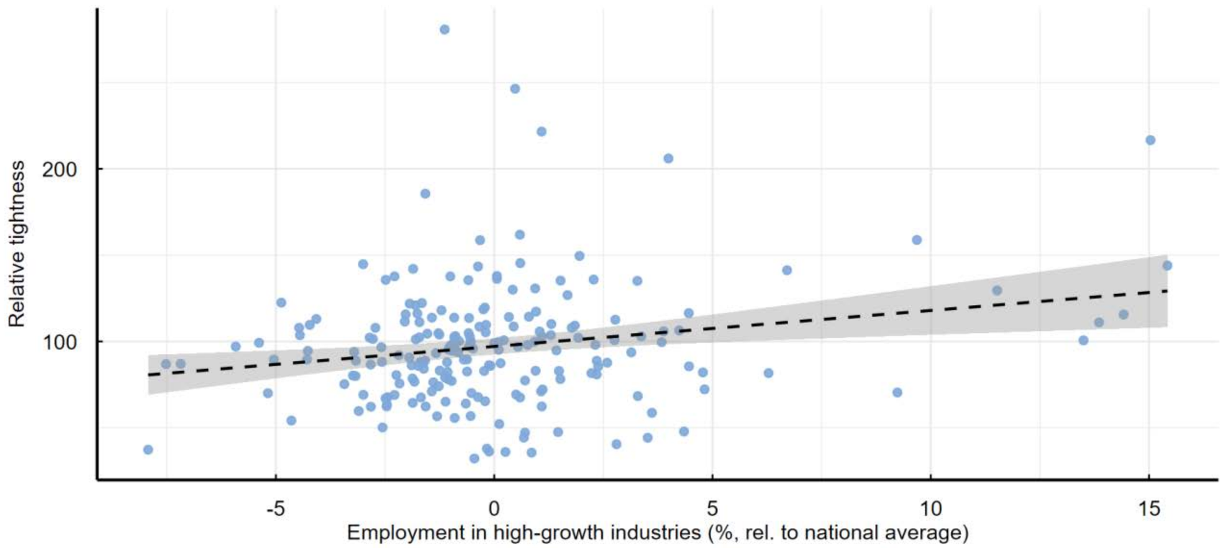
Note: Relative labour market tightness by industry is calculated at the regional level as the number of vacancies over employment for a given industry and region, divided by the regional labour market tightness average. The horizontal axis shows the average relative labour market tightness across regions (weighted by employment) in the United States, the United Kingdom, Europe and Australia. Occupations are classified according to broad industries (i.e., the highest level) of the respective industry classification, namely NAICS the US, NACE in the EU, UK SIC in the UK and, ANZSIC in Australia.

Source: Own elaboration (see Box 2.3); Lightcast; EU-LFS, UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics.

Labour shortages are larger in regions that rely more on high-growth industries (defined at the national level), highlighting the regional economic structure as a driver of shortages. Regions with a one percentage point higher employment share in high-growth industries show a 2% higher tightness level (relative to the country mean) on average (Figure 2.12). For this analysis, high-growth industries are defined as the three (1-digit) industries with the largest employment growth between 2019 and 2022 at the country level. As demand for workers in high-growth industries is high in many parts of the country, companies in regions with a higher reliance on these industries are likely to face more difficulties in finding adequately skilled employees given increased labour force needs and increased competition from other companies within the region and other regions.

Figure 2.12. Regions that are more reliant on high-growth industries experience stronger shortages

Regional tightness relative to the national level (vertical axis) and the share of employment in high-growth industries, defined at the national level (horizontal axis), 2022.



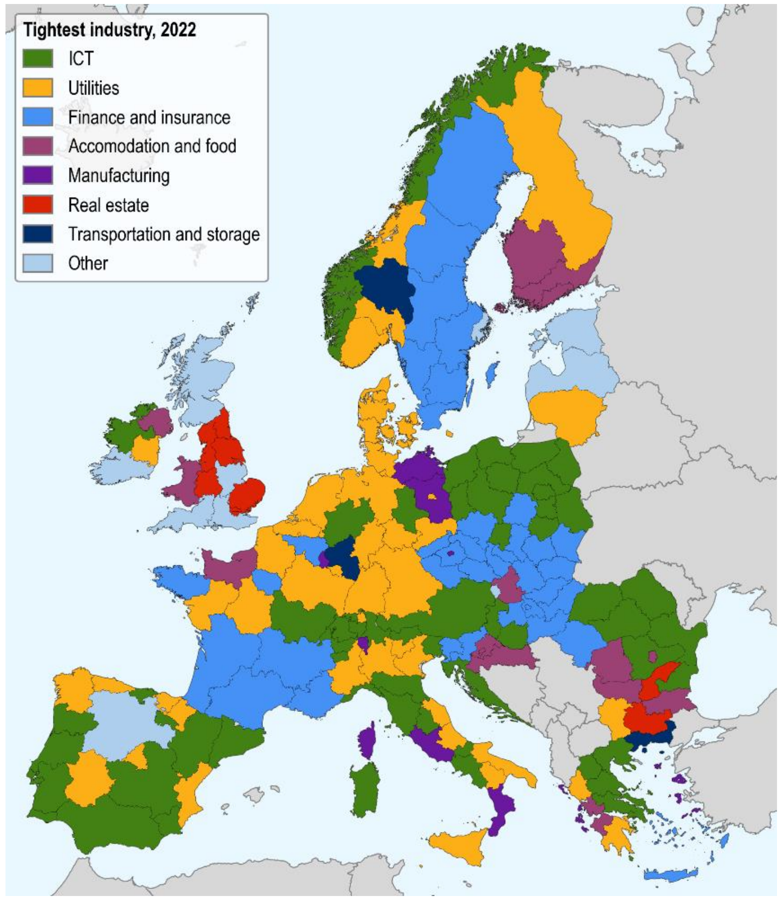
Note: The figure shows regional tightness relative to the national level on the vertical axis and the share of employment in high-growth industries on the horizontal axis. High-growth industries are defined as the three (1-digit) industries with the largest employment growth between 2019 and 2022 at the country-level. For example, the most common high-growth industries in Europe are "information and communication" in 18, "water supply; sewerage, waste management and remediation activities" in 9 and "real estate activities" in 9 out of 27 countries.
Source: OECD elaboration based on Lightcast, the OECD Region and Cities databases and labour force surveys: EU-LFS, UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics.

The interpretation of tightness estimates for nascent, often high-growth industries requires some caution. By definition, such newly emerging industries are initially characterised by a low number of workers, leading to high levels of tightness compared to other industries (provided that sufficiently many vacancies exist already). Conventional tightness measures can be misleading in this context, since nascent industries recruit from other industries, particularly those that employ workers with a similar skill set. While this caveat is important to keep in mind, it is mitigated in this chapter as the latter examines tightness for approximately 15 broad industry groups per country, within which emerging industries make up a relatively small share.

A look at each region's tightest industry in Europe and the United Kingdom reveals a mixed pattern (Figure 2.13). In some countries, most regions experience the strongest shortages in finance and insurance (e.g. France, Sweden, and the Czech Republic), while in others, most regions' tightest labour markets are ICT (e.g. Spain, Portugal, Switzerland, and Poland) or utilities (e.g. Germany). Italy presents a mixed picture, as regions vary in terms of their tightest industry (utilities, ICT, and manufacturing).

Figure 2.13. ICT and utilities are the tightest industries in more than half of all European regions

Tightest industry in each region, 2022.

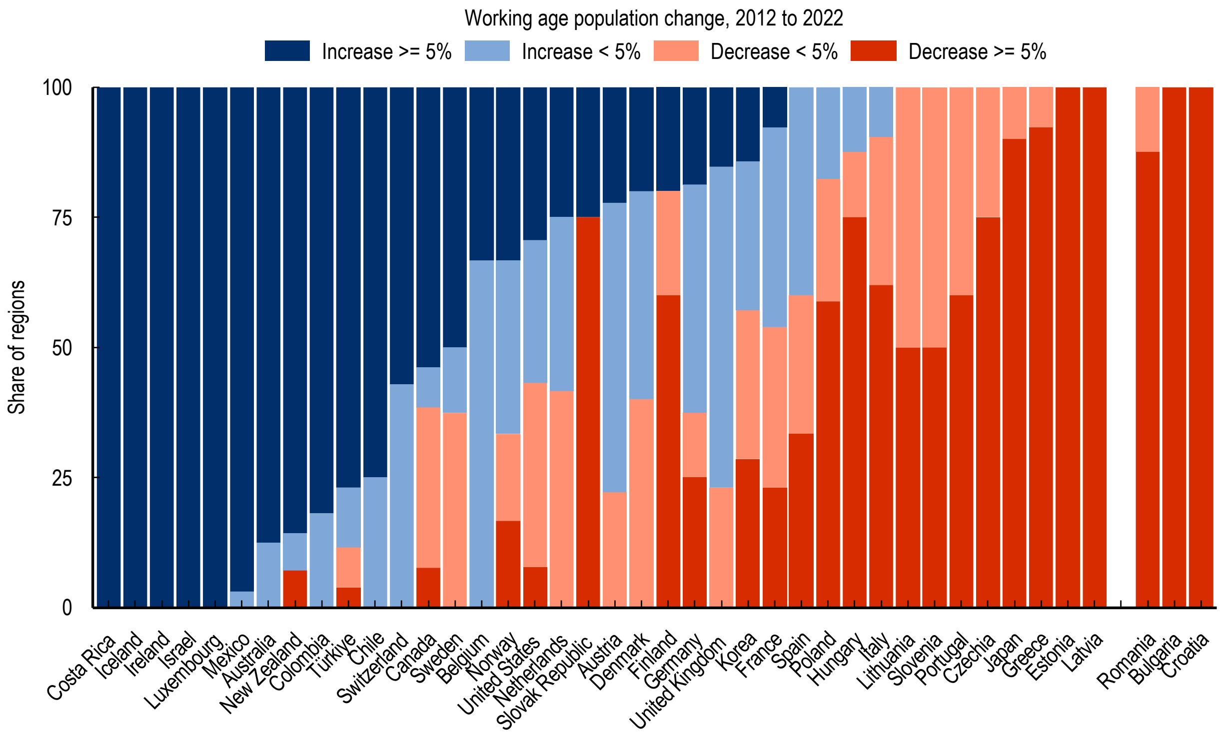


Note: The figure shows each region's tightest industry in 2022. Industries whose employment is below 5% of a region's median are excluded.
Source: Own elaboration (see Box 2.3); Lightcast; EU-LFS, UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics.

Demographic change will put additional pressure on labour market tightness

More than four in ten OECD regions saw their potential labour force shrink over the past decade (Figure 2.14)**.** This proportion increased from almost 30% in 2008 to over 40% in 2022 (OECD, 2020[18]). In almost 10% of regions the working age population (15- to 64-year-olds) shrank by more than 10%, in many cases as a result of both ageing and outmigration. On average, OECD regions experienced modest growth in their potential labour force of about 3%. Notably, more than a quarter of regions grew their potential labour force by more than 10%. Thus, the varied trends in the evolution of the working age population across regions suggests the need for tailored support for those regions facing a significant contraction, especially as it potentially aggravates labour market tightness.

Figure 2.14. Over 40% of OECD regions experienced a decline in the working age population over the past decade



Note: The figure shows the share of regions in each country which belong to each of the four categories representing the percentage change in the working age population in 2012 and the working age population in 2022. The sample of countries includes the OECD accession countries of Bulgaria, Croatia and Romania.
Source: OECD calculations based on OECD Regional Labour Database.

By 2042, the median local labour market tightness across OECD regions is projected to increase by almost 9%, solely due to the decrease in the working age population in ageing regions (Figure 2.15). Most OECD countries are ageing resulting in shrinking working age populations (OECD, 2022[19]; OECD, 2023[20]). These ageing populations will further exacerbate local labour market tightness, especially in the places that face the greatest demographic change. Using information on regional population structures, this chapter calculates the projected percent change in labour market tightness that can be directly attributed to regional demographic shifts. Information on the methodology behind the calculation is detailed in Box 2.7.

Box 2.6. Lower labour force participation and employment rates among older workers intensify labour shortages

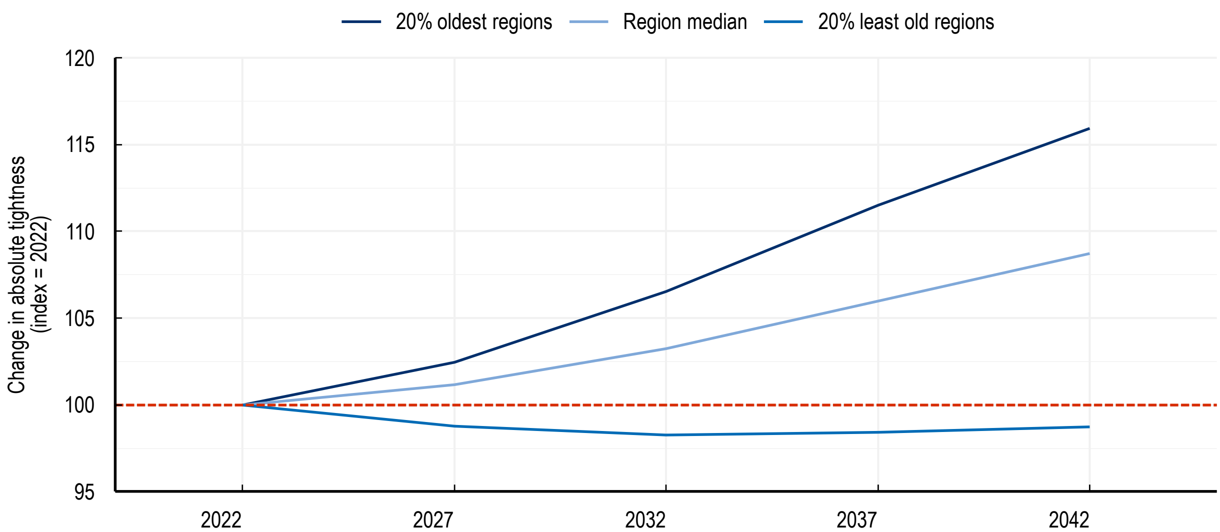
A pandemic-induced increase in labour market attrition (i.e. labour force exits) among older workers intensifies demographic pressure and contributes to shortages in the US labour market. Older workers' (aged 55-70) likelihood of retiring during the first year of the COVID-19 pandemic rose by 6.7 percentage points (43%). This effect was particularly strong for older workers without a college degree and those in contact-intensive jobs (Davis et al., 2023[21]), suggesting that health concerns played a role in these retirement decisions. Furthermore, labour force participation rates among workers aged 55-74 have not recovered to pre-pandemic levels and remained below 40% at the end of 2022 (Botelho and Weißler, 2022[22]). At this point it remains unclear to what extent older workers who left the labour force (mainly to retire) during COVID-19 in the United States will return to the labour market in the long run.

In contrast, the European Union only experienced a temporary drop in labour force participation rates of older workers during the COVID-19 pandemic. In Euro area countries, labour force participation quickly returned to its pre-COVID growth path, which is largely in line with ageing population trends, after the pandemic. As a result, in 2022 more (41.5%) workers aged 55-67 than before the pandemic (40%) were working or actively looking for employment (Botelho and Weißler, 2022[22]). However, employment rates show a different pattern: about the same share (95%) of older workers in the labour force (aged 60-64) in the European Union are employed in 2022 compared to 2018, while employment rates increased for all other age groups over the same period. This stagnation suggests that older workers in the European Union face difficulties in finding employment even if they are willing to participate in the labour market. These difficulties may include negative perceptions of older workers by employers and a lack of skills in an increasingly digital job market (see below).

In the regions with the oldest population structure, demographic change will increase labour market tightness by 2042 almost twice as much as in the OECD median region. The difference between older regions, defined as those currently in the top 20% of regions with the highest old-age dependency ratio (i.e. the ratio of the population aged 65 and over to the working age population), and the OECD regional median will be increasing over time. In contrast, for younger regions in the bottom 20% of the regional distribution of old-age dependency ratios, labour market tightness will only marginally decrease by about 2% by 2027 and remain relatively stable up to 2042. Even in regions where the working-age population is expected to grow, the easing of labour market tightness is limited, especially compared to the impact of ageing populations.

Figure 2.15. Demographic pressure will tighten labour markets, especially in older regions

Projected labour market tightness given net working age population change, 2022 to 2042.



Note: The figure shows the projected increase in labour market tightness over the years 2022 to 2042, where 2022 is indexed to 100. The figure shows the evolution of absolute tightness for regions in the top 20%, bottom 20% and the regional median of the old-age dependency ratio. The group of regions in the top and bottom 20% each account for at least 20% of the population in the region.
Source: OECD elaboration based on Lightcast, the OECD Region and Cities databases and labour force surveys: EU-LFS (including the OECD accession countries of Bulgaria, Croatia and Romania), UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics.

Box 2.7. Calculating demographic pressure on labour market tightness

"Back-of-the-envelope" exercise

Regions are ageing across the OECD (OECD, 2022[19]; OECD, 2023[20]). This demographic change is likely to have diverse implications for local economies and local labour markets in particular. In the case of labour market tightness, shifts in the population structure are especially pertinent since the degree of tightness is directly related to the available supply of potential workers, i.e. the working age population.

To gain insight into the expected impact of population change within regions on the intensity of labour market tightness, this note uses a simple exercise. In short, the exercise seeks to answer the question: **By how much would labour market tightness increase given the projected net change in the working age population?**

Methodology

The first step calculates the projected working age population for five-year periods from 2022 to 2042 (i.e. up to 20 years from the last available year, 2022). The projected working age population takes into account the hypothetical net change in the working age population, defined as 15- to 64-year-olds, given current demographic age structures. For example, in the year 2027, the projected working age population is calculated as the working age population in 2022 minus those individuals expected to retire by 2027 (i.e. those aged 60 and over in 2022), plus those individuals expected to join the working age population by 2027 (i.e. those aged 10 and over in 2022). The projection for 2042 assumes that births in the next five years will be the same as the currently youngest 0- to 5-year-old cohort. Information on the demographic structure of regions is taken from the OECD Regions and Cities databases (OECD, 2024[23]).

Next, the projected working age population is used to calculate an alternative measure of labour market tightness. The main measure of labour market tightness defines tightness as the number of vacancies over the number of employed persons (see Box 2.3). **For the purpose of this exercise, labour market tightness is instead defined as the number of vacancies over the working age population (15- to 64-years-old).**

This change in methodology avoids additional assumptions on employment rates and their evolution across demographic groups. For example, using the projected number of employed persons would either require knowing the employment rate of young people and of older workers over the next twenty years, or assuming that the rate is constant over this period and for each group. Both of these scenarios seem unlikely, as employment rates differ greatly across age groups and over time.

Furthermore, as the interest of this exercise is to calculate the projected percent change in tightness given a demographic change, the most important aspect is the comparability of the measure to 2022, the last year with available data. By redefining the measure, comparability is maintained with minimal confounding assumptions. Additional assumptions, which are important to keep in mind, are that the regional fertility in the next five years is the same as the past five years, that no fatalities occur over the next two decades, and that net migration in the region is constant.

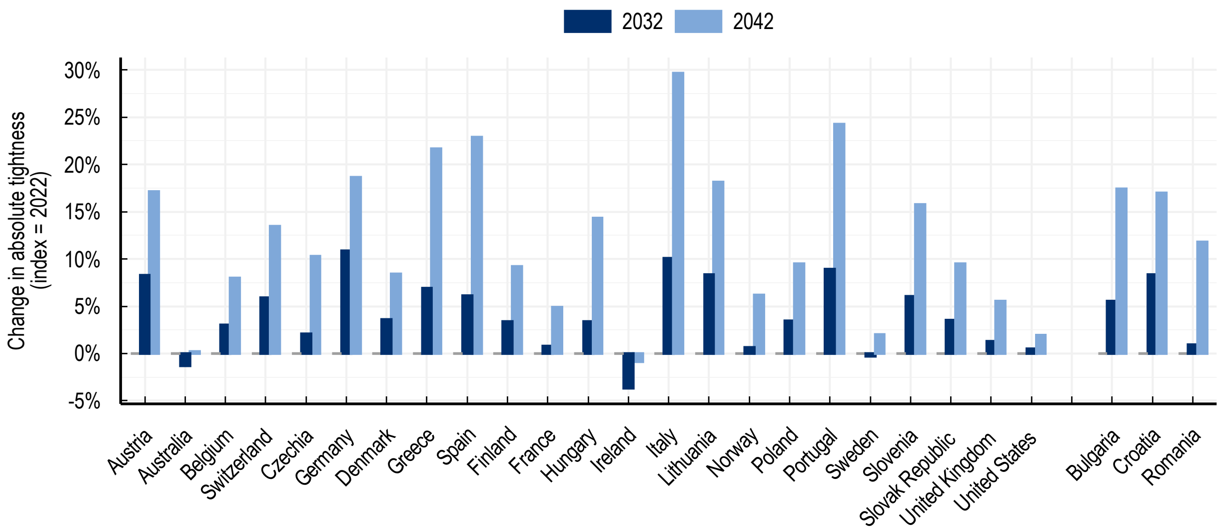
Lastly, to calculate the percent change in labour market tightness given the projected working age population, each five-year period is indexed to 2022, the last available year**. In this way, the exercise describes the change in labour market tightness attributed only to the predicted change in the working age population.**

This implies that the exercise does not take into account how the change in the population structure could affect the number of vacancies. Vacancies are taken as the value in 2022, which is kept constant. It could be that a fall in the labour force affects the number of vacancies. This correlation could be either positive or negative: vacancies could rise due to increased demand for labour-intensive care work, or they could fall since older populations tend to demand less goods and services. The net effect of these two dynamics could also be country or region-specific and so, different from the average net correlation. The exercise keeps vacancies constant in order to clearly attribute the change in tightness solely due to the change in the labour force.

Notes: Job vacancies are provided by Lightcast; population data comes from the OECD Regions and Cities database (OECD, 2024[23]).

Figure 2.16. Ageing populations will affect almost all OECD countries, albeit to varying degrees

Average projected change in labour market tightness given net working age population change by country, indexed to 2022.



Note: The figure shows the mean of the projected increase in labour market tightness for 2032 and 2042, relative to 2022 (indexed to 0), for OECD countries with available data.
Source: OECD elaboration based on Lightcast, the OECD Region and Cities databases and labour force surveys: EU-LFS (including the OECD accession countries of Bulgaria, Croatia and Romania), UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics.

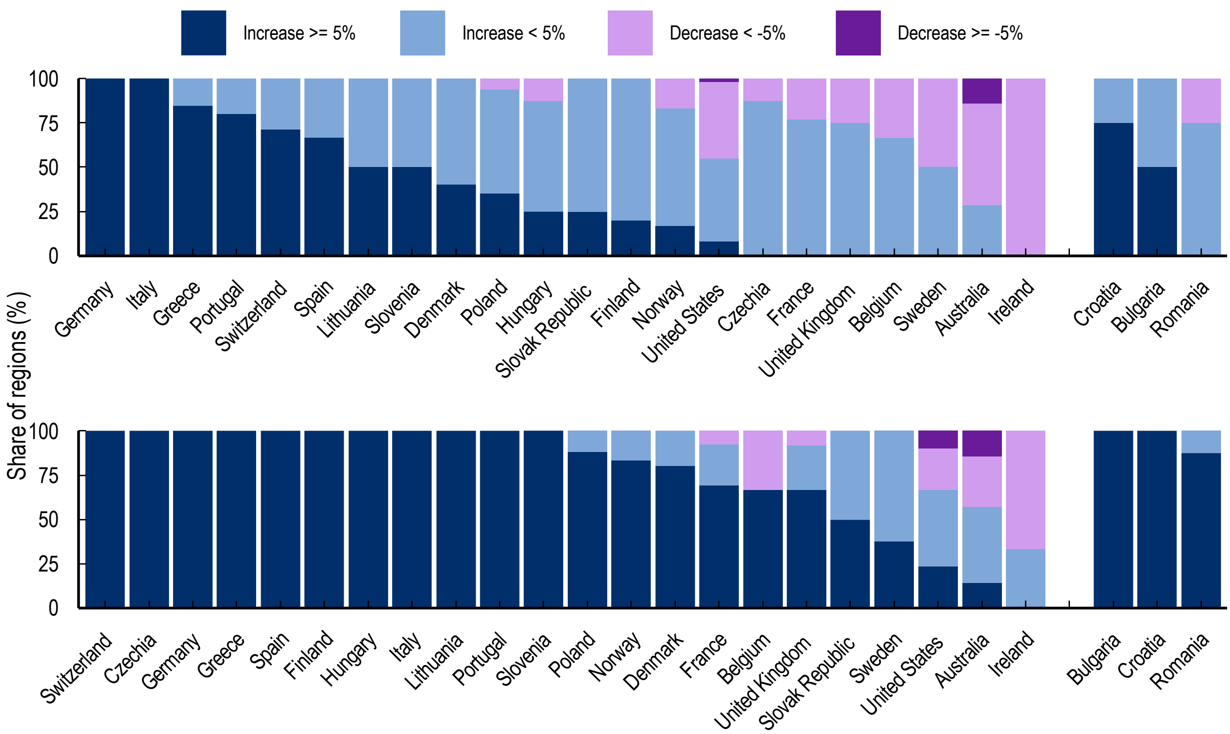
Most OECD countries will be affected by demographic pressure on labour market tightness. By 2042, in 25 out of the 26 countries for which data is available, the national mean of regional labour market tightness is expected to increase due to demographic pressure (Figure 2.16). Yet, the degree of this increase varies greatly across countries. The highest increase is projected to be in Italy, where labour market tightness is projected to increase by almost 30%, followed by Portugal (24.2%), Spain (22.9%), and Greece (21.7%). In contrast, Ireland is the only country where demographic change will decrease labour market tightness in 2042, but the degree is negligible (-0.9%).

Over the next 10 and 20 years, demographic change is projected to lead to increased labour market tightness in a majority of OECD regions. Labour market tightness will increase by over 5% in 38% of OECD regions by 2032, and 72% of OECD regions by 2042 (Figure 2.17). Asturias (Spain), Sardinia (Italy), and Liguria (Italy) are the most affected regions, where labour market tightness in 2042 will be more than 40% higher relative to 2022.

Some regions will experience a notable easing of labour market tightness due solely to demographic change. For example, in Utah (United States), labour market tightness is projected to decrease by nearly 14% by 2042, followed by North Dakota (United States) and the Northern Territory (Australia) with a projected decrease of almost 7% in each. This finding contrasts with the aggregate results at the OECD and country levels, which found minimal projected decreases in labour market tightness. Thus, it highlights the diversity of regional demographic structures and challenges.

Figure 2.17. Most OECD regions will experience increases in tightness due to demographic change

Projected change in labour market tightness given net working age population change for 2032 (top) and 2042 (bottom), indexed to 2022.



Note: The figure shows the share of regions where the projected change in absolute labour market tightness is over 5%, under 5%, under -5% and over -5%, for OECD countries with available data. The projected change is shown for 2032 (top) and 2042 (bottom), relative to 2022.
Source: OECD elaboration based on Lightcast, the OECD Region and Cities databases and labour force surveys: EU- LFS (including the OECD accession countries of Bulgaria, Croatia and Romania), UK-LFS, Bureau of Labour Statistics (USA), and Australian Bureau of Statistics.

Potential policy levers to alleviate labour shortages

Local and national governments can turn to multiple policy levers to mitigate local labour shortages. This section gives an overview of the key policy areas, namely labour-saving technologies, supporting the economically inactive, labour market intelligence tools, up- and reskilling, and (im)migration. For each of these policy areas, this section provides tangible policy examples that contribute to alleviating labour shortages in OECD regions.

Leveraging labour-saving technologies

In the context of addressing labour shortages, technology presents an opportunity to increase productivity, enhance job quality, and attract workers to jobs previously considered less desirable – while also recognising the need to mitigate the potential risks of technological change. From Plato to Keynes, concerns about technology and automation's disastrous impact on work and society are often expressed (Frank et al., 2019[24]; Keynes, 1930[25]). While historical fears of a worker-less future have failed to manifest, evidence does show adverse effects of technological change on some workers. For example, workers who lose their jobs in mass layoffs — including in sectors subject to significant automation — often never recover their previous wage, and some workers and places may be left behind, even as there is net job growth (Vermeulen and Braakmann, 2023[26]; Autor and Dorn, 2013[27]; Acemoglu and Restrepo, 2019[28]). With regard to artificial intelligence, for example, Generative AI such as Chat-GPT, its impact on work is difficult to measure. So far, the evidence suggests that the impact of AI on jobs is limited to large firms experimenting with the technology. Where firms have adopted these technologies, they are reluctant to fire workers as a first step, opting instead to adjust hiring practices (OECD, 2023[3]; Acemoglu et al., 2022[29]). In the future, the potential effects remain to be seen but are likely to differ from these early effects, as the technology will progress and expose a much larger and different pool of workers to its impact (Eloundou et al., 2024[30]).

The use of AI can help alleviate pressures in industries from healthcare to manufacturing that are suffering from labour shortages (see Chapter 3). In the healthcare sector, AI technologies focused on streamlining hospital operations, diagnostic assistance, and nursing practices can free up time for patient care. In regions experiencing labour shortages in manufacturing, robotic automation can reduce operating costs significantly, ensure a more optimised production, help avoid injuries and human error, and increase the quality of output and reduce product defects. Regions with a strong presence of agriculture could also benefit from AI through precision farming technologies, automated irrigation and pest control, enhancing crop yields and reducing the need for some types of human skills. Box 2.8 gives examples of industries in which AI are already used to mitigate labour shortages.

Box 2.8. AI to the rescue: how automation alleviates local labour shortages in manufacturing and agriculture

Significant labour shortages are evident in both manufacturing and agriculture in countries such as the United States, jeopardising economic stability, growth and productivity. However, AI can offer a number of solutions to alleviate labour shortages. For example, robotic automation can enhance efficiency by handling repetitive tasks in manufacturing, while precision farming and drones can help to maintain crop yields in agriculture and thereby profitability. Consequently, funding for research and development of AI and automation in these industries can help address the challenges posed by persistent labour shortages.

Manufacturing

In manufacturing, AI and robotic automation can enable continuous production, with safer and more efficient operations, help with heavy material handling and repetitive movements, and facilitate quality checks (Forbes, 2022[31]; World Economic Forum, 2024[32]). Tool Gauge, an aerospace component manufacturing company based in Tacoma, Washington, turned to automation to address its labour shortage when the company needed to hire around 100 new employees who were not available in the local labour market (International Society of Automation, 2020[33]). As a solution, Tool Gauge instigated the use of collaborative robots (cobots) to operate repetitive and high-labour applications in its metal and plastic parts areas. The use of cobots reduced labour needs by 75%, as it only requires one operator to work with the cobot to produce four hundred units per day (International Society of Automation, 2020[33]).

Agriculture

In the US agriculture industry, labour shortages pose an ongoing threat to the industry's profitability and crop yields (BBC, 2024[34]). AI can be one way to mitigate these issues. A recent estimate puts the economic value of AI to US agriculture – through labour and input cost savings, and increased crop yields – at USD 100 billion (McKinsey, 2024[35]). Indeed, some estimates show an increase in AI adoption among US agricultural businesses – from 54% in 2018 to 87% in 2022 (RELX, 2021[36]). To unlock these potentially large economic benefits, the Japanese government promotes "smart agriculture" through its "Smart Agriculture Demonstration Project", specifically to mitigate current and future labour shortages in the industry. The project is aimed at automising operations, for example through the use of robot tractors and water management systems that can be operated via smartphones, thereby reducing the demand for on-farm workers. Additionally, AI-based analysis of remotely sensed data and weather data taken by drones and satellites improves the accuracy and efficiency of many aspects of farming, including disease control, water management, and crop prediction. These technologies are often known as "precision farming" and further reduce the need for on-farm workers (Ryan, 2023[37]) (Japanese Ministry of Agriculture, 2023[38]).

By reducing the need to do repetitive tasks, the use of automation and AI allows workers undertake more valued work, addressing one of the main drivers of the post-COVID-19 rise in labour shortages: low-paid and low-quality jobs. Studies report that some of the largest recent increase in labour shortages is observed in industries with difficult work environments (such as *Food and Services, Manufacturing, and Retail Trade)*, noting that a rise in quit rates accompanies the rise in labour shortages (Duval et al., 2022[39]; Pizzinelli and Shibata, 2023[40]; Causa et al., 2022[6]; Zwysen, 2023[7]). At the same time, in firms that are early adopters of the technology, workers report a positive impact on job quality (OECD, 2023[3]). However, this is likely to be limited to jobs that do not require constant face-to-face human interactions, excluding some service sector jobs in hospitality, catering, and retail sales, for example. Where job responsibilities permit, improving job quality through AI could alleviate a contributing factor to labour market shortages, although special attention must be given to support workers whose jobs are potentially displaced.

Bringing the economically inactive (back) to the labour market

Local economies can also harness untapped potential in their population by removing barriers to work for specific groups with low labour force participation. This section focuses on mothers, youths and elderly people, discussing the reasons for their often-low economic activity as well as policies that facilitate their return to the labour market.

Women, and in particular mothers, are less likely to work than men of similar age, which is highlighted by a 15 percentage points lower employment rate among 15-65 year old women (62%) than among men (77%) in 2022. One reason for this is that mothers often engage more in child care than fathers, impeding them from taking up paid work. Regional governments can facilitate the return to work for mothers, by improving the accessibility, affordability, and quality of their early childcare systems (European Commission, 2023[41]). A study of the 1990s reforms in Spain that led to an expansion of subsidised childcare for 3-year-olds finds an increase in maternal employment of 9.6% (Nollenberger and Rodríguez-Planas, 2015[42]). The impact of region-based policy is further evidenced in recent years, as the federal government of Canada implemented a "CAD-10-a-day" childcare framework through agreements with all provinces and territories, with adaptations between them (Box 2.9). This policy was developed with the aim to bring more women into the labour force. Since its implementation, the labour force participation among working age mothers with young children has reached a record high of 79.7%. The government is now making further progress by increasing inclusive access to child care, with funding focused on underserved communities (Employment and Social Development Canada, 2024[43]).

Box 2.9. Unlocking women's labour force participation: The case of the CAD 10 a day child care programme

In 2021, the Government of Canada announced CAD 30 billion investments towards affordable child care, with one of the goals being increasing women's labour force participation. The federal government negotiated Canada-wide Early Learning and Child Care (ELCC) Agreements with each province and territory to address their specific needs. These investments also include funding for Indigenous early learning and childcare through partnerships tables.

