OECD Social, Employment and Migration Working Papers
No. 297

The effects of the EU Fit for 55 package on labour markets and the demand for skills

Francesca Borgonovi,

Elisa Lanzi,

Helke Seitz,

Ruben Bibas,

Jean Fouré,

Hubert Plisiecki,

Laura Atarody

https://dx.doi.org/10.1787/6c16baac-en

OECD

Organisation for Economic Co-operation and Development

DELSA/ELSA/WD/SEM(2023)15

Unclassified **English text only**

28 July 2023

DIRECTORATE FOR EMPLOYMENT, LABOUR AND SOCIAL AFFAIRS
EMPLOYMENT, LABOUR AND SOCIAL AFFAIRS COMMITTEE

Cancels & replaces the same document of 25 July 2023

The effects of the EU Fit for 55 package on labour markets and the demand for skills

OECD SOCIAL, EMPLOYMENT AND MIGRATION WORKING PAPERS No. 297

Keywords: climate mitigation, employment, skills, computable general equilibrium models

JEL classification: Q54, Q43, C68, J24, J44, J21

Authorised for publication by Stefano Scarpetta, Director, Directorate for Employment, Labour and Social Affairs

All Social, Employment and Migration Working Papers are now available through the OECD website at www.oecd.org/els/workingpapers.

This working paper was prepared in the framework of the OECD Skills Outlook 2023, supported by the European Commission through the Erasmus+ programme.

Francesca Borgonovi, Francesca.Borgonovi@oecd.org
Elisa Lanzi, Elisa.LANZI@oecd.org
Helke Seitz, Helke.SEITZ@oecd.org
Ruben Bibas, Ruben.BIBAS@oecd.org

JT03523760

OECD Social, Employment and Migration Working Paper

Acknowledgements

This working paper was prepared within the framework of the OECD Skills Outlook 2023, supported by the European Commission through the Erasmus+ programme. The opinions expressed and arguments employed herein do not necessarily reflect the official views of the OECD member countries or the European Union.

The authors would like to acknowledge Eleonora Mavroeidi's contribution on initial scoping work on this project. The authors would also like to thank OECD colleagues Andrea Bassanini, Martin Borowiecki, Enrico Botta, Andrea Garnero, Andrew Green, Lukas Kleine-Rueschkamp, Julie Lassébie, Fabio Manca, Thomas Manfredi, Luca Marcolin, Anja Meierkord, El Iza Mohamedou, Glenda Quintini, Stefano Piano, Michele Tuccio, Toon Vandyck, and Ada Zakrzewska for their valuable comments and feedback on previous versions of this manuscript. The authors would also like to thank Mauro Pelucchi for help with Lightcast data; Duniya Dedeyen and Jennifer Cannon for their editorial work.

Abstract

This paper quantifies changes in employment and the demand for skills in the European Union following the implementation of Fit for 55 policies. Between 2019 and 2030, the economy is projected to grow by 1.3% in the Fit for 55 scenario (3% in a Baseline scenario without the Fit for 55 policies). Employment growth is projected to be lower in the Fit for 55 than the Baseline scenario. Employment in the Fit for 55 scenario is projected to decrease by 3% for blue collar and farm workers (2% in the Baseline) and increase by 4-5% for other occupations (5-6% in the Baseline). The most demanded skills following the implementation of Fit for 55 will be those related to inter-personal communication and the use of digital technologies, whereas the demand for skills related to the use of traditional tools and technologies is projected to decline. Anticipating changes in employment and the demand for skills as well as the socio-demographic profile of those most affected can facilitate the design of upskilling and reskilling efforts and promote the reallocation of workers across sectors and occupations.

Table of contents

Tables

Figures

Executive Summary

If countries are to achieve ambitious climate targets, climate policies will need to be accompanied by strong investments in skills policies. Skills policies, which comprise education and training policies targeted at both young people and adults, can play an essential role in ensuring that greening the economy does not lead to new forms of vulnerability. Skills policies can facilitate the reallocation of workers away from sectors that will shrink because they are responsible for a large share of carbon dioxide (CO_2) emissions into sectors that will expand. To help workers effectively transition requires identifying not only economy-wide changes in skills demands but also the degree of similarity in the skillsets needed to perform different jobs, as well as projected trends in employment and the relative size of different employment opportunities.

This paper considers the case of the European Union's Fit for 55 policy targets aimed at reducing greenhouse gas emissions and quantifies the impact of the policy package on labour markets and the demand for skills. In particular, the paper explores the effect of the Fit for 55 policy targets on five occupational categories: 1) Managers and Officials; 2) Professionals; 3) Service and Sales Workers; 4) Clerical Workers; and 5) Blue collar and Farm Workers.

The paper combines a modelling analysis of the impacts of the Fit for 55 policy targets on labour markets with an empirical analysis on the demand for skills, which is based on matching labour market changes for sectors and occupations to skills information from positions advertised online in those same sectors, on the demand for skills. Given the distribution of workers in 2019 in different European Union countries, sectors, and occupations, the paper also considers distributional implications and key target groups for the design of upskilling and reskilling interventions to facilitate the reallocation of workers across sectors and occupations that are projected to decline most. Key demographic groups include gender, level of education, age, and propensity to engage in adult education and training.

Key findings include:

- Overall employment is projected to increase by 1.3% in the Fit for 55 scenario between 2019 and 2030, whereas it would have grown by 3% had the Fit for 55 policy package not been implemented.
- By 2030, the employment of blue collar and farm workers is projected to decrease by 3% in the Fit for 55 scenario (whereas it is projected to decrease by 2% in a scenario in which the policy was not implemented) and increase by 4-5% for other occupations (whereas it is projected to increase by 5-6% in a scenario in which the policy was not implemented).
- Upskilling and reskilling interventions to facilitate the reallocation of workers across sectors and occupations should consider the distribution of affected workers in different countries. For example, blue collar workers in the 'mining of coal and lignite' sector will be highly negatively affected. Most of these workers in 2019 were employed in five countries: Bulgaria, the Czech Republic, Germany, Poland and Romania.
- Participation in training is low among workers in general but appears to be especially low among highly impacted workers, such as blue collar workers in the 'mining of coal and lignite' sector. In four out of ten countries with blue collar workers employed in the 'mining of coal and lignite', none

of these workers reported having participated in any form of formal or non-formal training in the four weeks preceding the interview.

- The skills categories that are projected to grow the most in demand between 2019 and 2030 with the implementation of the Fit for 55 policy include: interacting with computers; thinking creatively; analysing data and information; and communicating with persons outside an organisation, skills for which demand will grow as a result of technological adoption.
- Other skills for which demand will increase include sales and marketing; computers and electronics; language; economics and accounting; customer and personal service; administration and management; and communications and media. Most of these skills are essential in the business services and public services sectors.
- Skills related to operating and maintaining equipment and tools are projected to decline the most in demand with the implementation of Fit for 55 targets.

1 Introduction

1. Anthropogenic greenhouse gas (GHG) emissions lead to climate change, including an increase in the frequency of extreme events and a higher risk of reaching irreversible changes in the climate system, usually referred to as climate tipping points. As such, they reduce people's health and well-being. Climate damages also have repercussions on economic activities and infrastructures, imposing high financial costs to the economy. As a response to deteriorating conditions and mounting public pressure, in 2015, 196 Parties adopted the Paris Agreement, a legally binding international treaty on climate change with the goal to "limit global warming to well below 2, preferably to 1.5 degrees Celsius, compared to pre-industrial level" (United Nations Framework Convention on Climate Change, 2015[1]). Since the adoption of the Paris Agreement, many countries worldwide have implemented policy initiatives to reduce GHG emissions and stated their intention to achieve carbon neutrality – i.e. the situation in which carbon emissions do not exceed carbon sequestration – by the middle of the century. Furthermore, the economic stimulus packages implemented to sustain economic growth following the COVID-19 pandemic have served as a way to accelerate both the digital and green transitions.

2. The European Union (EU) is at the forefront of promoting ambitious climate policies. Besides meeting the objectives of the Paris Agreement, with the European Green Deal, the EU has also set the objective to achieve carbon neutrality by 2050. While many countries have set climate targets, the EU has also ensured that the targets are binding by translating them into the legislations. In particular, the EU has adopted a set of legislative proposals that have been integrated in the Fit for 55 policy package,[1] which sets an intermediate target of reducing net greenhouse gas (GHG) emissions by at least 55% by 2030, compared to 1990 levels.[2] The package also indicates that the total emission reduction of 55% should be achieved with differentiations across sectors: emissions in sectors covered by the EU Emission Trading System (ETS) need to be reduced by 61% in 2030 compared to 2005 levels while emissions in other sectors – referred to as Effort Sharing Regulation (ESR) sectors – need to be reduced by 40% by 2030 compared to 2005 levels.

3. If EU countries are to achieve ambitious climate targets alongside economic growth and high-quality working conditions, climate policies will need to be accompanied by strong investments in employment, social, and skills policies to promote the socioeconomic well-being of resident populations. Understanding the labour market impacts of greening EU economies is a key first step in preparing adequate policy responses to mitigate any adverse impacts the transition might have for certain population groups, and ensuring that the green transition will be a just transition.

4. In recent years, a growing number of studies have attempted to estimate the effects climate change mitigation policies might have on labour markets, with the aim of identifying – and eventually preventing – potential mismatches arising from the reallocation of workers from sectors and occupations

[1] The Fit for 55 package is described in a series of legislations from the European Parliament and the Council (2009[29]; 2009[30]; 2018[31]; 2003[32]; 2008[33]). Following the Fit for 55 package (EU Commission, 2021[69]) , EU Member States need to reach more ambitious targets than those stated in the Nationally Determined Contributions (NDCs). Furthermore, in June 2022, the Fit for 55 package has been revised to include more sectors and more stringent targets for 2030 (European Council and Council of the European Union, 2022[71]).

[2] Net emissions include emissions and removals from land-use change and forestry (LULUCF).

that are heavy emitters of greenhouse gas emissions into sectors and occupations that emit comparatively few greenhouse gas emissions – also referred to as 'green' in the literature (Vona, 2021[2]). Such mismatches are likely to arise not only because of the geographical distribution and occupational composition of sectors that may grow or shrink as a result of structural transformations leading to increased environmental sustainability, but also because of the difference in the skillsets required to perform tasks prevalent in economic production processes characterised by high or low levels of greenhouse gas emissions.

5. Anticipating how the skills needed to work in economies characterised by low levels of GHG emissions will differ from the skills that are needed in today's workplaces is a key first step in the design of upskilling and reskilling programmes and initiatives (Vona, 2021[2]). Such policies will, in turn, not only play a pivotal role in ensuring that individuals possess the skills needed to facilitate the green transition but also to ensure that workers who will be displaced because of the transition will be able to find employment in expanding sectors (Valero et al., 2021[3]). Adult education in particular will have to be tailored to promote the upskilling and reskilling of adults who will be affected by structural transformations in the short and medium-term. At the same time, education and training systems will have to adapt to equip young people with the set of skills that are projected to gain in demand as a result of the green transition. This will require potentially wide-ranging changes in school and vocational education and training curricula and, in turn, professional development of teachers and trainers (International Labour Organization, 2017[4]).

6. The degree to which initial education, further education and training, and adult education will have to adapt, largely depends on the degree to which the skills required are similar to or different from those workers possess today. Empirical studies suggest that reallocation costs associated with the redeployment of workers across different occupations depend on how similar the skills needed to perform different jobs are (Gathmann and Schönberg, 2010[5]; Kambourov and Manovskii, 2009[6]; Poletaev and Robinson, 2008[7]). Therefore, minimising reallocation costs for individuals and societies crucially depends on adequately anticipating how similar the skills demanded of workers employed in a low emission economy will be compared to the skills workers currently possess and using such information to inform the design of programmes in education and training systems so that they will effectively develop such skills.

7. A growing literature has attempted to quantify the number of jobs aligned with the achievement of green objectives, i.e. ***green jobs*** (Valero et al., 2021[3]; Georgeson and Maslin, 2019[8]; Vona, 2021[2]; Vona and Bontadini, 2022[9]; OECD, 2023[10])***.*** Although results from different studies in this literature are not directly comparable because they often adopt different estimation methodologies and definitions (Peters, Eathington and Swenson, 2011[11]; Valero et al., 2021[3]), they generally indicate that only a small number of workers are employed in green jobs. Broadly speaking, studies either identify green employment by considering the relative importance of tasks that directly contribute to achieving green objectives in different jobs, or by considering the environmental footprint of jobs in different sectors or industries, or by combining the two given difficulties in quantifying the extent to which tasks, sectors or industries contribute to or actively reduce different forms of environmental degradation. Studies using a task-based approach indicate that green jobs account for around 2 to 3% of overall employment in the United States and Europe (Bontadini and Vona, 2022[12]; Vona, Marin and Consoli, 2019[13]) and 4% in the United States (Georgeson and Maslin, 2019[8]). Estimates can be substantially higher if green employment is considered to reflect all jobs that require at least a small number of tasks that contribute to achieve green objectives. For example estimates suggest that as many as 18% of employment contains at least 10% of green tasks across OECD countries (OECD, 2023[10]) Similarly, Saussay and colleagues (2022[14]) estimated a prevalence of less than 1.5% of online vacancies being advertised in the United States between 2010 and 2019 for low-carbon jobs.[3] When considering green employment using sectoral data, Curtis and Marinescu (2022[15])

[3] Such estimated were obtained using a modified version of the task-based approach which further restricted green tasks in the O*NET programme to a set of 250 keywords contained in the O*NET task descriptors describing tasks

estimate that by 2019 the share of vacancies posted online for jobs in the wind sector was 0.17% of the total volume of postings advertised online in that year in the United States whereas the share of vacancies posted on line for jobs in the solar sector reached 0.03% of the total volume of postings advertised on line in that year in the United States.[4] Estimates for green employment can be substantially higher if estimates consider not only jobs in which individuals perform tasks that directly contribute to achieve environmental objectives but also indirect green jobs, i.e. jobs that are expected to be positively but indirectly impacted by the transition such as administrators supply work of environmental engineers or booking appointments for the installation of solar panels. These 'augmented' estimates identify green employment to account for around 17% of all jobs in the United Kingdom (Valero et al., 2021[3]), and between 20% (Valero et al., 2021[3]), and 40% (Bowen and Hancké, 2019[16]) for Europe as a whole. Virtually all these studies are based on data on occupations coming from the United States O*NET Occupational Information Network and thus reflect production processes in the United States. Therefore, a key assumption underpinning most studies in the literature based on data from the O*NET network is that production processes in the United States reflect production processes in other countries. This is an important assumption that is relaxed in this paper.

8. Results from these studies can be used to map what skills are needed in the small number of jobs that are well aligned with the achievement of green objectives. However, the transition to net zero will require economy-wide adaptations. Such adaptations will not only reduce employment in sectors that are heavy producers of CO_2 emissions and increase employment in sectors that are carbon neutral but will also change the allocation of workers both across and within sectors in all economic activities. As a result, analyses of the existing skill content of green jobs should be accompanied by analyses of projections in skills needs induced by changes in employment in the overall economy resulting from structural transformations needed to meet economy-wide climate targets (Weitzel et al., 2023[17]).

9. Results from past modelling exercises conducted by Cedefop and the OECD produced projections of the effect of policy interventions aimed at reducing greenhouse gas emissions on employment in different sectors and, in some cases, on the employment of individuals in roles typically requiring different levels of educational qualifications (OECD, 2012[18]; Chateau, Bibas and Lanzi, 2018[19]; OECD, 2020[20]) (Château, Saint-Martin and Manfredi, 2011[21]; Cedefop, 2021[22]). Estimates indicated that climate change mitigation policies will create small overall long run effects on labour markets but potentially large effects in some sectors. In particular, previous work suggests that the implementation of climate change mitigation policies will determine job destruction in fossil-fuel sectors and job creation in renewable energy sectors, sectors that currently employ few workers overall (OECD, 2012[18]; Chateau, Bibas and Lanzi, 2018[19]; OECD, 2020[20]) (Château, Saint-Martin and Manfredi, 2011[21]), but may nonetheless employ relatively large number of workers in certain local communities (OECD, 2023[10]). At the global level, estimates suggest that meeting by 2050 the net-zero emissions objectives that countries set for themselves will have

relevant to CO_2 mitigation or adaptation. The study then maps these keywords onto descriptors of skills present in the text of online vacancies collected by Lightcast using a mix of natural language processing methods and expert consultation and then identified the prevalence of the resulting 445 low-carbon skills onto vacancies to identify how many postings were advertised containing at least one of the 445 identified low-carbon skills.

[4] Curtis and Marinescu (2022[15]) used data from online vacancies collected from Lightcast and defined green jobs using a mix of the top-down approach – defining as green all jobs containing the words 'solar', 'photovoltaic' or 'wind' in the full vacancy job title and/or in the occupational title classified by Lightcast which is more granular than classifications available in official statistics and that is retroactively applied to time-series data – and bottom-up approaches – defining as green all vacancies that explicitly require skills labels extracted by Lightcast that contain the words 'solar', 'photovoltaic' or 'wind' or that are posted by firms that advertise a relatively high share of jobs that require wind or solar skills (i.e. firms for which 40% of postings are green according to the first two criteria or 10% in the case firm's name contains the words 'solar', 'sun', 'renewable', 'green' or 'sol').

a positive, albeit limited, impact on employment, creating 30 million jobs by 2030 and determining the loss of 8 million jobs over the same period (IEA, 2021[23]).

10. This paper extends previous modelling exercises conducted by the OECD to quantify changes in sectoral employment and in the demand for skills in the European Union that will likely result from structural transformations needed to meet the EU Fit for 55 policy targets. As such, it complements micro-approaches estimating the skills content of green jobs with macro-level estimates of changes in overall skills demands resulting from changes in the employment of workers in different sectors and broad occupational groups. To do this, it presents a modelling analysis of the impacts of the Fit for 55 policy targets on labour markets, driven by the policy-induced changes in the structure of the economy. The analysis distinguishes employment impacts by sector for five occupational categories: (i) Managers and officials, (ii) Professionals, (iii) Service and sales workers, (iv) Clerical workers and (iv) Blue collar and farm workers.[5] An empirical analysis, based on matching labour market changes for sectors and occupations to skills information from positions advertised online in those same sectors, enables to quantify the effects of the policy targets on the demand for skills.[6] Given the distribution of workers in 2019 in different European Union countries, sectors, and occupations, the paper considers distributional implications and key target groups for the design of upskilling and reskilling interventions to facilitate the reallocation of workers across sectors and occupations that are projected to decline most. Key demographic groups include gender, level of education, age, and propensity to engage in adult education and training.

11. The modelling analysis relies on the OECD ENV-Linkages dynamic global Computable General Equilibrium (CGE) model (Chateau, Dellink and Lanzi, 2014[24]) to quantify the effect of policies on structural change, with a 2030 time horizon. The analysis compares a Baseline scenario reflecting current policies, such as the Emission Trading System, with a Fit for 55 scenario. The EU Fit for 55 enhances projected sectoral changes, such as servitisation, and create additional incentives to increase production in less energy intensive sectors, with a significant shift in energy production from fossil based towards renewables. The empirical analysis uses the job postings database for the 2019-2022 period assembled by Lightcast (formerly known as Emsi Burning Glass) (Lightcast, n.d.[25]), to understand the distribution of skills across sectors and occupations. The analysis of distributional impacts relies on 2019 EU-LFS data.

12. The remainder of the paper is structured as follows. Section 2 presents projected trends in employment between 2019 and 2030 resulting from the implementation of the Fit for 55 policy targets in the European Union. Section 3 details how projected trends in employment will shape the demand for skills and Section 4 considers some of the sectors and occupations that are estimated to be severely impacted by structural transformations and considers challenges and opportunities for education and training policies given the socio-economic and demographic profile of affected populations – with a focus on gender, age, educational attainment and current level of participation in training. Section 5 concludes and discusses implications for education and training policies.

[5] The category ‘Managers and officials’ includes both Managers and Professionals (ISCO level 1 major groups 1 and 2). The category ‘Professionals’ includes Technicians and associate professionals (ISCO level 1 major group 3). The category ‘Clerical workers’ includes Clerical Support Workers (ISCO level 1 major groups 4), the category ‘Service and sales workers’ includes Service and Sales Workers (ISCO level 1 major groups 5), The category ‘Blue collar and farm workers’ includes Skilled agricultural; Forestry and fishery workers; Craft and related trades workers; Plant and machine operators, and assemblers; Elementary occupations (ISCO level 1 major groups 6, 7, 8 and 9).

[6] In line with information provided in the context of the OECD Skills for Jobs database, the term ‘skills’ is used both as a generic indicator for human capital as well as a term indicating a specific set of proficiency in manipulating data and things (OECD, 2017[70]). As a generic indicator of human capital, the term skills refers to the broad set of cognitive abilities, physical abilities, socio-emotional abilities, and metacognitive abilities (e.g. information processing skills, dexterity, teamwork, self-organisation) as well as to abilities in performing specific jobs or tasks (e.g. accounting or hair colouring) (OECD, 2017[70]). At the same time, in the context of official classifications of the different set of skills individuals possess, the term *skills*, in italics, is used to refer to a particular category of competences.

2 Projected employment changes resulting from the implementation of the Fit for 55 policy targets

Scenario design and modelling strategy

13. The analysis of changes in sectoral employment relies on the OECD ENV-Linkages model, which is a dynamic global Computable General Equilibrium (CGE) (Chateau, Dellink and Lanzi, 2014[24]).[7] The model is used to quantify the overall economy-wide effects of the mitigation policies needed to meet the Fit for 55 emission reduction targets, with a 2030 time horizon. The main advantage of using a CGE model is that, exploiting its sectoral and regional dimensions, the analysis can consider the interlinkages between the economy's supply and demand sides, capturing adjustments to new policies in both quantities and prices. CGE models thus capture the changes in the prices of commodities, used as production inputs and for consumers, whether produced domestically or imported, and the shifts in demand and sourcing.

14. The modelling analysis compares two scenarios, with a focus on the European Union: (i) a Baseline scenario reflecting the implementation of current policies, and (ii) a Fit for 55 scenario. The time horizon of the analysis extends to 2030, in line with the Fit for 55 targets.

15. The **Baseline** scenario reflects projected socio-economic trends as well as current policies. Projected population trends follow the World Population Prospects (United Nations, 2018[26]) ("medium scenario"). Following the OECD long-term economic projections (Guillemette and Turner, 2021[27]),[8] the European Union is projected to show a steady GDP growth in the Baseline scenario (2% per year on average between 2014 and 2030, but with variations across countries). The Baseline scenario incorporates policies that were implemented by 2021[9] as well as policies that were by then already legislated but not yet implemented.[10] This approach is applied not only EU countries, but also the rest of the world. The

[7] The ENV-Linkages model is calibrated using the Global Trade Analysis Project (GTAP) 10 database (Aguiar et al., 2019[35]) for 2014.

[8] Specifically, for OECD countries and a number of emerging economies, the macroeconomic projections follow the OECD's short-term economic forecasts (OECD, 2021[66]) and the long-term projections of OECD Economics Department (Guillemette and Turner, 2021[27]).[8] For regions that are not covered by the OECD databases, short-term economic forecasts of the International Monetary Fund (IMF, 2020[67]) are combined with long-term macroeconomic projections from the OECD ENV-Growth model, which expands the OECD long term projections methodology to other countries (OECD, 2022[68]).

[9] The cut-off date for the Baseline policies derives from IEA's World Energy Outlook (IEA, 2021[23]).

[10] Some jurisdictions have enacted climate policies after the publication of the World Energy Outlook (IEA, 2021[23]), such as the Inflation Reduction Act in the United States of America. These climate policies have not been included in the Baseline.

Baseline considers the EU carbon market – the European Emissions Trading System (ETS), which is already in place. Using information on energy supply and demand from the Stated Policies Scenario (STEPS) from the World Energy Outlook (IEA, 2021[23]), policies in the energy sector imply that the EU economy becomes less energy-intensive over time.

16. In the **Fit for 55** scenario, the European Union meets its target to reduce CO_2 emissions by 55% in 2030 compared to 1990 levels.[11] This economy-wide target is also specified for sectoral groups: an emission reduction of -61% in 2030 compared to 2005 in ETS sectors, and -40% in Effort Sharing Regulation (ESR) sectors - ESR sector including all sectors outside of ETS. Table 2.1 summarises the emission targets, as well as the sectoral coverage for ETS and ESR sectors. The Fit for 55 scenario assumes that the rest of the world also undertakes strict policies to reduce emissions', on the way to reach global net-zero emissions, as presented in Fouré et al. (2023[28]).[12] Given that the scenario assumes a global transition, there is very limited potential for carbon leakage so that the Carbon Borden Adjustment Mechanism was not included in the analysis.