- **Nunavut,** a territory with the smallest population in the country, was the first jurisdiction to reduce fees to a flat rate of CAD 10-a-day under the federal programme, which resulted in an 82% reduction in parent fees in Iqaluit, on average, – the largest fee reduction of any city in Canada in 2023. Families in Nunavut are now saving up to CAD 14 300 per year, per child.
- In Fall 2024, **Newfoundland and Labrador** started a new non-standard hours of care trial to provide family child care services funding for up to 13 hours of extended daytime child care or up to 13 hours of overnight child care.
- In **Manitoba**, the Ready-to-Move (RTM) Child Care project offers a collaborative approach to construct a large number of child care facilities servicing infant and pre-school spaces within the province under expedited timelines and in areas with a demonstrated child care need. Under this initiative, RTM construction costs will be fully funded under the Canada-Manitoba Canada-wide ELCC Agreement in exchange for land, servicing and free rent for the child care operator.
- **Ontario**, one of the most populous and urbanised provinces, has enrolled 92% of licensed child care providers in the Canada-wide ELCC program for children aged 0-5 as of June 2024. The province has implemented a phased approach to reducing parent fees in licensed child care. In 2022, Ontario introduced a fee reduction of up to 25% retroactively by April, reaching a 50% reduction by the end of the year. Moving forward, Ontario plans to introduce a parent fee cap of CAD 22 per day for eligible children starting January 1, 2025, with the goal of achieving an average of CAD 10 per day by 2026.

Preliminary results suggest that these investments in ELCC and jurisdictional adaptations have likely increased female labour force participation. The Bank of Canada noted that "the rise in the participation rate of women could be due to lower average fees for child care since April 2022". The Statistics Canada Labour Force Survey continues to show positive trends, including a 79.7% labour force participation rate among mothers aged 25-54 with young children in 2023, up from 75.9% in 2019.

Source: (Employment and Social Development Canada, 2022[44]) (Government of Newfoundland and Labrador, 2024[45]) (Government of Manitoba, 2023[46]) (Government of Ontario, 2022[47]) (Employment and Social Development Canada, 2024[43]) (Statistics Canada, 2024[48])

For young economically inactive persons, support programmes can facilitate their labour market participation. Across OECD countries, 12.6% of young people (15-29 years) were neither in employment, education, nor training (NEET) in 2022. To reduce the NEET rate, governments in OECD countries run various programmes that equips youths with job experience and new skills. For example, the Seoul Metropolitan Government (SMG) in South Korea, under its City of Global Professionals framework, has made use of several mechanisms to enhance youth employment. These mechanisms include free training on software development with the aim to reduce job mismatches, and an internship camp to provide on-the-job experience. In this way, the SMG facilitates the entry of unemployed youths into SMEs, as it actively connects them with employers, provides professional work experience, and skills training (Seoul Metropolitan Government, 2024[49]). Additionally, Mexico implemented the programme Youths Building the Future which provides financial support for apprenticeships, training, and social security for young people (aged 18-29). The programme has to date benefited almost 3 million youths who are on average 2.7 times more likely to find employment than those who did not participate (Secretaria del Trabajo y Prevision Social, 2024[50]) (Comision Nacional de los Salarios Minimos and Secretaria del Trabajo y Prevision Social, 2023[51]).

Decentralising the higher education system by opening new higher education institutions (HEIs) in non-metropolitan regions can have the potential to increase place attractiveness — in particular for young workers and firms. Many youths and young workers in OECD countries migrate from remote to metropolitan regions, in which educational (and professional) opportunities are often concentrated (OECD, forthcoming[52]). To counter the out-migration of young people from remote regions, which exacerbates labour shortages in regions in demographic decline, and to support the latter's regional economic development, some OECD countries decentralize the education system by strategically placing new Higher Education Institutions (HEIs) away from metropolitan areas. By opening new HEIs in less developed regions, governments – apart from attracting students – also aim at attracting innovative companies which can recruit directly among the new HEIs' pool of highly skilled graduates. This can in turn create new job opportunities for workers in these regions.

To enable HEIs in remote regions to create economic opportunities for workers and firms, their educational programme needs to reflect the local skills demand. Innovation spillovers between universities and firms can foster employment and wage growth at the local level (Hausman, 2022[53]). Yet, bringing these positive dynamics to remote regions, for example by strategically opening new HEIs, remains challenging. Openings of new HEIs in Italy from 1985 - 2000 and Switzerland between 1997 and 2003 increased firms' innovation activity (i.e., measured as patents) by 7% per university (Cowan and Zinovyeva, 2013[54]) (Pfister et al., 2021[55]). In Switzerland, especially small and medium-sized enterprises in regions outside major innovation hubs benefitted. However, a similar policy in Germany in the 1980s and 1990s shows that newly opened HEIs may mostly benefit already dynamic labour markets (Berlingieri, Gathmann and Quinckhardt, 2022[56]). For HEIs to contribute to sustained economic development in remote areas, for example by attracting workers and firms, the HEIs' educational content needs to be adapted the needs of local businesses as Närpes, a small locality in Finland, shows (Box 2.10).

Box 2.10. Answering the needs of business and the local community: The case of vocational schools in Närpes, Finland

Närpes, a small locality in Western Finland, provides and adapts vocational education that suits the needs of the local economy, which has been part of the success of its regional attractiveness. This is achieved as the region closely collaborates with the main businesses, resulting in a curriculum that includes logistics, metalwork, constructions, and home care, reflecting the needs of the locality. The educational curriculum is repeatedly adjusted, as evidenced in a recent pilot initiated with the purpose of satisfying the high demand of welders from the Närpes Trä & Metall (NTM) company. This pilot study was the result of close collaboration between the school, Närpes municipality and government which provided funding and the Regional Centre for Economic Development, Transport and the Environment (ELY-Centre) which developed the pilot. The pilot offered a specialization in wielding techniques and was designed for 30 people which were filled immediately.

Despite its rather remote location, Närpes has had a positive population inflow over the last decade, and a 10% higher employment rate in comparison to the national average, partly attributed to its vocational school approach that answers the needs of business, good immigration policies, and an efficient healthcare system. The number of people in adult education has been growing, and most students find a job in the region upon graduating. The customized education system is part of the reason that attracts new workers internally and internationally, as well as retaining local workers by offering ways to switch into other professions.

Source: (Michael Kull, 2019[57])

Older workers also show low labour force participation rates due to the challenges they face in the labour market. This is evidenced by the fact that, in 2022, only 67.4% of people aged 55-64 participated in the labour force, compared to 86.4% of adults aged 25-54. Some older workers may struggle to keep up with technological advancements, such as the ongoing digitalisation of many job tasks, as they are less likely than younger workers to participate in job-related training. Additionally, employers often perceive older workers as "too expensive" due to tenure-based pay progression, which is a common human resources practice (EBRD, 2020[58]) These factors make older workers particularly vulnerable to lay-offs in work force restructuring (ILO and IFC, 2021[59]), after which they struggle to be reemployed. Japan addresses some of these issues through its Act on Employment Security of Elderly Persons (AESEP) (Box 2.11).

Box 2.11. Japan's Act on Stabilization of Employment of Elderly Persons

For activating the older population, Japan's Act on Employment Security of Elderly Persons (AESEP) promotes employment security of older individuals. AESEP prohibits employers from imposing mandatory retirement under 60 and requires them to take measures that aim at providing job opportunities for elderly persons up to 70, including continuous employment. Continuous employment involves allowing workers to retire at the standard retirement age but then rehiring them or extending their employment under new terms, including adjusted wages. Unlike raising or abolishing the mandatory retirement age, which continues employment under the same conditions, continuous employment typically involves a formal retirement followed by re-contracting workers. Wages may decrease under the new contract depending on the job duties after the re-contracting

Data from 2023 show that 3.9% of firms with 21 or more employees have abolished the mandatory retirement age, 26.9% have raised the mandatory retirement age, and 69.2% introduced a continuous employment system as measures to secure employment for elderly persons up to 65. As efforts to secure job opportunities for elderly persons up to 70, 3.9% abolished the mandatory retirement age, 2.3% have raised the mandatory retirement age, and 23.5% introduced a continuous employment system. The Ministry of Health, Labour and Welfare also introduced a wage subsidy of up to YEN 500 000 (roughly USD 3 200 in 2024) to employers who improve their employment management systems for older workers and up to YEN 300 000 (roughly USD 2 000 in 2024) for raising the retirement age to 65.

Source: (Kajitani, 2023[60]; Ministry of Health, Labour and Welfare of Japan, 2023[61])

The barriers to work for older people also include age-based discrimination (e.g. in the hiring process), leading to difficulties finding and applying for jobs. To combat age-based discrimination in the hiring process, France's Public Employment service is now using aptitude tests to select candidates for interviews and help overcome the age bias in hiring (OECD, 2019[62]). In an alternative approach, the Government of Canada promotes awareness initiatives to promote labour force participation of older individuals by informing employers, unions, and general society about the advantages of recruiting and retaining older workers. The federal government funded various awareness projects in provinces, predominantly in Quebec and Prince Edward Island, while other provinces such as Alberta, Nova Scotia, and British Columbia have implemented their own awareness action plans (Employment and Social Development Canada, 2018[63]).

Using effective labour market intelligence tools

Labour market intelligence tools can help identify labour shortages and facilitate better matching between local vacant positions and available workers, including among the unemployed. Knowledge about current and future trends in the labour market is crucial to anticipate which occupations and industries are vulnerable to labour shortages. For example, CEDEFOP's European Skills Forecasting model provides information about labour market trends for occupations and industries. By 2035, it estimates that France will need to fill roughly 880 000 positions for science and engineering professionals, consisting of 305 000 new positions and 575 000 workers who will need to be replaced (Cedefop, 2023[64]).

Novel approaches produce timely estimates on regional occupation and skills demand, going beyond more aggregate information based on employer surveys that usually come with a larger time lag. While many statistical offices provide estimates of job vacancy rates and the extent of labour shortages at a rather aggregate level, for example at the industry-level or by firm size, and sometimes for an entire country, advances in data availability (e.g. from online job postings) and text analysis (i.e. natural language processing) have given rise to more fine-grained insights. NESTA, the United Kingdom's innovation agency for social good, provide demand estimates for roughly 100 occupations and their required skills in 228 UK Travel-to-Work Areas using online job vacancy data. Similarly, Skills Future Singapore, a government agency, created a Jobs Skills Dashboard with which users can see the most common hiring companies and industries for a given job title and skill (SkillsFuture Singapore, 2023[65]). Using online vacancy data, Skills Future Singapore also identifies priority skills for specific industries, such as the green, digital and care economies (SkillsFuture Singapore, 2024[66]). The Austrian PES launched a large language model-based AI tool, called Jobinformat (Job Informant), that provides jobseekers with information on job profiles and related training paths (box 1.20 in chapter 3). Box 2.12 gives additional examples of innovative approaches used by PESs in OECD countries.

Box 2.12. PES increasingly use labour market intelligence tools to facilitate job matching

New types of labour market data, such as job vacancies, along with advances in statistical and artificial intelligence (AI) methods, allow PES in many OECD countries to better support job seekers and employers. More precisely, through the use of novel data sources and AI, PES can support a larger number of clients in a more personalised manner and with more up-to-date insights.

As of 2024, half of OECD PES augment their services with some form of AI technologies. Yet, the use cases and tools substantially differ between PES. Matching systems that recommend suitable job opportunities to job seekers, which are currently used by 20% of OECD PES, are the most common application. These systems are increasingly competency-based through the use of occupation and skills taxonomies. Other use cases include the provision of information (e.g. on available services, measures and benefits), jobseeker profiling tools to better understand their needs (both 17% of PES), and tools to guide career management and job-search strategies of jobseekers (15% of PES). In recent years, PES also started supporting employers in creating vacancy postings (20% of PES), for example by drafting vacancy descriptions and correctly classifying occupations using AI technologies.

The PES in Flanders, Belgium (VDAB), uses the Jobbereik (Job Reach) tool which provides jobseekers with occupations that jobseekers could pursue based on their current role's competencies and transferable skills. Based on data from job vacancies and deep learning, this tool supports job mobility and transitions. VDAB currently also develops a new functionality which identifies a jobseeker's skills gap with alternative career paths and suggests training courses to close the gap. Additionally, Competentiecheck (Competency check) allows jobseekers to assess whether their skills are up-to-date by letting them evaluate their level of familiarity with their occupation's most important competencies. This tool is also designed to provide training and job suggestions for the user.

France Travail, the French PES, uses two versions of an AI-powered tool to help job counsellors and job seekers navigate available active labour market policies (ALMP) if a job seeker is unlikely to find a job quickly. Since 2017, job counsellors can use the Mon Assistant Personnel (MAP – My Personal Assistant) tool to obtain individual-specific recommendations for ALMP support and job opportunities, based on a jobseeker's CV. This tool, based on various types of AI (reinforcement learning, machine learning and an expert model), assists job counsellors and allows them to spend time on other important tasks rather than replacing them. Similarly, jobseekers can access their version of this tool (Personalised Recommendations) in France Travail's online portal to obtain recommendations for services and measures – including suitable training opportunities and available workshops (e.g. to improve their CV and/or interview skills).

Source: (Brioscú et al., 2024[67])

In combination with job-level information on skills requirements, AI and traditional statistical tools can also steer job seekers towards future career paths that match their skill set. Using online job vacancy and regional employment data from Italy, the United Kingdom and the United States, (Basauri, Kleine-Rueschkamp and Vermeulen, 2025 (forthcoming)[68]) identify feasible career transitions based on a sufficiently high skills overlap between the old and the new job, and the regional availability of the new job as most workers look for jobs within their region. This framework can guide career transitions from polluting to neutral and green jobs. The analysis also shows that workers in polluting jobs share between 57% and 86% of skills (depending on the country) with the five closest neutral jobs, on average.

Updating the skills provision to reflect local needs

Labour shortages are also the result of a gap between the skills required by employers and those available in the workforce, particularly in the context of growing demand for certain skills arising from megatrends like the green and digital transitions. Vocational education and training (VET) and adult education can mitigate labour and skills shortages by equipping the workforce with sought-after skills.

Vocational education and training (VET) can provide students with necessary technical skills and practical experience at the start of their career. VET offers the potential to prepare students for technical professions, many of which experience shortages, while also facilitating the school-to-work transitions and offering a pathway to higher education (OECD, 2023[69]; European Commission, 2023[1]). For example, 90% of VET students in Germany pursue studies in the dual system in which trainees split their time between studying at a vocational school and working at a company, which usually takes around three years to complete (OECD, 2022[70]). This dual system provides trainees with practical experience and broadens their employment opportunities (OECD, 2022[70]).

Governments are increasing the attractiveness of VET education, to reduce the shortage of skilled workers. For example, Germany anticipates a shortage of 240 000 skilled workers in 2026, yet the VET system experiences high dropout rates of apprentices (26.7% in 2019) and a significant decline in VET training contract numbers (Affairs, 2022[71]; Cedefop, 2023[72]). In 2022, the German government introduced the Excellence for VET initiative that addresses these issues through financial support for high-performing trainees, improved vocational guidance (including digital formats), a push for international education of trainees, and overall greater promotion of VET programmes (Affairs, 2022[71]). In 2024, Austria introduced more advanced vocational training cycle (i.e. at the fifth out of eight levels of the European

Qualifications Framework) to offer further specialization for skilled workers, namely those who have already completed initial vocational training or have sufficient job experience (Austrian Ministry of Labour and Economy, 2024[73]). Educational and industry experts as well as social partners are currently designing the new degrees such that they target the needs of the economy, including green and digital skills.

Governments should adapt their skills and training systems to reflect shortages of skilled workers at the regional level. For example, Australia has acknowledged VET as key to tackling regional and rural skills shortages, particularly for nurses, teachers, and engineers (Australian Ministry of Employment and Workforce Relations, 2023[74]). Since 2018 the French national government establishes regional agreements, the so called Pactes Régionaux d'Investissements dans les Compétences (Regional Agreements for Investments in Skills), to improve the regional offer of training programmes. The programmes are designed to equip two million low-skilled jobseekers and youths distant from the labour market with the skills for regional shortage occupations until 2022 (Box 2.13).

Box 2.13. France adapts its large-scale national skills agenda to regional needs

The French government supports low-skilled youths and the long-term unemployed through the Plan d'Investissements dans les Compétences (PIC), introduced in 2018. This policy promotes the skills development of these target groups by financing both already existing and new training programmes and is embedded in France's strategy to equip the workforce with the skills for the digital and green transition. To provide training (and other support services) to the 2 million planned participants between 2018 - 2022, PIC received 15 billion Euros in funding (French Ministry of Labour, 2018[75]).

Regional agreements, the Pactes Régionaux d'Investissements dans les Compétences (PRIC), receive half of the funding and ensure that the training programmes address the regions' needs. Regions and the national government define the content and the financing of the educational offer in the PRICs. To do so, regional actors determine the priorities of the training programmes, both in terms of content and target group, based on available labour market data on employment, (anticipated) recruitment difficulties, and businesses' skills needs. As a result, training programmes target regional shortage occupations (France Stratégie, 2018[76]). Regions, which commit to spending at least the same amount as before the introduction of the PIC in 2017, and the national government share the costs of the training programmes (French Ministry of Labour, 2018[75]). Regions and the national government currently negotiate new PRICs for the period 2024-2027.

The PRICs improve the training offer at the regional level via increased capacity of training programmes and additional measures, such as lowering financial barriers. The Occitanie region planned to train 20 000 additional youths and job seekers, elevating the number of trained job seekers to 80 000. Additionally, the regional agreement includes remote learning options, the on-the-job training, information activities in rural urban priority areas, and a labour market observatory to better understand the companies' skills needs. The regional and the national governments share the associated costs, financing 877 million EUR and 569 million EUR, respectively (Occitanie Region, 2024[77]). To lower financial barriers, the majority of regions has put into place financial aid for commuters and child care. The Bretagne, Normandie, and Pays de la Loire regions have also raised the pay of apprentices (Dares, 2024[78]).

A scientific committee evaluates the training programmes on a regular basis. In their third report, the committee finds that, relative to 2017, regions that signed a PRIC showed a 48% (+0.73 billion EUR) increase in training-related expenditure per year on average, and a 44% (+169 000) increase in the number of participants in 2021. However, regions differ in the effectiveness of their regional agreements as some regions struggle with a lack of information among potential trainees, competition with other training programmes, training providers selecting among interested individuals, and a lack of attractiveness of additional training in the context of a tight labour market (Dares, 2022[79]).

Note: An interactive map shows examples of PRIC initiatives around France: https://travail-emploi.gouv.fr/carte-decouvrir-les-initiatives-en-region-du-plan-dinvestissement-dans-les-competences (accessed on 14 October 2024).

Similarly, the curricula of VET programmes need to be updated to reflect emerging skills demands for green and digital jobs, thereby mitigating current and future shortages. As part of the European Green New Deal, many European countries are introducing programmes that aim at redesigning their VET systems such that they teach the skills required for digital and green jobs (Cedefop, 2024[80]). For example, Estonia started updating its VET curricula based on labour market monitoring and future skills forecasts (Cedefop and Refernet, 2023[81]). Furthermore, Austria has adapted the educational content of more than eighty apprenticeship programmes to the needs of the green and digital transitions in collaboration with companies and social partners. To this end, it also created new apprenticeship programmes, such as Climate-Oriented and Urban Gardening ("Klimagärtner/-in") or Community Heating ("Fernwärmetechnik") in 2024 (Austrian Ministry of Labour and Economy, 2024[82]). Box 2.14 gives further examples of initiatives that redesign VET systems to tackle skills shortages.

Box 2.14 Skills for Success: Modernising VET and adult learning towards the twin transition

Regions are redesigning their VET and adult learning systems to equip their workforce with skills required for the digital and green transitions. This box presents selected educational programmes, including both public and private initiatives, from OECD regions that equip workers with the technical skills for green jobs, for example in the renewable energy sector.

The Technical Skills for Harmonised Offshore Renewable Energy project (T-Shore) addresses the skill shortages in the offshore wind industry by building and strengthening regional partnerships between VET schools, industry partners and governmental organisations across five countries spread in northern Europe. Through the six Centres of Vocational Excellence (CoVEs), T-Shore aims to provide skills and competencies in five countries, through partnerships with 13 partners. This effort also aims to support regional development by anticipating sector specific skill needs and addressing challenges such as worker mobility, aging workforces, and the need for reskilling. In Denmark, T-Shore helps with the demand to retrain workers form industries such as oil and gas towards offshore wind sector. In the Netherlands T-Shore aimed to address the severe labour market shortages in technical labour, however two CoVEs were established to better reflect the differences between the focus and development of the North and South Netherlands. The North emphasizes supported SME in participating in the offshore wind supply chains, with partners like Noorderpoort and TCNN. In contrast, the South, where the Winddock CoVE was already established in 2018, focuses on innovation in wind turbine maintenance.

In France, regions are launching specialized training centres through public-private partnerships focused on green transition roles, such as the new Douvrin Battery Training Centre in the electric vehicle (EV) sector. The Douvrin Battery Training Centre is a public-private initiative between the region, the Union of Metallurgies Industries (UIMM) Hauts-de-France and Stellantis, an automotive company. The Training aims to prepare and retrain active workers and job seekers for EV roles in a 400 hours training programme. The region plans to train 6 600 workers – compared to a projected 20 000 jobs in the EV sector over the next decade -- to support EV gigafactories and enhance their international competitiveness.

In the Navarra region in Spain, the regional government, in collaboration with the Confederation of Entrepreneurs and the Navarre Industry Association, set up the Training Centre for Renewable Energies and Energy Efficiency skills, CENIFER. The aim is to address skills shortages in the region by offering training adapted to firms' needs that differs in length usually between 420 and 700 hours spread in an academic year, and some specialization courses include a training module in work centres. It offers a wide range of courses for professions such as technicians in power plants, water management, thermal and fluid installations, solar thermal energy. The trainings range from offerings to the unemployed, to specialized classes offered in the evening to accommodate schedules of those employed.

In the United States, the Workforce Innovation and Opportunity Act (WIOA) Adult Program supports low-income and low-skilled workers transitioning into high-quality, in-demand jobs through reskilling and upskilling since 2014. Each state's Local Workforce Development Board — composed of representatives of local businesses, labour, community-based organizations and higher education — submits a four-year plan that outlines its strategy for service delivery in its workforce development system. The WIOA funds occupational training and support services, such as employment search assistance, and child care assistance while in training (US Department of Labor, 2024[83]). In 2022, WIOA supported almost 300 000 participants, of which 130 000 also received training services, throughout the United States. 72% of participants were in unsubsidised employment one year after exit from the programme, with a median salary of 8 272 USD among those employed (US Employment and Training Administration, 2024[84]).

Notes: State-level success indicators for the Workforce Innovation and Opportunity Act can be accessed under https://www.dol.gov/agencies/eta/Performance/results (15 October 2024).
Sources: (T-Shore, 2024[85]) (Region Hauts-de-France, 2023[86]) (OECD, 2023[12]) (Educacion Navarra, 2024[87]) (CENIFER, 2024[88]) (OECD, 2023[12]).

For experienced workers, governments can foster life-long learning to give workers the opportunity to adapt to ongoing trends in the labour market. An example of this is RES-SKILL, a European initiative that seeks to equip current and former coal mining industry workers with the skills needed in renewable energy jobs, such as solar photovoltaic installers or wind turbine technicians (RES-SKILL, 2024[89]). The Scottish government's Adult Learning Strategy 2022 to 2027 aims at creating accessible learning opportunities for adults. The strategy emphasises community-based learning by encouraging local organisations to offer tailored educational programmes to address community needs. It promotes partnerships between government, educational institutions, and businesses to develop and deliver relevant training programmes. This includes addressing digital literacy to ensure all adults can participate in the digital economy and adapt to technological change (Scottish Government, 2022[90]).

Managing migration to ease labour shortages

Migration policies, through both international immigration and promotion of internal migration, can serve as a tool for mitigating labour shortages, with OECD countries such as Canada, Australia, and Germany implementing reforms to facilitate this. Many factors, including the declining working age population across most OECD countries, increase the shortage of high and low-skilled workers, and third-country immigration offers an opportunity to increase the number of adequately skilled workers (Kate Hooper, 2021[91]; Katrin Sommerfeld, 2023[92]). To do this, countries need to look at broadening existing policies, such as easier visa application processes, better recognition of foreign credentials, and by offering a clear path to residency or citizenship (Kate Hooper, 2021[91]; Katrin Sommerfeld, 2023[92]).These can be adapted to the needs of regions that struggle the most with labour shortages.

Some OECD countries implemented regional immigration programs to address labour shortages. The Canadian Atlantic Immigration Program facilitates the hiring process of skilled immigrants for employers who are unable to fill their vacancies in Canada's four Atlantic provinces (Government of Canada, 2022[93]; Government of Canada, 2024[94]). This program started as a pilot in 2017 and has since filled more than 9 800 vacancies in key sectors experiencing shortages including in health care, manufacturing, accommodations and food services. Over 90% of applicants still live in the region after a year (Government of Canada, 2022[93]). Following the success of this pilot, Canada has announced new immigration pilots to support rural and Francophone minority communities (Government of Canada, 2022[95]). Australia has implemented a similar regional immigration framework through the Designated Area Migration Agreements (DAMAs) that allow regional employers to sponsor overseas workers (Australian Department of Home Affairs, 2024[96]). These agreements are tailored to the specific economic and labour needs of each region, providing a strategic solution to local shortages by attracting skilled migrants to underpopulated areas. Similar immigration policies could be implemented in other OECD countries to tackle labour shortages.

Various OECD countries have introduced direct incentives for internal migration in the form of tax incentives, housing subsidies, and overall regional development. Such policies can contribute to mitigating labour shortages in communities facing declining populations by bringing back workers. An example of such policies is Japan, which projects that by 2040 the population in almost half of its municipalities will decline by 50% or more. To address this, the government implemented its Regional Revitalisation Policy. The policy is aimed at managing population decline in affected regions and at alleviating the concentration of population in the Tokyo area by providing subsidies and incentives to encourage migration from urban to rural areas (Government of Japan, 2019[97]). This includes support for business relocations, housing subsidies, and grants for individuals and families moving to less populated areas (up to YEN 1 million per child) (Government of Japan, 2019[97]). Portugal implemented the Interior Employment Plus - Supported Mobility for a Sustainable Interior" in 2020, which aims to stimulate the competitiveness of regions (Government of Portugal, 2020[98]). Through this policy, workers and teleworkers who move to the interior have access to direct financial support of up to EUR 4 827 including an additional 20% for each member of the household, and moving costs (Government of Portugal, 2020[98]).

Better systems for the recognition of foreign credentials can mitigate labour shortages through labour market integration of third-country immigrants. The foreign credential recognition process (or lack thereof) can be a major roadblock for labour market integration. In Canada, 25.8% of immigrants with a degree completed outside of Canada were overqualified for their job according to 2021 Census data, meaning that over a quarter of all immigrants would have the skills to work in more highly skilled professions (Statistics Canada, 2022[99]). In 2012, Germany introduced the Federal Recognition Act which facilitated non-EU credential recognition. This reform raised employment in regulated occupations, such as nurses, by 18.6% among non-EU immigrants. Furthermore, these immigrants did not have lower skills or receive lower wages than the native-born (Anger, Bessetto and Sandner, 2022[100])

Box 2.15. Building teleworking potential: Ireland, Trento, and The Netherlands Case Studies

Teleworking Strategy in the Autonomous Province of Trento, Italy

Trento implemented a teleworking strategy in 2021 with the goal to lower commuting demands and expand the talent pool by attracting skilled professionals through teleworking opportunities. To achieve this, multiple policies have been put in place, including the creation of teleworking spaces in villages by repurposing buildings and redesigning telecentres. Employers are encouraged to offer flexible work arrangements through hybrid work to allow less frequent commuting and family-friendly arrangements. To promote, encourage and share learnings and best teleworking practices, a community of human resources practitioners has been created.

Ireland's Rural Development Plan 2021-2025

This plan has been introduced as a post-COVID-19 rural recovery initiative and aims to build the teleworking potential of rural Ireland. This includes optimising internet infrastructure, supporting rural employment and careers, improving public services, revitalising towns, and reaching a climate neutral community. Teleworking is emphasised as it reduces transport emissions, supports local businesses, and offers opportunities for youth employment in their communities. The plan includes investing in teleworking infrastructure to help people remain living in their communities. The plan looks to achieve this to by building 400 teleworking facilities, as well as moving 20% of the public sector to remote work and progressively increasing that percentage. Finally, the plan also explores incentives for relocation to rural towns by providing funding to local authorities to build a strategy to attract talent.

The Netherland's Flexible Working Act

Adopted in 2016, this legislation encourages flexible working arrangements. Consistently, several cities have undertaken their own initiatives aimed at promoting flexible working arrangements, such as Amsterdam which established the Smart Work Centres as shared office spaces where employees can work closer to their homes. Other cities such as Leeuwarden and Rotterdam developed initiatives for flexible work with the objective of decreasing traffic congestion and air pollution. Nation-wide, the act includes the right to request flexible working hours (allowing for reasoned refusal of the request), and protections against discrimination. The Flexible Working Act applies to all employees and employers regardless of the size or type of organisation.

Source: (OECD, 2023[101])

The rise of teleworking offers a parallel to traditional migration policies, delivering similar economic benefits without the physical relocation of workers. Teleworking has become a common practice among OECD countries and has the potential to alleviate regional labour shortages by allowing firms to tap into a broader range of talent (OECD, 2023[101]). This approach can complement traditional migration strategies, providing a flexible and cost-effective solution to address the growing demand for skilled workers. However, it is important to note the teleworking potential can vary across regions and industries, as it is more common in services than in industrial production. Teleworking potential can be improved by upgrading internet infrastructure, promoting digital skills, fostering automation and establishing regional or sectoral teleworking agreements (OECD, 2023[101]). Additionally, attracting teleworkers working for employers elsewhere may not directly address local labour shortages, but can yield benefits such as increased tax revenue, higher consumption, and expanded professional networks (OECD, 2023[101]).

Policy recommendations to alleviate labour shortages

In conclusion, governments have various policy options to mitigate regional labour shortages. The following place-based recommendations aim at easing labour shortages through AI-induced productivity gains, worker re- and upskilling, talent attraction, support to the economically inactive and the use of labour market intelligence tools.

- **Identify opportunities where AI can drive productivity growth in regions:** By building local AI capabilities, regions can modernise traditional industries, attract new investments, and harness emerging technologies for sustainable development. This approach can be particularly valuable for regions facing labour shortages, for example driven by demographic pressure.
- **Improve the uptake of AI tools across businesses to reap potential productivity gains:** Businesses may need additional resources to fully utilise AI tools, such as targeted training programmes, guidance on implementing AI technologies, and workforce retraining. Special attention should be given to SMEs, which often lag behind in technology adoption, by providing the support they need to remain competitive in an AI-driven economy.
- **Revise regional skill provisions to address workforce needs:** Addressing changing skill needs requires updating the skills provision system to better align with current demands. This includes

revising vocational education programmes, expanding access to adult education, and introducing targeted programmes for critical roles in emerging industries.

- **Provide tailored reskilling and employment support for displaced workers:** Technological advancements, such as AI and automation, lead to shifts in the labour market and may cause worker displacement. Targeted support for these workers, including retraining programs and re-employment assistance, can help mitigate long-term economic losses and prevent vulnerable groups and regions from being left behind amid technological changes.
- **Expand training opportunities in non-metropolitan areas:** Establishing training opportunities in remote regions can enhance regional attractiveness and help retain young people. By tailoring these programmes to local skill demands, non-metropolitan areas can provide local businesses with a skilled workforce and stimulate economic growth.
- **Promote regional talent attraction to address labour shortages:** Regions can focus on creating more opportunities to attract skilled workers, such as simplifying administrative processes, recognising relevant qualifications, and providing clear long-term career pathways. Incentives like tax benefits, and housing subsidies can also help draw workers to regions with rising labour demand.
- **Increase the participation of hard-to-get groups to alleviate labour shortages:** Local economies can tap into untapped potential by removing barriers to employment for groups with traditionally low labour force participation, including women (especially mothers), young people, and older workers. Flexible work arrangements, accessible childcare, targeted training, and incentives for hiring, can support these groups, fostering inclusivity.
- **Increase the use of labour market intelligence tools:** Advanced intelligence tools provide timely, granular data on regional occupations and skills demand, and can help policymakers understand future needs, as well as the underlying causes of shortages, informing the design of place-based policies. In PES, AI tools can improve job matching, connecting job seekers and employers more effectively, and help anticipate labour shortages.
- **Foster collaboration with local stakeholders to strengthen policy intelligence:** Engaging local stakeholders, such as employers, educational institutions, and community organisations, provides valuable, real-time insights that can enhance the effectiveness of workforce policies. Such collaboration promotes better-informed, widely accepted, and adaptable policies that respond to regional economic conditions.

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Notes

1 Tradeable services consist of the ISIC 1-digit industries wholesale and retail trade; repair of motor vehicles and motorcycles (G); Transportation and storage (H); Accommodation and food service activities (I); Information and communication (J); Financial and insurance activities (K); Real estate activities (L); Professional, scientific and technical activities (M); Administrative and support service activities (N).

2 Regions with the highest and lowest ICT jobs shortages are, respectively, the top and bottom ICT jobs tightness regions with at least 20% of a country's employment. The same applies to green jobs in the following paragraph.

3 The details for Eurostat's definition of ICT specialists can be accessed here: https://ec.europa.eu/eurostat/cache/metadata/en/isoc_skslf_esms.htm#:~:text=216)%2C%20Eurostat%20defines%20ICT%20specialists,main%20part%20of%20their%20job%22. (as of 4 July 2024).

3 Beyond automation: Decoding the impact of Generative AI on regional labour markets

Automation technologies can augment labour productivity but can also serve as a substitute for people by automating functions entirely. In the past, the geography of this impact has been stronger in semi-urban and rural areas. Generative AI, an emerging form of AI, may represent a new leap in technology and is impacting higher-skilled jobs located in urban areas. While the full extent of its impact is still uncertain, the effects on jobs or skills will likely be context- and place-specific. This chapter explores both the observed and anticipated impacts of AI technologies as they mature and achieve widespread adoption. It provides novel regional estimates to contrast previous forms of automation technologies with Generative AI and the geography of those impacts. Furthermore, it analyses which sectors and types of jobs might be most transformed, zooming in on specific occupations. Finally, it discusses possible actions going forward that could help regions seize new opportunities and manage the challenges AI poses.