Table 2.1. Economy-wide emissions targets in 2030 in the EU Fit for 55 package

Scope	Sectors covered	Emission reduction objective in 2030	Compared to
Economy-wide target	All the economy	-55%	1990 levels
European Emission Trading System (ETS) sectors	• Fossil-fuel powered electricity • Other energy-intensive industries (e.g. steel, cement, glass, paper) • Air transport • Maritime transport (added in new Fit for 55 package)	-61%	2005 levels
Effort Sharing Regulation (ESR) sectors	• Road transport • Buildings • Agriculture • Waste • Small industries	-40%	2005 levels

Note: The emission objectives are for net emissions and cover all GHG and all uses.
Source: European Parliament and the Council (2009[29]; 2009[30]; 2018[31]; 2003[32]; 2008[33]).

17. To ensure that the Fit for 55 package overall target is reached while also respecting the differentiation between the two sectors groups, two separate carbon markets are included in the scenario and in the ENV-Linkages model: the ETS and a market for ESR sectors, covering all sectors and agents of the economy. The resulting levels of the carbon prices needed to achieve the targets are provided in Table 2.2. Besides carbon markets, the scenario also includes the removal of fossil fuel supports as well as non-pricing instruments, including regulations on firm behaviour and household subsidies (Fouré, Dellink and Lanzi, 2023[28]). The non-pricing instruments are calibrated on the Net-Zero Emissions scenario of the World Energy Outlook (IEA, 2021[23]). The package brings additional revenues to EU governments

[11] While this analysis focuses on emission reductions, the Fit for 55 package also includes other targets, such as achieving a 40% share of renewable energy in total energy consumption and an emission reduction of 55% for new cars and of 50% for new vans. Furthermore, this analysis applies the targets to CO_2 emissions.

[12] Overall, the scenario reduces global CO_2 emissions to 29.8 Gt by 2030, equivalent to a 19% reduction from 2019, with non-OECD countries covering 75% of these emission reductions in 2030 (22.5 Gt). More details are provided in Fouré, Dellink and Lanzi (2023[28]).

thanks to both carbon pricing and fossil fuel subsidy removal. Some of these revenues are used to finance household subsidies, while the remaining is transferred to households as a lump-sum.[13]

Table 2.2. Economy-wide average carbon prices in the European Union in the modelled scenarios

Carbon price levels (USD/tCO_2)

	2019	2020	2023	2025	2030
Baseline scenario	12	14	14	14	16
Fit for 55 scenario	12	14	50	90	202

Note: The Fit for 55 specific instruments start in 2023. The Baseline and Fit for 55 scenario carbon prices correspond to economy-wide weighted average carbon prices (over both ETS and ESR sectors).
Source: OECD ENV-Linkages model.

18. When a policy is introduced in ENV-Linkages, the model adjusts its sectoral production and consumption patterns, including inputs and outputs, until a new equilibrium is reached. Consequently, the production factors and intermediate inputs needed by the various sectors are also adjusted. This mechanism drives changes in sectoral employment, as they are adjusted to meet the new sectoral demand for labour. This also leads to changes in wages that lead to additional adjustments in the supply and demand for labour. The response from workers to a new resource allocation leading to changes in wages is modelled through a positive labour supply elasticity. This implies a certain degree of labour mobility across sectors to changes in wages (Chateau, Dellink and Lanzi, 2014[24]).

19. For this project, the ENV-Linkages model has been enhanced to distinguish employment for five different job categories: (i) Managers and officials, (ii) Professionals, (iii) Service and sales workers, (iv) Clerical workers and (iv) Blue collar and farm workers, following the ILO ISCO-88 classification (Walmsley and Carrico, 2019[34]). Additional adjustments take place in the model as the relative wages change for the five categories. For instance, there are indirect effects in terms of sectoral and regional reallocation of production, which also result in employment changes.

20. When interpreting the results, it is important to keep in mind that in a CGE model like ENV-Linkages the labour market is cleared so that labour demand equals labour supply (see Annex A) for additional details on ENV-Linkages). Therefore, while the policy simulations result in a reallocation of sectoral employment by occupation, they do not take into account temporary under-employment. While an advantage of CGE models is that they can reflect economy-wide impacts of policies and the reallocation of sectoral and regional economic activity that follows policy implementations, they are generally better fit to study long-term reallocations than short-term changes.[14]

21. In this paper, total employment for each job category is assumed to vary with the corresponding average netof-taxes real wage, therefore the modelling framework can lead to positive (or negative) net-employment impact of the policies. This simplifying assumption about employment changes in response to wage aims at representing a more realistic functioning of labour markets in the long run without an explicit characterisation of the underlying sources of under-employment.

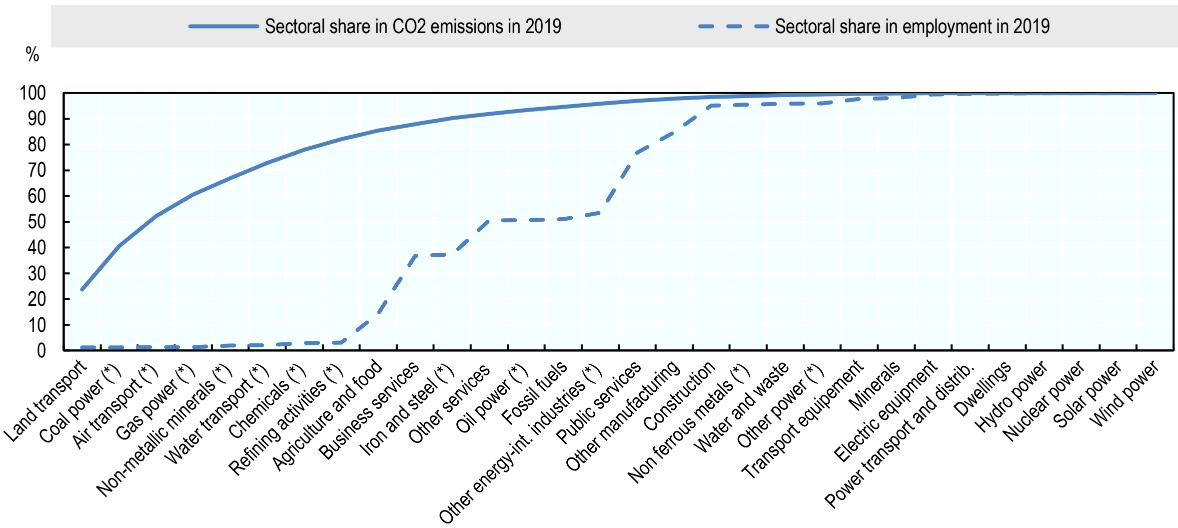
[13] An alternative assumption could have modelled a reduction of labour taxes. Given that the remaining revenues are limited, this should not affect results significantly, as discussed in Fouré et al. (2023[28]).

[14] Future work might focus on improving the labour market modelling specification in ENV-Linkages.

Current distribution of employment across sectors

22. The projected changes in sectoral employment depend on the current sectoral structure of the economy and on the emission and labour intensity of each sector. Most employment losses can be expected to take place in high emitting sectors, which represent a low share of the labour force (Figure 2.1). In 2019, in the European Union (EU), the four sectors with the highest CO_2 emissions (Land transport, Coal-powered electricity, Air Transport and Gas-powered electricity) accounted for almost 61% of overall CO_2 emissions but employed only 1.4% of the total workforce. The Fit for 55 package is also expected to boost employment in other sectors, specifically in services sectors. In 2019, the services sectors provided a large share of employment (59%) in the EU.

Figure 2.1. Cumulative shares of CO_2 emissions and employment per sector in 2019



Note: Sectors sorted by total CO_2 emissions (mega tonnes) and by total level of employment (millions of persons employed) in 2019. Sector followed by (*) indicate European Emissions Trading System (ETS) sectors. An overview of ENV-Linkages sectors displayed in this figure and how sectors are combined from the GTAP database (Aguiar et al., 2019[35]) that underlies the model is provided in Table A A.2.
For ease of presentation, for this figure, "Agriculture and food" combines "Animal agriculture", "Other agriculture" and "Food" and "Fossil fuel" combines "Gas", "Coal" and "Oil" in Table A A.2.
Source: OECD ENV-Linkages model.

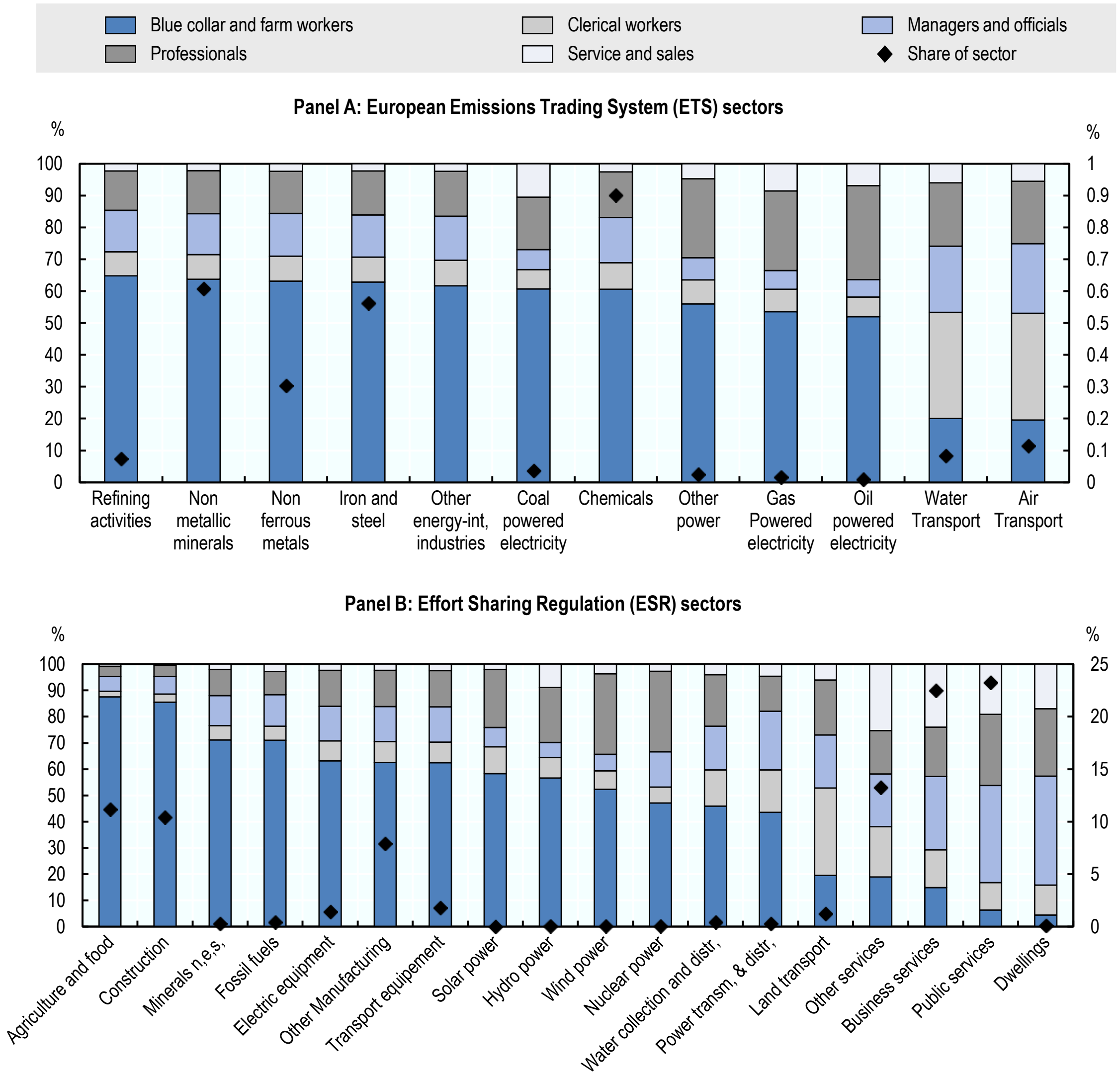
23. The Fit for 55 package distinguishes between ETS and ESR sectors and is more stringent on ETS sectors, which are on average more emission intensive. There are also differences in labour intensity across sectors and specifically between ETS and ESR sectors. On average, ETS sectors are less labour intensive than ESR sectors. Altogether, ETS sectors account for less than 6% of total employment in the EU in 2019 (and 64% of emissions). Within ETS sectors, most people are employed in other energy-intensive industries (e.g. steel, cement, glass, paper), which represent around 3% of total employment (and 1% of emissions).

24. The distribution of workers across the five job categories also varies across sectors (Figure 2.2). ETS sectors rely most on blue collar and farm workers, followed by professionals, and managers and officials, with the exception of air and water transport, which rely most on clerical workers while also having a high share of managers and officials. In ESR sectors, a salient difference appears between services sectors and other sectors (i.e. agriculture, construction, manufacturing, and other industrial sectors). Services sectors rely most on managers and officials and have a low share of blue collar and farm workers. Other sectors rely most on blue collar and farm workers.

25. Managers and officials, professionals and service and sales workers represent a larger share of total employment in ESR sectors (53% of total employment) than in ETS sectors (31% of total employment). Blue collar and farm workers represent the largest share of employment in ETS sectors as well as a large share (24%) of employment in the construction sector (ESR sector), which has a relatively high employment level. Clerical workers represent 11% of total employment with similar shares for ETS (9%) and ESR (11%) sectors. They are the most employed category in transport sectors, which however correspond to a relatively low employment level (1.4% of total employment).

Figure 2.2. Employment level by occupational category and sector and employment share by sector

Share of each occupational category in sectoral employment and sectoral share in total employment (secondary axis), EU, 2019



Note: The figure shows the share of the five occupational categories in employment by sector. In parallel, it also shows the share of employment of each sector in total employment. Together, these indicators provide an idea of the contribution of each occupational category in each sector to total employment. An overview on all ENV-Linkages sectors displayed in this figure and how sectors are combined is provided in Table A A.2 and Table A A.3.
Source: OECD ENV-Linkages model.

The projected impact of the Fit for 55 scenario

Sectoral production

26. The Fit for 55 scenario achieves significant reductions in CO_2 emissions, reducing CO_2 emissions to 1.7 Gt in 2030 from 3.3 Gt in 2019. Emissions are reduced in both ETS (0.8 Gt in 2030, from 1.7 Gt in 2019) and ESR sectors (0.9 Gt in 2030, from 1.5 Gt in 2019) but the reduction in emissions is stronger in ETS sectors, in accordance with the Fit for 55 package targets.

27. The Fit for 55 scenario results in continued economic growth but also in a small reduction in gross domestic product (GDP) for the EU (-3% in 2030), compared to the Baseline. This decrease is due to the fact that the ENV-Linkages model is conservative on assumptions related to innovation. The modelling approach reflects the technological progress that is projected to take place in energy production and use, following the IEA's World Energy Outlook (IEA, 2021[23]). However, the model does not include explicitly the possibility of innovation or further development of technologies that are not yet marketed. With additional investments in research and development and assuming that these investments would result in faster technological development and innovation, reaching net-zero emissions by the middle of the century would be less costly and possibly also boost economic growth.

28. Sectoral production decreases most in sectors regulated by the ETS, and especially in coal, oil and gas-powered electricity, and air transport (Figure 2.3, Panel A).[15] These are one of the most emission-intensive sectors and therefore a reduction in sectoral production contributes strongly to abate CO_2 emissions. Production losses are more limited in most ESR sectors (Figure 2.3, Panel B), except for mining and fossil fuels extraction and distribution, which are also emission-intensive sectors. Production substantially increases instead in renewable energy (solar, wind and hydro powered electricity) and nuclear-powered electricity.

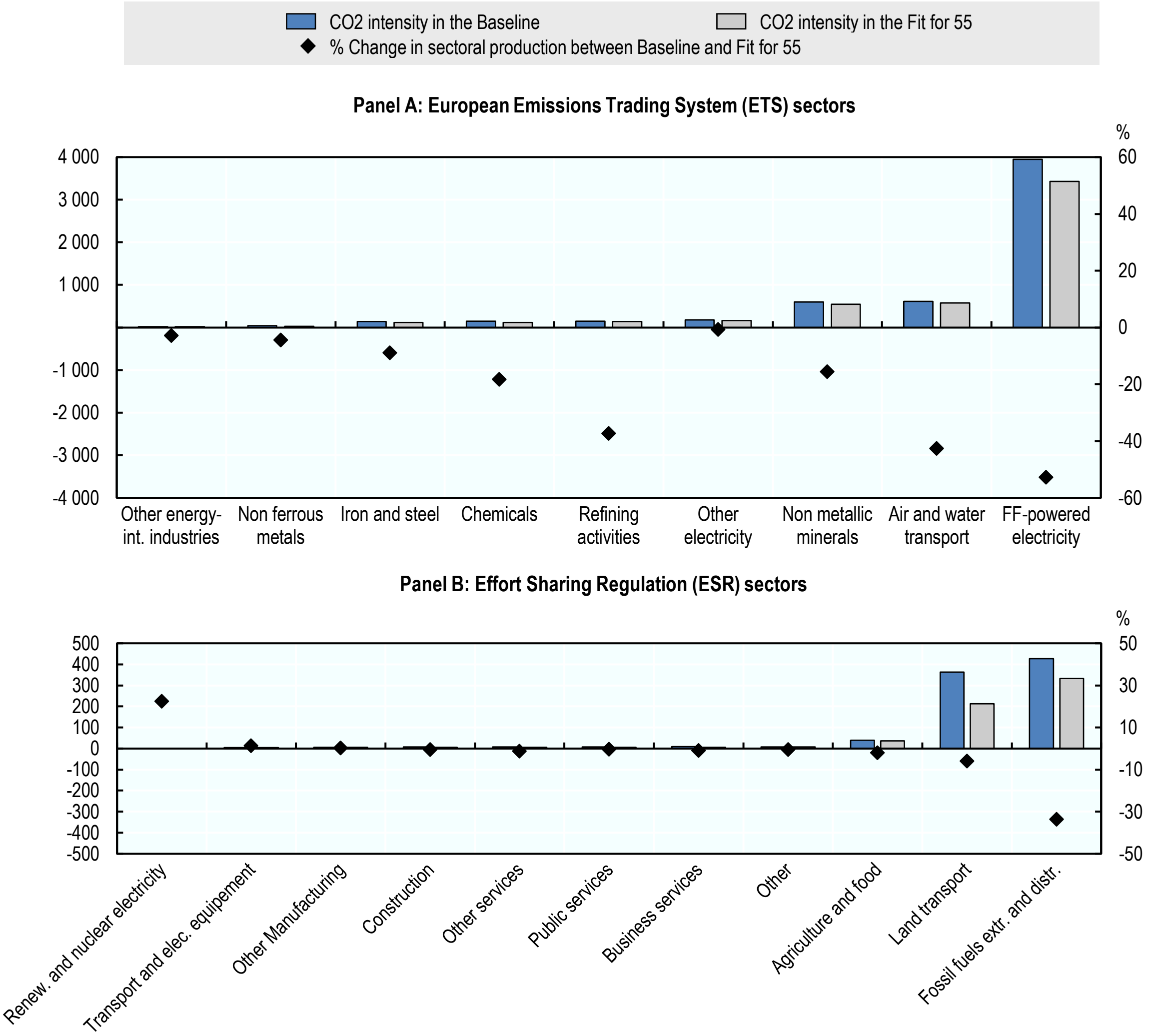
29. The Fit for 55 scenario also reduces the CO_2 intensity of key sectors, compared to the Baseline. For ETS sectors, the largest decreases in CO_2 intensity take place in the production of 'non-ferrous metals' (-25%), 'chemicals' (-19%), 'iron and steel' (-17%) as well as 'other energy intensive industries' (-19%) and other CO_2 intensive sectors ('fossil-fuel powered electricity'; -13%).[16] In ESR sectors, CO_2 intensity decreases particularly for 'land transport' (-41%), 'fossil fuels extraction and distribution' (-22%), and for the 'services sectors'.

[15] The new Fit for 55 package is more ambitious for EU-ETS sectors: -61% between 2005 and 2030 levels, vs -43% for the former target.

[16] In these sectors, a decrease in emission intensity implies that CO_2 emissions decrease more than production.

Figure 2.3. Change in sectoral production in the Fit for 55 scenario

CO_2 intensity in $ktCO_2$/USD and % change sectoral production in million USD (secondary axis) in 2030



Note: Sectors are ranked by CO_2 intensity in the Baseline scenario. An overview on all ENV-Linkages sectors displayed in this figure and how sectors are combined is provided in Table A A.2 and Table A A.3.
Source: OECD ENV-Linkages model.

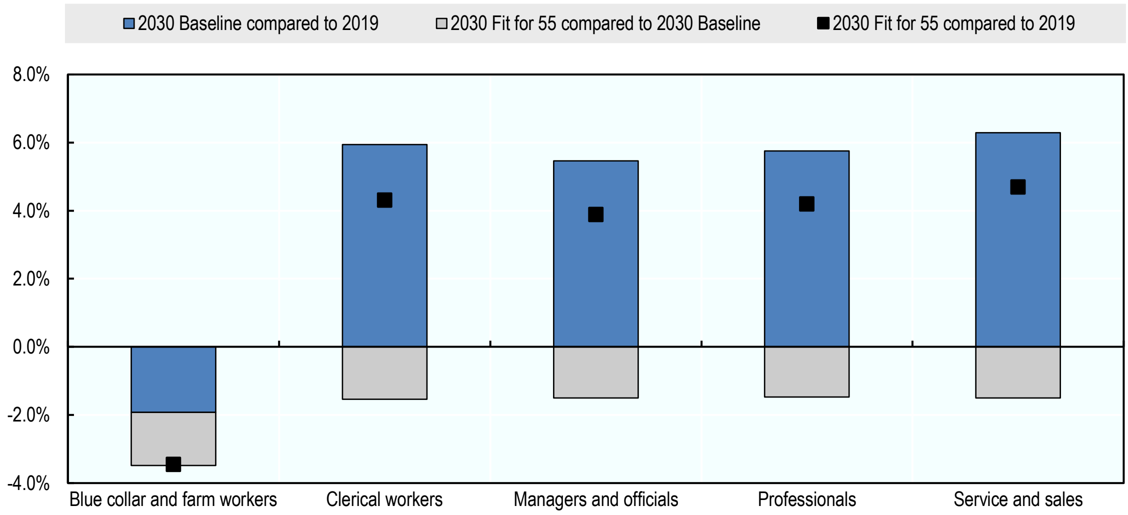
Sectoral employment

30. Changes in sectoral employment result from two main interacting effects. First, changes in aggregate employment affect the size of the sectoral employment effects. In the Baseline scenario, employment is projected to increase by 3% overall, compared to 2019. However, the contraction in GDP in the Fit for 55 scenario results in a lower increase in employment compared to 2019 (1.3%). This implies a decrease in employment by 2% in the Fit for 55 scenario in 2030 compared to the Baseline. Second, the changes in the structure of the economy that follow the implementation of the Fit for 55 scenario lead to a reallocation of employment across sectors that accentuate the changes that already take place in the Baseline scenario. Specifically, these include a switch from fuel-based energy towards renewable energy and a structural reallocation towards the service sectors.

31. Together these effects result changes in employment by occupational category (Figure 2.4). In particular, the reorientation of the economy towards more labour-intensive sectors, in which blue collar and farm workers represent a lower share of employment, is a key driver of the effects by occupational category. Employment decreases for blue collar and farm workers compared to 2019 (-3%), while it increases for other categories (4-5%).