In Brief

Generative AI has the potential to affect a wide range of high-skilled workers in OECD regions, including many who have historically been less affected by technology.

AI has the potential to transform local labour markets by boosting productivity, creating or destroying jobs, and changing the very nature of some jobs, including job quality. This chapter examines exposure to automation technologies across regional labour markets in OECD regions, exploring the potential effects on job creation and productivity, as well as their distribution across different regions, industries, and workers.

- **Generative AI will likely have a much wider labour market impact than other recent digital technologies, affecting a broader group of people and places.** Digital technologies that predate Generative AI had a narrower focus, being designed to excel in one or few specific tasks. Generative AI, on the other hand, excels at many tasks. Around a quarter of workers are exposed to Generative AI, meaning 20% (or more) of their job tasks could be done in half the time with the help of Generative AI, but this figure ranges from 13% to 48% across regions.
- **As Generative AI tools find greater adoption and integration with existing software, exposure to Generative AI could exceed 90% of workers in some regions.** As new software is developed or integrated with Generative AI technologies, over 70% of OECD workers could be exposed, with almost 40% being highly exposed (meaning at least 50% of their job tasks could be done in half the time with the help of Generative AI). Metropolitan regions, such as Greater London (United Kingdom), Prague (Czechia) or Zurich (Switzerland), are expected to be significantly more exposed than less urban regions. Within countries, the most affected regions are around 60% more exposed than the least affected regions. Furthermore, in some countries such as Colombia, the top region is expected to be three times more exposed than the least affected region. These strong regional disparities can be explained in large part by differences in industrial composition, as regions with a focus on services, such as education, healthcare, Information and communication technology (ICT), and finance, are most exposed to Generative AI.
- **Regions previously considered to be at comparatively low risk of automation are the most exposed to Generative AI.** While previous automation technologies, including other forms of AI, affected mostly non-metropolitan and manufacturing regions, Generative AI has the potential to alter a significantly higher share of jobs in metropolitan regions and cities. On average, 32% of workers in urban areas are exposed to Generative AI, compared to 21% in non-urban regions. Furthermore, this gap can exceed 17 percentage points in some countries such as Colombia, Greece, and Romania. A similar reversal becomes evident when analysing worker exposure by gender and education level. Exposure to Generative AI is greater for high-skilled workers and women, while previous technologies mainly affected low-skilled workers and men.
- **While the exact effects of Generative AI on the geography of job creation and displacement remain to be seen, little evidence exists on technology-led automation leading to mass job destruction.** Instead, empirical results link automation technologies in regional labour markets with regional productivity growth. A small but significant number of regions across the OECD have experienced automation-led job displacement in the last decade.

In these regions, job displacement was outpaced by the creation of new jobs. Nevertheless, there is no assurance that these new jobs went to the workers that lost their jobs and could instead have been taken up by, for example, new workers entering the labour force. There is no reason to believe that the full effects of automation technology adoption have been realised, which means regional labour markets may still see further impact.

- **AI technologies could offer OECD regions a strategic tool to address critical economic and labour market challenges, including labour shortages, stagnant labour productivity growth, or workforce inclusivity.** AI technologies can be leveraged to supplement workers, helping to ease labour shortages and the effects of an ageing workforce. The same technologies that threaten some jobs can help regions access untapped talent in low-skilled workers or workers with disabilities for whom many jobs were previously out of reach. If used to augment or complement workers' skills, AI could also help catalyse new labour productivity growth. However, training and upskilling will be required, with 61% of European workers believing that they will need new knowledge and skills to cope with the impact of AI tools on their work.
- **Although Generative AI holds potential to improve labour productivity and job satisfaction, it also poses risks for workers.** On the one hand, Generative AI can allow workers to perform tasks quicker and with greater accuracy, automating routine tasks and freeing up time for more meaningful work. On the other hand, practices such as algorithmic management raise questions about AI's impact on job quality, along with concerns about privacy and potential biases in AI systems. Collaboration with social partners and establishing clear, transparent guidelines for AI use will be important in protecting workers' rights.
- **To harness the benefits of Generative AI and address its potential risks, regions should adopt data-driven, place-specific solutions that foster workforce adaptation.** This includes identifying opportunities for AI-driven growth, updating skills provision systems, and developing comprehensive skills inventories to address mismatches and prepare workers for new demands. Supporting SMEs in AI adoption, fostering collaboration with local stakeholders, and providing tailored support for displaced workers are also key to sustainable and equitable regional development amid technological changes.

Technological progress and AI: The future of local labour markets

Technological progress has been an important driver of economic development. In many cases, such progress has had direct labour market consequences, with implications for firms, workers, and the skills required in many jobs. Generative Artificial Intelligence (Generative AI)[1] is one of the latest waves of innovation in Artificial Intelligence (AI) and has captured the attention of people around the world. Progress in AI, with its easy access, practical use and showcased applications, has become highly tangible for a much larger proportion of the population. Yet, the current state of Generative AI might only be the start, with companies around the world working on further applications. While the adoption of Generative AI might provide tangible benefits for its users, the exact impact on workers, firms, and different communities are yet to fully materialise. One major concern is the potential for job displacement through task automation.

The discussion around the effects of automation encompasses both positive and negative aspects, including job losses, greater productivity, and overall economic growth. In broad terms, the concept of automation can be understood as the application of technology to achieve outcomes with minimal human input (Box 3.1). In assessing its impact, on the one hand, there is automation anxiety (Akst, 2013[1]) which is the real concern that technology will lead to the loss of jobs. On the other hand, automation can lead to productivity gains, thus possibly translating into higher incomes for workers.

In the past, new technologies have impacted regions and groups of people differently, and this uneven development is expected to continue. As new technologies spread throughout the economy, they often become concentrated in specific geographical areas, influenced by factors such as infrastructure, culture, natural resources, institutions, industrial composition, and workforce skill composition, among other regional characteristics.

One of the main motivations for adopting AI and automation technologies is to increase productivity while reducing labour costs. Firms using AI tend to be, on average, more productive than other firms (Calvino and Fontanelli, 2023[2]). For instance, studies show that robot adoption in Spanish firms can result in productivity gains of 20–25% within four years, a reduction of the labour cost share by 5–7 percentage points, and net job creation of 10% (Koch, Manuylov and Smolka, 2021[3]). One explanation for these findings is that automated firms become more productive and competitive, which allows them to lower product prices, gain market share, and ultimately increase labour demand (Banco de España, 2023[4]; Aghion et al., 2022[5])

However, productivity gains do not solely materialise through the adoption of new technology. Instead, these gains often come from a combination of factors, including how well the technology works alongside other digital technologies, a firm's resources (including its workers' skills), and overall economic policy. Firms with better access to key technical, managerial, and organisational skills have benefitted more from digital technologies than other firms. These varied impacts are relevant to other topics in this report, as technologies can address labour shortages, introduce new challenges related to digitalisation, drive the need for upskilling among workers, and influence overall employment levels, among others. (OECD, 2019[6]).

The actual impact of new technologies on regional labour markets and workers will likely be more nuanced than scenarios of mass job losses or significant productivity gains. Furthermore, labour market impacts may not be evenly distributed, may interact with each other, and potentially be felt disproportionately by specific groups of workers. For example, automation can lead to job polarisation and wage inequality (Acemoglu and Loebbing, 2022[7]), job losses concentrated within some sectors of the economy and particularly among workers with lower education (Georgieff and Milanez, 2021[8]), or reduce the quality of jobs even if the quantity is not affected (Autor, 2015[9]).

As technologies evolve, they often transform job roles and thus local labour markets, rendering some jobs unrecognisable from their previous iterations or giving rise to entirely new occupations. Bank tellers serve as a pertinent illustration of this phenomenon. As automated teller machines (ATMs) were introduced in the 1970s, their widespread adoption accelerated notably throughout the 1990s and 2000s. Nevertheless, human bank tellers as an occupation did not disappear (although their share in the US economy did decline). While the number of bank tellers per bank decreased, the number of banks increased in parallel due to lower operating costs (Bessen, 2015[10]). This allowed banks to expand their urban branches by 43% and focus on customer needs that machines could not address, particularly small business clients who may have previously been overlooked. Overall, the tasks carried out by bank tellers expanded to encompass soft skills more akin to those of salespersons.

Although the labour market impacts of technology and automation are a main topic of concern, knowledge regarding the effects of Generative AI remains limited. Given this recent wave of technology, research on the subject is sparse, with most existing studies predominantly focusing on a single country. Furthermore, empirical work has so far mainly neglected subnational differences, resulting in a gap in our understanding of variations across regional labour markets. This chapter presents new evidence on the geographic distribution of exposure to Generative AI, addressing a significant data gap and examining how the labour market impacts of this latest advancement differ from previous technologies.

The following sections explore and discuss the impact of modern digital technologies, at least some of which can be categorised as AI, on local labour markets and workers. These technologies can be grouped based on both the scope of tasks they perform and the ease of accessibility to the user. First, an overview of the different technologies involved in automation and AI is provided. Next, a set of empirical estimates on risk of automation and exposure to Generative AI in OECD regions is presented and discussed. The last section addresses policy-relevant issues aimed at helping regions harness the benefits of new technologies, mitigate associated risks, and leverage AI to both tackle labour market challenges and enhance the work of the public administration, including public employment services (PES).

Understanding the foundations: AI, automation, and labour market dynamics

AI developments over the last decades: Narrow-purpose technologies

AI encompasses various technologies – some of which have been around for decades – and has seen remarkable advancements in the 2010s. In fact, AI development dates back to the early days of computers, with foundational work such as the 1943 perceptron model (McCulloch and Pitts, 1943[11]) leading to today's neural network models a - centrepiece of modern AI technology. AI progress in the latter half of the 20th century and in the early 21st century has been marked by periods of advancement but also setbacks (Anyoha, 2017[12]). Over the last 15 years, this sector has boomed with deep learning, for example, being named one of 10 breakthrough technologies in 2013.[2] These technical advancements have powered the gears behind major new technologies such as image recognition (with applications ranging from medical imaging to crop monitoring), text and speech recognition, or language translation among others.

Box 3.1. Automation involves an ever-growing set of technologies

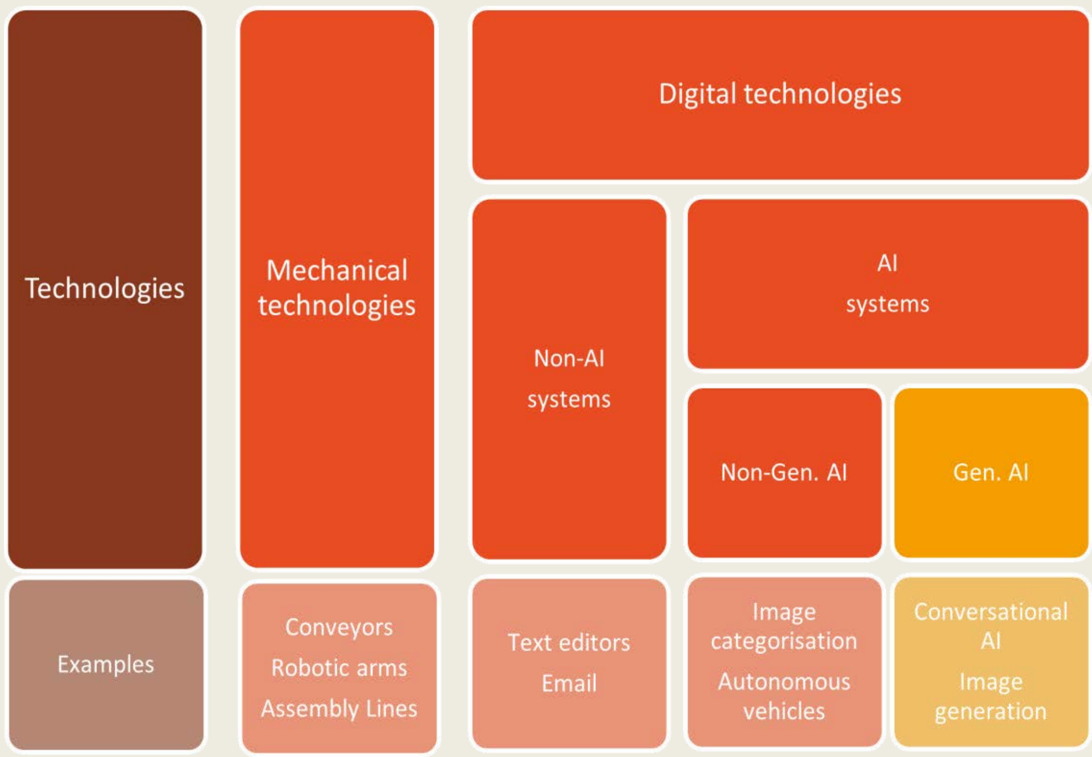
Automation can be understood as the application of technology to achieve outcomes with minimal human input. Automation technologies encompass then a large set of technologies, including digital technologies – which include both conventional and AI powered software, which may or may not be Generative AI – and mechanical systems, among others (Figure 3.1).

The use of technology most commonly leads to the automation of specific work tasks and only rarely leads to the automation of entire jobs (Bonney et al., 2024[13])**.** A given job can be understood as a set of diverse tasks carried out by the worker. While technology adoption has led to the disappearance or creation of jobs, it typically replaces specific tasks within a job rather than eliminating the entire job. In other words, automation technologies can potentially displace tasks, not jobs. Nevertheless, technology-led task automation may still lead to job losses (typically productivity enhancing) as, with the use of technology, one worker can do the work that previously required several workers, which may prompt employers to scale down their labour force.

It is useful to classify automation-related technologies based on their format, scope of application, and accessibility. Figure 3.1 illustrates a non-exhaustive classification of technologies associated to task automation, along with examples. Mechanical technologies refer to physical technologies that provide engineering solutions for human tasks, with robotics and various manufacturing technologies being prominent examples. Digital technologies involve the use of computers and range from simple software, such as email clients and text editors, to conversational AI platforms such as ChatGPT. Although technology groups are visualised as separate, these are often used together as, for example, delivery robots might use image recognition software to navigate their environment. However, the technology groupings presented serve as an intuitive and broad illustrative classification, though they are not exhaustive.

Figure 3.1. Automation technologies involve a large set of technologies with varied degrees of generality

Examples of digital and mechanical technologies

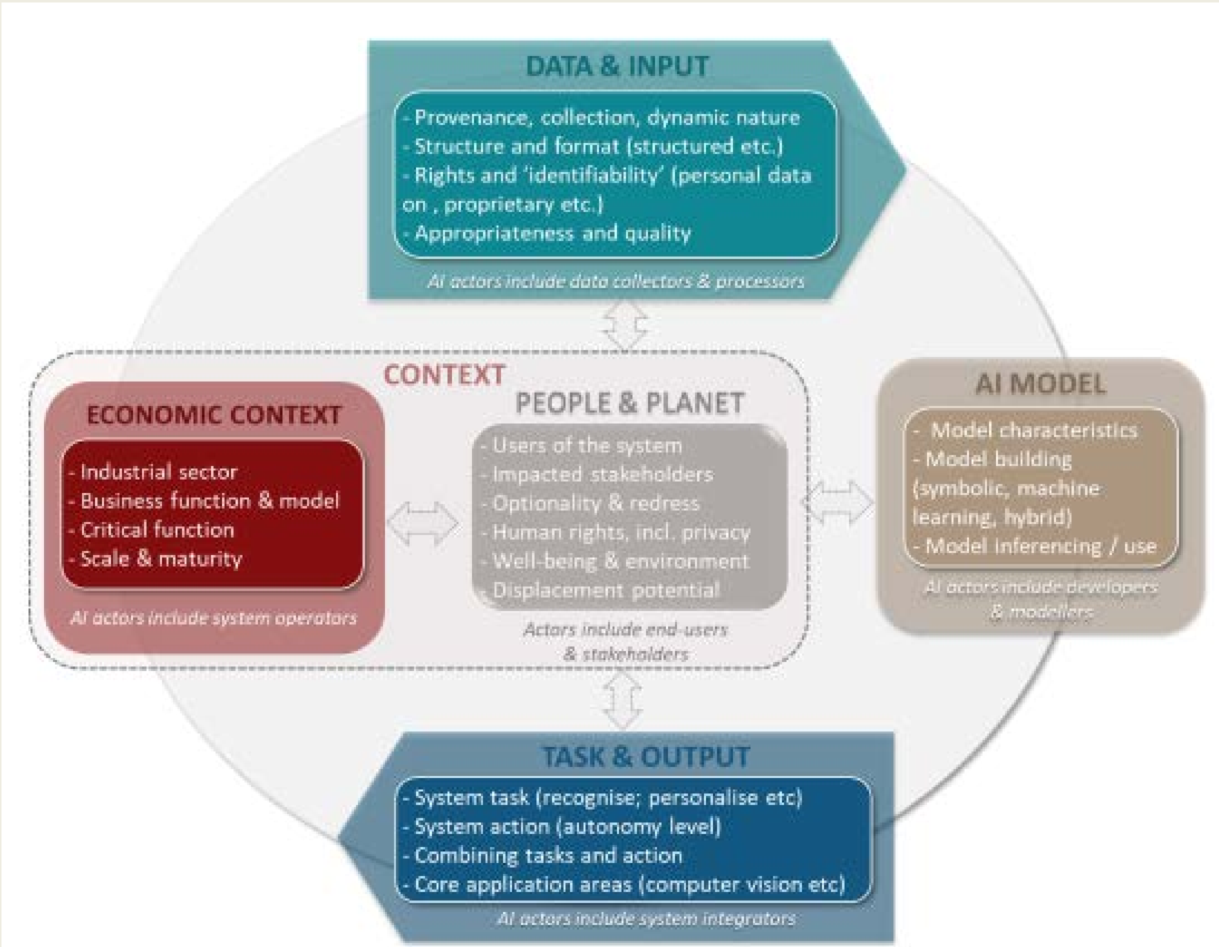


Note: Although categories are illustrated as separate, some technologies might fit into more than one group depending on their specific application.
Source: OECD elaboration.

AI technologies can in turn be classified based on the context of their development, their inputs and outputs, the specific underlying model or the economic context they are deployed in. The *OECD Framework for the Classification of AI systems* (OECD, 2022[14]) provides a structure to characterise the application of an AI system deployed in a specific project and context (Figure 3.2). The framework allows for a systematic characterisation of AI systems across various dimensions. In this context, it is both relevant and practical to classify Generative AI technologies as distinct from earlier AI technologies. This distinction arises, at least in part, from the varying degrees of generality among AI technologies.

Figure 3.2. Key high-level dimensions of the OECD Framework for the Classification of AI Systems

Characteristics per classification dimension and key actor(s) involved



Note: Actors are illustrative, non-exhaustive and notably relevant to accountability.
Source: (OECD, 2022[14]).

The degree of generality of an AI system refers to its ability to perform several tasks including ones for which it was not initially trained. While there is no single indicator of generality, several criteria in this framework can indicate generality when combined (OECD, 2022[14]) such as the (1) s*cale of the AI system*, (2) its *model development/maintenance* and (3) *its ability to combine tasks and actions into multi-task, composite systems.*

Generative AI significantly differs from previous AI systems in at least these three criteria, indicating a higher degree of generality. First, the training datasets behind Generative AI models are larger than most if not all previous AI models and are only getting larger (Epoch, 2024[15]). Second, these models can be universal, customisable or tailored depending on the needs and budget of its user, and in practice the most popular platforms have universal models which are free to use and widely available. Third, by themselves or when integrated with other technologies, Generative AI systems can combine many tasks, at least as many as previous technologies.

For the purpose of this chapter, it is useful then to separate Generative AI technologies from previous AI technologies. Following the *OECD Framework for the Classification of AI systems,* Generative AI can be considered as a separate group of AI systems that, given its more general purpose, is expected to have a different labour market impact relative to previous technologies. In addition, these Generative AI systems are more accessible than previous waves of AI. For practical purposes, this chapter classifies automation technologies that predate Generative AI as *narrow-purpose technologies* (left side of Figure 3.1), as under this framework, their development and use characterise them as less general purpose than Generative AI (bottom right of Figure 3.1).

Source: (OECD, 2022[14]).

Technology, either AI or non-AI, designed to solve specific problems or address specific work tasks can be grouped in the category of narrow-purpose technologies (Box 3.1). Such models and technologies have in common, at their core, their ability to perform strongly in one or few specific tasks. Therefore, their scope is limited, as one technology is unable to generalise its knowledge to different, unrelated tasks outside of its designed purpose. For example, an algorithm might recognise tumours in medical images better and faster than a qualified doctor, but it may not be able to recognise other symptoms, describe what a tumour is or suggest a treatment. Moreover, narrow-purpose technologies have not been accessible to a wide range of users, at least in part because they were not originally designed for a broad audience.

The impact of AI in the labour market is expected to shift as new frontier technologies are adopted. The labour market impacts of narrow-purpose technologies tend to align with the specific and limited scope of the technology, affecting mostly low-skilled workers within certain primary or resource-based industries. Nevertheless, recent advancements in AI have broadened the capabilities of digital technologies into a growing set of cognitive non-routine tasks which is not limited to the initial intended use of the technology. Therefore, the labour market impacts of these new technologies should be felt by a broader group of potentially different workers.

Recent waves: Towards a more general use AI

Recent developments have supported the broadening use of AI technologies, leading to the emergence of Generative Artificial Intelligence (Generative AI). During the last three to five years, the technology industry has seen a shift away from narrow-purpose technologies to more broadly applicable AI technologies (Filippucci et al., 2024[16]). Generative AI, one of the latest advancements, is designed to create human-like outputs – usually text, images, or video – based on existing data. In practice, it can assist with a wide range of applications, from content creation to problem solving. Furthermore, this technology has been integrated into platforms that are easily accessible to a wide, non-technical audience through intuitive, natural language interfaces, often in the form of chat-based systems.

The broader scope and easy accessibility of Generative AI technologies suggest they will have a more widespread impact on the labour market compared to previous waves of AI. Although Generative AI is trained to excel in a single task — content generation — it does so effectively across many diverse contexts, themes, and formats (including not only text but also speech, images, and video), giving it a more general purpose than previous AI technologies. In addition, its use can extend beyond the original intentions of its creators, significantly broadening the range of tasks at which it excels. Consequently, many industries and occupations may find utility in its capabilities.

Although early studies identified low-skilled workers as the most exposed to narrow-purpose technologies, recent research suggests frontier AI may increasingly impact high-skilled workers as well (Nedelkoska and Quintini, 2018[17]; Autor, Levy and Murnane, 2003[18])**.** As AI technologies mature, it becomes possible for them to automate increasingly cognitive and non-routine tasks, such as analysing text, drafting documents, or searching for information. Therefore, the impact of this new wave of technology is expected to be concentrated in jobs associated with knowledge work in high and upper-middle income countries (Gmyrek, Berg and Bescond, 2023[19]). At the occupation level, recent research indicates that AI technologies are directed at high-skilled tasks (Webb, 2019[20]), correlate with higher wages (Felten, Raj and Seamans, 2023[21]) and increasingly impact women and highly educated workers (Pizzinelli, 2023[22]).

Generative AI technologies could contribute to the displacement of some jobs while others could instead be augmented, but in most cases the overall impact remains unclear. Job augmentation refers to technology enhancing or supporting human workers, therefore complementing human work. High-skilled workers with higher incomes are on average more exposed to AI, but they also exhibit high potential for complementarity (Pizzinelli, 2023[22]). Occupations that require a high level of cognitive engagement and advanced skills are better positioned to benefit from increased productivity while minimising the risk of job losses. Recent analysis that classifies occupations based on the potential for augmentation or displacement finds that more occupations could be augmented rather than automated by Generative AI. However, a significant share of occupations[3] remain where both the potential for displacement and augmentation exist (Gmyrek, Berg and Bescond, 2023[19]).[4] While AI is unlikely to fully replace many jobs, highly exposed jobs share certain characteristics such as belonging to occupations that can be done remotely (Hering, 2023[23]).

Within economies and local labour markets, AI technologies may contribute to increased income inequality and job polarisation. The benefits of new technologies not only tend to accrue to high-skilled labour and owners of capital (in the form of higher capital incomes and returns), but may also lead to wage stagnation in some workers, therefore increasing inequality (Moll, Rachel and Restrepo, 2022[24]; Manning, 2024[25]). Advanced economies may also face increased job polarisation in the face of AI adoption – more so than emerging economies – as their employment structure is better positioned to benefit from growth opportunities but also makes them more vulnerable to job displacements (Pizzinelli, 2023[22]). On the other hand, research indicates that there is no relationship, or even a negative one, between AI and overall inequality, although there is an indication that higher occupational exposure to AI may be associated with lower wage inequality within occupations (Georgieff, 2024[26]; Webb, 2019[20]) possibly because AI technology may act as a skill leveller (Box 3.14). The following sections explore this idea further and substantiate it with quantitative estimates.

Narrow-purpose technologies and automation: The consequences for local labour markets

Even before the emergence of Generative AI, the impact of automation technologies differed across local labour markets. While the adoption of technology can bring tangible benefits, it can also lead to job losses. This impact depends on the nature of the tasks performed by workers, resulting in varying benefits and risks across different regions and economic groups, and can be quantified by examining the skills and abilities required for each occupation and the composition of local labour markets (Box 3.2). This measure of risk of automation serves as a useful metric to examine the effects of narrow-purpose technologies. As the underlying survey considers all available technology in late 2021, this measure considers all advanced automation and AI technologies up to that point (Lassébie and Quintini, 2022[27]).[5] The metric is then used to measure the share of employment at high risk of automation, with Figure 3.3 illustrating the results for OECD regions.

While slightly more than a tenth (12%) of the workforce is at high risk of automation, those risks differ widely across regions. On average, regions in Latin America, Eastern Europe, Asia, and the United States tend to have a higher share of jobs at high risk of automation, especially compared to regions in Central, Southern, and Western Europe, Oceania, and Canada. The share of jobs at high risk of automation ranges from under 1% (Greater London, United Kingdom) to almost 29% (La Guajira, Colombia), highlighting the great diversity in automation risks across regions in the OECD (Figure 3.3).

Box 3.2. Measuring jobs impacted by narrow-purpose automation technologies

The O*NET database

The O*NET programme is a US-based effort to, among other things, collect and classify information on occupations, skills, abilities, knowledge, and work tasks. It is made up of several relational datasets which are updated on a regular basis and describe over 1 000 occupations[a]. Skill and ability requirements of occupations are measured in terms of importance and level. The former indicates whether the particular skill or ability is important to perform the job, while the latter indicates the level of mastery or proficiency in that skill or ability needed for the job. This information can be combined with other datasets and surveys to explore different dimensions of work as well as labour market impacts of other phenomena such as the green transition (OECD, 2023[28]; Vona, Marin and Consoli, 2019[29]; OECD, 2024[30]), or remote work (OECD, 2020[31]; Dingel and Neiman, 2020[32]), among others.

Automation of skills and abilities

To examine the relationship technologies have had with local labour markets, a measure of risk of automation is developed. Drawing from expert surveys and detailed information on skills and abilities (O*NET), several metrics are developed to measure the extent to which occupations are automatable. (Lassébie and Quintini, 2022[27]). These metrics explore the *risk of automation* of occupations given available technologies, where the available technologies include all technologies which existed at the end of 2021 when the surveys were conducted. One measure considers that occupations are at high risk of automation if over 25% of its skills and abilities are highly automatable with available technologies. This measure serves as both an expansion and an update of the measure of risk of automation presented in the 2018 Job Creation and Local Economic Development report (OECD, 2018[33]).

The group of experts was comprised mostly of AI experts who were asked to rate the degree of automatability of skills and abilities in general, but they were not asked to distinguish between the specific technologies that might be driving automation. Therefore, even if the most recent advances have occurred in the field of AI, their ratings reflect the capabilities of older and newer automation technologies.[b] Furthermore, experts recognised that it would be best to focus on the capabilities of current technologies, since predictions regarding the distant future made in the past proved to be far from reality.

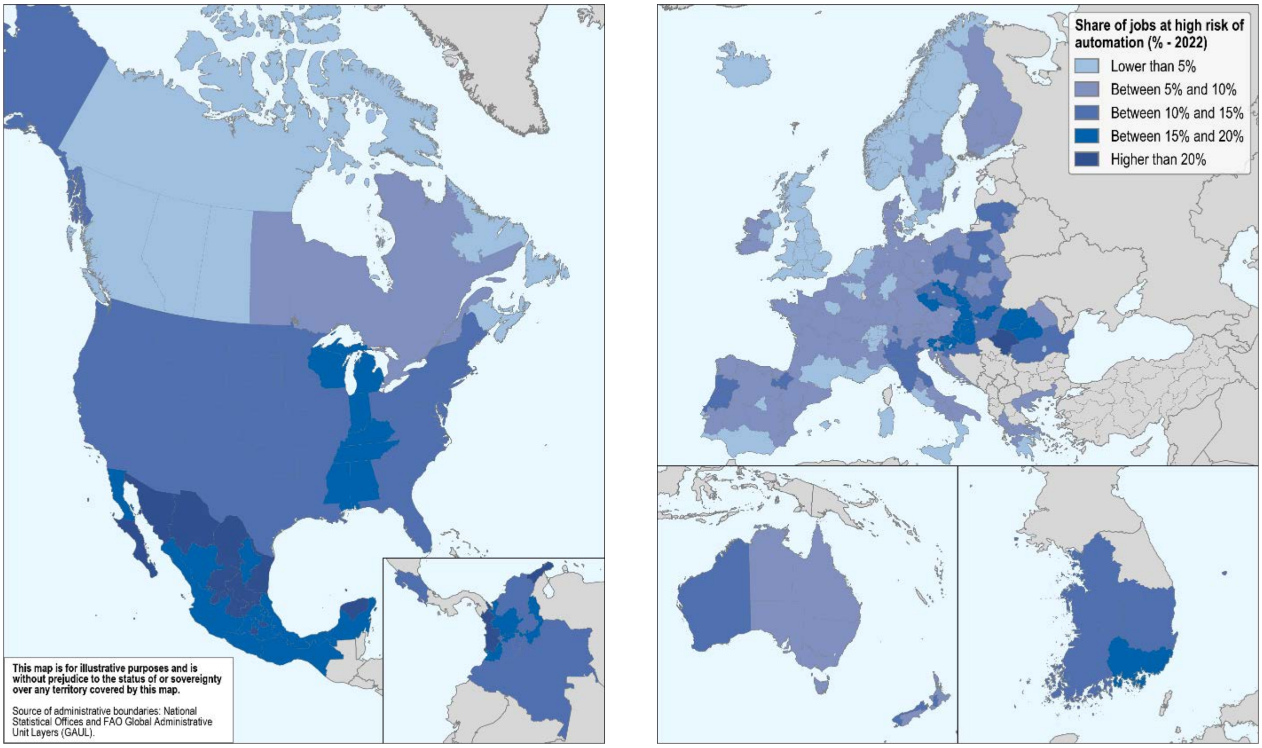
Measuring the automation potential of narrow-purpose technologies

The resulting dataset considers all technologies available in December 2021 and is therefore a practical metric to examine the impact of narrow-purpose technologies on labour markets. As experts were instructed to consider all available technologies at the time, this measure serves as a baseline estimate for that specific point in time. For the purpose of this chapter, the share of occupations at high risk of automation serves as proxy for labour market exposure to narrow-purpose technologies.

Note: [a] See full taxonomy in https://www.onetcenter.org/taxonomy.html. [b] The responses were averaged without removing outliers. Those skills and abilities that had a mean value larger than 3.5 were considered to be highly automatable.
Source: (Lassébie and Quintini, 2022[27])

Figure 3.3. The share of jobs at high risk of automation can range from under 1% to 29% across OECD regions

Share of employment at high risk of automation in OECD regions, latest available year



Note: Estimates for TL-2 regions where available except for Slovenia which is TL-3. Last available year is 2024 for Canada and Korea, 2023 for Australia, Colombia, Costa Rica, Mexico, New Zealand, the United Kingdom, and the United States, 2022 for all others.
Source: OECD calculations based on (Lassébie and Quintini, 2022[27]), labour force survey and employment by occupations tables. See Annex 3.A for more details.

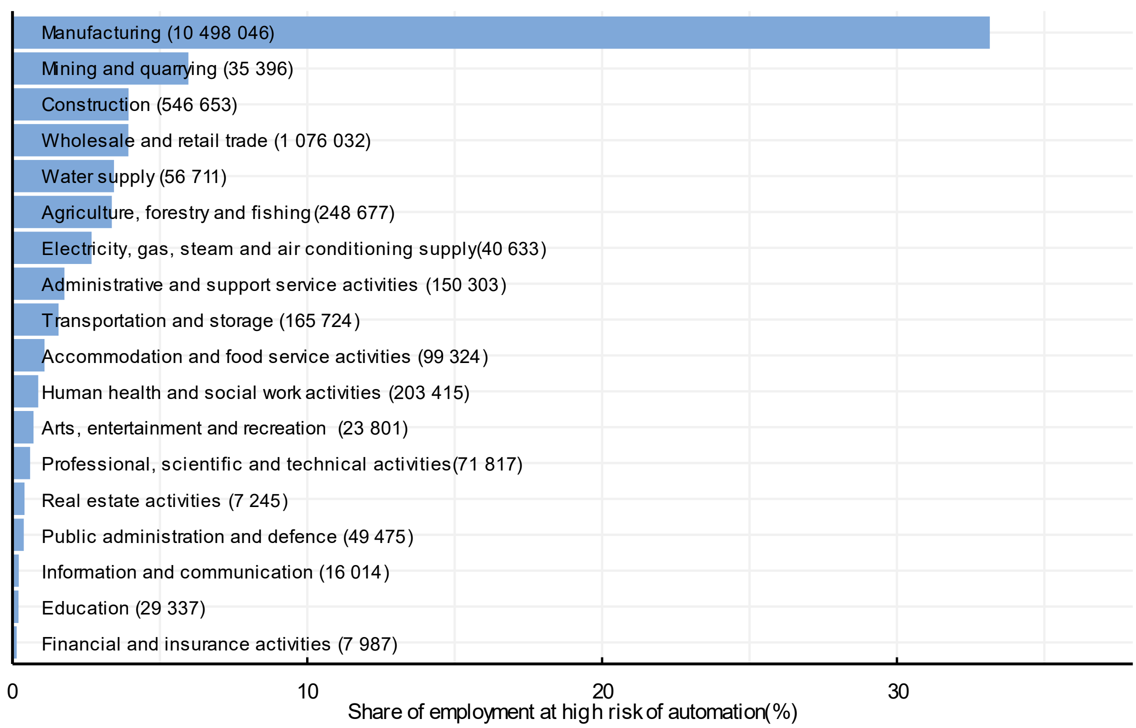
The share of employment at high risk of automation also varies significantly within countries. On average, the share of workers at high risk of automation in the most affected regions is almost four times larger than in the least affected regions within the same country (Figure 3.3). The largest subnational differences can be found in Czechia, where the top region is 9 times more exposed than the bottom region. Furthermore, such regional differences are also considerable in Spain and the United States where the top region is between 7 and 8 times more exposed than the bottom region.[6] Even though the very low risk of automation in the District of Columbia (DC) affects the degree of dispersion in the United States, regional differences remain large (2.3 times) if DC is excluded.