Figure 2.4. Employment in the Fit for 55 and Baseline scenarios

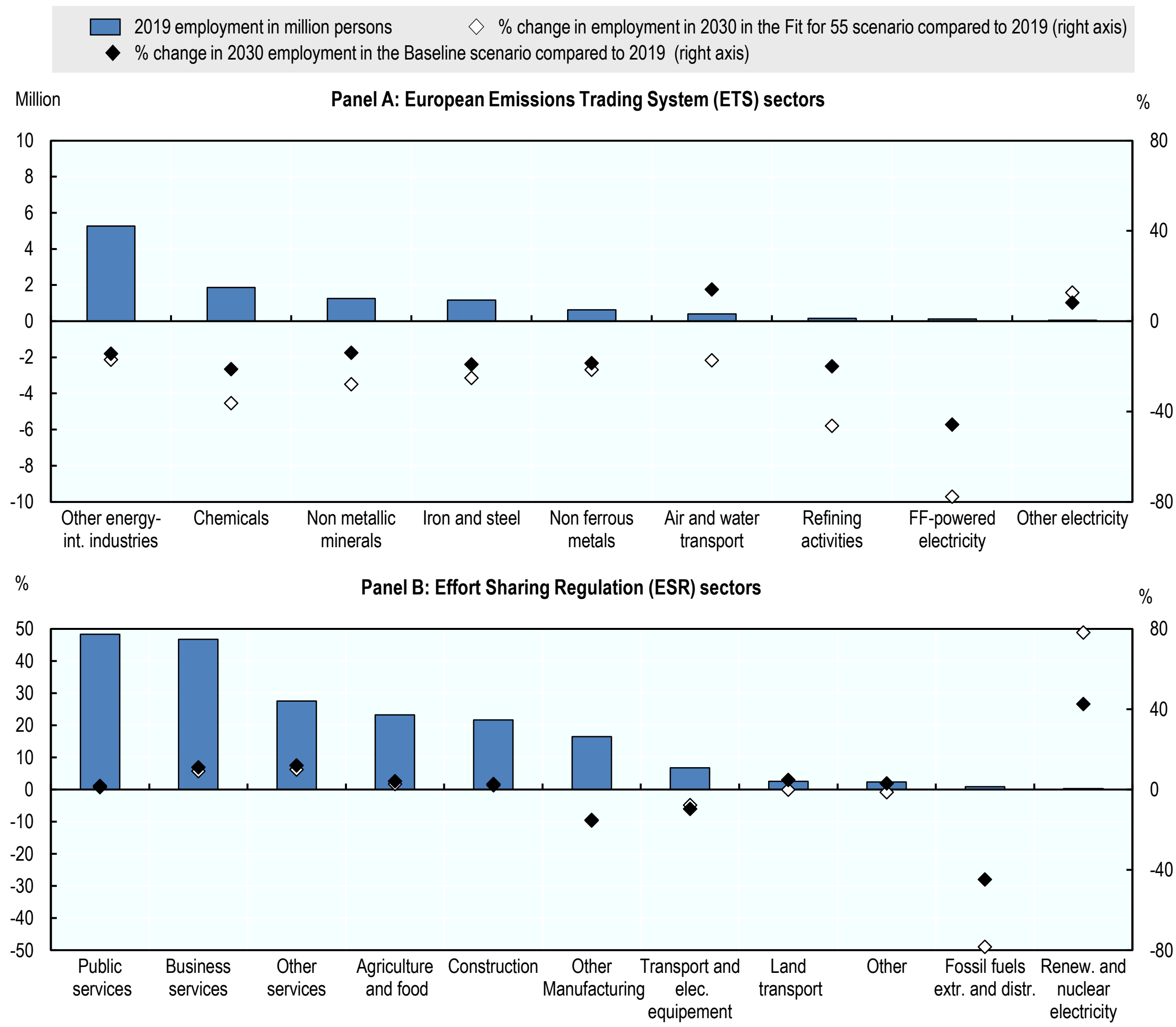
% changes in employment compared to 2019



Note: The figure shows changes in employment in the Baseline from 2019 to 2030 (blue bars), as well as the additional changes that take place in 2030 with the Fit for 55 scenarios. The figure also displays the overall net change in employment in the Fit for 55 scenario from 2019 to 2030 (black squares).
Source: OECD ENV-Linkages model.

32. The changes in aggregate employment result from the reallocation of employment across sectors. In particular, employment increases significantly in sectors not covered by the ETS, where it grows by 3% between 2019 and 2030 in the Fit for 55 scenario (Figure 2.5). Employment increases in ESR high-employment sectors (6% in total services, which include 'public services', 'business services' and 'other services', and 2% in 'construction' between 2019 and 2030) but declines in other sectors, including 'fossil fuels extraction and distribution' (-87%), 'other manufacturing' sectors (-15%), and 'transport and electronic equipment' (-8%). Employment grows the most in 'renewables and nuclear electricity' (78%). Employment decreases the most in fossil-based energy sectors, which are covered by the ETS. However, employment in these sectors accounts for less than 1% of total employment in the EU in 2030 in the Fit for 55 scenario, so that this decrease has limited impacts on overall employment. Overall, employment losses and gains will not be equally distributed across different sectors and occupations. In particular, sectors that will be most severely impacted in relative terms in terms of job creation and job destruction will be concentrated in sectors that currently employ relatively few workers and that pay relatively well whereas sectors that currently employ many workers will be less affected by structural transformations. Job destruction will be especially large for blue collar and farm workers.

Figure 2.5. Evolution in sectoral employment in the Fit for 55 scenario



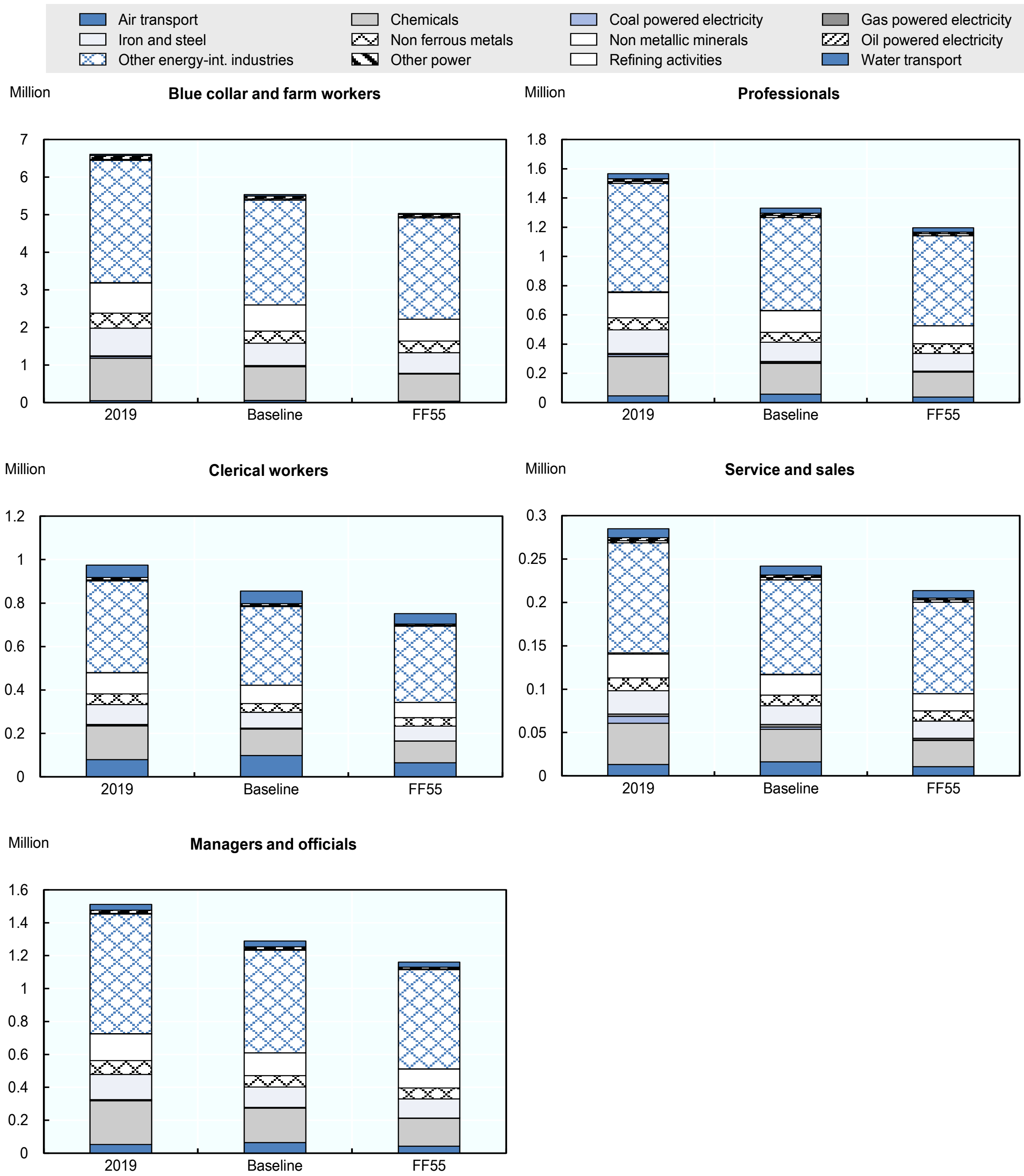
Note: Sectors are ranked by employment in 2019 (blue bars). The dots illustrate changes in employment in 2030 compared to 2019 for the Baseline scenario (black diamonds) and the Fit for 55 scenario (white diamonds). An overview on all ENV-Linkages sectors displayed in this figure and how sectors are combined is provided in Table A A.2 and Table A A.3.
Source: OECD ENV-Linkages model.

Sectoral employment by occupational category

33. With the Fit for 55 package, employment in the European Union by 2030 increases in all job categories except for blue collar and farm workers by 2030 compared to 2019 (Figure 2.6 illustrates results for ETS sectors while Figure 2.7 for ESR sectors). As described above in Figure 2.1, the ETS sectors only employ a very small share of workers, while emitting a very large share of the GHG emissions. For the blue collar and farm workers occupational category, while employment remains at a similar level between 2019 and 2030 for ESR sectors (-0.1%), it decreases strongly for ETS sectors (-24%). For all other categories, the increase in employment in ESR sectors compensate for the decrease in ETS sectors. Employment increases for service and sales workers, managers and officials, clerical workers and professionals as these categories are most employed in sectors with a large share of total employment (services sectors) and/or in sectors in which employment increases the most between 2019 and 2030 (renewables and nuclear electricity).

Figure 2.6. Change in sectoral employment by occupational category in the Fit for 55 scenario, European Emissions Trading System (ETS) sectors

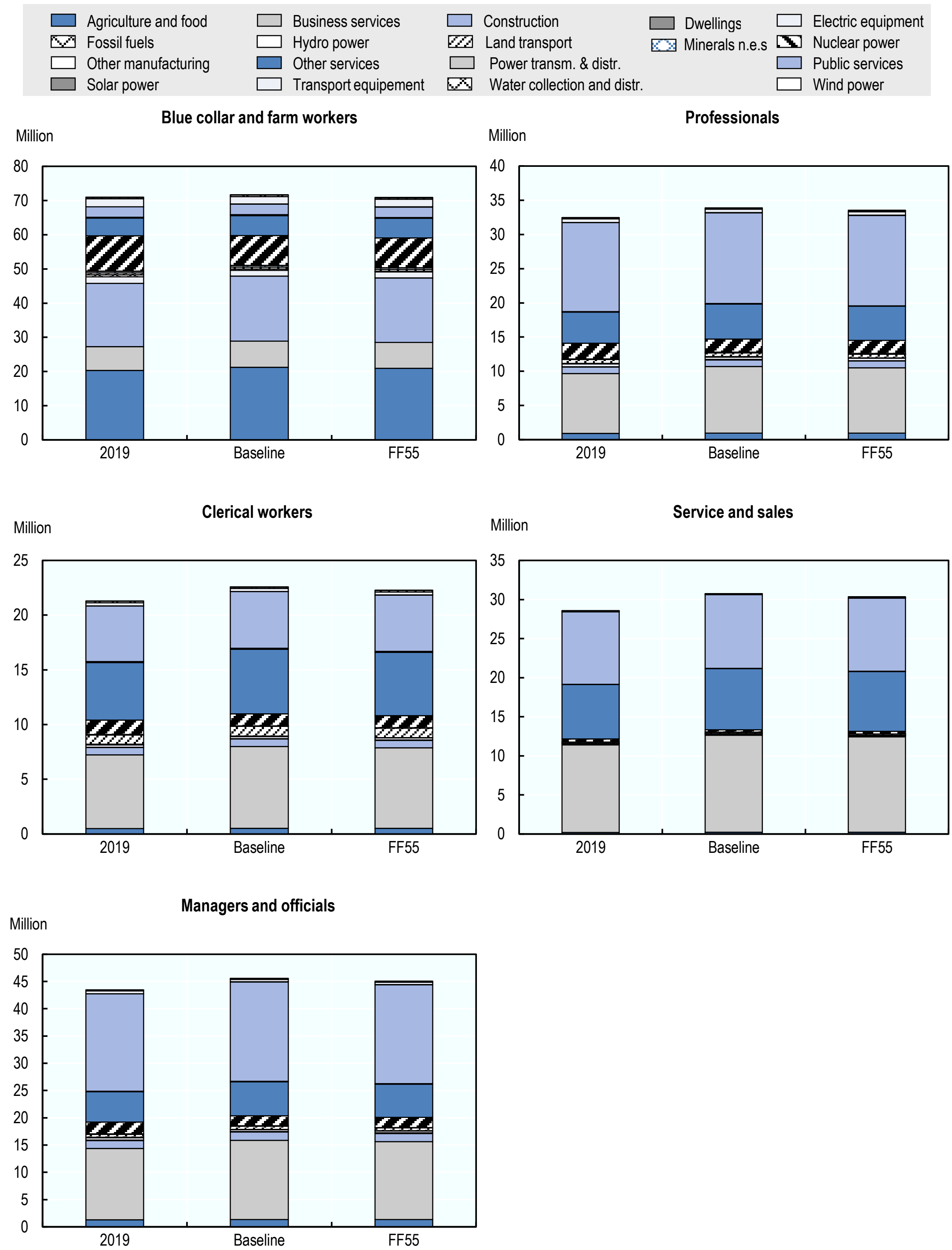
Employment level relative to total employment of the category in 2019 and in 2030 (in million persons)



Note: For each occupational category, the figure illustrates employment for all European Emissions Trading System (ETS) sectors, for the base year (2019), as well as for the Baseline scenario and the Fit for 55 scenario in 2030. An overview on all ENV-Linkages and sectors displayed in this figure and how sectors are combined is provided in Table A A.2 and Table A A.3.
Source: OECD ENV-Linkages model.

Figure 2.7. Change in sectoral employment by occupational category in the Fit for 55 scenario, Effort Sharing Regulation (ESR) sectors

Employment level relative to total employment of the category in 2019 and in 2030 (in million persons)



Note: For each occupational category, the figure illustrates employment for all ESR sectors, for the base year (2019), as well as for the Baseline scenario and the Fit for 55 scenario in 2030. An overview on all ENV-Linkages sectors displayed in this figure and how sectors are combined is provided in Table A A.2 and Table A A.3.
Source: OECD ENV-Linkages model.

3 Projected changes in the demand for skills

Obtaining skills projections from employment projections

34. This section considers the implications of changes in the distribution of employment for changes in the demand of skills, to aid the development of effective skills policies and their successful implementation in support of workers at the greatest risk of displacement. Data collected by Lightcast, a labour market analytics company, covering information contained in over 80 000 online job sites were used to estimate the skills content of jobs in the sectoral-by-occupational combinations that were used in Section 2. To aggregate skills demanded in individual job vacancies to economy-wide skills demands, three sets of analyses were performed.

35. In a first step, Lightcast used natural language processing models to extract from the individual job vacancy text information on the set of skills employers sought (but not the level of proficiency desired or expected) in their prospective employees. The dataset used in the analysis includes information about the following European Union countries: Austria, Belgium, Bulgaria, Croatia, the Czech Republic, Denmark, Estonia, Finland, France Germany, Greece, Hungary, Italy, Ireland, Latvia, Lithuania, Luxemburg, Malta, the Netherlands, Poland, Portugal, Romania, Slovenia, the Slovak Republic, Spain and Sweden.

36. In a second step, the skill requirements of jobs in different sectors and occupations were measured in terms of their Relative Comparative Advantage (RCA) within sector-occupation groups using the methodology applied in Alabdulkareem et al. (2018[36]), which was also adopted in the OECD Skills for Jobs database (OECD, n.d.[37]). RCA measures the importance of a specific skill in a specific sector-by-occupation category by considering whether this skill is more frequently found in job vacancies in that sector-by-occupation category compared to how frequently other skills are found in job vacancies in that sector-by-occupation category and how frequently this skill is found in vacancies in other sector-by-occupation categories.[17] RCA reduces the effect of the tendency of some employers' to understate (because such skills are considered to be 'implicit') or overstate (because such skills are listed even though they are not essential to perform a job) the importance of certain skills in different online vacancies on estimates of the skills content of different occupations based on online vacancies.

37. In a third step, skills RCAs were multiplied by employment numbers in different sector-by-occupation categories for different scenarios: in the absolute scenario, RCAs were multiplied by EU-wide employment numbers in 2019 as well as projections in 2030 under the Baseline and the Fit for 55 scenario. In the relative scenario, RCAs were multiplied by projected growth rates in employment in different sector-by-occupation categories between 2019 and 2030 both in the Baseline and the Fit for 55 scenarios. An

[17] Mathematically for each skill the RCA was calculated as the ratio of the frequency of vacancies demanding a certain skill for a given sector-by-occupation category over the sum of all skill frequencies across all skills for the same category divided by ratio of the sum of the frequency of vacancies demanding such skill in all other sector-by occupation categories over the sum of all skill frequencies across all skills for all other categories.

important caveat of estimates of the skills content of occupations based on RCA is that estimates have ordinal but not numerical meaning. Therefore, whereas it is possible to describe which skills are projected to increase the most and consider if differences in projected growth under different scenarios for one skill are larger or smaller than those projected for a different skill, it is not possible to say if a skill is projected to grow by a given percent or, for example, double in demand. However, estimates reflect if demand is projected to increase or decrease, projected changes can be ranked, and can be grouped into quartiles of projected growth. Rank position and quartiles of growth were used in the following analyses to describe projected changes in skills demand.

38. In the context of this work, the term skills is used as an overarching term to refer to skills, knowledge and abilities as identified in the European ESCO and the United States' O*NET (Occupational Information Network) classifications. Each skill is viewed independently without considering the complementarities that exist between different skills to perform a specific job and to map skills bundles in different occupations. Furthermore, no information on level of mastery or proficiency in the use of a specific skill in different jobs is integrated in the model.[18]

39. Contrary to most empirical work, which assumes that the skill requirements of occupations in different countries reflect the skill requirements observed in the United States as specified in the context of the O*NET database, in this work emerging skill requirements contained in job postings for the European Union region were used. The use of skills requirements specified in online job vacancies also allows to better approximate the emerging skills content of different occupations, given the intention of this work to consider projected changes in skills demands related to structural transformations in production processes to meet ambitious environmental policy targets rather than mapping the distribution of skill requirements in the past in different occupations. To aid comparability with other work such as the OECD Skills for Jobs Database, skill requirements expressed in the European ESCO taxonomy were mapped onto the O*NET classification (the crosswalk between the two taxonomies can be requested from the authors).

40. The detailed skills classifiers contained in job vacancies were aggregated into six main skills categories according to the O*NET system: *Skills, Knowledge*, *Abilities*, *Technology Skills and Tools*, *Work Activities,* and *Work Styles*. To avoid confusion between individual skills and the broad *Skills* category, in this paper whenever referring to a specific aggregate category of skills, italics is used. By contrast, the term skills not italicised is used to refer to all the categories together and general human capital.

41. In the O*NET classification, the following six categories are used to describe broad aspects of job-related competencies and characteristics (O*NET, n.d.[38]):

- ***Skills*****:** *Skills* refer to specific abilities or proficiencies that are necessary to perform a job effectively. They can be categorized as either "hard" skills, which are technical or specialized skills that are typically learned through formal education or training, or "soft" skills, which are interpersonal or behavioural skills that are generally developed through experience and practice.
- ***Knowledge***: *Knowledge* refers to the understanding and awareness of facts, information, concepts, principles, and procedures. It includes both theoretical and practical knowledge required to perform tasks and responsibilities associated with a particular job.
- ***Abilities*****:** *Abilities* are enduring attributes that enable individuals to perform tasks or activities required for a specific job. Examples of abilities include cognitive abilities (e.g. analytical thinking, problem-solving), physical abilities (e.g. strength, dexterity), and sensory abilities (e.g. vision, hearing) and psychomotor abilities (e.g. capacity to manipulate and control objects).
- ***Technology Skills and Tools***: *Technology Skills and Tools* refer to the proficiency in using and working with different types of technology and tools relevant to a job. This can include computer

[18] Annex B and Annex C provide details of the skills dataset, how information on the skills content of different sectors and occupations was aggregated.

skills, software proficiency, equipment operation, and other technical competencies required for a specific occupation.

- **Work Activities**: *Work Activities* refer to the tasks, duties, and responsibilities that are typically performed in a particular occupation. They describe the specific actions and behaviours required to carry out job-related functions. Work Activities may include physical tasks, communication and coordination activities, problem-solving, decision-making, and other activities related to the job.
- **Work Styles**: *Work Styles* refer to the personal characteristics, behaviours, and attitudes that are relevant to how individuals approach their work. It includes aspects such as work ethics, work values, work preferences, and work habits. Work Styles can influence how individuals interact with others, manage their time, handle stress, and approach their job responsibilities.

Projected trends in the demand of skills by broad skill categories

42. The modelling analysis reveals that sectors that employ few people, such as 'fossil fuel powered electricity' and 'renewable and nuclear energy generation', are projected to be highly impacted (some negatively and others positively) by the implementation of Fit for 55 (Figure 2.5). At the same time, because such sectors employ few people, large relative changes in employment translate into smaller changes in the number of workers employed in these sectors than those experienced by sectors, such as services, that employ a large number of people. Because economy-wide estimates of skills demands are determined by the skills requirements for workers in different sectors and occupations, calculations of skills demands depend on which measure of employment is adopted, and whether it is a relative or an absolute definition. Because under the Fit for 55 scenario employment is projected to be lower (1.3% versus 3%) than in the Baseline scenario (Figure 2.5), changes in skills categories based on relative and absolute changes in employment presented in the following section reveal a weaker demand for all skills categories in the Fit for 55 scenario than the Baseline scenario.

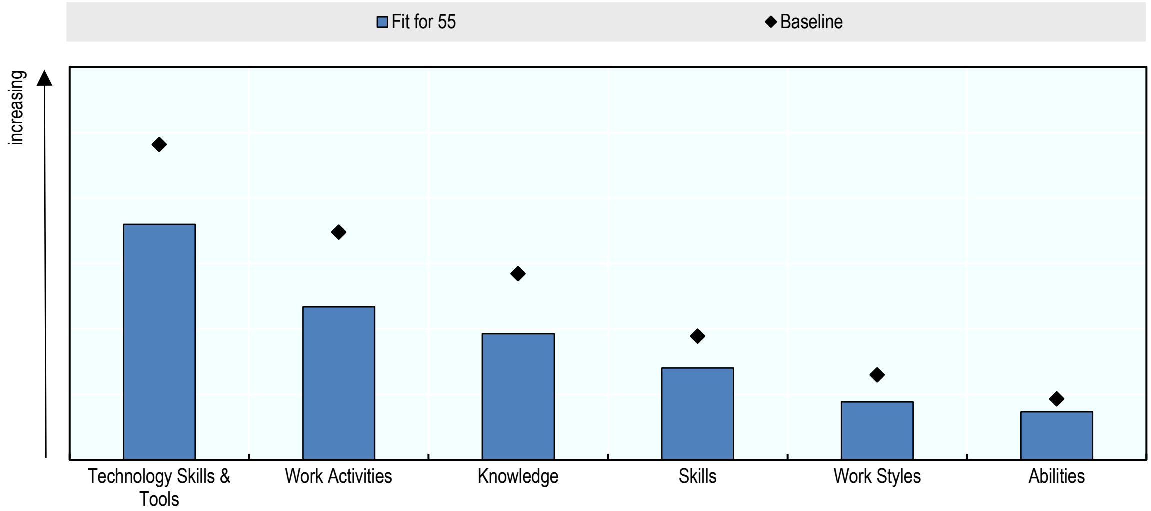
43. When considering **relative changes in employment**, the skills categories that are projected to grow the most in demand are *Technology skills and tools* and *Work Activities* Figure 3.1.[19] These two skills categories group a large number of skills that are used in occupations and sectors projected to grow sharply between 2019 and 2030. The difference between the two Fit for 55 and Baseline scenarios in projections for different skills categories reflects the different demand for skills in each of the six categories in sectors and occupations with different projected growth rates in the two scenarios.

44. When considering **absolute changes in employment** between 2019 and 2030, *Knowledge* and *Work Activities* are the skills categories that are projected to grow most sharply whereas *Skills* and *Abilities* are projected to grow the least (Figure 3.2).

[19] Relative changes correspond to the projected percentage changes in employment by 2030 under the Fit for 55 and Baseline scenarios over 2019 employment levels.