In most countries, capital regions have a significantly lower share of workers at high risk of automation. In 22 out of 28 countries with data for multiple regions, the capital region has the lowest share of jobs at high risk of automation in the country. Australia, Canada, Colombia, Mexico, Portugal, and Spain are notable exceptions. However, even in those countries, capital regions or regions with very large metropolitan areas have a relatively low exposure to automation (e.g., New South Wales in Australia, which contains the city of Sydney). A subsequent section discusses in more detail how the impact of technology is distributed among urban and rural regions.

Regional dispersion is primarily driven by the significant variation across industries, with the manufacturing sector being the most affected over the last decade. Over 33% of employment in the manufacturing sector is (and has been) at high risk of automation, which is 5 times more than mining and quarrying, the next most exposed industry, and around 9 times more than the following four most exposed industries (Figure 3.4). Furthermore, 8 out of the 18 industries analysed have under 1% of employment at high risk of automation and only three industries (manufacturing, wholesale and retail, trade, and construction) account for almost 90% of employment at high risk. This shows the high specificity of most of these technologies, affecting only a small portion of the economy.

Figure 3.4. The manufacturing sector leads in jobs at risk of automation by a significant margin

Share of employment at high risk of automation by industry – EU, Iceland, Norway, and Switzerland, 2022



Note: In addition to Iceland, Norway, Switzerland, and the United Kingdom this data includes the following EU countries: Austria, Belgium, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Romania, Slovak Republic, Spain, and Sweden. Numbers represent total employment, as measured by LFS surveys.
Source: OECD calculations based on (Lassébie and Quintini, 2022[27]) and EU-LFS. See Annex 3.A for more details.

The impact of technological progress on automation: Job losses, productivity gains, or job creation

A common concern among policy makers is that automation technologies will lead to the displacement of workers and the destruction of jobs. However, recent evidence points to more nuanced implications. Based on economic theory, task automation could lead to both job destruction and job creation, while stimulating productivity growth. It could result in falling employment, as employees are replaced by frontier technologies and displaced from the labour market, or in an increase in employment as labour demand is boosted by more productive workers (Acemoglu and Restrepo, 2019[34]). In addition, completely new jobs might be created by new technologies, as, for example, new machines need a specialised workforce to fix and maintain them. Furthermore, productivity gains from these technologies can lead to income growth, which may stimulate expansion in unrelated sectors, such as the leisure industries.

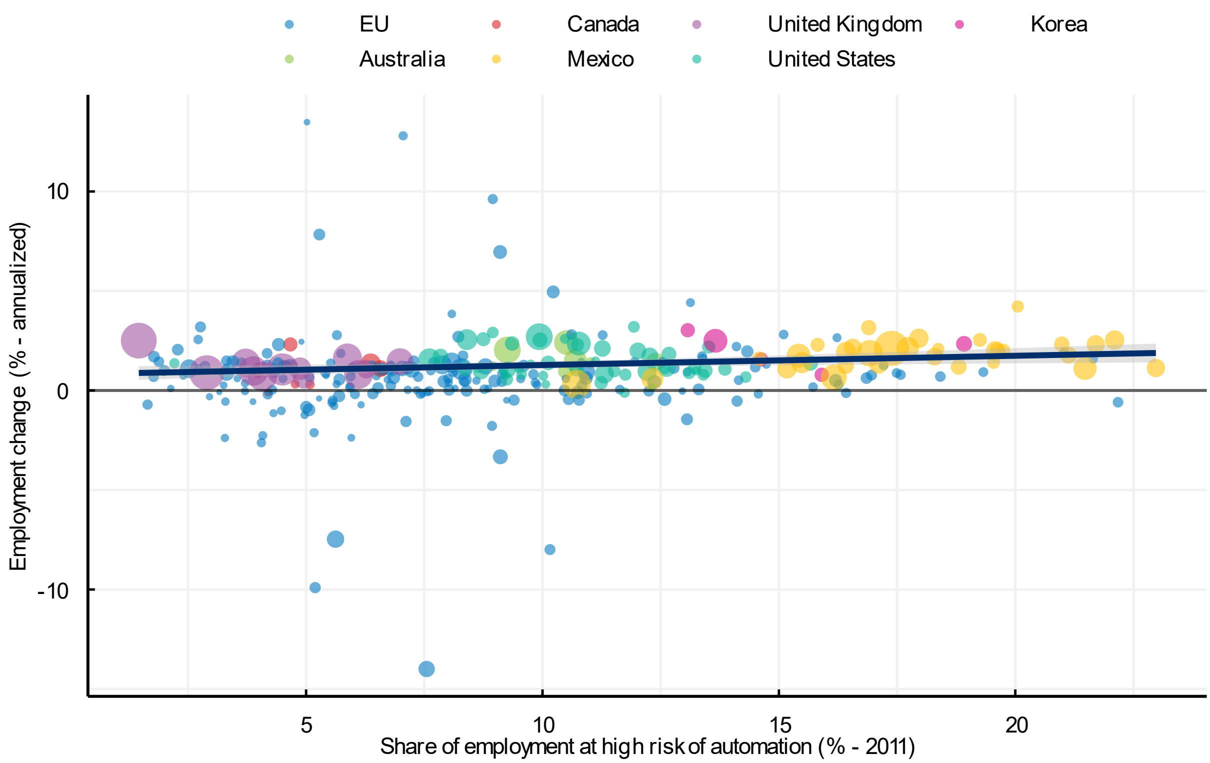
Empirical evidence on the labour market effects of automation has been mixed and suggests that both negative and positive consequences are unequally distributed. Recent analysis shows that automation of job-tasks is concentrated within routine tasks mainly held by low-skilled workers (Acemoglu and Restrepo, 2021[35]; Schwabe and Castellacci, 2020[36]). Between 50% and 70% of all changes in the wage structure in the United States (between 1980 and 2016) appear to be directly linked to automation-related changes in tasks. For instance, young men with no high school degree have experienced a 15% decline in real wages during this period, largely due to their heavy concentration in various routine occupations in manufacturing, mining, retail, and wholesale industries (Acemoglu and Restrepo, 2021[35]). Evidence from European countries suggests that between 2011 and 2019, employment has increased, overall, in occupations more exposed to AI-enabled automation, which also tend to have younger and more skilled workers. However, the results vary largely across countries (Albanesi et al., 2023[37]).

In the United States, a slowdown of wage and employment growth has been linked to an acceleration in the adoption of automation technologies. While the creation of new jobs due to technological advancement has been significant, it has been outpaced by the substitution of workers by new technologies (Acemoglu and Restrepo, 2022[38]). However, empirical work on this topic is so far limited and existing results may not translate outside of the United States (Acemoglu, Manera and Restrepo, 2020[39]) as taxation in the United States is much lower for capital than labour (especially capital involved in automation, such as equipment and software).

So far, there is little evidence of a significant fall in overall employment in local labour markets with a higher share of jobs at high risk of automation. On average, regions with a higher risk of automation have neither recorded significant job losses nor experienced slower job creation than other regions (Figure 3.5).[7] However, this regional analysis may overlook more subtle impacts, such as the reduction in work hours rather than the complete loss of jobs. For instance, exposure to AI has been linked to a decline in average working hours in occupations with low levels of computer usage (Georgieff and Hyee, 2021[40]). Moreover, significant employment changes may still be observed in the future as technologies may still be adopted in lagging regions or industries.

Figure 3.5. Although it is too early to assess the full impacts of automation in the labour market, there is currently little evidence of job destruction in regions more exposed to automation

Annualised increase in employment and share of employment at high risk of automation (2011–2019) in selected OECD regions



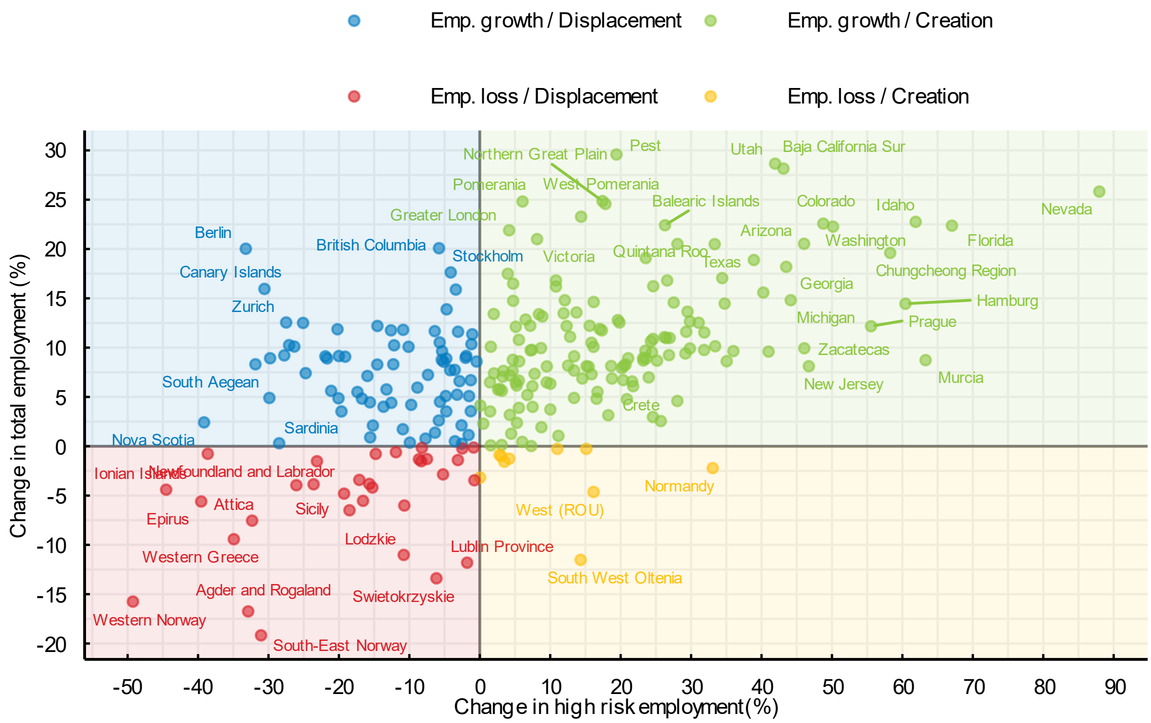
Note: Selected countries based on data availability at the regional level. Base year is 2012 for the regions of Bremen (DEU), Mecklenburg-Vorpommern (DEU), Saarland (DEU) and Ireland, 2013 for the regions Warsaw (POL), Mazowiecki (POL), Hungary, Korea, Lithuania, and Mexico, 2014 for the regions Corsica (FRA), Guadeloupe (FRA), Martinique (FRA), French Guiana (FRA) and La Réunion (FRA) and 2011 for all others. Size of bubbles represent labour market size (employment).

Source: OECD calculations based on (Lassébie and Quintini, 2022[27]), (OECD, 2024[41]), labour force surveys, employment by occupations table. See Annex 3.A for more details.

Nevertheless, this does not necessarily imply that jobs were not destroyed. Instead, evidence suggests that in many regions job losses were offset by job creation in other sectors of the economy. In fact, in most OECD regions (70%) which exhibited a drop in employment at high risk of automation, more than enough jobs were created to make up for this (top-left quadrant in Figure 3.6). On the other hand, in 70% of the regions where employment increased between 2011 and 2019, part of this growth can be attributed to occupations considered at high risk (top-right quadrant of Figure 3.6), highlighting the possible role of technology in facilitating labour expansion. However, this expansion of labour into high-risk jobs may prove to be a double-edged sword, as a potential future wave of job displacement may impact an even larger share of workers in these regions.

Figure 3.6. Most regions have seen employment growth and a large share of those that did not experienced a drop in employment at high risk of automation

Regions by change in total employment (%) and change in high-risk employment (%), 2011-19



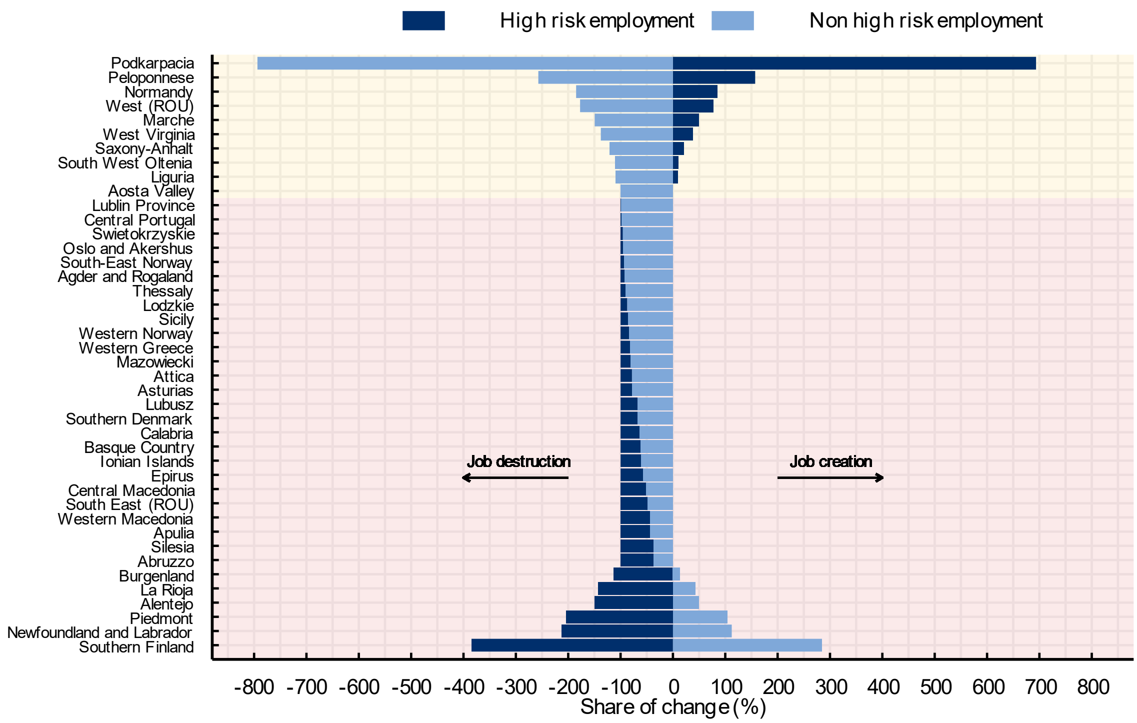
Note: Selected regions based on data reliability. 2011 or nearest available year. Regions marked with employment growth had *growth* in overall employment. Regions marked with employment had a decrease in overall employment. Regions marked with *displacement* had a reduction of total jobs at high risk of automation. Regions marked with *creation* had an increase in of total jobs at high risk of automation.

Source: OECD calculations based on (Lassébie and Quintini, 2022[27]), (OECD, 2024[41]) ,labour force surveys, employment by occupations table. See Annex 3.A for more details.

Overall job destruction across OECD regions can be attributed to automation in only a handful of cases. Figure 3.7 illustrates how the percentage change in employment is distributed among high-risk and non-high-risk occupations for regions that had overall negative employment growth. In only 11 out of the 42 (26%) regions that experienced a fall in overall employment between 2011 and 2019 was the decrease higher in occupations at high risk of automation. Furthermore, only six (14%) recorded employment losses exclusively for occupations at high risk of automation (bottom regions in Figure 3.7). For the latter group of regions, the fall in employment could be attributed, at least in part, to the job destruction of high-risk employment. In other regions, various economic factors may have been more influential than automation; however, automation-related job displacement could still occur in occupations deemed lower risk, albeit to a lesser extent.

Figure 3.7. Overall job destruction across regions can be attributed to automation in only a handful of cases

Share of job change by occupation type in regions with overall job destruction, 2011-19



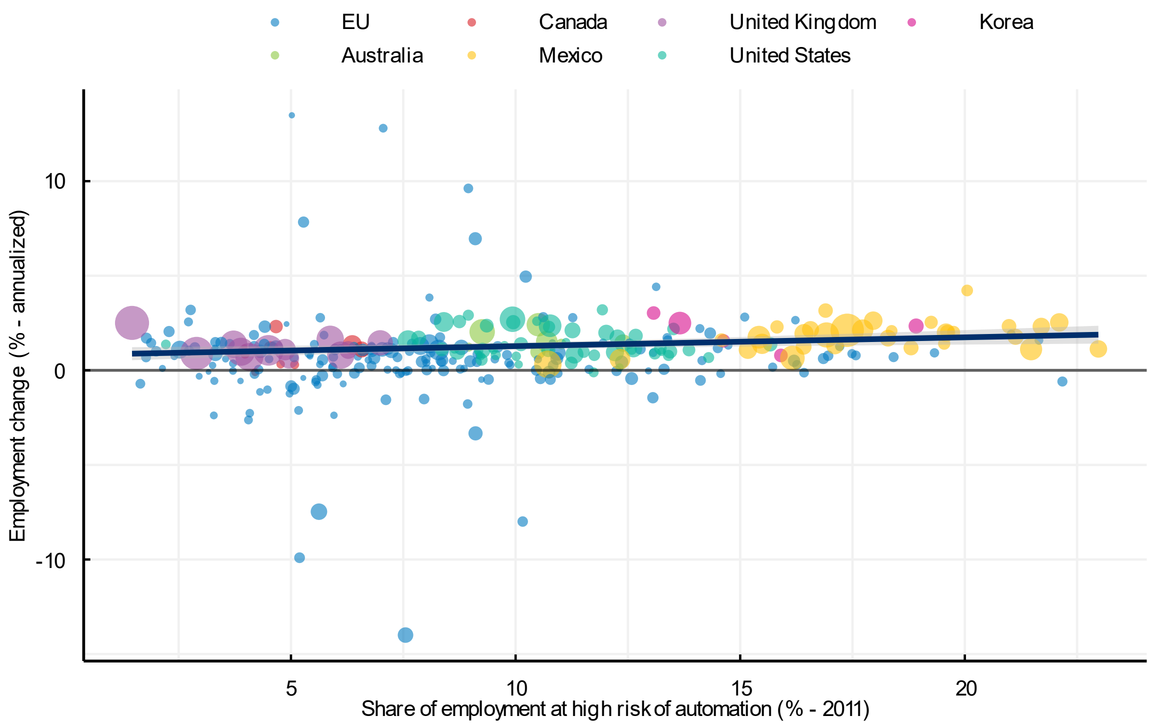
Note: Selected regions which had less employment in 2019 compared to the 2011 (or nearest year available). Value in both bars sum up to -100%, which is represent 100% of the negative change in employment. Background colours relate to quadrant colours in Figure 3.6.
Source: OECD calculations based on (Lassébie and Quintini, 2022[27]), (OECD, 2024[41]), labour force surveys, employment by occupations table. See Annex 3.A for more details.

Even though new job creation outweighed job losses in most regions, newly created jobs might not have benefitted those workers who lost their jobs. In fact, regions that experienced job losses due to automation may have seen these workers enter long term unemployment or leave the labour force, potentially through early retiring, with new jobs taken up by workers either transitioning from other jobs or recently entering the workforce. Labour market policies that target affected workers could facilitate their reintegration into the workplace by, for example, providing them with the skills needed in their local labour market and which enable them to take advantage of new AI technologies (Box 3.3).

Across the OECD, regions with a higher share of employment at risk of automation saw a small but significant increase in productivity. The annualised increase in productivity[8] from 2011 to 2019 tended to be significantly higher in those regions where industrial activities were at higher risk of automation (Figure 3.8). This positive impact on productivity holds even when one considers heterogeneity across countries as, when including country fixed effects, an increase of 10% in the share of jobs at risk of automation is related to an increase of 1.1% in annual productivity, which amounts to a 5.6% increase over five years. The limited magnitude of this effect may be explained by the fact that some technologies were still under development during the 2010s and even when available may not have been instantly adopted[9]. Therefore, some regions may still stand to benefit from the untapped potential of technology.

Figure 3.8. Regions with a higher share of employment at risk of automation saw a small but significant boost in productivity

Annualised increase in productivity and share of employment at high risk of automation (2011 – 2019) in selected OECD regions



Note: Selected countries based on data availability at the regional level. Base year is 2012 for the regions of Bremen (DEU), Mecklenburg-Vorpommern (DEU), and Saarland (DEU), 2013 for Hungary, Lithuania, and Mexico, 2014 for the regions of Corsica (FRA), Guadeloupe (FRA), Martinique (FRA), French Guiana (FRA) and La Réunion (FRA) and 2011 for all others. Size of bubbles represent labour market size (employment).
Source: OECD calculations based on (Lassébie and Quintini, 2022[27]), (OECD, 2024[41]), labour force surveys, and employment by occupation Tables. See Annex 3.A for more details.

Box 3.3. Digital upskilling in Australia, Romania, Korea, and Japan

Upskilling in Australia

The five-year National Skills Agreement in Australia seeks deliver high-quality and responsive Vocational Education and Training (VET) to support the development of a skilled workforce for current and future needs. The government will work with states and territories to deliver on shared national priorities which includes building Australia's digital and technology capability. The government also collaborates with industry leaders to provide apprenticeships and traineeships that combine formal education with on-the-job training. This approach aims to help learners acquire practical skills that are immediately applicable in the workplace.

Romania's initiatives to address digital skill gaps

Through the National Employment Strategy (NES) 2021-2027 and the Education and Employment Programme (EEP) 2021-2027, the Ministry of Labour and Social Solidarity (MLSS) in Romania implements measures to enhance digital skills in the labour force. These include revising vocational training regulations, providing digital skills training for job seekers, and establishing funding mechanisms for employee professional development. Digital skills training, for instance, will be provided starting in 2024 for unemployed individuals through county employment agencies.

Romania is involved in the European Commission's pilot project for the European Certificate of Digital Competences (EDSC), alongside countries such as Finland, Spain, Austria, and France. The EDSC aims to promote digital skills, increase recognition of these skills, and support citizens in understanding and improving their digital competence levels. This initiative is part of the European effort to address the digital skills gap and achieve the goal of 80% of adults having basic digital skills by 2030.

South Korea's AI National Strategy

South Korea's AI National Strategy includes significant investments in education and training to prepare the workforce for an AI-driven economy. The strategy supports the establishment of AI education centres at universities and research institutions, offering specialised programs in AI and machine learning. The South Korean government also provides subsidies for workers and students to enrol in AI courses and certifications. Additionally, the strategy includes initiatives to foster industry-academia collaboration, so that the training programmes align with the needs of the market.

Korea facilitates use of the acquired data by establishing an AI hub to provide companies and researchers with AI training data and cloud-based high-performance computing (an essential tool to process large amounts of data efficiently). The ecosystem will include big data platforms to produce and manage data, especially for sectors such as finance and healthcare. Korea also provides AI vouchers to SMEs and start-ups that need AI-powered products or services. Using the vouchers, the beneficiary companies can purchase necessary AI solutions from AI-solution suppliers.

Japan's strategic support to the private sector for adopting AI

Japan, through the Ministry of Economy, Trade, and Industry (METI), launched the J-Startup programme in 2018 to foster innovation and help Japanese startups succeed. This public-private programme identifies and supports top startups and provides them with resources and opportunities to innovate in various sectors, including healthcare, with a strong focus on new technologies and AI. This initiative, beyond empowering the ecosystem in Japan, looks to foster better partnerships between the private and public sectors. J-Startup describes the support offered by the private sector to the government as working together to do experimental studies with robots, products, and infrastructure networks. The support by the government includes applying supportive frameworks for startups such as subsidies and simplifying procedures.

Regions in Japan have their own J-Startup programmes, aimed at supporting regional growth and development. For example, J-Startup Kansai identifies promising startup companies that will serve as a role model for the region and supports their growth within the region (J-Startup Kansai, 2024[42]). Similarly, Central Japan implemented J-Startup Central to give robust regional support for their development (Central Japan Startup Ecosystem, 2024[43]).

Source: (Australian Department of Employment and Workplace Relations, 2023[44]), (Ministry of Science and ICT of Korea, 2021[45]), (Song, 2022[46]) (J-Startup Kansai, 2024[42]) (Central Japan Startup Ecosystem, 2024[43]).

The implications of Generative AI for regional labour markets

The rise of large language models (LLMs) might have an impact on a much larger share of workers than previous digital technologies. LLMs such as Generative Pre-trained Transformers (GPTs) have characteristics of a general-purpose technology (Eloundou et al., 2023[47]) and can generate high-quality text, images and other content based on large amounts of training data. While technology in the past focused on specific parts of the production of goods and services, Generative AI in the form of LLMs can intervene in manifold ways.

This section provides novel estimates on the exposure of different workers and local labour markets to Generative AI. It expands the work done by (Eloundou et al., 2023[47]), which examines how the tasks of individual jobs can be done significantly faster via the use of LLMs and associated user interfaces (Box 3.4). It constructs four related estimates that examine occupational exposure at two levels of intensity (exposed and highly exposed) and two points in time (now and in the near future).[10] Table 3.1 provides example occupations and their respective exposure to Generative AI. Overall, the analysis covers regional labour markets in 36 OECD countries (further details on country coverage and data can be found in Annex 3.A).

Box 3.4. Measuring exposure to Generative AI at the occupation level using O*NET data and expert surveys

Eloundou et al. (2023[47]) **measure the potential implications of Generative AI, specifically frontier LLMs such as General Pre-trained Transformers (GPT's), on the US labour market.** They classify jobs according to their task content. This methodology is based on the idea that jobs can be decomposed into distinct tasks, which can then be analysed in detail (Box 3.2). Conclusions for jobs are then inferred from the tasks that make up these jobs.

The authors along with AI experts classify tasks based on how much faster they could be completed by a human using an LLM or an LLM-powered system. This optimisation is conditional on the fact that the quality of output is not compromised. If the time required for a human to perform a task can be reduced by at least 50% with the use of an LLM, then this task is classified as exposed. For example, online merchants commonly "deliver e-mail confirmation of completed transactions and shipment", which could be optimised with the use of Generative AI models.

Although LLMs are advanced in their capabilities, their use in everyday work may remain limited due to poor software integration or restricted access to relevant data. For example, LLMs are commonly used to write or de-bug software code, but writing prompts and copying code can be done faster if the LLM is embedded directly in a developer's software tool (such as their integrated development environment), as is the case with GitHub Copilot (Box 3.10). In addition, some Generative AI platforms have restrictions that could be relaxed if necessary. For example, prompts given to early LLM powered chatbots were limited to 2 000 words, but this limit has since expanded. In addition, some LLM platforms cannot access the internet to retrieve up-to-date facts, which is not necessarily a limitation. In fact, some LLM-powered systems could be more useful for certain occupations if they were trained on internal company data, thereby also enhancing safety by reducing exposure to misinformation from the internet. Some tasks could theoretically be optimised with the use of LLMs, but the technology is either unnecessarily restricted or has not yet been converted into tools easily adoptable by users. As a result, some tasks are not yet exposed but are likely to become exposed in the (near) future.

To address this, the authors create multiple measures of exposure for occupations. Two of them are the most relevant: *exposure now* and *exposure now or in the near future.* As implied, the second measure is an expanded version of the first. Exposure now is defined as the share of tasks within an occupation that can be completed in half the time by using LLMs in their current form, i.e., Chat-GPT 3.5 or similar. Exposure now or in the near future is defined as the share of tasks within an occupation that can be completed in half the time by using with LLMs in their current form (the same as the first scenario) plus those tasks where it is easy to imagine additional software that could be developed on top of the LLMs that would reduce the time taken to complete the task by half. It is important to note that this last definition does not presume major advances in technology, but it merely expects software tools to catch up to integrate frontier LLMs and specialise in certain applications.[a] Neither of these measures necessarily imply that highly exposed occupations will face displacement. It could also be the case that those occupations can be done more efficiently with the use of Generative AI tools.

This report expands on the work of Eloundou et al. (2023[47]) **and applies a modified methodology for OECD regions.** Occupations are considered to be exposed if these measures – the share of tasks that can be done with a set of technologies – exceed 20%. Furthermore, occupations are considered to be highly exposed if these measures exceed 50%. These thresholds were chosen to reflect two particular dimensions of labour market exposure. In short, a threshold of 20% measures those occupations that have a low but significant exposure while a threshold of 50% measures those occupations where most of the job can be optimised by the use of Generative AI. Table 3.1 summarises the four resulting measures and provides examples.

Note: [a] Annex 3.A contains more details on these measures.
Source: (Eloundou et al., 2023[47]).

Table 3.1. Example of occupations by their exposure to Generative AI

Occupations affected	Not exposed (No tasks)	Exposed (20% of tasks)	Highly exposed (50% of tasks)
Now	- Home Health Aides - Sound Engineering Technicians	- Materials Scientists - Sales Engineers Financial Examiners	- Programmers - Interpreters and Translators
Now or near future	- Cleaners of Vehicles and Equipment - Slaughterers and Meat Packers	- Camera Operators - Opticians	- Insurance Underwriters - Database Architects

Note: Selected occupations.
Source: (Eloundou et al., 2023[47]).

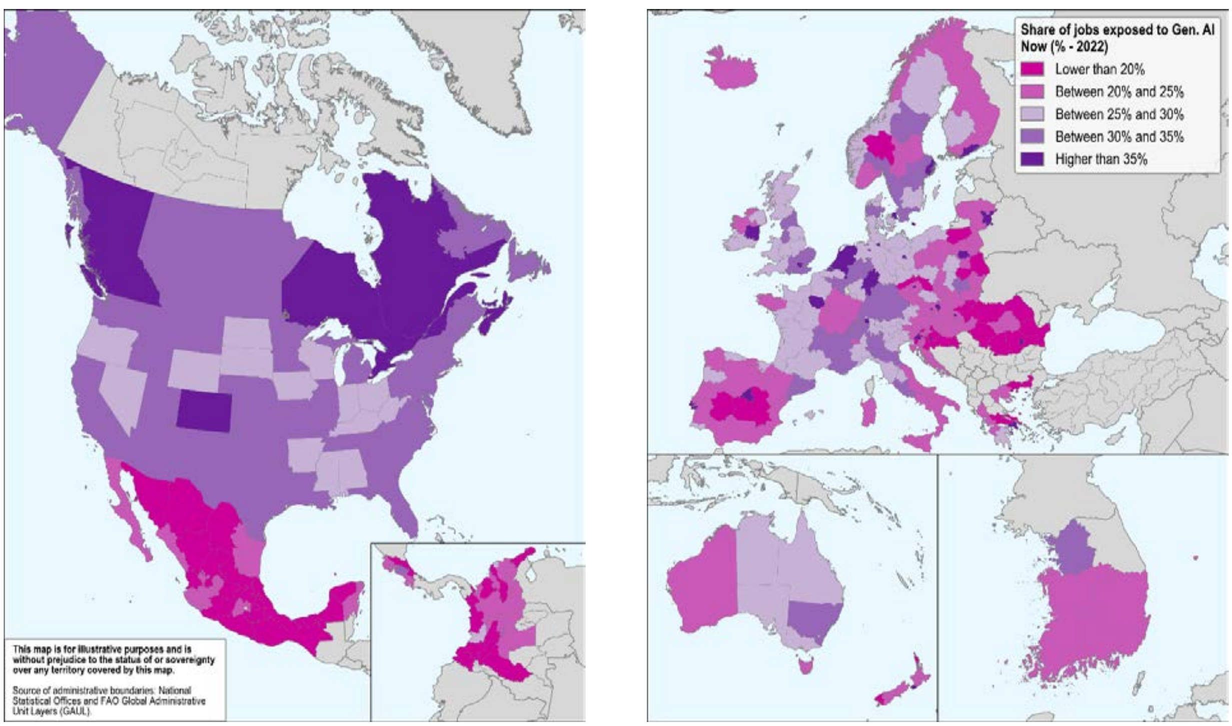
Most occupations exhibit some degree of exposure to Generative AI, though the extent of this exposure varies significantly across different fields. Higher paying occupations tend to be more exposed to Generative AI, while occupations heavily reliant on science and critical thinking skills are less exposed on average. Similarly, jobs that require more education and/or training tend to, on average, be more exposed to Generative AI (Eloundou et al., 2023[47]).

A quarter of workers are currently exposed to Generative AI, but this share is expected to grow

Across the OECD, around 26% of workers are exposed to Generative AI, but only 1% are considered to be highly exposed. Nevertheless, as Generative AI technologies are integrated into the workplace, up to 70% of workers could be exposed to Generative AI in the near future, with 39% of these considered to be highly exposed. Table 3.1 provides examples of occupations within each category. The extent to which these estimates materialise in regions depends on the actual uptake by workers and firms, which in turn hinges on both investment and training.