Figure 3.1. Projected change in the demand for skills between 2019 and 2030 when considering relative growth in employment, by main skill category

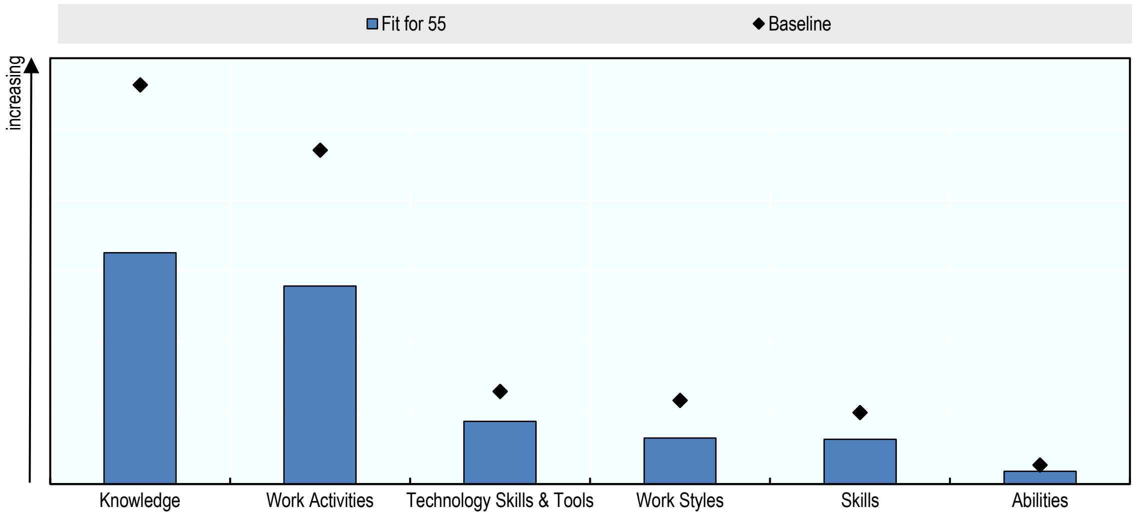
Estimated change in the demand for skills given projections in relative employment growth in different sectors and occupations in the Fit for 55 and Baseline scenarios



Note: The figure shows the projected change in the demand for each of the six main skills categories between 2019 and 2030 under the Fit for 55 and Baseline scenarios across European Union countries when considering relative employment growth in different sectors and occupations identified in Section 2. Detailed description of the underlying analyses are provided in Annex C.
Source: Authors' own compilation based on OECD ENV-Linkages model, Lightcast™ (April 2023) and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

Figure 3.2. Projected change in the demand for skills between 2019 and 2030 when considering absolute changes in employment, by main skill category

Estimated change in the demand for skills given projections in absolute employment change in different sectors and occupations in the Fit for 55 and Baseline scenarios



Note: The figure shows the projected change in the demand for each of the six main skills categories between 2019 and 2030 under the Fit for 55 and Baseline scenarios across European Union countries when considering absolute employment growth in different sectors and occupations identified in Section 2. Detailed description of the underlying analyses are provided in Annex C.
Source: Authors' own compilation based on OECD ENV-Linkages model, Lightcast™ (April 2023) and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

45. Table 3.1 categorises all skills demanded in online vacancies into five groups. The first four groups reflect quartiles of projected skills growth between 2019 and 2030 under the Fit for 55 scenario, with group one being composed of the 25% of skills that are projected to increase the most in demand whereas group four comprising the 25% of skills that are projected to increase the least in demand. The fifth group comprises all skills that are projected to decline in demand under the same scenario. Projections in demand were obtained by multiplying changes in **absolute employment numbers** between 2019 and 2030 in the Fit for 55 scenario.

Table 3.1. Projected change in the demand for skills between 2019 and 2030 when considering absolute growth under the Fit for 55 scenario

Top quartile of absolute increase	Second quartile of absolute increase	Third quartile of absolute increase	Bottom quartile of absolute increase	Skills declining in demand
Oral Expression	Originality	Mathematical Reasoning	Memorization	Physics
Sales and Marketing	Fluency of Ideas	Fine Arts	Written Comprehension	Mechanical
Computers and Electronics	Law and Government	Transportation	Information Ordering	Repairing
Language	Chemistry	Philosophy and Theology	Therapy and Counseling	Equipment Maintenance
Economics and Accounting	Biology	History and Archeology	Design	Offset printing presses
Customer and Personal Service	Public Safety and Security	Telecommunications	Systems Evaluation	Injection molding machines
Administration and Management	Engineering and Technology	Sociology and Anthropology	Service Orientation	Computer aided manufacturing CAM software
Medicine and Dentistry	Administrative	Judgment and Decision Making	Active Listening	Lasers
Production and Processing	Mathematics	Management of Material Resources	Critical Thinking	Milling machines
Communications and Media	Building and Construction	Management of Personnel Resources	Resource Management Skills (general)	Handling and Moving Objects
Personnel and Human Resources	Psychology	Monitoring	Program testing software	Repairing and Maintaining Mechanical Equipment
Food Production	Education and Training	Systems Analysis	Music or sound editing software	
Programming	Geography	Graphics or photo imaging software	Metadata management software	Controlling Machines and Processes
Time Management	Management of Financial Resources	Data base user interface and query software	Automatic teller machines ATMs	
Web platform development software	Complex Problem Solving	Enterprise application integration software	Information retrieval or search software	
Operating system software	Quality Control Analysis	Web page creation and editing software	Cloud-based data access and sharing software	
Analytical or scientific software	Data base management system software	Spreadsheet software	Business intelligence and data analysis software	
Interacting With Computers	Object or component oriented development software	Internet browser software	Geographic information system	
Thinking Creatively	Office suite software	Desktop publishing software	Access servers	
Analyzing Data or Information	Configuration management software	Computer based training software	Word processing software	
Assisting and Caring for Others	Development environment software	Inspecting Equipment, Structures, or Material	Computer aided design CAD software	
Communicating with Persons Outside Organization	Enterprise resource planning ERP software	Operating Vehicles, Mechanized Devices, or Equipment	Optical character reader OCR or scanning software	

Top quartile of absolute increase	Second quartile of absolute increase	Third quartile of absolute increase	Bottom quartile of absolute increase	Skills declining in demand
Performing General Physical Activities	Customer relationship management CRM software	Scheduling Work and Activities	Network monitoring software	
Provide Consultation and Advice to Others	Application server software	Identifying Objects, Actions, and Events	Transaction security and virus protection software	
Guiding, Directing, and Motivating Subordinates	Presentation software	Training and Teaching Others	Video creation and editing software	
Performing Administrative Activities	Documenting/Recording Information	Coaching and Developing Others	Object oriented data base management software	
Establishing and Maintaining Interpersonal Relationships	Communicating with Supervisors, Peers, or Subordinates	Getting Information	Safety harnesses or belts	
Organizing, Planning, and Prioritizing Work	Performing for or Working Directly with the Public	Evaluating Information to Determine Compliance with Standards	Blow molding machines	
Selling or Influencing Others	Judging the Qualities of Things, Services, or People	Developing and Building Teams	Compliance software	
Monitoring and Controlling Resources	Staffing Organizational Units	Updating and Using Relevant Knowledge	Interpreting the Meaning of Information for Others	
Developing Objectives and Strategies	Monitor Processes, Materials, or Surroundings	Stress Tolerance	Processing Information	
Making Decisions and Solving Problems	Resolving Conflicts and Negotiating with Others	Concern for Others	Repairing and Maintaining Electronic Equipment	
Dependability	Self Control	Attention to Detail	Estimating the Quantifiable Characteristics of Products, Events, or Information	
Initiative	Analytical Thinking	Cooperation	Coordinating the Work and Activities of Others	
Achievement/Effort	Adaptability/Flexibility	Innovation	Integrity	
Leadership			Persistence	

Note: Individual skills are grouped into five groups depending on the size of projected changes in demand between 2019 and 2030 when considering absolute growth under the Fit for 55 scenario. Each skill is assigned a colour depending on the skill category to which the skill belongs to. Estimates of changes in skills demands were computed by multiplying RCAs with overall employment numbers in 2019 and in 2030 under the Fit for 55 Scenario.

- Abilities
- Knowledge
- Skills
- Technology Skills & Tools
- Work Activities
- Work Styles

Source: Authors' own compilation based on OECD ENV-Linkages model, Lightcast™ (April 2023) and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

46. As many as 11 skills out of the 32 skills in the *Knowledge* category (or around 34%) are projected to be in the group of skills with the strongest estimated demand increase. Examples of these skills are: 'sales and marketing', 'computers and electronics', 'language', 'economics and accounting', 'customer and personal service', 'administration and management', 'medicine and dentistry', 'production and processing', 'communications and media', 'personnel and human resources', and 'food production'. Most of these skills are essential in the business services and public services sectors, employing a large number of workers in European Union economies. A further 11 of the 32 skills in the *Knowledge* category (or around 34%) are

estimated to be in the group with the second highest demand. These are: 'law and government', 'chemistry', 'biology', 'public safety and security', 'engineering and technology', 'administrative', 'mathematics', 'building and construction', 'psychology', 'education and training', and 'geography'. Only 4 skills in the *Knowledge* category are projected to decline in overall demand or be in the group of skills that are estimated to grow the least in demand.

47. Many of the skills in the *Work Activities* category are also estimated to be in the largest increase group: 15 of the 41 skills are in the largest increase group (around 38% of all skills in the *Work Activities* category). Examples of *Work Activities* skills that are estimated to grow the most in demand include: 'interacting with computers'; 'thinking creatively'; 'analysing data and information'; 'assisting and caring for others'; 'communicating with persons outside an organisation'; 'performing general physical activities'; 'providing consultation and advice to others'; 'guiding, directing, and motivating subordinates'; 'performing administrative activities'; 'establishing and maintaining interpersonal relationships'; 'organizing, planning, and prioritizing work'; 'selling or influencing others'; 'monitoring and controlling resources'; 'developing objectives and strategies'; and 'making decisions and solving problems'. By contrast, only three skills in the *Work Activities* category out of 41 (around 10%) are projected to decline in demand. These are: 'handling and moving objects'; 'repairing and maintaining mechanical equipment'; and 'controlling machines and processes'.

Table 3.2. Projected change in the demand for skills in 2030 between between the Fit for 55 and Baseline scenarios

Top quartile of change in demand due to FF55 relative to Baseline (Skills for which Fit for 55 is projected to have the weakest negative effect on skills demand)	Second quartile of change in demand due to FF55 relative to Baseline	Third quartile of change in demand due to FF55 relative to Baseline	Bottom quartile of change in demand due to FF55 relative to Baseline (Skills for which Fit for 55 is projected to have the strongest negative effect on skills demand)
Information Ordering	Fluency of Ideas	Oral Expression	Written Comprehension
Mathematical Reasoning	Economics and Accounting	Originality	Language
Memorization	Medicine and Dentistry	Administrative	Building and Construction
Sociology and Anthropology	Food Production	Mathematics	Production and Processing
History and Archeology	Fine Arts	Personnel and Human Resources	Transportation
Service Orientation	Sales and Marketing	Philosophy and Theology	Engineering and Technology
Management of Personnel Resources	Public Safety and Security	Computers and Electronics	Design
Critical Thinking	Psychology	Telecommunications	Physics
Active Listening	Communications and Media	Law and Government	Mechanical
Systems Evaluation	Biology	Chemistry	Quality Control Analysis
Offset printing presses	Education and Training	Therapy and Counseling	Complex Problem Solving
Network monitoring software	Geography	Management of Material Resources	Equipment Maintenance
Geographic information system	Customer and Personal Service	Time Management	Resource Management Skills (general)
Program testing software	Administration and Management	Enterprise resource planning ERP software	Repairing
Video creation and editing software	Programming	Object oriented data base management software	Information retrieval or search software
Enterprise application integration software	Management of Financial Resources	Graphics or photo imaging software	Word processing software
Compliance software	Systems Analysis	Computer based training software	Spreadsheet software
Data base management system software	Judgment and Decision Making	Automatic teller machines ATMs	Blow molding machines
Business intelligence and data analysis software	Monitoring	Optical character reader OCR or scanning software	Internet browser software
Access servers	Web platform development software	Office suite software	Lasers
Transaction security and virus protection software	Object or component oriented development software	Assisting and Caring for Others	Computer aided design CAD software

Top quartile of change in demand due to FF55 relative to Baseline (Skills for which Fit for 55 is projected to have the weakest negative effect on skills demand)	Second quartile of change in demand due to FF55 relative to Baseline	Third quartile of change in demand due to FF55 relative to Baseline	Bottom quartile of change in demand due to FF55 relative to Baseline (Skills for which Fit for 55 is projected to have the strongest negative effect on skills demand)
Safety harnesses or belts	Customer relationship management CRM software	Judging the Qualities of Things, Services, or People	Injection molding machines
Presentation software	Milling machines	Thinking Creatively	Computer aided manufacturing CAM software
Desktop publishing software	Development environment software	Performing General Physical Activities	Inspecting Equipment, Structures, or Material
Metadata management software	Web page creation and editing software	Establishing and Maintaining Interpersonal Relationships	Repairing and Maintaining Electronic Equipment
Configuration management software	Analytical or scientific software	Documenting/Recording Information	Monitor Processes, Materials, or Surroundings
Music or sound editing software	Cloud-based data access and sharing software	Training and Teaching Others	Operating Vehicles, Mechanized Devices, or Equipment
Operating system software	Guiding, Directing, and Motivating Subordinates	Interacting With Computers	Developing and Building Teams
Application server software	Coaching and Developing Others	Monitoring and Controlling Resources	Getting Information
Data base user interface and query software	Provide Consultation and Advice to Others	Interpreting the Meaning of Information for Others	Processing Information
Coordinating the Work and Activities of Others	Selling or Influencing Others	Organizing, Planning, and Prioritizing Work	Estimating the Quantifiable Characteristics of Products, Events, or Information
Identifying Objects, Actions, and Events	Developing Objectives and Strategies	Evaluating Information to Determine Compliance with Standards	Repairing and Maintaining Mechanical Equipment
Resolving Conflicts and Negotiating with Others	Communicating with Supervisors, Peers, or Subordinates	Self Control	Repairing and Maintaining Mechanical Equipment
Staffing Organizational Units	Scheduling Work and Activities	Attention to Detail	Handling and Moving Objects
Performing Administrative Activities	Communicating with Persons Outside Organization	Initiative	Controlling Machines and Processes
Performing for or Working Directly with the Public	Making Decisions and Solving Problems	Leadership	Dependability
Analyzing Data or Information	Updating and Using Relevant Knowledge	Achievement/Effort	Integrity
Persistence	Analytical Thinking	Concern for Others	Stress Tolerance
Innovation			Adaptability/Flexibility
			Cooperation

Note: Individual skills are grouped into four groups depending on the size of the difference in projected skills demands in 2030 under the Fit for 55 scenario and the Baseline scenario. Each skill is assigned a colour depending on the skill category to which the skill belongs to. Estimates of changes in skills demands were computed by multiplying RCAs with the percentage change in employment numbers in 2030 under the Fit for 55 and the Baseline scenario.