Figure 3.9. A quarter of workers are now exposed to Generative AI

Share of employment exposed to Gen-AI now, latest available year

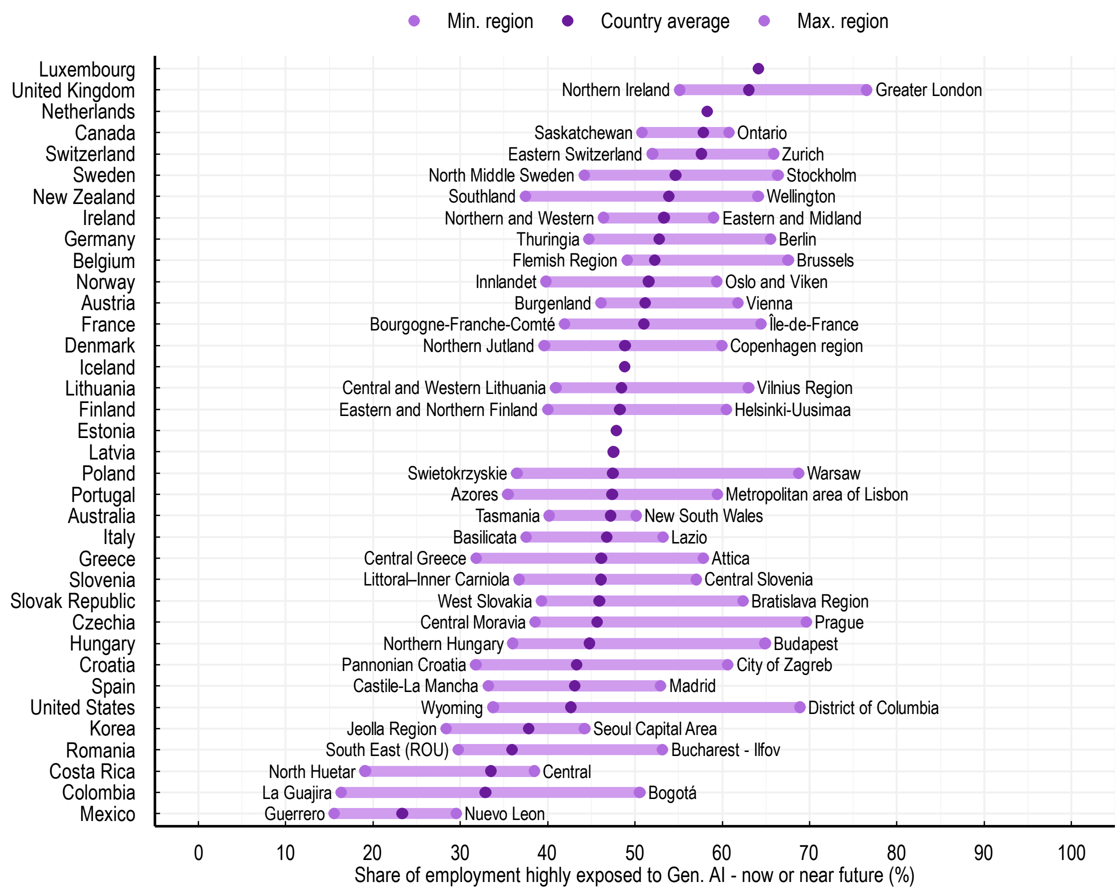


Note: Estimates for TL-2 regions except for Slovenia which is TL-3. Last available year: 2024 for Canada and Korea, 2023 for Australia, Colombia, Costa Rica, Mexico, New Zealand, the United Kingdom, and the United States, 2022 for all others.
Source: OECD calculations based on (Eloundou et al., 2023[47]) , labour force survey and employment by occupations tables. See Annex 3.A for more details.

The exposure of jobs to Generative AI across OECD regions varies significantly. The share of workers highly exposed to Generative AI in the near future is expected to range from 16% in Guerrero (Mexico) to 77% in Greater London (United Kingdom) (Figure 3.10). The within-country dispersion for this measure averages around 14 percentage points, indicating that the top region in a country is, on average, 1.6 times more exposed to Generative AI compared to the bottom region. In Colombia, the country with the highest regional dispersion, the top region (Bogotá Capital District) is over 3 times as exposed as the bottom region (La Guajira). Capital regions tend to account for the high share in the within-country dispersion, pointing to an urban-rural divide in this dimension.

Figure 3.10. Labour market exposure to Generative AI could range from 16% to 77% across regions

Share of employment highly exposed to Gen-AI now or in the near future, latest available year



Note: Estimates for TL-2 regions except for Slovenia which is TL-3. Last available year: 2024 for Canada and Korea, 2023 for Australia, Colombia, Costa Rica, Mexico, New Zealand, the United Kingdom, and the United States, 2022 for all others.
Source: OECD calculations based on (Eloundou et al., 2023[47]), labour force survey and employment by occupations tables. See Annex 3.A for more details.

Box 3.5. Alternative measures of AI exposure in labour markets

Exposure to AI and automation technologies can be viewed through more than one lens. The results presented in this section examine labour market exposure to Generative AI when this is embedded in an accessible platform. At least three different datasets have been developed to examine this issue through other vantage points and present complementary results.

AI Occupational Exposure (AIOE)

This dataset individually links 10 AI application to 51 skills and abilities (O*NET). It does this by surveying online gig workers and combines their responses into an occupation level indicator which describes the extent to which a given occupation is exposed to each AI application, as well as AI in general. The main indicator is the Artificial Intelligence Occupational Exposure (AIOE) and has been used to examine the geographical and industrial distribution of AI exposure (Felten, Raj and Seamans, 2021[48]), the AI exposure of labour markets across developed and developing economies (Pizzinelli, 2023[22]) and a detailed analysis of labour market exposure in Canada (Mehdi and Morissette, 2024[49]), among others. National level estimates of the share of exposed workers ranges from around 25% (India) to 65% (United States), with 57% of employment considered exposed in Canada.

A global analysis of potential task exposure to Generative AI

This dataset evaluates ISCO occupations, including their description and task content, in regards to their potential exposure to Generative AI (Specifically GPTs). The study used ChatGPT-4 to score individual occupations and creates national and global estimates on the share of jobs exposed (Gmyrek, Berg and Bescond, 2023[19]). In addition, the study evaluates which occupations have augmentation potential (they are likely to be complemented by Generative AI) and which have automation potential (they are likely to be displaced by Generative AI). Results show that 15.3% of jobs across the globe are considered exposed, with 13% having augmentation potential and 2.3% having automation potential. Nevertheless, this figure can reach 18.5% in high income countries, with 13.4% and 5.1% of jobs having augmentation and automation potential respectively.

Source: (Felten, Raj and Seamans, 2021[48]; Gmyrek, Berg and Bescond, 2023[19]).

It may be too early to determine the full impact of Generative AI on local labour market composition. While certain labour markets are highly exposed to AI, this has not yet resulted in significant changes. It may take some time before we observe shifts in employment figures in response to the impact of Generative AI. An analysis of online job postings in the United States (Box 3.6) indicates no structural changes in hiring practices since Generative tools were launched. While these results may not fully represent the OECD, it is anticipated that the United States will act as an early indicator for the rest of the OECD, given its likelihood to be among the first to respond to the impact of Generative AI.

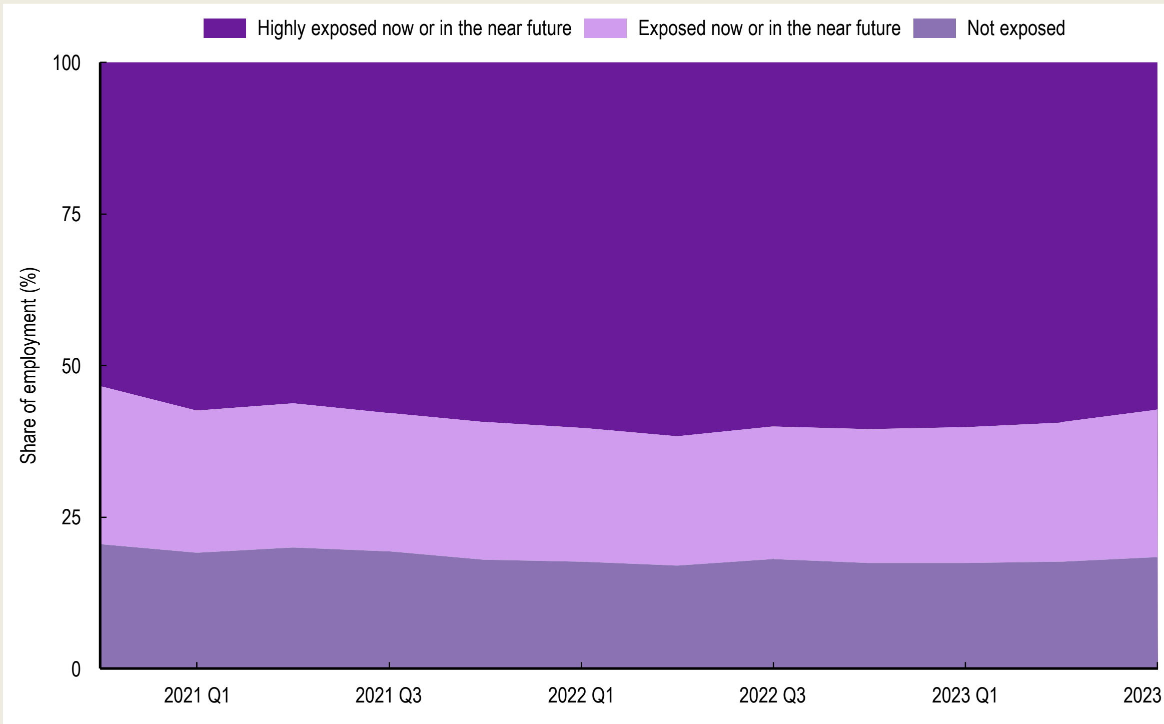
Box 3.6. The impact of Generative AI on job creation and destruction remains uncertain

So far, labour demand has not reacted to exposure to Generative AI, as evidenced in the United States. The share of job postings of occupations expected to be exposed to Generative AI has not changed significantly in the last three years. Around 82% of US online jobs postings in 2023 are considered to be exposed to Generative AI either now or in the near future, of which 59% are highly exposed (). This share of employment was also around 82% in 2021[11], before Chat-GPT 3 was released to the public. Although there has been no observable change, it might still be too early as at least part of the impact of Generative AI may have not materialised yet. In other words, although the correlation is non-existent right now, stronger effects may be observed in the future.

Nevertheless, labour markets may change as they integrate Generative AI tools. These exposure estimates do not imply job displacement, but they should correlate with productivity as they measure the tasks that can be done faster with the help of Generative AI. Therefore, Generative AI may lead to both job destruction and creation. Nevertheless, employers may decide to postpone both hiring and layoffs until the practical uses of new technologies yield results.

Figure 3.11. Labour demand has not yet reacted to Generative AI exposure

Share of online job postings by exposure to Generative AI, United States



Source: (Eloundou et al., 2023[47]) and Lightcast data on online job postings.

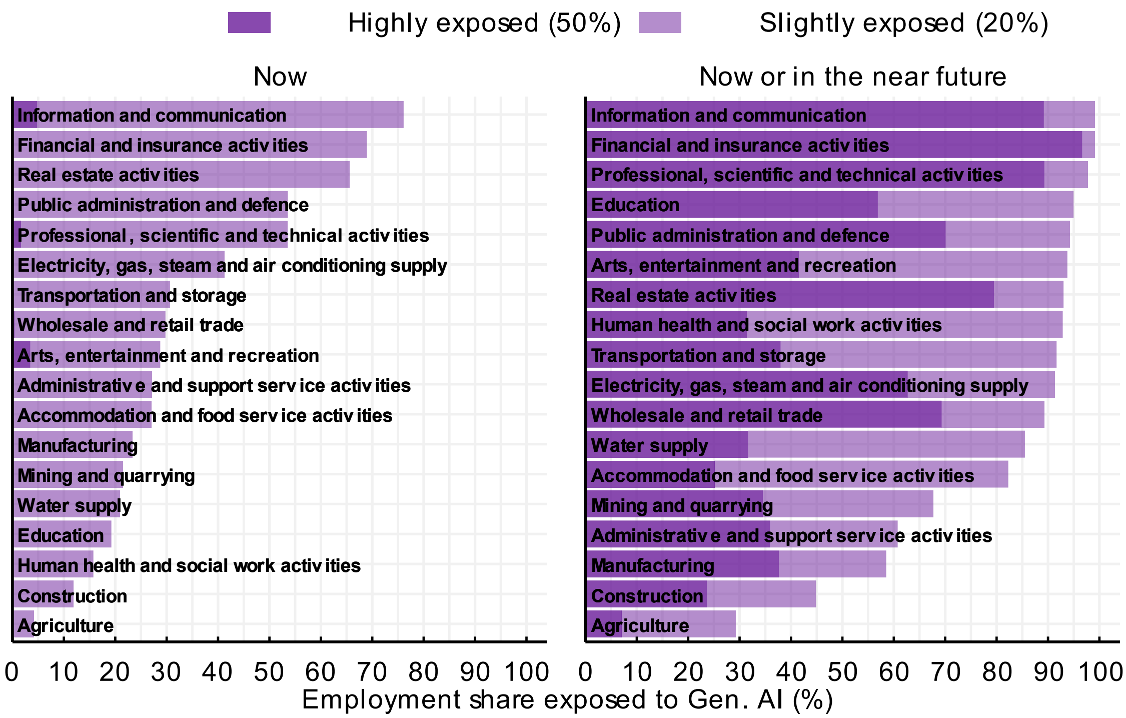
Most sectors of the economy can benefit from Generative AI

Industrial composition is the main driver of differences in exposure to Generative AI across local labour markets. Across sectors in the EU, only 5% of workers in agriculture are considered exposed to Generative AI compared to 71% of workers in the information and communications industry (Figure 3.12). Among the latter, a small share of workers (5%) is considered to be highly exposed right now (i.e., half of their tasks could be significantly accelerated through the use of Generative AI), but this figure might reach almost 90% in the future. The share of highly exposed workers in the financial and insurance industry in the future could be even higher at almost 97%.

Almost half of all sectors could see the majority of their workers highly exposed to Generative AI. In eight out of the eighteen sectors analysed in the European Union, over 50% of employment could be highly exposed in the near future. In four industries, real estate activities, information and communication, professional and scientific activities, and financial and insurance services, the share of exposed workers could exceed 80%.

Figure 3.12. Exposure to Generative AI varies greatly across industries

Labour market exposure to Gen-AI by industry for EU countries, 2022



Source: OECD calculations based on (Eloundou et al., 2023[47]), EU-LFS and employment by occupations tables. See Annex 3.A for more details.

Only a few sectors, such as construction, accommodation, and agriculture appear to not face significant changes due to Generative AI. In those three sectors, less than a quarter of workers could be highly exposed to AI in the future. The common factor across these sectors is the more limited use of Information technology (IT) than elsewhere. In fact, the agriculture sector is expected to have only 7% of its workers highly exposed to Generative AI.

Generative AI exposure is expected to intensify, with industries that currently have a high share of exposed workers being those with a high share of highly exposed workers in the near future as well. It is reasonable to conclude that occupations that make use of Generative AI now will continue to do so in the future. Furthermore, as this technology evolves it is expected that its future use cases will align with its current use cases, therefore deepening exposure levels within the same occupations. Industry level estimates (Figure 3.12) support this conclusion as the most and least exposed industries, in terms of exposure to Generative AI, are expected to remain relatively unchanged.

Box 3.7. How complementary is Generative AI to different occupations?

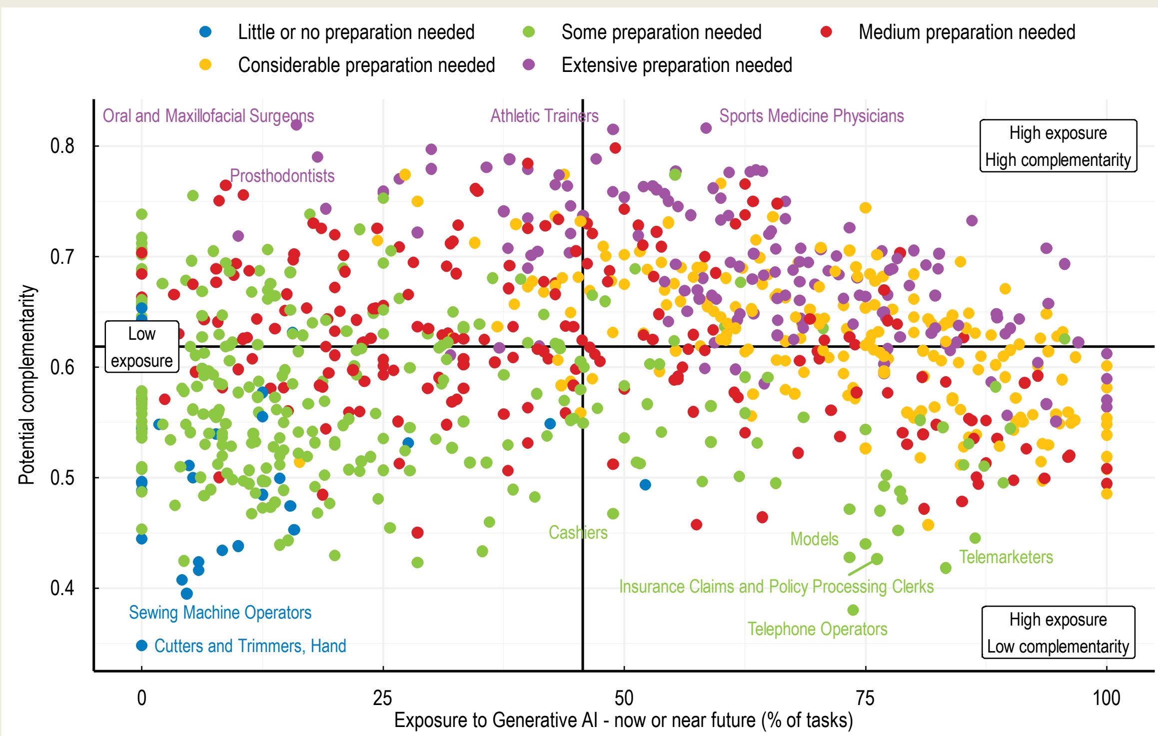
Measuring complementarity with AI technologies across occupations

It is unclear whether these measures of exposure to Generative AI correspond to the replacement or complementarity of workers' tasks. Some occupations involve some aspects that are necessarily human, such as physical presence, responsibility, or face-to-face communication. This methodology (Pizzinelli, 2023[22]) leverages O*NET data on *work context* and *job zones* to propose a framework that conceives complementarity as driven by a set of factors – social, legal, technical – that are independent of exposure itself.

Workers significantly exposed to Generative AI are expected to be impacted differently depending on the extent to which this technology complements or substitutes their work. This methodology attempts to shed some light on this issue by grouping workers into three categories: (1) high exposure-high complementarity, (2) high exposure-low complementarity and (3) low exposure (Figure 3.13).

Figure 3.13. Occupations with higher complementarity tend to require more education and/or training

Exposure to Generative AI now or in the near future and potential complementarity to AI



Source: (Pizzinelli, 2023[22]; Mehdi and Morissette, 2024[49])

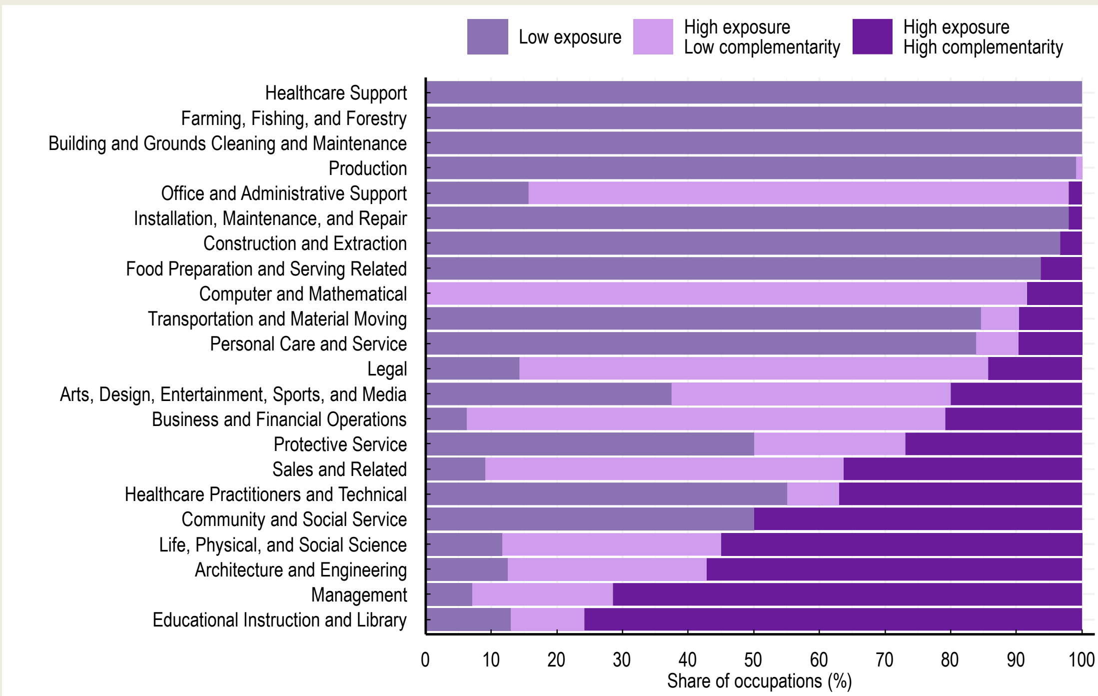
Contrasting exposure to Generative AI and potential complementarity

The relative positioning of occupations in terms of their exposure to Generative AI and potential complementarity provides insights into the likelihood of job displacement and opportunities for productivity enhancement. Occupations on the right-hand side of Figure 3.13 are relatively more exposed while occupations on the top-half present relatively higher levels of complementarity. Occupations on the top right are better positioned to be complemented by Generative AI while occupations on the bottom-right are better posed to be displaced. Nevertheless, as this is a relative measure it is not perfect and can only shed light on the potential for productivity or displacement relative to other occupations. Therefore, it can still not be determined which occupations will be displaced or have their productivity enhanced.

On average, occupations that require more education tend to have higher levels of complementarity with AI technologies. On the other hand, the opposite is true for occupations that only require little or some preparation[a]. The level of preparation refers to a composite measure which combines the levels of education, experience, and training necessary to perform the occupation (O*NET[50]).

Figure 3.14. Most job families contain occupations that can use Generative AI as a complement to their work

Exposure to Generative AI now or in the near future and potential complementarity to AI by job family



Note: Y-axis categories corresponds to job family as defined by O*NET (O*NET, 2024[51]).
Source: (Pizzinelli, 2023[22]; Mehdi and Morissette, 2024[49]).

In most job families, more than half of their relatively highly exposed occupations are complemented by AI technologies. Nevertheless, there are 5 job families that contain mostly occupations that are relatively highly exposed with low levels of complementarity, illustrated at the bottom of Figure 3.14. For example, over 70% of occupations in Management and Educational Instruction and Library have relatively high levels of exposure with low complementarity which indicates they are more susceptible to job displacement. At the opposite end, Healthcare Support; Farming, Fishing, and Forestry; and Building and Grounds Cleaning and Maintenance present low levels of exposure.

Note: [a]Note that the complementarity measure considers job zones as a measure of complementarity as occupations with longer periods of required professional development would have a greater ability to integrate AI knowledge into their training programs and thus equip future workers with complementary skills. Therefore, some of this dispersion across skills is a mechanical result given the way the complementary measure is constructed. Nevertheless, job zones make up only a small part of the complementarity measure with work contexts making up largest part.
Source: (Pizzinelli, 2023[22]; Mehdi and Morissette, 2024[49]).

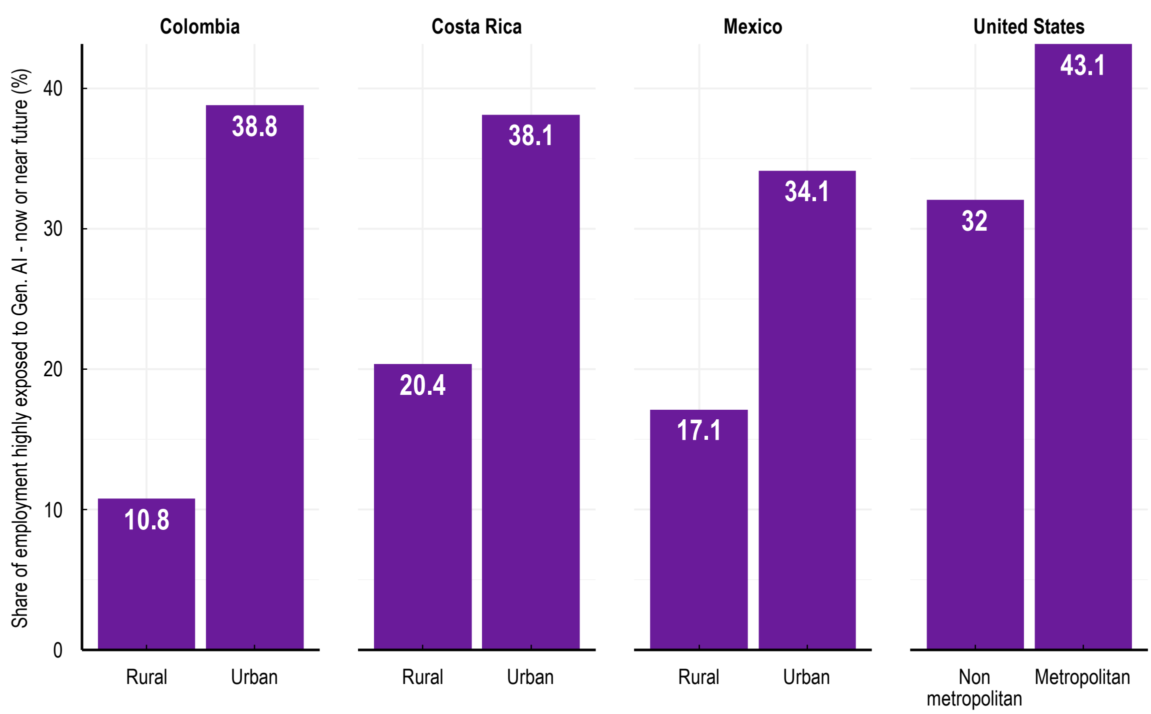
Metropolitan workers experience higher exposure to Generative AI than non-metropolitan workers

The concentration of industries within or outside cities drives disparities in Generative AI exposure between urban and non-urban labour markets. Certain industries, such as financial services or technology development, often concentrate around metropolitan areas while non-metropolitan or rural areas tend to rely on industries with a different production structure, such as agriculture or manufacturing. Similarly, workers are also spatially concentrated, with highly skilled workers often being more present in clusters in or around a few metropolitan areas.

Workers in urban and metropolitan areas are significantly more exposed to Generative AI than workers in the rest of the country, by every measure (Figure 3.15). The exact gap varies by country but, on average, labour markets in urban areas are over twice as exposed than non-urban labour markets. This average is primarily driven by Colombia where urban regions are 2.6 times more exposed than non-urban regions. Nevertheless, if we Colombia is not included, urban regions are 74% times more exposed than their non-urban counterparts, on average.

Figure 3.15. Labour markets in urban areas are significantly more exposed to Generative AI than non-urban areas.

Share of workers highly exposed to Gen-AI now or in the near future by area type – 2023

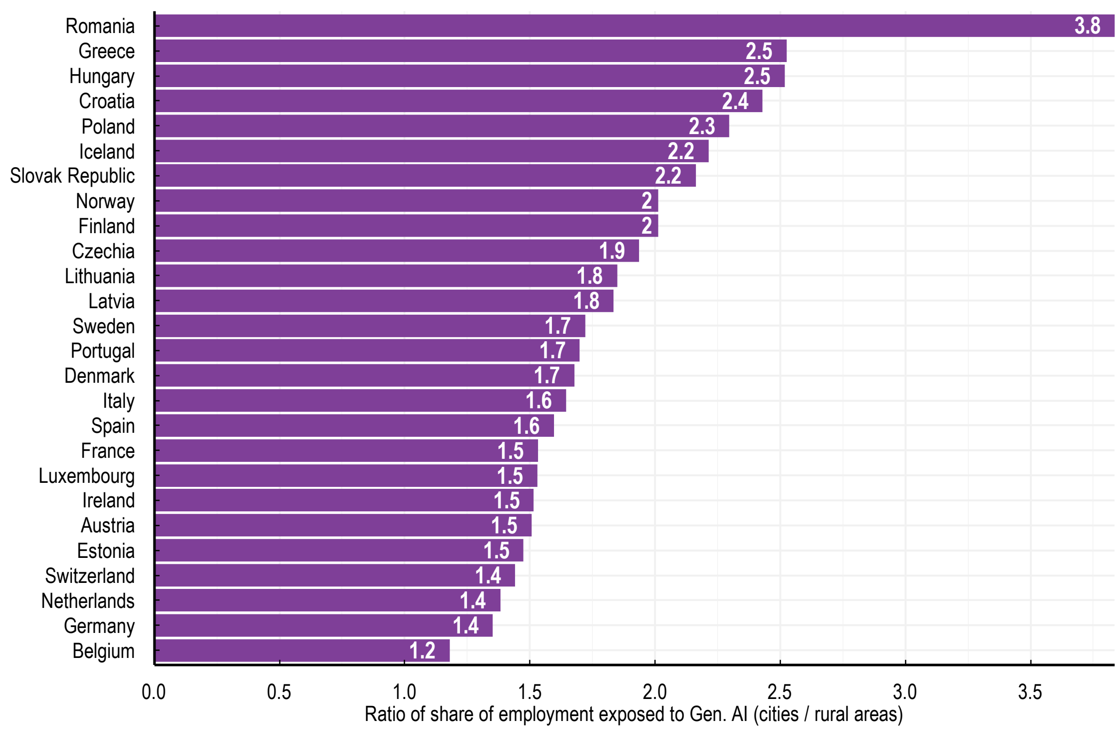


Note: The definition of urban and rural may differ across countries so estimates are not directly comparable. Country selection is based on data availability. The use of different category names is done to align with each country's classification. In the US, Metropolitan and non-metropolitan areas are groups of US counties and are defined and named accordingly the US-BLS.
Source: OECD calculations based on (Eloundou et al., 2023[47]), metropolitan level Occupational Employment and Wage Statistics (OEWS) and labour force survey data (LFS). See Annex 3.A for more details.

In European Union countries, workers in cities are significantly more exposed than elsewhere. Examining the exposure of workers to Generative AI by the degree of urbanisation (DEGURBA[12]), shows that cities are significantly more exposed than rural areas (Figure 3.16). Across the European Union, over 36% of jobs in cities are exposed to Generative AI. In contrast, in rural areas, only 21% of jobs are considered exposed to Generative AI. In some countries, such as Poland, Hungary or Greece, the share of employment exposed to Generative AI is at least twice as high in cities compared to rural areas.

Figure 3.16. Cities are significantly more exposed than rural areas

Ratio of share of employment exposed to Generative AI in EU countries - 2022



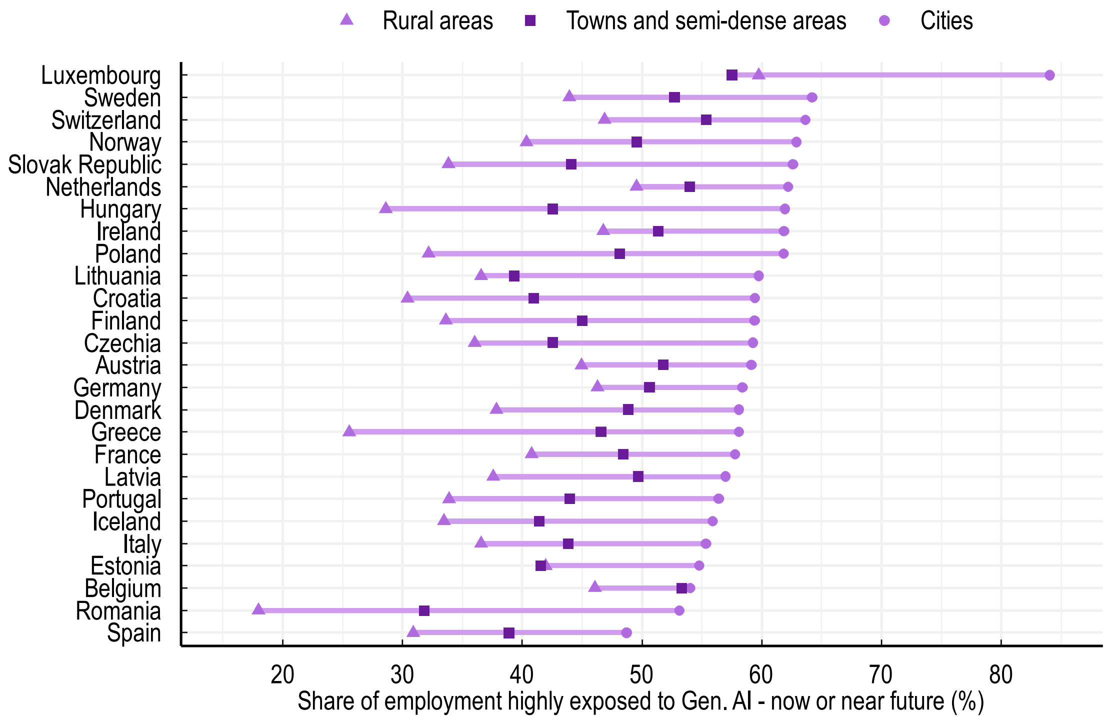
Note: The degree of urbanisation (DEGURBA) is a classification that indicates the character of an area. It classifies the territory of a country on an urban-rural continuum.
Source: OECD calculations based on (Eloundou et al., 2023[47]) and EU-LFS. See Annex 3.A for more details.

The gap between rural areas and cities in exposure to Generative AI is expected to vary significantly by country. In the near future, the rural-urban gap in exposure could vary from just under 8% in Belgium to close to 35% in Romania (Figure 3.17). Luxembourg is the only country where rural areas are more exposed than towns and/or semi-dense areas. In addition, Luxembourg is expected to have the most exposed urban population in the European Union with 84% of employment in cities expected to be exposed to Generative AI in the near future.

Aside from a few outliers, cities across EU countries are expected to have a similar average exposure to Generative AI. Setting aside Luxembourg and Spain, which have the most and least exposed cities respectively, the share of exposed workers in EU cities is expected to differ by up to 11 percentage points, ranging from 53.1% in Romania to 64.2% in Sweden. However, the difference between exposure (now or in the near future) in rural areas differs by 31 percentage points across countries in the European Union, with the Netherlands having the most exposed and Romania the least exposed rural areas (Figure 3.17).

Figure 3.17. Cities are, and will be, significantly more exposed to Generative AI

Share of workers highly exposed to Gen-AI now or in the near future by the degree of urbanisation in EU countries,-2022



Note: The degree of urbanisation (DEGURBA) is a classification that indicates the character of an area. It classifies the territory of a country on an urban-rural continuum.
Source: OECD calculations based on (Eloundou et al., 2023[47]) and EU-LFS. See Annex 3.A for more details.

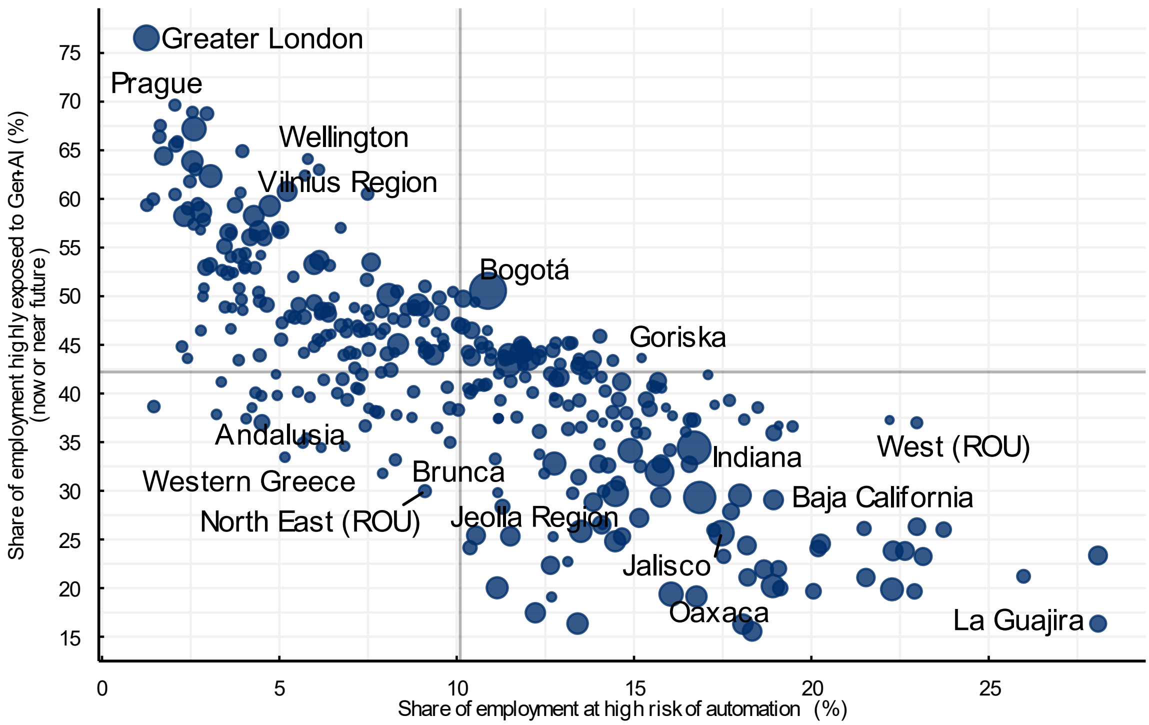
Shifting landscapes: The impact of AI on people and places

The latest wave of AI technologies represents a departure from the development of narrow-purpose digital technologies towards more general-purposed solutions. This section explores how labour market impacts differ between narrow-purpose technologies and Generative AI technologies, examining in detail which economic groups are most exposed and how relative exposures are distributed across regions. Results indicate that the impact of these technologies differs according to a worker's level of education and gender. Furthermore, a massive shift is observed in the distribution of this impact across OECD regions.

OECD regions previously only mildly at risk of automation are now significantly exposed to Generative AI and vice versa. There is a clear negative correlation between the expected share of highly exposed workers to Generative AI in the near future, and a region's share of workers at high risk of automation (Figure 3.18). This trend is statistically significant despite the presence of a few regions that display low values in both estimates, such as Andalusia (Spain), Central Greece, and Sicily (Italy), among others.

Figure 3.18. Regions with a low risk of automation are now highly exposed to Generative AI, and vice-versa

Share of employment highly exposed to Gen-AI now or in the near future and at high risk of automation, latest available year

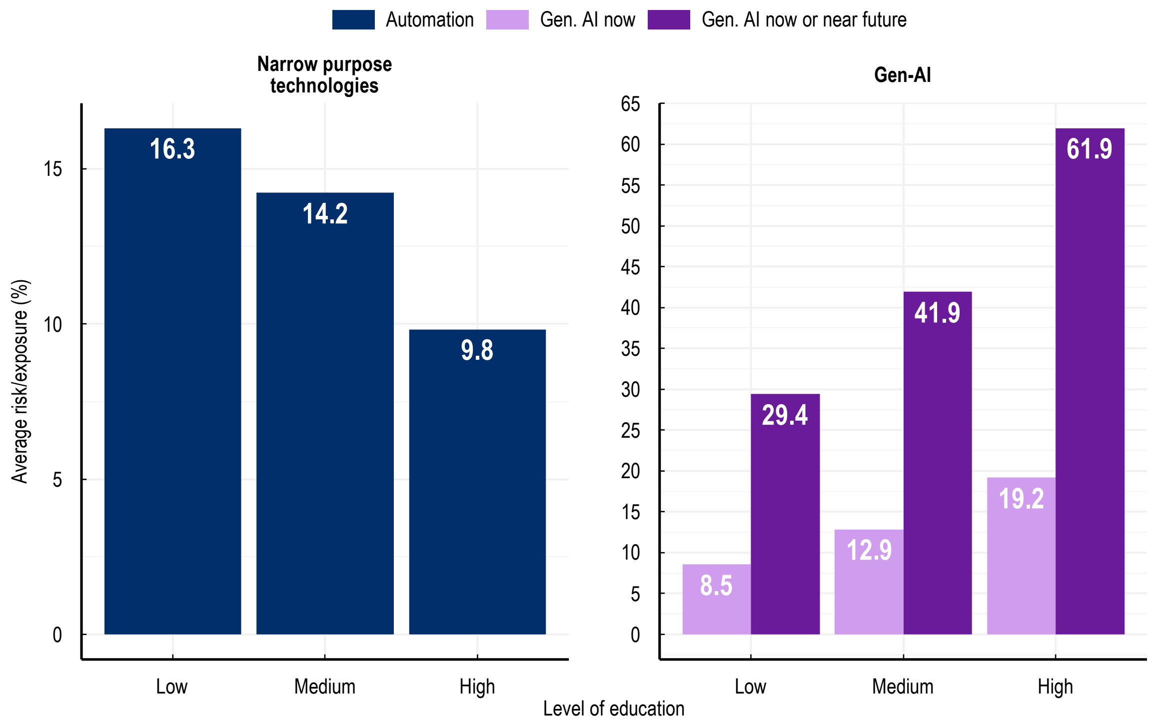


Note: Horizontal and vertical lines represent unweighted regional averages. Size of bubble represents labour market size (employment).
Source: OECD calculations based on (Eloundou et al., 2023[47]), (Lassébie and Quintini, 2022[27]), labour force survey and employment by occupations tables. See Annex 3.A for more details. Estimates for TL-2 regions except for Slovenia which is TL-3. Last available year is 2024 for Canada and Korea, 2023 for Australia, Colombia, Costa Rica, Mexico, New Zealand, the United Kingdom, and the United States, 2022 for all others.

Workers with a higher level of education, who were previously at lower risk of automation, are now significantly more exposed to Generative AI than their less educated peers. Generative AI is causing a large shift in the impact of technology on local labour markets, as previous waves of innovation – not only involving digital technologies but also other technologies – had a stronger impact on less educated workers who were more exposed (Figure 3.19). Less educated workers tended to be between 60% and 70% more at risk of automation than their highly educated counterparts. Workers with higher levels of education are now more than twice as exposed relative to less educated workers, and this gap is expected to be maintained as both groups of workers become more exposed to Generative AI over time. The expected gap in the exposure to Generative AI between workers with high and low levels of education can be attributed to the large overlap between Generative AI and the tasks carried out by highly educated workers. This technology is not only useful for a larger set of tasks but it also is increasingly helpful with both cognitive and non-routine tasks, which are significantly more common among highly skilled workers.

Figure 3.19. Highly educated workers are significantly more exposed to Generative AI, and this gap will only increase

Average exposure to Gen-AI and risk of automation by level of education, last available year



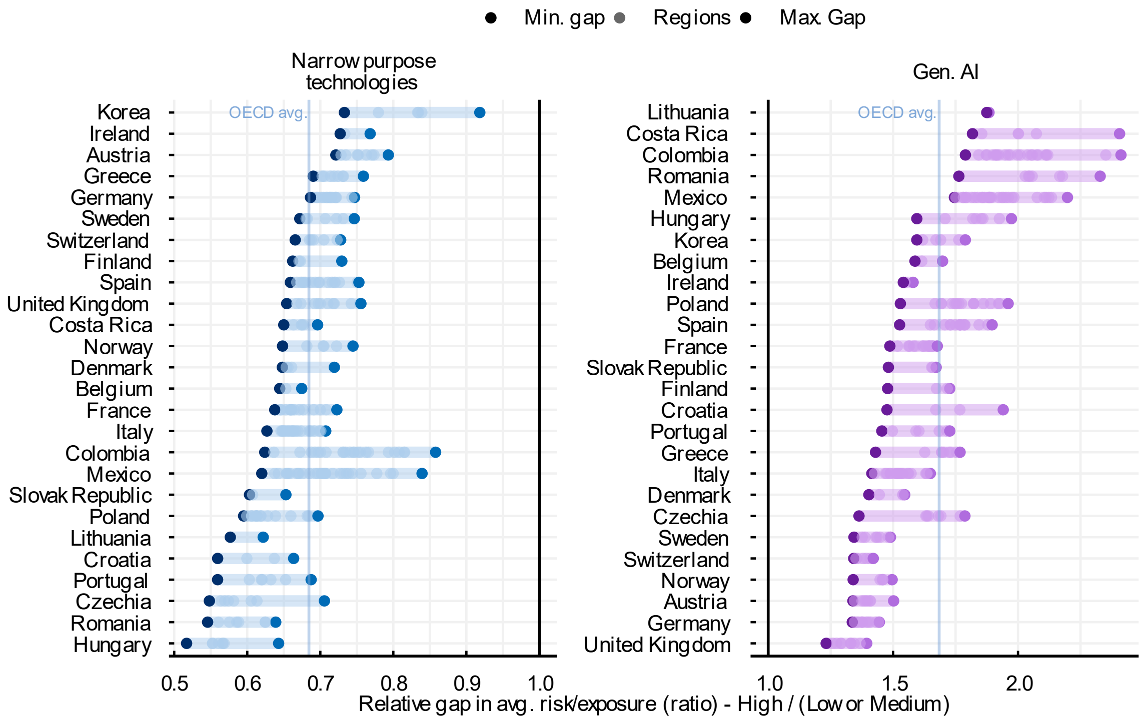
Note: Level of education according to ISCED 2011 (UNESCO, 2012[52]). Low corresponds to first digits 0-2, medium corresponds to first digits 3-4, high corresponds to first digits 5-8. Figure represents the weighted average across all OECD countries for which there is data. The estimates are weighted averages based on employment by level of education.

Source: OECD calculations based on (Eloundou et al., 2023[47]), (Lassébie and Quintini, 2022[27]), labour force survey and employment by occupations tables. See Annex 3.A for more details.

The large differences in exposure and risk of automation across levels of education is consistent across all regions (Figure 3.20). High-skilled workers are expected to be more exposed to Generative AI than the rest of the workforce in all regions. In just over 10% of regions, mostly non-urban regions in Latin America and Romania, high-skilled workers are expected to be at least twice as exposed to Generative AI as the average non-high skilled workers. As shown in Figure 3.20, the relative gap is much lower regarding narrow-purpose technologies as, across regions, the risk of automation for high-skilled workers ranges from 50% to 90% of the risk faced by low- and medium-skilled workers.

Figure 3.20. The overall trend in exposure across levels of education holds for all regions individually

Relative gap in exposure estimates between highly educated workers and low- and medium-educated workers across regions, last available year

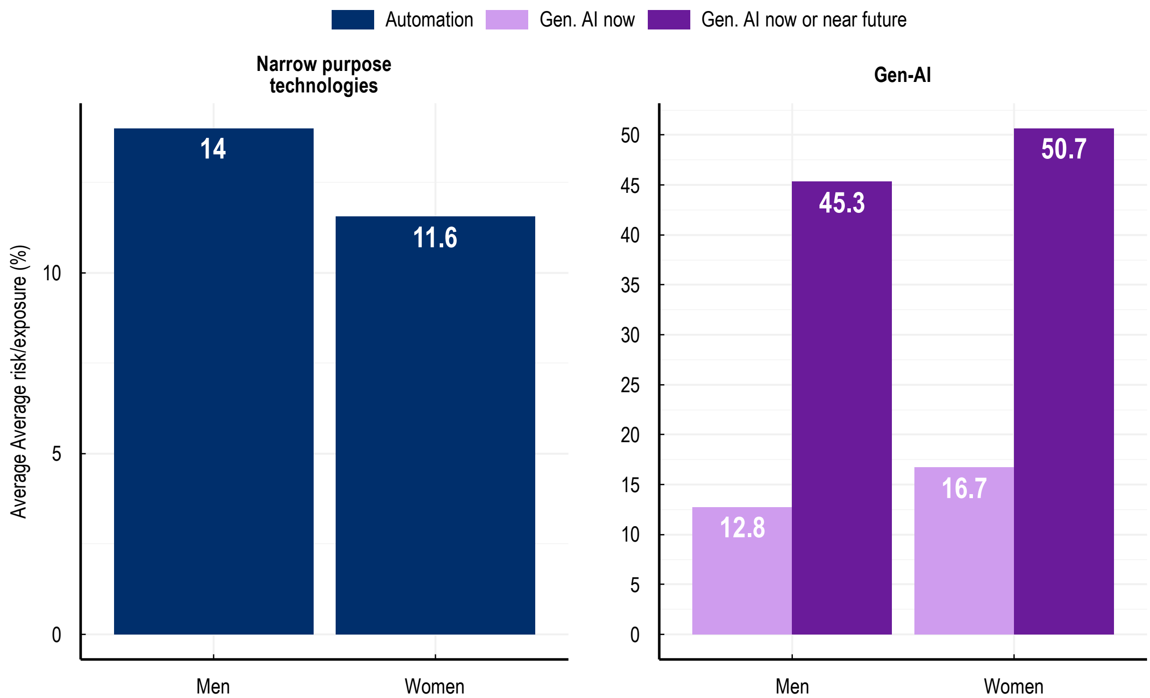


Note: Figure represents the un-weighted regional average for all OECD for which there is reliable data. Relative gap represents the average exposure of highly educated workers relative to the average exposure of medium low educated workers. Level of education according to ISCED 2011 (UNESCO, 2012[52]). Low corresponds to first digits 0-2, medium corresponds to first digits 3-4, high corresponds to first digits 5-8.
Source: OECD calculations based on (Eloundou et al., 2023[47]), (Lassébie and Quintini, 2022[27]), labour force survey and employment by occupations tables. See Annex 3.A for more details.

Women are somewhat more exposed to Generative AI than their male counterparts, which is again a reversal of previous trends. On average, the share of tasks done by women that can be sped up by the use of LLMs is currently 4 percentage points higher than that of men, and this gap is expected to slightly increase to over 6 percentage points in the near future (Figure 3.21).

Figure 3.21. Women are slightly more exposed to Gen-AI, a different trend from prior forms of automation

Average exposure to Gen-AI and risk of automation by sex, last available year

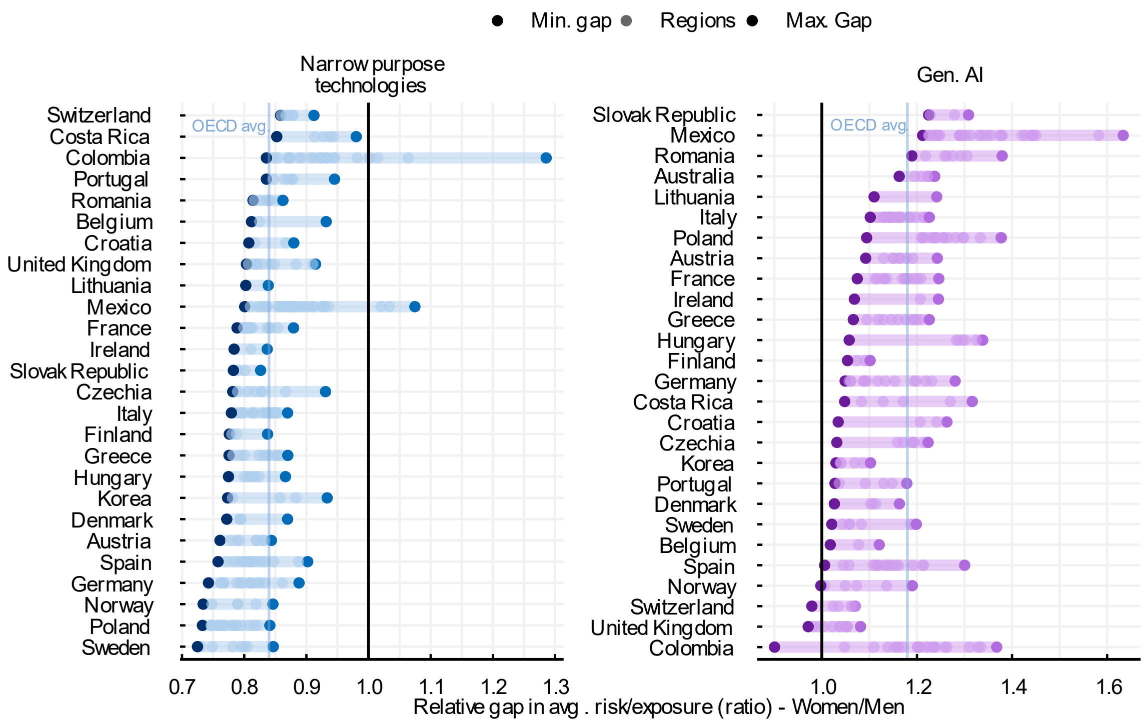


Note: Figure represent the weighted average across all OECD countries for which there is reliable data. The estimates are weighted averages based on employment by gender.
Source: OECD calculations based on (Eloundou et al., 2023[47]), (Lassébie and Quintini, 2022[27]), labour force survey and employment by occupations tables. See Annex 3.A for more details.

The disparity in exposure between men and women is generally consistent across regions except for a few regions where men are significantly more exposed to Generative AI than women (Figure 3.22). Men tend to take on jobs that are at higher risk of automation in all regions studied. On the other hand, women tend to perform jobs that are expected to be more exposed to Generative AI in most but not all regions. Notable exceptions to this are La Guajira (Colombia), Oslo and Viken (Norway), Zurich (Switzerland), Yorkshire and The Humber (United Kingdom), Greater London (United Kingdom) and South East England (United Kingdom). In addition to differences in occupational uptake, these regional disparities also reflect variations in sectoral composition across regions.

Figure 3.22. Men are consistently more exposed to narrow-purpose technologies across regions, while women are most exposed to Generative AI in most regions

Relative gap in exposure estimates between men and women across regions, last available year



Note: Figure represents the un-weighted regional average for all OECD for which there is reliable data. Relative gap represents the average exposure of women relative to the average exposure of men.

Source: OECD calculations based on (Eloundou et al., 2023[47]), (Lassébie and Quintini, 2022[27]), labour force survey and employment by occupations tables. See Annex 3.A for more details.

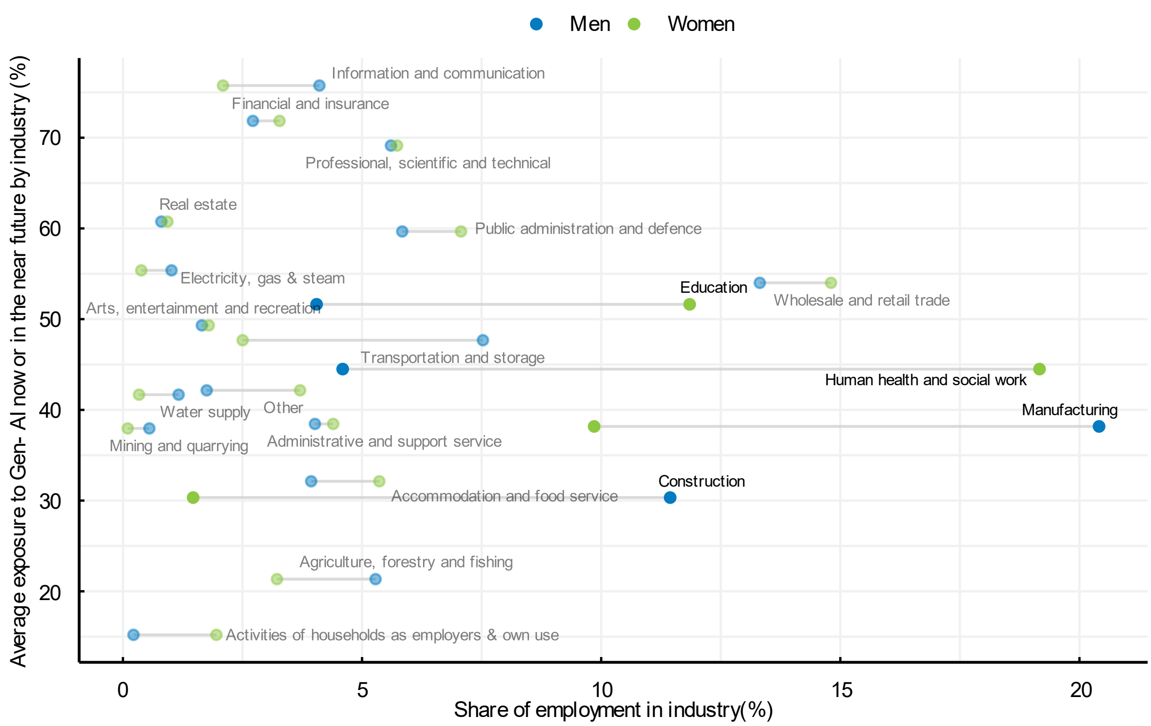
Examining the gender composition of industries sheds some light on the determinants of gender differences in Generative AI exposure. This further highlights the ripple effects of varying industrial compositions on the exposure of different economic groups. The share of men and women in each industry (as opposed to the share of employment in an industry that are men or women) varies greatly across industries (Figure 3.23). For example, in the real estate sector, approximately 2% of men and 3% women are exposed. This similar share is understandable, as the industry is relatively small in terms of employment, and its gender composition is balanced. On the other hand, manufacturing and construction (less exposed) concentrate a significantly higher share of men while health (more exposed) concentrates a significantly higher share of women.

Education, human health and social work are the primary industries driving high exposure to Generative AI for women. These industries account for over 30% of female employment but only for around 9% of male employment. In addition, these industries are expected to have a relatively high level of exposure to Generative AI. Education, which concentrates close to 12% of female employment, is expected to have an exposure to Generative AI that is 4 percentage points larger than average (44.4%), while human health and social work is close to the mean. Nevertheless, the occupations that make up these industries are quite broad as, for example, human health and social work includes both office jobs (often clerical) and physical jobs such as doctors or physicians. This simple analysis does not reflect potential gender differences within these industries that might further explain the gender gap in Generative AI exposure.

Conversely, industries with mainly male workers are less exposed to Generative AI. Construction and manufacturing, which together account for nearly 32% of male employment, have a below-average exposure to Generative AI, with construction approximately 18 percentage points and manufacturing 9 percentage points below the average. Furthermore, the gender gap in these industries is substantial as they account for only 12% of female employment. Other industries with a higher exposure to Generative AI employ a significant share of both men and women, but the distribution of employment between genders in these industries is more balanced, therefore contributing less to the gender gap in Generative AI exposure (Figure 3.23).

Figure 3.23. The gender gap in exposure to Generative AI reflects higher shares of women in exposed sectors

Share of employed men and women in each industry for EU countries, 2022



Notes: Highlighted sectors are the industries where the employment gap between men and women is most relevant, this is further discussed in the text.
Source: OECD calculations based on (Eloundou et al., 2023[47]), labour force survey and employment by occupations tables. See Annex 3.A for more details.

Zooming in on specific occupations

The latest wave of AI will not affect all groups of occupations to the same extent. While most occupations are, or will be, affected in some way or another by the latest wave of AI, some occupations may face more considerable change. The rest of this section zooms in on possible implications for jobs and workers in cultural and creative occupations (OECD, 2022[53]), healthcare[13], and software-related occupations[14].

At least some cultural and creative occupations are extensively using Generative AI, which has already sparked tensions in the industry. Generative AI tools can help creative workers come up with ideas, write scripts and text, and generate audiovisual content, among others. This has raised concerns about copyright, as the way Generative AI models handle copyrighted content remains unclear, and existing legal frameworks often fall short in addressing these issues. Workers in the industry have expressed concerns over the use of this technology, with some escalating their grievances to the point of strike action (Box 3.8).

Box 3.8. Use of AI in cultural and creative sectors

Cultural and creative sectors (CCS) is a term used to describe a range of activity which has its basis in creativity and can typically be exploited through intellectual property rights. Broadly, CCS includes the following sectors: advertising, architecture, book, newspaper and magazine publishing, dance, design, fashion, film and television, libraries and archives, museums, art galleries and heritage sites, music, radio, theatre, video games, and visual arts. Each of these subsectors require different skills and have different dynamics and business models. Many jobs in CCS are non-cultural and creative jobs (e.g., an accountant working for a film company) and therefore these sectors are exposed to AI risks associated with many occupations beyond just cultural and creative ones. There are several examples of the impact of AI in these sectors.

Film and television

AI has had a significant impact on the film and television industry in multiple areas. Machine learning has been used in the visual effects industry (VFX) for over a decade in tasks such as Rotoscoping (tracing the outline of an element of an image to move or replace it), motion tracking for computer generated images (CGI), and picture or colour adjustments. Recently, AI use in VFX includes extensive moving picture generation and digital asset manipulation, as well as helping to generate code for some of the underlying programming of VFX engines.

Generative AI also has applications in idea generation, script writing and editing. While there is yet to be a blockbuster hit with a screenplay written by AI, Generative AI is being used to help generate ideas, edit, and even provide first drafts of scripts. Concerns over the implication of Generative AI for the writing industry in the United States contributed to the Writers Guild of America strike action in 2023. This large-scale industrial dispute was primarily due to differences in contract terms for writers working on live broadcast vs streaming content. However, the issue of Generative AI was also raised as a significant concern during the action. Resolution of the strike included agreements on new regulations for the use of Generative AI in script writing.

Music

AI has been used in music production for a number of years, but advances in generative AI models could lead to greater use of AI-generated vocals, instrumentals, and lyrics. Free AI music generators are already on the market, allowing people to create new musical pieces with ease. Similar to concerns with the use of LLMs in the publishing industry, this type of Generative AI raises significant issues in relation to copyright and the ownership of AI-generated music. Machine learning models are also playing an increasing role in shaping musical tastes, with major streaming platforms such as Spotify using machine learning algorithms to recommend music to listeners. In addition, AI is being used in less obvious ways in the music industry by, for example, helping rights management companies to identify use of copyrighted material in film, television, and the internet to establish royalty payments and protect copyrights.

Source: (OECD, 2023[54]).

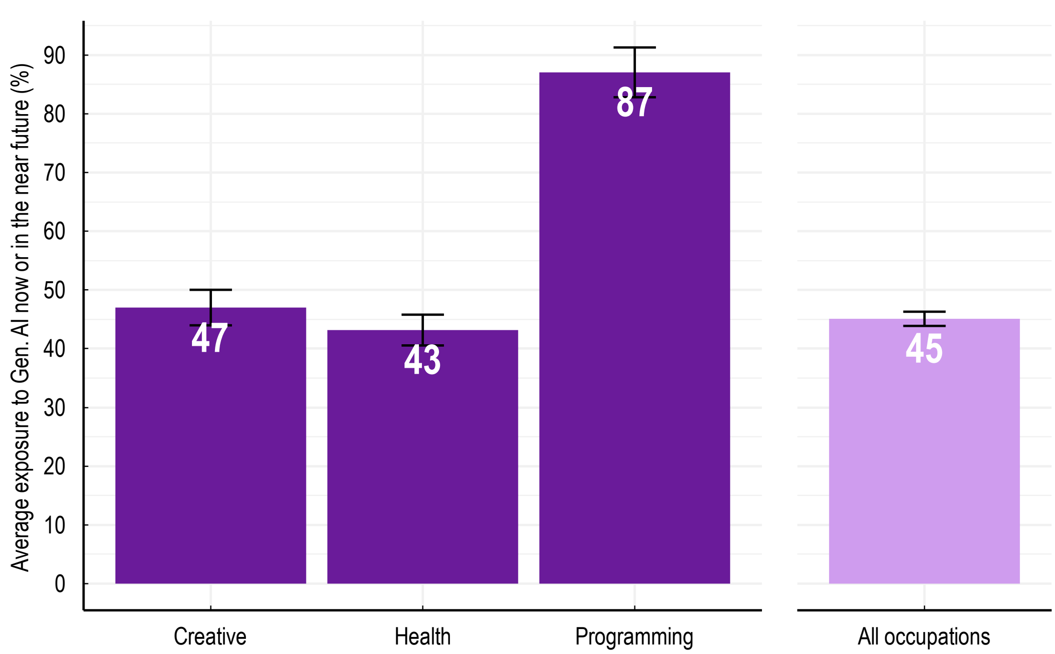
Similarly, software related occupations are also extensively using Generative AI and qualitative evidence suggest they have benefited from increased productivity and job satisfaction. These occupations, which include programmers, database architects and software developers, for example, already have multiple tools at their disposal which help them write and correct code, organise and clean data, and produce digital designs, among others (Box 3.10).

The health sector faces significant labour shortages in certain regions and occupations (Box 3.9**).** Although this sector has a lower labour market exposure to Generative AI (Figure 3.24) than average, this technology could still help address labour shortages as there is a relevant share of occupations that are highly exposed and therefore offer scope for Generative AI adoption (Figure 3.26). Health professionals in charge of records, such as medical record specialist, are the most exposed within this group. In regard to doctors, physicians, dietitians, and general physicians count among the most exposed. On the opposite end of exposure are medical professionals whose jobs are not limited to diagnosis and who conduct physical procedures, such as surgical assistants, dental hygienists, and paramedics.

In addition, applications of AI in the health sector are diverse, including development of pharmaceuticals, diagnostics, and behavioural interventions through chatbots. For example, Japan has been at the forefront of AI innovation and strives to actively integrate AI into its healthcare system to enhance efficiency and address challenges, such as labour shortages (Cabinet Secretariat, 2024[55]; Ministry of Health, 2023[56]). The Japan Agency for Medical Research and Development (AMED) is working to support the development of medical devices that utilize AI (AMED, 2024[57]). These efforts aim to improve patient outcomes, streamline hospital operations, and mitigate the effects of an ageing population and workforce shortages (Box 3.9).

Figure 3.24. Software jobs are significantly more exposed while the cultural, creative and health occupations are closer to the labour market average

Average exposure to Gen-AI now or in the near future by occupation type



Note: Figure represents the weighted average across all OECD for which there is data, see Annex 3.A for more details. Top and bottom lines indicate the 95% confidence interval. Source: (Eloundou et al., 2023[47])

Box 3.9. Using AI to deal with labour shortages in the health sector

Nursing care industry in Japan

Japan's nursing care industry is facing a serious labour shortage. The number of people requiring nursing care is increasing due to the declining birthrate and ageing population. According to estimates done by the Ministry of Health, Labor and Welfare, 570 000 new nursing care workers will be needed by 2040. Under these circumstances, providing high-quality nursing care services efficiently to those requiring care by actively utilizing digital technology has become an important issue in Japan.

AI has attracted a great deal of attention to solve these issues in the nursing care and welfare industry. There are solutions already available, including DRIVEBOSS, which helps to plan transportation routes and schedules to take facility users to and from nursing care facilities. AI Sakura-san, a voice conversation customer service system, is also attracting attention as a solution to labour shortages. AI Sakura-san takes over the work of in-house help desks, call centres, and inbound customer service. Given the prevalence of night shifts in the nursing care and welfare industry, there are high hopes for the system to be able to communicate with the elderly on behalf of staff.

AI innovation for the health sector in Japan

Japan's J-Startup program (Box 3.3) links the public and private sector to foster AI in various industries. Startups are selected among a pool of over 10 000 projects, with examples in the healthcare sector including:

- ***Aillis***: Uses AI for real-time diagnostic assistance and aims to alleviate the shortage of specialists by providing an emergency medical coordination system to share medical information remotely. This includes remote support through live video streaming, surgery support, and linking doctors to depopulated and remote areas to provide medical support.
- ***Ubie***: Optimises the patient experience by streamlining in-hospital operations through AI online interviews and matches patients with the relevant medical institution. This shortens not only the process of patient uptake but also their stay in the hospital. It is currently used by over 1700 hospitals and clinics.
- ***AIM***: Specialises in AI-driven endoscopic diagnostic support for GI cancers, improving early detection and treatment planning. There is a shortage of endoscopists in Japan and the world, and 20% of cancers are overlooked due to limitations of human observation.

AI to address shortages of medical professionals in the United Kingdom

The UK is experiencing a significant shortage of medical professionals and is turning to AI to help address this challenge. By 2036, England is expected to face a shortfall of 260 000 to 360 000 doctors, nurses, and other health professionals, despite increasing recruitment of foreign-trained staff. Administrative demands and documentation requirements are further compounding this problem, decreasing the time available for patient care, and leading to greater workloads and burnout.

The National Health Service (NHS) in the UK has convened an expert group to explore ways in which AI can support healthcare by automating routine tasks and augmenting the abilities of clinical professionals. Technologies under consideration include speech recognition and natural language processing (NLP) for clinical documentation, which could help free up time for medical professionals to focus on patient care, as well as automated image interpretation, robotics for interventions and rehabilitation, and predictive analytics using AI.

Planning and commissioning of local services will differ across regions. This approach aims to enable each region to tailor technologies to their unique needs and challenges, addressing regional priorities, and supporting the best use of available workforce and talent.

COVID-19 vaccines in El Chaco, Argentina

Argentina took a different approach on AI and healthcare, aiming to use behavioural nudges through a Whatsapp chatbot to increase vaccination rates. In 2022, in a randomised controlled trial (RCT), the country launched a WhatsApp chatbot, integrated with a booking system, aimed at increasing vaccination rates in the province with the lowest COVID-19 vaccination rates, El Chaco. The Ministry of Health of El Chaco collaborated with the private sector through a social impact company to increase vaccination rates by helping people to schedule their appointments and sending reminders.

The programme was highly effective as the treatment group's vaccination rate was three times higher than that of the control group. Following the success of the RCT, the province of Tucuman launched a chatbot in 2024 with the aim to increase routine vaccinations such as influenza and COVID-19 boosters.

Sources: (AISmiley, 2024[58]), (Brown et al., 2024[59]), (Aillis, 2024[60]), (J-Startup, 2024[61]), (Ubie, 2024[62]), (AI Medical Services Corporation, 2024[63]), (NHS England, 2024[64]), (NHS, 2023[65]).

The use of AI in healthcare presents significant ethical and privacy concerns. One of the main risks involves the handling of large volumes of personal health data, raising concerns about how this information is collected, stored, and used, and whether it could lead to breaches of patient confidentiality (Khan et al., 2023[66]). AI algorithms also risk perpetuating biases if they are trained on biased data, potentially resulting in unequal treatment for certain patient groups. Additionally, concerns about accountability arise when AI makes errors in diagnosis or treatment, as assigning responsibility can become challenging in such cases (Nicholson Price II, 2019[67]). Setting standards to protect patient data, maintaining confidentiality, and avoiding exacerbation of inequalities are key ethical considerations that need to be tackled as the use of AI solutions in the healthcare sector become more common. Changes in medical education may also be required to prepare healthcare professionals for evolving roles and responsibilities.

Generative AI could lead to a greater transformation of cultural, creative and software occupations than other types of occupations. On average, the potential of Generative AI to support or take over specific work tasks are expected to lead to a 2 percentage points higher share of exposure in cultural and creative occupations than for all occupations on average. In software occupations, the already existing integration of AI tools and the progress in development of new tools that facilitate programming by creating or optimising software code, such as GitHub Co-pilot (Box 3.10), results in even greater exposure to Generative AI, which could reach up to 87% of workers (42 percentage points above the average).

Box 3.10. Use of AI in the programming industry

GitHub Copilot is an AI-powered coding assistant developed by GitHub in collaboration with OpenAI. It leverages machine learning models to assist developers by providing code suggestions and autocompletions directly within their integrated development environment. Copilot can help generate whole lines or blocks of code, making it easier and faster to write software, reducing repetitive tasks, and enhancing productivity.

The tool has a significant positive impact in the production of software developers. A study quantifying GitHub Copilot's impact on developer productivity demonstrates that its users had a higher rate of completing tasks and did so 55% faster than developers who did not use the tool. Letting GitHub Copilot shoulder the routine and repetitive work of development reduced the cognitive load of developers and allowed for better productivity. This tool is being used by 90% of the Fortune 100 companies and by more than 100 million developers.

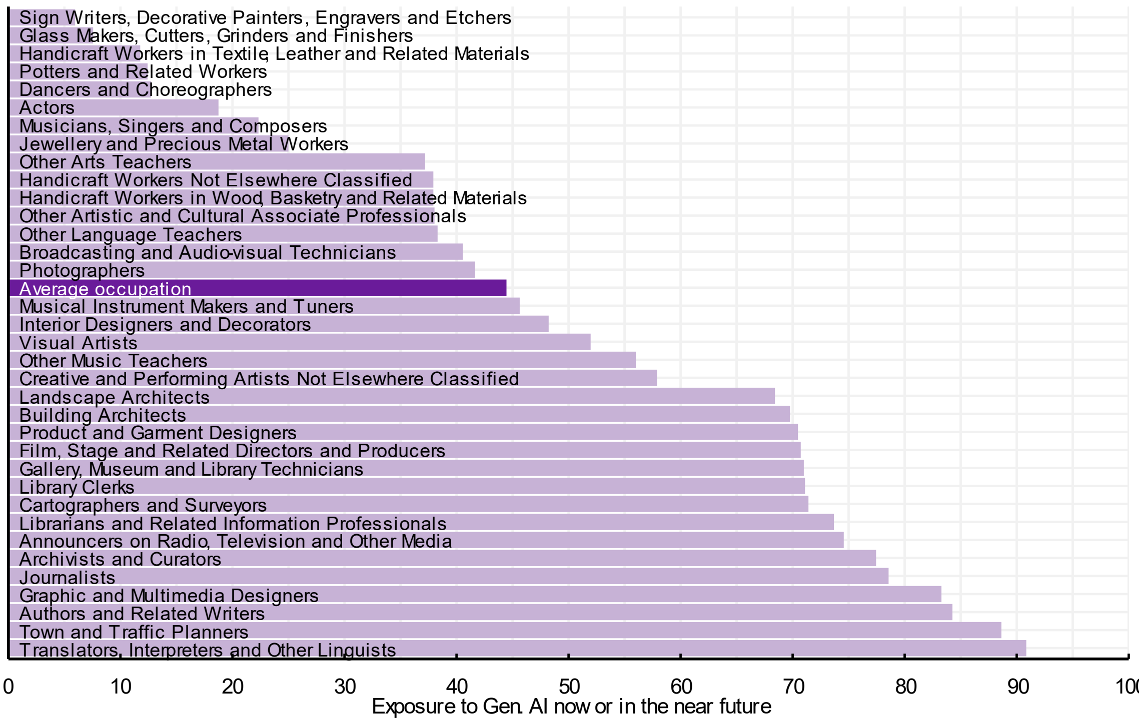
Between 60–75% developers reported feeling more fulfilled in their job, less frustrated when coding, and able to focus on more satisfying work when using the tool. It also helped with conserving mental energy, as developers reported that GitHub Copilot helped them stay in the flow (73%) and preserve mental effort during repetitive tasks (87%). That is associated with developer happiness, since previous research shows that certain types of work are mentally draining, and that context switches and interruptions can ruin a developer's day.

Source: (Kalliamvakou, 2022[68]).

Some cultural and creative occupations are expected to be up to 90% exposed now or in the near future, unlike many others that are much less exposed. The more cultural occupations such as dancers, choreographers, glassmakers, or potters, mainly consist of tasks that are least likely to be significantly accelerated through the use of Generative AI (Figure 3.25). These occupations generally require more physical skill or presence, meaning they generally involve a greater share of low-exposure tasks. Conversely, occupations such as journalists, translators, or graphic designers, involve more computer-related tasks and do not have a substantial physical aspect, so these occupations are expected to be highly exposed. Moreover, other types of Generative AI technologies beyond LLMs (such as image and sound generation technologies) are already beginning to make an impact in cultural occupations that may have been thought to be low risk for example, generative image technology can create and manipulate so-called 'digital doubles', replicating an actor's likeness for film or television. Similarly, in music, generative sound technology can automate the generation and production of music.

Figure 3.25. Most cultural and creative occupations are more exposed than the average occupation, up to more than double

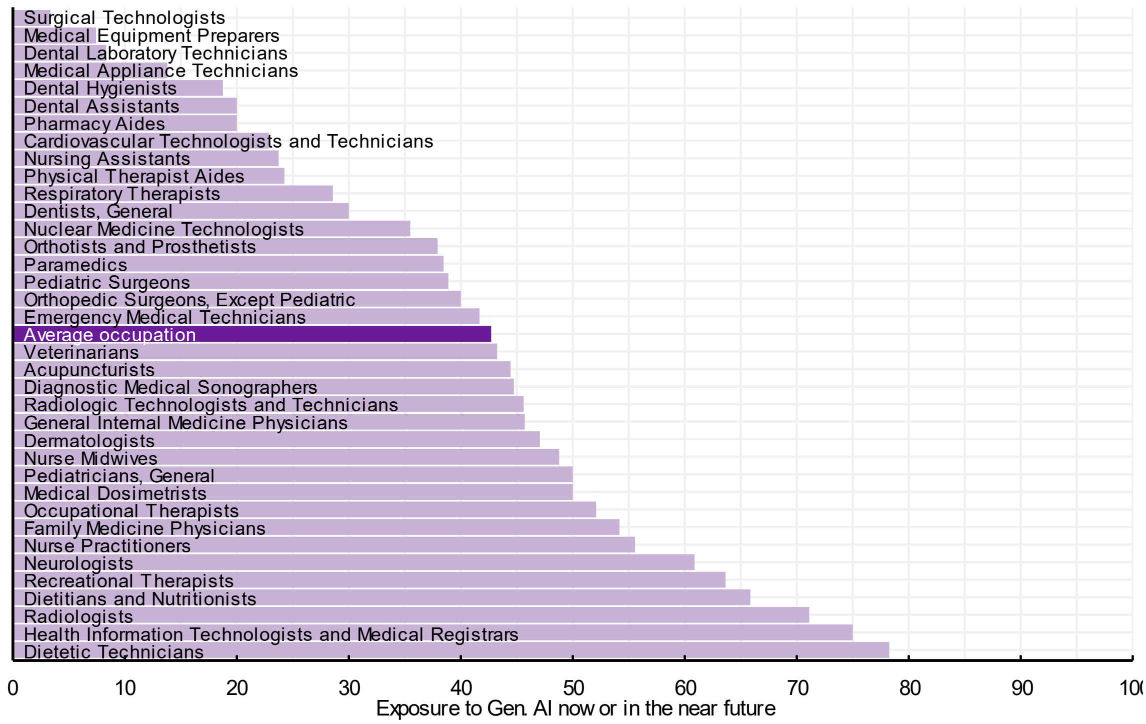
Average exposure now or in the near future, cultural and creative occupations



Note: Cultural and creative occupations are defined in ISCO at the 4-digit level according to the Eurostat definition used by the OECD.
Source: (Eloundou et al., 2023[47]), (OECD, 2022[53]).

Figure 3.26. Almost half of health occupations are more exposed than the average occupation

Average exposure now or in the near future, health occupations



Note: Selected health occupations.
Source: (Eloundou et al., 2023[47]).

The role of AI in driving regional productivity and addressing labour market challenges

AI holds potential to improve productivity and support regional growth

AI, particularly new general-purpose models which can work autonomously, hold potential to address stagnating productivity gains and enhance innovation across OECD economies (see Chapter 1). This can be particularly relevant in tackling the demographic challenges of an ageing society. As the working-age population shrinks, AI can help maintain productivity by enabling fewer workers to achieve a higher output, thereby sustaining economic growth despite demographic decline. Micro-econometric studies find that the productivity gains from non-generative AI on firms are comparable to those from previous digital technologies (up to 10%). However, performance benefits from using Generative AI in tasks such as writing, programming, or handling customer services requests can range from 10% to 56% (Filippucci et al., 2024[16]). These gains are especially impactful for workers with less experience.

As AI adoption is still low, the long-term, and broad economic impact of this technology remains uncertain. In the US, less than 5% of firms report using Generative AI, making it difficult to observe macroeconomic gains at present (Filippucci et al., 2024[69]). Although the user-friendly nature of new AI tools may accelerate their adoption, realising their full potential still requires substantial complementary investments in data, skills, and software. Estimated aggregate gains suggest AI could contribute between 0.25 and 0.6 percentage points to annual total factor productivity (TFP) growth over the next ten years, boosting annual labour productivity by 0.4 to 0.9 percentage points. However, these estimates carry significant uncertainty (OECD, 2024[70]).

AI research and development, as well as adoption, is uneven across places, potentially deepening existing societal divides. AI activities could bring significant benefits to cities and regions, with the sector projected to grow from USD 184 million in 2024 to USD 826 billion by 2030 (Statista, 2024[71]). Some places, however, are better positioned to benefit from the opportunities in AI than others. In Europe, Germany, France, and Spain have traditionally been the strongest AI economic players (Righi et al., 2022[72]). In the US, AI firms are highly concentrated in the San Francisco Bay Area, with other important hubs across the country such as New York, Boston and Seattle, where large companies are already driving early adoption (Muro and Liu, 2021[73]). Factors such as regional skills, leading research institutions, and a strong innovation ecosystem, have proven to be some of the main aspects driving AI research, development, commercialisation, and adoption in these places.

There are concerns about market competition, as AI development and adoption is concentrated in a few dominant players. Adoption trends indicate a divide: larger firms and those in ICT sectors are integrating AI faster, while smaller and older firms are lagging behind (Calvino and Fontanelli, 2023[2]). This raises concerns about potential market distortions, particularly if early adopters gain substantial market power, making it challenging for other firms to compete. It remains uncertain whether the productivity gains achieved by early adopters will diffuse to other firms, potentially deepening existing economic divides (Filippucci et al., 2024[16]). Furthermore, the success of AI adoption often relies on complementary assets, including ICT skills and training, firm-level digital capabilities, robust digital infrastructure, access to quality data and computer power, as well as general workforce skills (Calvino and Fontanelli, 2023[2]). Not all regions or firms have equal access to these resources, which may exacerbate existing disparities and leave some regions struggling to keep pace. Additionally, the demand for AI talent is more widespread across sectors, which could provide evidence of the general-purpose nature of AI technologies.

The widespread use of AI also raises concerns about its impact on employment. While AI technologies have the potential to boost productivity, augment human abilities, and create new job opportunities, they also bring the risk of displacing workers. Generative AI, for instance, poses risks even for jobs traditionally viewed as secure from automation. However, recent evidence indicates that instead of reducing their reliance on human labour, companies across various sectors are responding to AI adoption by restructuring internally, reallocating workers to tasks where humans have a comparative advantage rather than displacing them (Filippucci et al., 2024[16]).

Effective public policy can maximise the benefits of AI technologies for workers and communities, while also addressing its potential negative effects. A key concern is promoting widespread AI adoption while preventing excessive market concentration. This means reducing barriers to adoption, supporting smaller firms, and ensuring fair competition without stifling innovation. Human complementarity with AI is also important, implying that AI should augment, rather than replace, human work. To achieve this, policies can encourage retraining and labour reallocation, helping workers transition into new roles and adapt to the use of AI technologies (Box 3.11). Preparing for rapid adaptation is equally important. AI-driven transformations are unpredictable, and responsive policy measures that adjust to these shifts can help technological progress benefit workers, communities, and industries, rather than contributing to inequality or causing disruption (OECD, 2024[70]). Furthermore, public policy can foster acceptance and trust by developing mechanisms to keep AI technologies in line with strict ethical standards, thereby improving transparency and accountability.

Box 3.11. Future Skills Centre: Improving AI skills and attitudes across Canada

The Future Skills Centre is promoting various initiatives to enhance professional development and equip workers with the skills to work with AI. The Future Skills Centre is a national organisation dedicated to preparing workers across Canada for the changing demands in the workforce by investing in skills development initiatives. Three examples of projects related to AI issues are:

- **Accelerating the appropriate adoption of Artificial Intelligence in healthcare:** This pan-Canadian project completed in 2024 aimed to overcome healthcare professionals' reluctance to adopt AI by offering tailored education and training. The project developed interventions such as certificate programmes and mentorships to equip healthcare professionals with the skills and confidence to integrate AI into their practice. As a result, the project saw improved attitudes toward AI adoption, enhanced patient care, more efficient workflows, and increased confidence in AI systems.
- **From data to decision: AI training and professional certification:** This pan-Canadian project addresses the growing demand for AI skills by offering a short-duration, online training programme developed by IVADO and Université de Montréal. The project aims to train 1 000 mid-career professionals and leaders across Canada on how to integrate AI into their organisations and make better use of the data they generate. The initiative includes self-assessment tools to identify skill gaps, a training path with up to seven courses, and professional certification for successful participants.
- **Facing the challenge of digital transformation in the insurance sector: Women at work:** This project in the Quebec region addresses the impact of digital transformation on female workers in the insurance sector, where AI and automation threatens low-skill positions typically held by women. Led by a consortium at Laval University, the project assesses the skills development needs of female insurance workers and creates training pathways to reskill and support them in transitioning to future-facing roles, helping them remain competitive in the changing labour market.

Source: (Chan and McDonough, 2024[74]), (Future Skills Centre, 2024[75]), (Future Skills Centre, 2024[76]).

Evidence suggests that policy attention could also benefit from considering the shifting geography and socio-economic effects of Generative AI compared to previous technological advancements. Unlike earlier waves of automation, AI's impact increasingly falls on urban labour markets, which could drive growth in cities but also risks widening disparities between urban and rural regions (Figure 3.18). Moreover, Generative AI is likely to impact a different set of workers compared to previous technologies. This changing landscape suggests the need for adaptive policies for a different and emerging group of workers and regions.

Regions with a high proportion of jobs at risk of automation could benefit from monitoring job displacement trends to facilitate timely responses. Tracking employment in specific sectors and occupations can help regions identify local needs and react with appropriate place-based policies. This approach allows for the timely development of reskilling programmes, support for affected workers, and strategies to foster new employment opportunities. A proactive policy response can help mitigate potential negative effects, while enabling regions to harness the benefits of new technologies.

Assessing the existing skills base in regions with high labour market exposure to Generative AI could help develop targeted programmes to strengthen AI-related competencies. Conducting a comprehensive inventory of available skills could help policy makers and businesses identify gaps and opportunities, enabling them to better prepare the workforce to adapt to the evolving skill demands.

By implementing tailored training and upskilling initiatives, these regions can mitigate potential disruptions, but also capitalise on the transformative potential of Generative AI. These efforts can include training programmes, grants, tax incentives and establishing innovation networks, among others.

By fostering AI local capabilities, regions can modernise traditional industries, attract investments, and leverage emerging technologies for sustainable growth. This is not only relevant for regions that are heavily impacted by automation, but also for those dealing with demographic challenges, low job creation, outmigration, and outdated industrial bases. For these regions, adopting AI strategies presents a dual opportunity: revitalising their economies while mitigating the potential adverse effects of automation (Box 3.12). Effective AI integration, paired with policies to support skills development and job transitions, can lead to more resilient regional economies and balanced growth across various sectors.

Box 3.12. Regional AI and automation strategies for economic revitalisation

La Rioja, Spain

La Rioja's industrial composition makes it particularly vulnerable to automation. La Rioja is a small region in Northern Spain with a strong industrial and agriculture sector. This industrial composition is particularly well suited for jobs at high risk of automation, as the region's industrial sector is mostly manufacturing, and in fact the region has the highest share of jobs at risk of automation within Spain (

Figure 3.3). The regions' decline in employment in the last 10 years can in large part be attributed to a drop in employment in these jobs (Figure 3.7).

The region is advancing initiatives to promote research and business development focused on the application of AI and big data. This includes initiatives like the *Parque Científico Tecnológico de La Rioja,* an initiative for which the first stone has already been set in the form of the *Tech FabLab* which aims to promote technological business initiatives based on AI and other disruptive technologies (Gobierno de La Rioja, 2024[77]). This aligns the regions path with the stated national goal of having at least 25% of companies use AI and big data in five years.

Piedmont, Italy

Piedmont is one of the most industrialised regions in the OECD, with around a fifth of its jobs in the industrial sector. The automotive industry has been historically a big part of this sector but has driven a 17% decline in industrial jobs between 2004 to 2018 (OECD, 2021[78]). A large part of this drop in employment can be attributed to automation-led job displacement (Figure 3.7) and most likely happened in waves, as this region has and above average number of mass layoff events in the last 10 years (Figure 1.27). Within the automation sector, the main actor is Fiat, an Italian automaker that has scaled down production in the region since it became part of Stellantis, a multinational automotive manufacturing company.

The region is aiming to shift its development strategy towards one of innovation by providing support for existing businesses and start-ups. These incentives take the form of grants, direct financing and financing guarantees, vouchers, and tax benefits, among others. Although the new development strategy is still ongoing, Piedmont has managed to leverage its existing industry and talent to establish itself as an R&D hub which concentrates over 20% of Italy's venture capital (VC) funding (EY, 2022[79]).

Georgia, United States

The state of Georgia has a high percentage of jobs at risk of automation (13.5%) compared to the OECD average (8.8%) (OECD, 2024[80])**.** Manufacturing is the second-largest contributor to Georgia's GDP, primarily in machinery, electrical equipment, and fabricated metals (IBISWorld, 2024[81]). However, Georgia's manufacturing industries face challenges that stem from a combination of global competition, reliance on traditional manufacturing, and a need for modernisation.

The Georgia AI Manufacturing (GA-AIM) coalition, supported by the U.S. Department of Commerce's Economic Development Administration, received a grant of USD 65 million through the American Rescue Plan Regional Challenge (Georgia AIM, 2024[82])**.** The initiative focuses on accelerating AI technology integration in key sectors like semiconductors, batteries, electrification, food production, aerospace, and defence. It aims to build regional resilience, catalyse local industries, and create quality jobs, while fostering economic growth, and serving as a national example for how to accelerate automation in manufacturing. The coalition will also establish an AI Manufacturing Pilot Facility at Georgia Tech and seeks to expand job training for underserved communities so that automation benefits workers rather than replace them (EDA, 2022[83]).

Source: (Gobierno de La Rioja, 2024[77]), (fDi Intelligence, 2023[84]), (OECD, 2021[78]), (Regione Piemonte, 2024[85]), (EY, 2022[79]), (EDA, 2022[83]), (Georgia AIM, 2024[82]).

AI can be a tool to alleviate current labour market challenges

With over 30% of OECD regions losing population and over 90% ageing,[15] a major challenge for policy makers is addressing workforce needs with a shrinking working-age population (OECD, 2024[86])**.** At the same time, labour shortages are pervasive across OECD regions (see Chapter 2) and may widen given current demographic trends.

AI and related technologies can be leveraged to address current region-specific labour market challenges and provide support to marginalised workers. Regions experiencing workforce shortages may benefit from increased use of AI – either through upskilling workers with AI tools or by directly implementing AI technologies – to fill positions left vacant due to demographic decline or other factors. This is particularly true for regions with a concentration of industries facing challenges in workforce availability (Box 3.13). In such cases, capital investment in AI becomes a viable alternative, with its applications broadening thanks to technological advancements. In addition, low- and medium-skilled workers can also benefit as AI may be used as a tool to close skill gaps.

These technologies can also help mitigate labour shortages by offering career guidance for critical occupations and enhancing labour market matching across regions. Labour markets shortages often arise in seemingly unattractive careers, but career guidance can help address misconceptions and attract talent. In the education sector, for example, Generative AI can be leveraged through chatbots aimed at answering questions and addressing doubts of high school students who are interested in becoming teachers (Box 3.13). There are already examples of AI technologies being used to better match skilled workers with open positions, enhancing regional mobility and, in turn, improving labour market efficiency.

Box 3.13. Using AI to alleviate labour shortages in industries with tight labour markets

Manufacturing

In the United States, the manufacturing sector has critical labour shortages. It is estimated that even if every skilled worker in the US was employed, there would still be 35% more unfilled job openings in the durable goods manufacturing sector than skilled workers capable of filling them (Gow, 2022[87]). Technology presents itself as a solution, as AI – with the support of robotic automation – can save at least 75% of the labour costs of using humans alone, enable 24-hour continuous production, and help avoid injuries. In fact, the use of technology in tight labour markets helps maximise the productivity gains from any potential automation of work (OECD, 2023[88]).

Generative AI provides novel, more advanced solutions for this sector. Additive manufacturing, such as 3D printing, requires highly skilled designers and engineers to draw on years of experience and a "best guess" approach to arrive at the best design solution. AI now empowers a rapid, generative approach to developing complex and highly optimised design solutions that can be produced quickly through 3D printing. Machine vision and product optimisation are also technologies that can help. For example, the use of cameras and AI that recognise the shape, orientation, and condition of assembly line products under various lighting conditions eliminate the need for human eyes and hands in the questions and answers process.

Education

The education sector is critical to a region's development, but filling essential positions can be challenging, leading to some of the most relevant examples of labour shortages. In the United States, for example, there were an estimated 55 000 vacant teaching positions at the start of the school year in 2023, 51% more than in 2022, and 270 000 teachers were working without meeting state qualifications. Chile is another example of a country facing a significant teacher shortage, with an estimated deficit of 26 000 qualified teachers for 2025, representing 19% of the required workforce. Regions far from the capital can have a much larger shortage, reaching 40% of the required workforce in regions such as Atacama, Magallanes, and the Chilean Antarctica. This deficit is caused by a low level of attractiveness of the profession and a high desertion rate as 19% of new teachers leave after their first year.

AI tools have emerged to produce learning materials, attract and retain talent, and provide mentoring and support for new teachers. *Bookbaker,* for example, is a Generative AI tool that allows teachers to create custom learning materials personalised for their students, and aligned with their curricula, therefore freeing up time and resources from already heavy teaching workloads. In Chile, the non-profit organisation *Elige Educar* has been pioneering the use of AI with two initiatives: *Quiero Ser Profe* and *Somos Profes, Somos Educadores.* The former uses chatbots alongside human tutors to provide personalised information and support to students interested in pursuing a teaching career, helping them make informed decisions. The latter employs AI tools to provide mentoring and support to new teachers and early childhood educators during their initial years in the profession.

And other sectors

The practical solutions offered by AI extend to several more sectors, from professional services to agriculture and life sciences. For example, in the legal sector, Latham & Watkins deployed a model that scans documents and produces accurate legal briefs. This tool can reduce contract review time by 60% (Virtasant, 2024[89]). In agriculture, AI-powered drones facilitate precision farming, while other technologies are being used to automate irrigation, pest control, and enhance crop yields. In addition, "smart farms" have emerged in San Francisco, where agricultural activities are conducted in highly controlled environments monitored and managed by digital systems. In life sciences, AI-powered tools designed to assist in patient diagnosis are expected to improve accuracy and free up medical professionals to spend more time on patient care, while AI technologies for drug development are expected to speed up the research process.

Source: (Gow, 2022[87]), (Elige Educar, 2020[90]), (Elige Educar, 2020[90]), (Post, 2024[91]).

The integration of AI in the workplace holds the potential to address skill gaps among workers. Workers with lower skill levels typically face more difficulties in the workplace, such as limited job opportunities, lower wages, and reduced job security. AI-powered tools can be used to enhance workers' capabilities, thereby levelling the playing field and providing access to better job opportunities. For example, AI-powered tools can assist workers in performing complex tasks that would otherwise be beyond their skillsets, such as coding, and data analysis.

AI can improve the participation in the workforce of people with disabilities who remain significantly underrepresented in the labour market. As of 2019, people with disabilities in OECD countries were 2.3 times more likely to be unemployed compared to their non-disabled counterparts, with 27 percentage points lower employment rate (OECD, 2023[92]). Equipping workplaces with AI tools and teaching workers with disabilities the skills to use them could increase the labour force, closing employment gaps and promoting greater inclusion.

AI-powered tools, such as automated vehicles, can enhance mobility, and improve accessibility in work environments. To harness these benefits, there is a need for pro-active government policies that promote inclusive AI development, and sustainable funding for AI research and accessibility solutions. Mobilising AI-solutions for workforce participation for people with disabilities could be particularly relevant in regions with poor communications or limited accessibility, as well as regions struggling with labour shortages. One example is the Minnesota's Autonomous Rural Transit Initiative (goMARTI) project in Grand Rapids, Minnesota, United States. This project offers a free self-driving shuttle service designed to help residents, particularly those with mobility challenges, access different locations under rural and winter conditions (goMARTI, 2024[93]).

Policies aimed at closing the AI skills gap could facilitate a more equitable access to technological advancements, benefiting workers of all skill levels. Demand for advanced AI skills - those needed to develop AI systems - such as natural language processing (NLP) or machine learning (ML) is growing rapidly, but they only account for around 1% of jobs postings (Borgonovi et al., 2023[94]). The main policy challenge lies in boosting AI skills which are useful for a larger segment of the population. Recent research shows that 61% of European workers agree that it is fairly or very likely that they will need new knowledge and skills to cope with the impact of AI tools on their work in the next five years, but 44% think it is unlikely that their organisation will provide the training (Cedefop, 2024[95]).

Reliable internet access is essential for workers to fully leverage AI tools, but limited or slow connectivity remains a challenge in certain OECD regions. On average, 84% of households have internet access across the OECD, but this figure can be as low as 50% in some OECD regions. Furthermore, cities experience 13% faster internet on average than the rest of the country (OECD, forthcoming[96]). Consequently, the internet is faster and more accessible in urban areas, which are also the regions with higher levels of exposure to Generative AI. This fact deepens the regional divide in Generative AI exposure as the fewer workers exposed may, in practice, experience even lower levels of adoption due to barriers posed by slow or limited internet access in their region. This underscores the importance of ensuring that, alongside training programmes and software tools, physical infrastructure also receives policy attention.

Navigating the future: public policy for jobs in the AI era

Impact of AI within the workplace

New roles are emerging to develop and deploy AI solutions, increasing the demand for AI-related skills. In the US, for instance, firms providing AI solutions have increased by 4 percentage points between 2010 and 2017, going from less than 1% to more than 5% of all technology firms (Muro and Liu, 2021[73]). Examples of roles that fine-tune AI tools include data annotators, who label and organise data — such as images, text, or audio — enabling AI models to learn and make accurate predictions; AI operations specialists, who oversee the performance and integration of AI systems in real-world settings; and AI trainers, who improve AI models by providing feedback and adjusting algorithms to enhance performance. Machine learning and natural language processing are some of the most sought-after skills in AI-related job vacancies. Despite the rapid growth of AI, however, less than 1% of all job postings are AI-related (Borgonovi et al., 2023[94]).

AI is also creating new roles to work alongside emerging technologies. Many of these new roles are focused on monitoring, maintaining, and improving the systems that integrate AI into existing operations. For instance, in the mining industry, robotic automation has led to new roles managing machines through digital twins, which are virtual replicas of equipment. These digital twins optimise mining operations and improve worker safety by allowing remote monitoring and control, reducing exposure to hazardous conditions, and increasing operational efficiency through predictive maintenance (Saes, 2024[97]). This example highlights how AI and automation can render some traditional jobs obsolete (e.g., conventional mining) while simultaneously creating new opportunities to work alongside AI technologies.

The labour market impact of AI extends beyond job displacement, job creation, and productivity, as recent evidence suggests that the most significant impact of AI is concentrated on tasks rather than jobs. Instead of fully displacing jobs, most European workers declare that AI has an impact on their job tasks. In fact, 30% of European workers who use AI technologies and tools to do their job experienced a reduction or disappearance of some tasks, while 41% reported new tasks in their jobs. In addition, for 68% of workers, the main effect of AI technologies, so far, has been to enable them to do their job tasks faster (Cedefop, 2024[95])[16]. This suggests that jobs will not only be created or destroyed but also transformed in their execution and processes. Therefore, issues are expected to arise within the workplace as new skills become essential (or obsolete), knowledge of AI systems becomes necessary, and the use of technology to monitor workers increases.

People are likely to experience AI's impacts within their existing roles, emphasising a growing need for widespread digital skills. To introduce AI solutions in the workplace, worker's will need to recognise how these tools can augment their capabilities at work and develop specialised skills to create a symbiotic relationship with AI-technologies (Zirar, Ali and Islam, 2023[98]). Digital skills, such as IT literacy or basic knowledge of machine learning models, will be important to work and interact with AI. These skills help workers comprehend how AI solutions operate, and understand AI system's capabilities, limitations, and underlying logic. Other high-level cognitive skills will also be important to understand how AI can fit within worker's specific tasks, and to make informed decisions based on AI-generated outputs (OECD, 2023[88]). To adapt to AI systems and implement them in their job, workers may need upskilling and reskilling, which could in turn increase trust in AI adoption. Furthermore, in an OECD survey, workers indicated that AI has increased the importance of human and interpersonal skills, such as creativity and communication, more than of AI specialised skills (Lane, Williams and Broecke, 2023[99]).

As AI is incorporated into everyday work life, workers may benefit from increased productivity and reduced time spent on tedious tasks, potentially leading to higher job satisfaction. Software programmers who have integrated an AI tool in their everyday work, for instance, are able to finish more tasks, more quickly, and reported feeling more fulfilled in their job (Box 3.14). In addition, a recent survey of the manufacturing and finance sector indicated that nearly two-thirds (63%) of workers reported AI had improved their enjoyment at work (OECD, 2023[88]). Experimental evidence in the consulting industry shows that real-world tasks can be done better and faster with the use of Generative AI tools. Research also shows that AI can act as a skill-leveller, boosting the performance of low-skilled workers with a smaller effect on high-skilled workers (Box 3.14). Regions that struggle to attract high-skilled workers may therefore benefit from AI as it could enable low- and middle-skilled workers to fill positions that were previously beyond their reach. These examples highlight the importance of AI as a tool to augment productivity rather than replace jobs.

Box 3.14. Experimental evidence on the impact of Generative AI in the workplace

In a recent paper, Dell'Acqua et al. (2023[100]) **experimentally tested the performance implications of AI on realistic, complex, and knowledge-intensive tasks.** Consultants from the Boston Consulting Group (BCG) were evaluated on their ability to carry out creative, analytical, writing, marketing, and persuasiveness tasks. A total of 7% of the firm's workforce participated in the experiment. This effort was multidisciplinary, involving multiple types of experiments and hundreds of interviews.

Participants were split into groups and asked to carry out several fictional tasks common to the consulting profession. The test group was allowed to use Chat-GPT 4, a widely utilised Generative AI platform, while the control group was not. All participants underwent a pre-test without any Generative AI technology to establish a baseline for measuring their improvement.

AI had a significant positive impact on all measures. Consultants using AI finished 12.2% more tasks on average, completed tasks 25.1% more quickly, and produced 40% higher quality results than those without AI. The quality of the output was rated by both human and AI graders. Introducing participants to the AI tools and giving them an overview of how they work had no significant effect.

Results suggests that AI is a skill leveller as poor performers were heavily boosted by AI while top performers were moderately boosted. The consultants who scored the worst when initially assessed experienced the largest jump in their performance, 43%, when they were able to use AI. Top consultants also received a boost, but a significantly smaller one.

In contrast, when faced with a particularly hard task, participants who did not have access to Generative AI came out on top. The authors constructed a specific task that was designed to be unsolvable by the Generative AI tool, or at least not correctly. Participants not using AI were successful 84% of the time while the treated group was successful only between 60% and 70% of the time. This result suggests that too much AI can potentially be harmful as users are over-confident of the platform's ability and fail to check its output. Similar research in a different work environment arrived at a similar conclusion (Dell'Acqua, 2021[101]).

Source: (Dell'Acqua et al., 2023[100]), (Dell'Acqua, 2021[101]).

On the other hand, the adoption of AI in some work processes can have negative effects on both job satisfaction and the quality of produced work. For instance, modern practices such as algorithmic management can lead to heightened stress and overall job dissatisfaction (Box 3.15). In addition, although the automation of routine tasks can free up time for more engaging work, it can also have negative effects as it can, if implemented poorly, increase work intensity, and reduce a worker's agency. The impact of technology on job satisfaction heavily depends on workers' ability to participate in its design and implementation (Gmyrek, Berg and Bescond, 2023[19]). Finally, using Generative AI can result in a lower quality of outputs if it is applied to tasks or activities that it is ill-suited to address (Box 3.14).

Organisational change management will play an important role in determining how AI technologies are embraced in the workplace. While AI has the potential to enhance productivity, improve decision-making, and increase job satisfaction, these benefits may remain unrealised without a proper approach to AI implementation. An OECD survey of employers and workers in the manufacturing and finance sectors showed that, although both employers and workers have generally positive attitudes about the use of AI, concerns over job loss, stability and potential pressures on wages also prevail (Lane, Williams and Broecke, 2023[99]). Early involvement of employees in the adoption process can help them understand the technology's value and potential benefits, reducing resistance to change (Lane, Williams and Broecke, 2023[99]; Hechler, Oberhofer and Schaeck, 2020[102]). Training is also relevant to help employees adapt to new tasks, improve worker's trust, and facilitate inclusivity in the use of AI systems (Lane, Williams and Broecke, 2023[99]). Companies such as IBM strive to improve technology skills and usage among employees by mandating 40 hours of annual learning. The training includes courses on AI, allowing employees to test IBM's in-house AI tools, which has increased both technology adoption and trust in AI systems within the company.

Box 3.15. AI for task management in the workplace

The effects of algorithmic management on job satisfaction and working conditions emphasises the importance of worker agency and participation in technological adoption. Algorithmic management, which uses data-driven algorithms to manage work tasks and evaluate performance, often reduces worker autonomy and feedback opportunities, while increasing surveillance. This can lead to heightened stress and job dissatisfaction, particularly in environments where workers have little control over their tasks and limited interaction with management (Baiocco et al., 2022[103]).

Amazon warehouse workers in the United Kingdom, for instance, have expressed feeling pressured to work at the fast pace set by automated systems to meet performance targets (GPAI, 2024[104]). Amazon employs a system in their warehouses called Associate Development and Performance Tracker (ADAPT) to monitor performance and provide feedback across a range of dimensions including productivity, quality, safety, and behaviour. The ADAPT system is able to track how many tasks each worker completes, such as how quickly items are packed or processed, and uses this data to assess performance. In some cases, it can generate automatic warnings if workers fail to meet set targets.

Algorithmic management systems for task assignment and monitoring are also common in call centres and in the gig economy (McKensey & Company, 2021[105]). In call centres, AI systems are used to monitor call quality, response times, and employee interactions. In the gig economy, platforms such as Uber and DoorDash rely on AI to track worker performance and manage job allocation. These systems use predictive analytics to match workers with tasks, monitor productivity, and assess customer ratings. While AI's role in managing both customer interactions and gig workers can improve operational efficiency, it also raises concerns about the balance between worker autonomy and automated oversight.

However, technology can also have positive effects on job satisfaction. A recent report shows that when workers are actively involved in the design and implementation of new technologies, the outcomes can be more positive (Gmyrek, Berg and Bescond, 2023[19]). Countries with strong frameworks for workplace consultation and decentralised decision-making, such as those in the Nordic region and Germany, demonstrate higher worker acceptance and better job satisfaction. Thus, the key to maintaining job quality in the face of technological advancements lies in robust worker participation and dialogue, which can help integrate technology in ways that enhance, rather than detract from, job satisfaction.

Platform cooperatives have emerged as alternatives to conventional platforms to help tackle challenges such as job quality, employer status and asymmetry in bargaining power. Unlike traditional platforms, platform cooperatives are owned and democratically managed by their workers that use websites and mobile apps to sell goods and/or services (OECD, 2023[106]), In the context of AI, workers in platform cooperatives could actively participate in decisions about how algorithmic systems are designed and implemented, such as determining the criteria for task allocation. By involving workers in these decisions, platform cooperatives offer a model that could mitigate the risks of low job quality often associated with traditional platform work, where workers have limited agency.

Source: (Gmyrek, Berg and Bescond, 2023[19]), (Baiocco et al., 2022[103]), (GPAI, 2024[104]), (McKensey & Company, 2021[105]), (OECD, 2023[106]).

AI's integration into the workplace raises important questions regarding workers' rights. Algorithmic management, where algorithms determine work assignments and evaluate performance, can result in heightened surveillance and work intensity as AI tracks worker behaviours, productivity, and movements in real-time (Box 3.15). This can lead to increased work pressure, stress, and risks to both mental and physical health (OECD, 2024[107]). This type of management can also reduce feedback and complicate collective bargaining, as it is challenging for workers to organise around a management system they cannot directly see or interact with (CLJE LAB, 2024[108]). Furthermore, algorithmic decision-making in hiring, promotions, or terminations is opaque and can lead to biases, potentially discriminating against certain groups. Extensive data collection without appropriate regulations may also compromise workers' privacy by exposing personal information to misuse or unauthorised access.

Putting transparency and responsibility at the core of AI use and giving workers a voice through strengthened social dialogue is critical to safeguarding worker's rights. Following OECD AI Principles, having *trustworthy AI* means that AI development and use are safe and respectful of fundamental rights such as privacy, fairness, and labour rights. Additionally, employment-related decisions made by AI should be transparent and understandable by humans (OECD, 2023[109]). It is important for employers, workers, and job seekers to be informed about AI usage and for accountability mechanisms to be clear in case issues arise. Collaboration with social partners can also be critical in shaping how AI is integrated into the workplace and to protect workers' rights (Kinder et al., 2024[110]). Robust policy measures and ethical guidelines are required to maintain fair treatment, protect worker's data, and provide retraining opportunities to mitigate the risks of displacement. The US Department of Labor (2024[111]), for instance, has published a set of AI Principles and Best Practices for integrating AI responsibly, emphasising worker engagement and training to prevent displacement and facilitate equitable benefits. In the EU, the AI Act (European Parliament, 2024[112]) addresses risks related to safety, health, and fundamental rights, with specific provisions for high-risk applications in the workplace. Although many OECD countries are developing similar initiatives, most AI-specific measures remain non-binding and depend largely on organisations' ability to self-regulate (OECD, 2023[109]).

Opportunities and challenges of AI adoption for SMEs

Small and medium size enterprises (SMEs) can leverage digital tools, such a Generative AI, to optimise their operations, but support for technology adoption is limited. Recent evidence suggests that SMEs tend to view the opportunities of Generative AI as higher than the risks. These enterprises face challenges in adopting digital technologies including higher cost, a lack of skills, or cybersecurity risks. Initiatives that support AI adoption for SMEs can help improve their operations, allow them to fully realise the potential of these technologies, and minimise risks, enabling SMEs to innovate without falling behind in the rapidly evolving digital landscape (examples in Box 3.16).

Box 3.16. Initiatives to support AI adoption in SMEs

***SMEs-Digital (Mittlestand-Digital*), Germany**

The *SMEs-Digital* initiative is designed to help small and medium-sized enterprises (SMEs), crafts, and start-ups in Germany to navigate the complexities of digital transformation. With 163 local and thematic centres across Germany, its primary goal is to provide these businesses with free orientation and resources to understand and leverage the opportunities presented by digitalisation while addressing the associated challenges.

To achieve this, the initiative offers a comprehensive range of support services specifically tailored to the needs of SMEs. Activities within *SMEs-Digital* include workshops and training sessions on various technologies, such as AI, which are designed for different levels of expertise. Additionally, SMEs can benefit from personalised consultations with experts, who provide tailored advice on how to implement digital solutions. The initiative also facilitates networking and collaboration opportunities, along with the chance to participate in demonstration projects, allowing SMEs to better understand how digital technologies can be integrated into their processes.

Starting in 2024, the initiative will place a heightened focus on AI and AI readiness. This shift aims to enhance the availability and preparation of high-quality data, which is crucial for the effective implementation of AI applications in SMEs. By fostering a deeper understanding of AI and its potential applications, *SMEs-Digital* seeks to equip businesses with the tools and knowledge necessary to integrate AI into their operations.

***SCALE-AI*, Canada**

***SCALE-AI* is a Canadian innovation supercluster programme focused on accelerating the adoption and commercialisation of AI across supply chains**. Supported by the Canadian government and managed from its headquarters in Montreal, the programme is a public-private partnership bringing together businesses, research institutions, and universities. The main goal of SCALE AI is to strengthen Canada's position as a global leader in AI by fostering innovation and collaboration among SMEs and large companies.

***SCALE-AI* provides a variety of tailored services and funding opportunities to help SMEs adopt AI technologies and improve their operational processes.** Activities include hands-on workshops, training sessions, and access to mentorship programmes that guide SMEs through the process of implementing AI solutions. The programme also helps SMEs connect with AI experts and larger organisations and offers funding for AI-based research and development projects, helping companies experiment with AI applications in real-world scenarios. This includes support for data analytics, machine learning, and automation projects, all aimed at improving logistics, optimising inventory management, and enhancing decision-making processes. By providing resources and expertise, *SCALE-AI* strives to help smaller companies harness the power of AI so they can remain competitive in a rapidly evolving digital economy.

Source: (Federal Ministry for Economic Affairs and Climate Action, 2024[113]), (SCALE AI, 2024[114]).

In contrast to earlier technological advancements that required significant infrastructure, Generative AI is more easily accessible. Businesses, including SMEs, can use generative AI through cloud-based software and applications, making it available at a low cost. These benefits, combined with the fact that anyone can use it with minimal knowledge through simple queries, make this application of AI very more accessible for businesses regardless of the limitations related to their size (OECD, 2024[115]).

Nearly 1 in 5 SMEs surveyed in the 2024 OECD D4SME Survey reported experimenting with generative AI less than a year after LLMs became available to the public in late 2022 (OECD, 2024[115]). This is in stark contrast with other applications of AI, which appear to be considerably less widespread among surveyed SMEs. For example, only 6% of SMEs reported they created or acquired tailored machine learning algorithms (produced by either internal or external experts) to be applied in their business functions (OECD, 2024[115]). However, it must be highlighted that many SMEs still lack a proper understanding of AI possible applications or uses in the tools they are already using. Policy should aim to provide tailored support for SMEs in adopting digital technologies, addressing their specific needs, as many SMEs report a lack of awareness of available assistance that meets their requirements (Box 3.17).

Box 3.17. Measuring SME digitalisation: 2024 OECD D4SME Survey

The widening gap across enterprises

SME's can adopt digital tools to optimise their operations, but recent data suggest that they have not kept pace with large enterprises. Digital tools can help streamline operations, operate flexibly, and diversify revenue streams, which can help withstand external shocks. Recent data, however, shows that large enterprises continue to outpace SMEs in the adoption of software technologies, despite progress in SMEs digitalisation.

The adoption of digital technologies by SMEs depends largely on its ability to increase sales, drive efficiency, and boost resilience. A recent survey[a] shows that the primary objective of SMEs when adopting digital tools is increasing domestic sales (47%) and expanding their customer base (41%). Automation, which can significantly enhance operational efficiency, is an objective for 40% of business. This objective is more important in the professional services sector (48%), and among more digitally mature business (48%). Reducing operational costs is also an objective, especially for those businesses that operate exclusively online.

However, SMEs face significant bottlenecks in adopting digital tools. Over 1 in 4 SME's point to bottlenecks to digitalisation, such as costs, skills shortages, and lack of time for training. Digital security practices are also a main concern as 1 in 3 business across surveyed European countries were aware of having been the target of cyber-attacks.

Generative AI has been rapidly embraced by SMEs, which generally view this technological advancement positively. Over half of the respondents (57%) reported a view that opportunities associated with Generative AI features surpassed the risks. Additionally, managers are more optimistic about generative AI than employees, with 62% believing the benefits of the technology outweigh the risks, compared to 48% of employees.

Despite this positive view of generative AI, many SMEs still lack a comprehensive understanding of its potential uses or how to embed it in the tools they already use. Overall, only 26% of respondent SMEs acknowledged their use of AI but, as the survey was distributed to SMEs active on large digital platforms, by design, all respondents in the sample were at minimum using it passively (through the machine learning algorithms embedded in platforms they were using). Overall, only about 5% of respondents recognised they were using AI passively in this sense, highlighting the need for continued support and understanding of AI among SMEs.

Support for SMEs in the adoption of digital tools remains limited. Overall, less than 1 in 5 SME's are aware of government support for the adoption of digital tools. Furthermore, respondents who were aware of support cited concerns about the suitability of programmes for their digital needs, red tape in accessing the programmes and capacity challenges to sustain digital improvements after the completion of the support programme.

Note: [a] The D4SME Survey gathered responses from 1 005 SMEs from Japan (561), Korea (249), Europe-4 [113, combining France (44), Germany (15), Italy (33), and Spain (21)], and the United States (82). The sample was drawn from a distinct set of digital platforms and so cannot be considered as being representative of the entire universe of SMEs in those countries or indeed the OECD.
Source: (OECD, 2024[115]).

AI in the public administration

AI also holds potential to improve productivity and optimise processes in the public administration. By leveraging AI, governments can automate routine tasks, streamline workflows, and enhance decision-making capabilities, thereby freeing up public servants to focus on more complex, citizen-centric activities. AI-driven tools, such as chatbots, predictive analytics, and automated document processing, can contribute to more efficient public service delivery, reduce bureaucratic bottlenecks, and ultimately improve transparency and responsiveness in government operations.

One-in-two OECD public employment services (PES) have already implemented AI solutions in 2024 (Brioscú et al., 2024[116]). Specifically, PES have used AI to understand the needs on jobs seekers and target support, improve their labour market matching and employment services and optimise their own back-office processes and knowledge generation. However, PES should be careful in managing the risks linked to AI, such as privacy concerns, and potential biases, while also supporting PES staff in developing the skills to effectively use AI tools (Box 3.18).

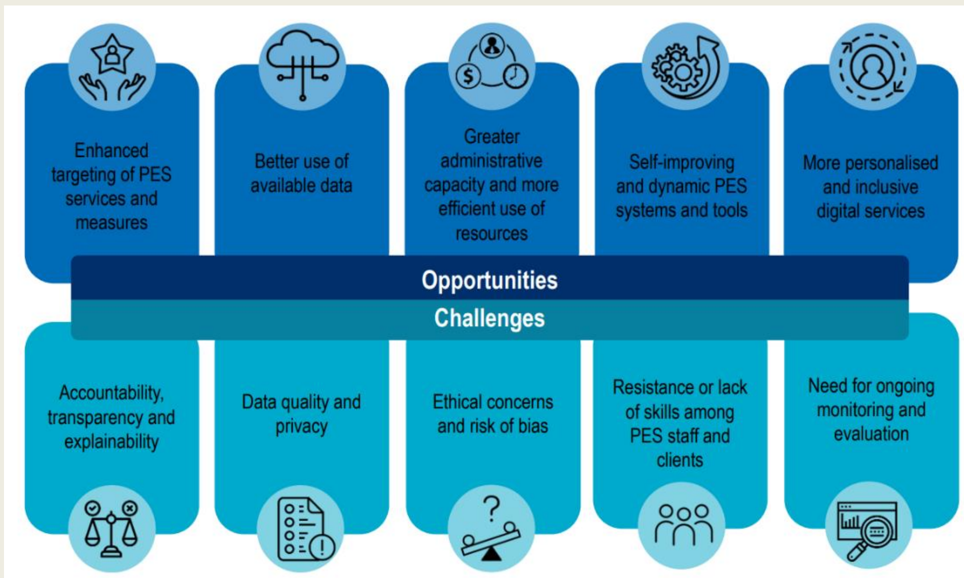
Box 3.18. Guidelines for AI adoption in public employment services (PES)

The adoption of AI presents significant opportunities for PES, but it will also require proactive measures to address and minimise the associated risks. The OECD paper "A new dawn for public employment services" (2024[116]) explores the impact of widespread AI adoption in PES. Some of the recommendations in the paper include:

- **Making accountability, transparency and explainability central in PES AI use**. Ensuring that those who design, deploy and operate AI systems are accountable for their proper functioning, creating well-design structures that foster transparency and explainability in AI outcomes, ultimately enhancing trust.
- **Implementing AI models that strive for data privacy and quality.** PES handle sensitive administrative data and must remain vigilant about their data privacy obligations. They should also verify that the data fed into AI systems is accurate and appropriate for the intended use.
- **Mitigating the risk of bias within AI systems.** PES undertake sensitive work that can have implications for the lives of citizens. Ensuring that biases and discrimination are minimised, while prioritising fairness and equality, should be a key focus for PES.
- **Developing skills among PES staff to work alongside AI and address resistance**. Employees may resist AI due to fears of job security or discomfort with new practices. Proactive steps should be taken to close the skills gap and build trust in AI tools, facilitating greater adoption among staff and minimising potential concerns.

- **Conducting continuous monitoring and evaluation of AI systems**. Positive results during development do not guarantee success of the tool post-implementation, making ongoing quality checks necessary to avoid unintended impacts.

Figure 3.27. Opportunities and challenges of adopting AI in public employment services



Source: (Brioscú et al., 2024[116]).

Tools to match job seekers to employers and tools to design vacancy postings are among the most common uses of AI in PES, with over 20% of PES across the OECD implementing at least one of these (Brioscú et al., 2024[116])**.** AI-powered job matching solutions have been implemented in counties such as Japan, Canada and Mexico. Supporting the improvement of jobseekers' CVs and employer's job postings is another common use of AI in PES. Both the PES of France and Flanders, Belgium use tools that analyses CVs and job ads to identify implicit skills not listed and provide suggestions that can refine job descriptions and candidate profiles (Broecke, 2023[117]). Other common uses include profiling tools that asses a jobseeker's job finding prospects, tools to provides PES clients with information (usually in the form of chatbots), and tools to help with career management and job search orientation (Box 3.19).

PES can harness AI to better tailor their services to the specific needs of regional labour markets. The services can then be scaled more efficiently while maintaining a strong focus on regional priorities, addressing the unique economic and employment challenges that vary between regions. Examples of this already exist, where counsellors work with AI tools to provide nuanced, region-specific solutions, or AI-powered chatbots that can boost the quality and accessibility of services (Box 3.19).

Box 3.19. Examples of AI applications in public employment services (PES)

AI for jobseeker profiling in the Basque employment service

The Basque Country is an Autonomous Community in northern Spain known for its strong manufacturing base and increasingly educated workforce. The region benefits from a robust Vocational Education and Training (VET) system and a variety of active labour market programmes tailoring training and labour market incentives to job demand. Low job quality and the demand for skills, however, are contributing to overqualification in the region (OECD, 2020[118]). Lanbide's, the region's PES established in 2011, has a range of responsibilities that include managing active labour market programmes and administering the region's main income support scheme, the *Renta Garantia de Ingresos* (RGI).

Recently, Lanbide has developed an AI tool to aid in their profiling process, which improves the management of active employment policies, and supports Lanbide's career advisors. A profiling process involves classifying or defining jobseekers according to their employability, functioning as a diagnostics tool that identifies the risk levels of individuals regarding their chances of re-entering employment. Lanbide developed a methodology that leverages big data and automates the analytical component of jobseeker profiling.

The main objective of this tool is to classify job seekers to better know them and address four key issues in running the PES. The tool is meant to provide a (1) more personalised and (2) reactive service that helped PES professionals (3) better match job seekers to vacancies and (4) address chronic long-term unemployment.

Machine learning is utilised to profile jobseekers based on their employability, with the resulting analysis presented to counsellors through a comprehensive dashboard. Counsellors can leverage this tool during interviews with jobseekers to guide them towards the most suitable opportunities in the labour market. The methodology can be applied in other organisations and can be tailored to the local needs by, for example, training it on region-specific datasets, as it has been in the Basque region. The tool is currently in an experimental phase, with plans to integrate additional variables, ESCO skills, and macroeconomic trends into the analysis to further enhance the profiling model.

AI-powered career information chatbot in the Austrian employment services

In Austria, the labour market is changing due to technological advances, evolving job roles, and a growing emphasis on digital skills. The Austrian Public Employment Service (AMS) is addressing these challenges through multiple initiatives aimed at facilitating career guidance and continuous education for both new entrants to the workforce, and those looking to reskill or upskill to access new roles.

The AMS Career Information Assistant (*Berufsinfomat*) is a Generative AI-powered chatbot to assist with career-related inquiries. This chatbot, based on OpenAI technology, provides accessible information about careers, education, and training opportunities. The tool is freely accessible and allows users to ask career-related questions through an interactive chat interface serving a broad audience, including young people, parents, teachers, job seekers, career changers, and those returning to work. It is also used by AMS advisors to help them research career-related questions.

The chatbot offers information on a variety of career-related subjects. These include (1) descriptions of over 2 500 professions, including typical tasks, required skills, and qualifications, (2) suggestions for courses, seminars, and other education pathways such as apprenticeships, schools, and universities, and (3) information on starting salaries, apprentice wages, and wages according to collective agreements.

The interactive chat format provides real-time, personalised responses. The chatbot is designed to be barrier-free, meaning users do not need to register or provide personal data, maintaining users' anonymity. It can direct users to local AMS offices for more specialised and in-person support. Supporting 90 languages, the Career Information Assistant facilitates accessibility to a broad audience, making the tool easy to use for individuals from different backgrounds and needs.

Source: (OECD, 2020[118]), (Lanbide – Basque Employment Service, 2024[119]), (Public Employment Service Austria, 2024[120]).

The use of AI can transform the work of public servants in various ways beyond optimising PES. One common application has been using AI for information processing and speeding up writing tasks. The Danish Environmental Protection Agency (EPA) and the Ministry of Digital Government and Gender Equality, in collaboration with the company cBrain, developed an AI-powered solution that assists with drafting briefing notes, speeches, translations, and summaries, which is being used, for instance, in the Copenhagen and Aarhus city governments. The tool works as a virtual assistant for public servants, using an on-premises LLM to ensure data security, and which is trained with thousands of government documents (cBrain, 2024[121]). Public servants and caseworkers can also use the assistant to ask questions and receive information on specific procedures, thereby improving productivity.

AI can be used for document processing and to sped up time-consuming bureaucratic tasks in public administration. The Danish EPA, for instance, is using an AI tool to accelerate environmental and building permitting processes. The tool is trained on local and national environmental and building permit documents, enabling it to handle case processing and filing, and improving the overall quality of decisions. This automation significantly reduces the workload for public servants and citizens by streamlining application self-service. The tool is currently to assist project developers, generate draft reports, and support civil servants who review and finalise decisions (Knudsen and Søndergaard-Gudmandsen, 2023[122]). cBrain is also piloting an AI chatbot in California, United States, specifically trained in environmental regulations, which can be used during the development of construction projects. A user might, for example, ask the chatbot, "What should I consider to improve the safety of birds in the development of my wind farm?", and the chatbot provides relevant information on applicable regulations and other pertinent resources Beyond permitting, this type of AI application has vast potential, as public administrations frequently manage complex and time-consuming bureaucratic tasks that could be automated with AI (Georgieff, 2024[26]).

Public administrations can leverage AI technologies to improve cybersecurity and address evolving security threats. In terms of system security, AI can accelerate the detection and mitigation of cyber threats, improving response times and safeguarding sensitive data, including user identities and key government datasets. These AI-driven systems can automatically identify vulnerabilities and neutralise cyber risks, offering greater protection against breaches. Additionally, AI is being used to track misinformation, monitor potential radicalisation, and detect other security dangers. For example, the AI tools developed by the company Cybara are being used in regional and local governments to track risks on social media, helping to combat misinformation, and identify early signs of foreign influence and coordinated disinformation campaigns. The company often collaborates with government intelligence units and police forces, and has worked on cases such as local elections, and to combat disinformation related to vaccines (Cyabra, 2024[123]).

The application of AI in public administration has great potential to improve productivity, but raises concerns similar to those seen with PES and that might impact their adoption (Box 3.18). One of the main challenges is the need for extensive training for personnel to effectively use AI systems, which often require new technical skills. There are also concerns about potential biases embedded in AI algorithms, which could perpetuate inequality or lead to unfair outcomes. Additionally, attitudes toward change play a significant role, as both employees and citizens may be resistant to the implementation of new technologies. Public acceptance is crucial, as citizens may be wary of AI's role in decision-making processes, fearing a lack of transparency or loss of human oversight. Striving for transparency, deploying AI ethically, and with careful consideration of its social impact will be central in maintaining public trust.

Policy recommendations to unlock Generative AI's potential in regional labour markets

In conclusion, by tailoring strategies to regional needs, policies can support economic growth, workforce development, and fair integration of AI technologies in the workplace. The following place-based recommendations aim to help local labour markets harness the benefits of Generative AI, while addressing potential risks and promoting equitable use.

1. **Identify opportunities where AI can drive regional growth:** By building local AI capabilities, regions can modernise traditional industries, attract new investments, and harness emerging technologies for sustainable development. This approach can be particularly valuable for regions facing demographic pressures, low job creation, or outdated industrial structures, and to close urban-rural divides.
2. **Assess regional labour market exposure to different forms of AI**: Monitoring the varied effects of AI and automation allows for targeted interventions that address specific needs in different regions. Tracking high-risk occupations can further enable regions to anticipate job displacement trends, address skill mismatches, and implement place-based policies to foster resilience and workforce adaptation.
3. **Use data to develop comprehensive regional skills inventories**: Developing a skills inventory involves assessing workforce's competencies and identifying gaps, providing a picture of available skills and areas for development. In regions with high exposure to Generative AI, this inventory can be particularly helpful in guiding efforts to adapt the workforce, address potential skill shortages, and capitalise on the opportunities AI offers.
4. **Foster collaboration with local stakeholders to strengthen policy intelligence**: Engaging local stakeholders, such as employers, educational institutions, and community organisations, provides valuable, real-time insights that can enhance the effectiveness of workforce policies. Such collaboration promotes better-informed, and adaptable policies, and can be particularly important for the integration of Generative AI, as it can improve its uptake, foster trust among stakeholders, and tailor policies to regional economic conditions.
5. **Build awareness of AI's benefits for workers and employers**: Emphasising how AI can enhance productivity by automating routine tasks and freeing up time for more meaningful work can help workers and firms see its value. Engaging employees early in discussions about implementing AI in the workplace, along with providing training, can build further acceptance and make adoption smoother.
6. **Improve the uptake of AI tools across businesses, with a special focus on SMEs**: Businesses may need additional resources to take full advantage of AI tools, such as targeted training programmes, guidance on implementing AI technologies, and workforce retraining. Special attention should be given to SMEs, which often lag behind in technology adoption, by providing the support they need to remain competitive in an AI-driven economy.
7. **Leverage AI in the public administration, including public employment services (PES):** Using AI in the public administration can automate routine tasks, enhance accuracy, and improve service

delivery through tools like multilingual chatbots and AI-powered document processing. In PES, AI tools can improve job matching, connecting job seekers and employers more effectively.

8. **Establish frameworks to control AI risks:** AI presents risks, including privacy concerns, biases, increased pressures on workers, and potential job displacement. Addressing these issues requires clear guidelines and ethical standards to enhance transparency and accountability, and safeguard workers' rights. Collaboration with social partners can further facilitate responsible AI implementation.
9. **Provide tailored support for displaced workers**: Technological advancements, such as AI and automation, lead to shifts in the labour market and may cause worker displacement. Targeted support for these workers, including retraining programs and re-employment assistance, can help mitigate long-term economic losses and prevent vulnerable groups and regions from being left behind amid technological changes.
10. **Revise regional skill provisions to address workforce needs**: Addressing changing skill needs, such as those driven by the adoption of Generative AI in the workplace, requires updating the skills provision system to better align with current demands. This includes revising vocational education programmes, expanding access to adult education, and introducing targeted programmes for critical roles in emerging industries.

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Notes

[1] Generative AI refers to artificial intelligence that can create new content by learning patterns from existing data. Current uses of Generative AI include content creation (including text and images), code generation, and personalised recommendations, with technologies such as ChatGPT, DALL-E, and GitHub Copilot being some recognised examples of Generative AI platforms.

[2] MIT Technology Review (2013[125]). "10 Breakthrough Technologies 2013". https://www.technologyreview.com/10-breakthrough-technologies/2013/ accessed on 18/07/2024.

[3] Authors name this middle group the “Big Unknown” and estimate that a full 8.6% of global employment (281 million workers) falls within this category.

[4]Note that this study uses the Generative AI platform GPT-4 to judge Generative AI itself, which might lead to bias. Nevertheless, the direction and magnitude of any potential bias is unclear.

[5] This includes mechanical technologies, and non-generative AI. This may include some early forms of LLMs but only to a limited extent as the most prominent Generative AI platforms were released after this date. For the purpose of this chapter, Generative AI encompasses models and platforms released in or after 2022.

[6] Note that regional dispersion is impacted by the size and number of regions, as countries with a higher number of smaller regions tend to have more regional dispersion. This explains, at least in part, the small variance in, for example, Australia and Canada.

[7]Once country-specific factors are considered, the correlation is insignificant. Qualitatively similar results are found by (Georgieff and Milanez, 2021[8]).

[8] Labour productivity is measured as gross value added per employment at place of work by main economic activity (OECD, 2024[41]).

[9] Additionally, some productivity gains may not have manifested as increased sales or income, but rather as consumer surplus, which would not be reflected in this particular measure of productivity.

[10] Exposure to generative AI does not make a job more or less likely to be displaced, it simply means that generative AI is a useful tool for enhancing efficiency in that occupation.

[11] This trend is described for the exposure now or in the near future, but it holds for exposure now as well.

[12] See Annex 3.A for more details.

[13] Healthcare occupations include general and specialist doctors, dentists, medical and dental practitioners, assistants and technicians, chiropractors, physical therapists and assistants, medical and health service managers, podiatrists, nurses, midwives, acupuncturists, veterinarians, opticians, genetic counsellors, pharmacists and complementary medicine associates. Exact occupations depend on occupation classification.

[14] Software-related occupations includes developers, programmers, computer technicians, ICT support, web and digital designers, computer operators, network and computer systems administrators, computer scientists and specialists, system and security analysts, database managers and designers, data entry keyers, statisticians, and data scientists. Exact occupations depend on occupation classification.

[15] An ageing region is one where the elderly dependency ratio has increased in the last 10 years (to 2022 or 2023 depending on last year available). Similarly, a region is losing population if it has less population than it did 10 years ago. This analysis is done at the TL-3 level where possible, and if not, it is done at the TL2 level.

[16] The survey was conducted between February and May 2024 in 11 EU countries. The sample size was around 500 adult workers in each country, with a total of 5 342 interviews.

Annex 3.A. Data coverage and measurements

Measuring exposure to Generative AI

The two measures of exposure to Generative AI are used in this report: *exposure now* and exposure *now or in the near future*. The former is defined as the share of tasks within an occupation that can be completed in half the time with the use of LLMs in their current form i.e., Chat-GPT 3.5 or similar. In particular, this measure includes those tasks classified under *E1* (Annex Table 3.A.1). The latter is defined as the share of tasks within an occupation that can be completed in half the time with LLMs in their current form or it is easy to imagine additional software that could be developed on top of the LLM that would reduce the time it takes to complete the task by half. In particular, this measure includes those tasks classified under *E1* and *E2.*

Annex Table 3.A.1. Summary of exposure rubric

Exposure category	Description
E0 (No exposure)	• Using the described LLM results in no or minimal reduction in the time required to complete the activity or task while maintaining equivalent quality *or* • Using the described LLM results in a decrease in the quality of the activity/task output.
E1	• Using the described LLM via ChatGPT or the OpenAI playground can decrease the time required to complete the Detailed Work Activity (DWA) or task by at least half (50%).
E2	• Access to the described LLM alone would not reduce the time required to complete the activity/task by at least half, but • Additional software could be developed on top of the LLM that could reduce the time it takes to complete the specific activity/task with quality by at least half. Among these systems, we count access to image generation systems.

Note: Tasks performed with the use of Generative AI should be of equivalent quality, this is, a third party would not notice or care about LLM assistance.
Source: (Eloundou et al., 2023[47])

Details on data sources and coverage

Annex Table 3.A.2. Employment by occupation data sources

Country	Type of data	Dataset	Source	Variables available
AUS	Table	Table EQ08	Australian Bureau of Statistics (ABS)	Sex
AUT, BEL, CHE, CZE, DEU, DNK, ESP, EST, FIN, FRA, GRC, HRV, HUN, IRL, ISL, ITA, LTU, LUX, LVA, NLD, NOR, POL, PRT, ROU, SVK, SWE	Survey	EU-LFS	Eurostat	Sex, Level of education
CAN	Survey	Labour Force Survey	StatCan	Sex, Level of education
COL	Survey	Gran Encuesta Integrada de Hogares (GEIH)	Departamento Administrativo Nacional de estadística (DANE)	Sex, Level of education
CRI	Survey	Encuesta Continua de Empleo	Instituto Nacional de	Sex, Level of

			Estadística y Censos (INEC)	education
KOR	Survey	Korean Labor & Income Panel Study (KLIPS)	Center for Labor Statistics Research, Korea Labor Institute	Sex, Level of education
MEX	Survey	Mexican National Survey of Occupation and Employment (ENOE)	National Institute of Statistics and Geography (INEGI)	Sex, Level of education
NZL	Survey	Household Labour Force Survey (HLFS)	Stats NZ Tatauranga Aotearoa (Stats NZ)	Sex, Level of education
SVN	Table	Statistical Register of Employment (SRDAP)	Republic of Slovenia Statistical Office (SURS)	Sex
USA	Table	Occupational Employment and Wage Statistics (OEWS)	U.S. Bureau of Labor Statistics (US-BLS)	-

Source: OECD elaboration

Annex Box 3.A.1. Measuring the degree of urbanisation

The degree of urbanisation (DEGURBA) is a classification that indicates the character of an area by classifying the territory of a country on an urban-rural continuum. The classification uses local administrative units (LAUs or communes) and classifies these as cities, towns and suburbs, or rural areas based on a combination of geographical contiguity and population density. The basis for the classification is the data for 1 km² population grid cells. The categories are described as follows:

- **Cities:** densely populated areas where at least 50% of the population lives in one or more urban centres.
- **Towns and suburbs:** intermediate density areas where less than 50% of the population lives in an urban centre and at least 50% of the population lives in an urban cluster.
- **Rural areas:** thinly populated areas where more than 50% of the population lives in rural grid cells.

Source: (Eurostat, 2018[124])

Job Creation and Local Economic Development 2024

THE GEOGRAPHY OF GENERATIVE AI

Regions across the OECD face a range of labour market challenges and are undergoing a significant transformation. An ageing workforce, low labour productivity growth, persistent regional disparities, pervasive labour shortages, and new technologies will require both people and places to undergo transitions. This report, Job Creation and Local Economic Development 2024: The Geography of Generative AI, examines the health of regional and local labour markets, including through new estimates on regional labour shortages and their drivers. New tools and technologies, such as Generative AI, could help policymakers address these challenges and seize new opportunities for job creation and local economic growth. This report provides novel evidence of the geography of the impact of Generative AI on jobs across the OECD. It examines which places within countries and types of workers are most exposed to Generative AI and contrasts this with the labour market impact of past waves of technologies that drove automation. Finally, it discusses local and place-based actions and policies for seizing the benefits of Generative AI, such as boosting productivity, mitigating labour shortages and demographic change, as well as for mitigating risks of job displacement.

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