Abilities
Knowledge
Skills
Technology Skills & Tools
Work Activities
Work Styles

Source: Authors' own compilation based on OECD ENV-Linkages model, Lightcast™ (April 2023) and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

48. By contrast, among the 44 skills identified in the *Technology Skills and Tools* category, 3 (corresponding to 7% of all skills in the *Technology Skills and Tools* category) belong to the set of skills that are projected to grow the most in demand between 2019 and 2030. These are: 'web platform development software'; 'operating system software'; and 'analytical or scientific software'. As many as 19 skills (corresponding to 43%) belong to the set of skills that are projected to grow the least in demand between 2019 and 2030 and 5 skills are projected to decline in demand (11%). These include: 'offset printing presses'; 'injection molding machines'; 'computer aided manufacturing CAM software'; 'operating lasers'; and 'operating milling machines'.

49. Among the *Skills* category, two skills namely 'programming' and 'time management' (corresponding to 12% of skills in the *Skills* category), are in the group of skills that are projected to increase the most in demand whereas 'repairing' and 'equipment maintenance' are in the set of skills that are projected to decline in demand. 'Oral expression' is the only skill in the *Abilities* category that is estimated to be in the group of skills projected to increase the most in demand, 'originality' and 'fluency of ideas' are in the second group of increased demand, whereas 'memorisation', 'written comprehension', and 'information ordering' are estimated to be in the group of skills projected to increase the least in demand.

50. Although the demand for most skills is projected to increase in absolute terms between 2019 and 2030 under the implementation of the Fit for 55 targets (Table 3.1), such increase is lower than the increase projected under the Baseline scenario since overall employment projections are lower in the Fit for 55 than in the Baseline scenario. At the same time, the effect of the Fit for 55 implementation is not equal across sectors and occupations so the contracting effect of Fit for 55 on skills demand varies depending on whether skills are especially used in sectors and occupations that will be most severely impacted by Fit for 55 or not.

51. Table 3.2 illustrates which skills are most affected by the Fit for 55 implementation relative to the Baseline scenario. Most of the skills that are projected to decline the most in demand as a result of the implementation of Fit for 55 targets refer to operating and maintaining equipment and tools. They include skills such as 'controlling machines and processes'; 'operating injection molding machines'; 'repairing'; 'physics'; 'handling and moving objects'; 'repairing and maintaining mechanical equipment'; 'estimating the quantifiable characteristics of products, events, or information'; 'equipment maintenance'; 'blow molding machines'. By contrast, most of the skills that are projected to be impacted the least by the contraction of employment in the Fit for 55 scenario are: 'mathematical reasoning'; 'using video creation and editing software'; 'program testing software'; 'network monitoring software'; 'persistence'; 'management of personnel resources'; 'business intelligence and data analysis software'; 'transaction security and virus protection software'; 'coordinating the work and activities of others'; and 'presentation software'.

Similarity in the skillset of workers employed in different sectors and occupations

52. Developing training opportunities to help workers effectively transition between economic sectors that are projected to shrink in the coming decade into other sectors that are projected to expand requires identifying not only economy-wide changes in skills demands but also the degree of similarity in the set of skills needed to perform different jobs, as well as projected trends in employment and the relative size of different employment opportunities. Jobs that are growing very rapidly in demand but represent a small share of the overall labour market might in fact offer fewer transition opportunities than jobs that are growing little in demand but represent a large share of the overall labour market.

53. Even after having identified the skills that adults should acquire to successfully transition into occupations or sectors that will expand in the medium term, a major challenge is to ensure that education and training systems are designed in a flexible way to enable smooth transitions. This requires adult education and training systems to have a certain degree of flexibility with respect to several dimensions: time (when does learning occur and for how long), place (where does learning occur), mode (which learning style) and content (which skills to learn) (OECD, 2023[40]). However, many adult education and training systems are not yet developed to meet these challenges. Scope for improvement exists in many areas such as the recognition of prior learning (OECD, 2019[41]) which is also closely linked to occupational entry regulations and for example has implications for labour mobility (von Rueden and Bambalaite, 2020[42]); and ensuring inclusiveness of learning systems as to date, a large share of workers still does not participate in training (OECD, 2019[41]).

54. Overall, blue collar and farm work occupations are projected to shrink in overall demand in the Fit for 55 and Baseline scenarios (Figure 2.4). As a result, many existing blue collar and farm workers will have to consider transitioning into non blue collar and farm work occupations. Therefore, young people should be made aware of shrinking/increasing labour market opportunities while they are in initial education and training and such information should be reflected in orientation programmes to help them make educational and career decisions that are aligne with labour market needs. At the same time, blue collar and farm work will not disappear and there are sectors in which demand is projected to increase. Identifying the degree of similarity in the skills required in different sectors and occupations and their capacity to absorb new workers because of labour market trends can aid both individuals who consider transition opportunities and policy makers to organise effective upskilling and reskilling programmes.

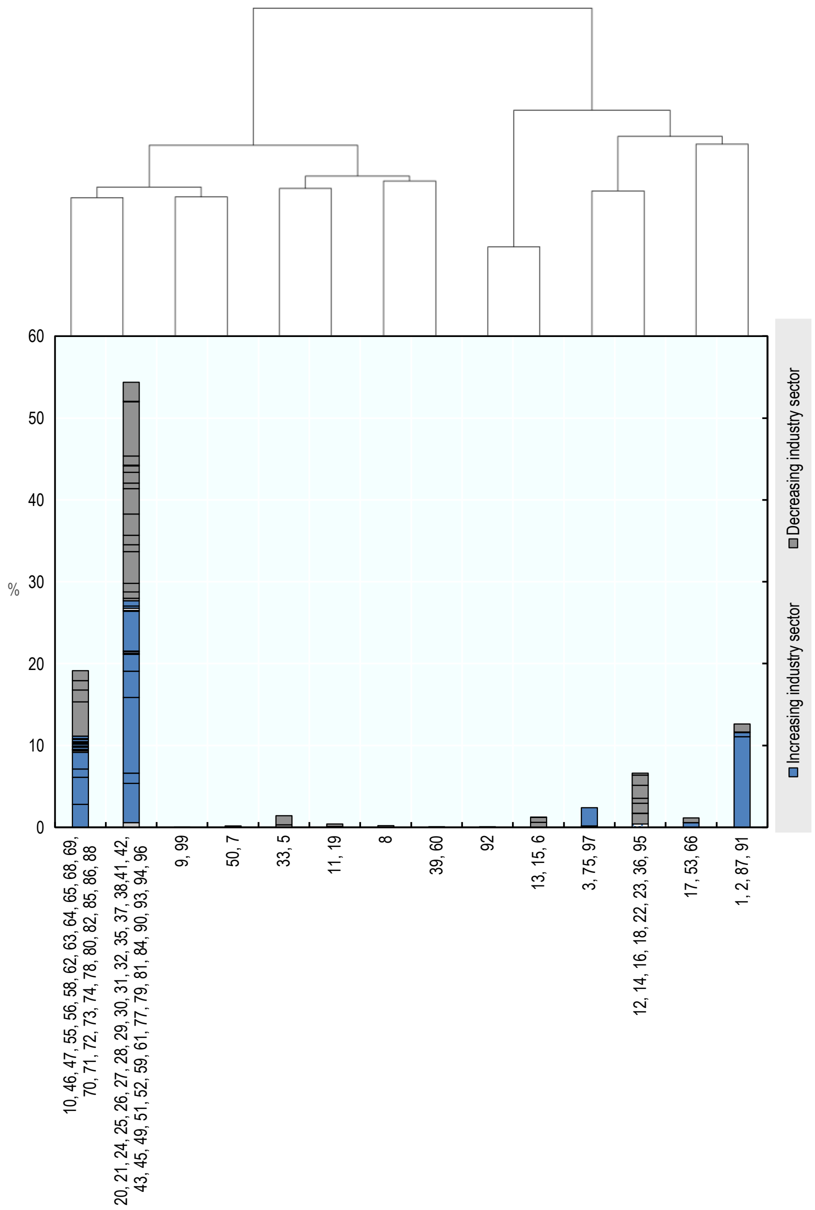
55. To identify skills similarity, in a first step, for each occupation, the cosine distance of vectors of skills (ESCO 3 digit) requirement between each sector pair was calculated using online vacancy information. The cosine distance ranges between -1 and 1 with -1 indicating orthogonal vectors (complete dissimilarity in skills requirements) and 1 indicating proportional vectors (exact match in skills requirements). Details on the exact value of the cosine dissimilarity can be requested from the authors. In a second step, hierarchical/agglomerative cluster analyses were conducted to identify clusters of sectors with similar skills requirements, based on their respective pairwise cosine dissimilarities. Although within each cluster skills requirements in different sectors can differ, they tend to be more similar than the skills requirements in sectors outside the cluster. Therefore, upskilling and reskilling should be less intense within each cluster and progressively more intense as individuals consider transitions into more ‘distant’ clusters. Because skills requirements are generally more homogeneous at the occupational than at the sectoral level, analyses were conducted for each occupation group separately.

56. Despite an overall decline in labour market opportunities for blue collar and farm work, for some blue collar workers employed in a shrinking sector transitioning into other blue collar jobs in growing sectors would entail moving into a sector with relatively high levels of skills similarity (Figure 3.3). For example, blue- collar workers employed in sector 20 (‘manufacture of chemicals and chemical products’) and 21 (‘manufacture of basic pharmaceutical products and pharmaceutical preparations’) are projected to decrease between 2019 and 2030 in the Fit for 55 scenario (these sectors are shown in the second cluster from the left). However, the skillset demanded of blue collar workers in these sectors is relatively similar to the skillset demanded in sector 35 (‘electricity, gas, steam and air conditioning supply’), sector 41 (‘construction of buildings’) and 42 (‘civil engineering’) (these sectors are shown in the second cluster from the left). These sectors are projected to increase between 2019 and 2030 under the Fit for 55 scenario, employ a relatively large share of blue collar workers and therefore exemplify relatively viable transitioning opportunities.

57. While some blue collar workers might have opportunities to transition into sectors with similar skills profiles (Figure 3.3), for other workers the skills requirements in sectors which are projected to increase in demand differ substantively from the skillset required in their current job. For example, the highest degree of similarity in the skillset demanded of blue collar workers employed in sectors 5 (‘mining of coal and lignite’) is the skillset demanded of blue collar workers in sector 33 ('repair and installation of machinery and equipment’) (these sectors are shown in the fifth cluster from the left in Figure 3.3). However, both sectors are projected to decline between 2019 and 2030, and there are no other sectors in the same cluster with a skillset that is relatively similar and that are projected to grow, thus providing more viable transition opportunities.

Figure 3.3. Skills similarity of employment opportunities for blue collar and farm workers

Dendrogram illustrating sectors based on skills similarity for blue collar workers, employment shares in 2019 and projected growth/decline between 2019 and 2030 under the implementation of Fit for 55



Note: The top part of the dendogram illustrates the degree of similarity in the skillset needed in jobs performed by workers in different sector: sectors that share the same tree of the dendogram are closest in terms of skills requirements, as estimated through cosine distance and hierarchical/agglomerative clustering, followed by sectors belonging to the same level one branch, followed by those belonging to the same level two branch etc. The bottom part identifies the share of blue collar and farm workers employed in each sector in 2019 (vertical axis, with stacked bar reflecting the size of sectors in increasing NACE code numbering). Each sector bar is colour coded to reflect if the sector is projected to increase or decline in demand between 2019 and 2030 under the Fit for 55 scenario. Sectors represented in blue are sectors for which the demand of blue collar workers is projected to increase in demand between 2019 and 2030 whereas sectors in grey are sectors for which the demand of blue collar workers is projected to decline.

Table A B.2 provides the sector names associated with the 2 digit sector codes shown in the figure. Underlying data are available upon request.

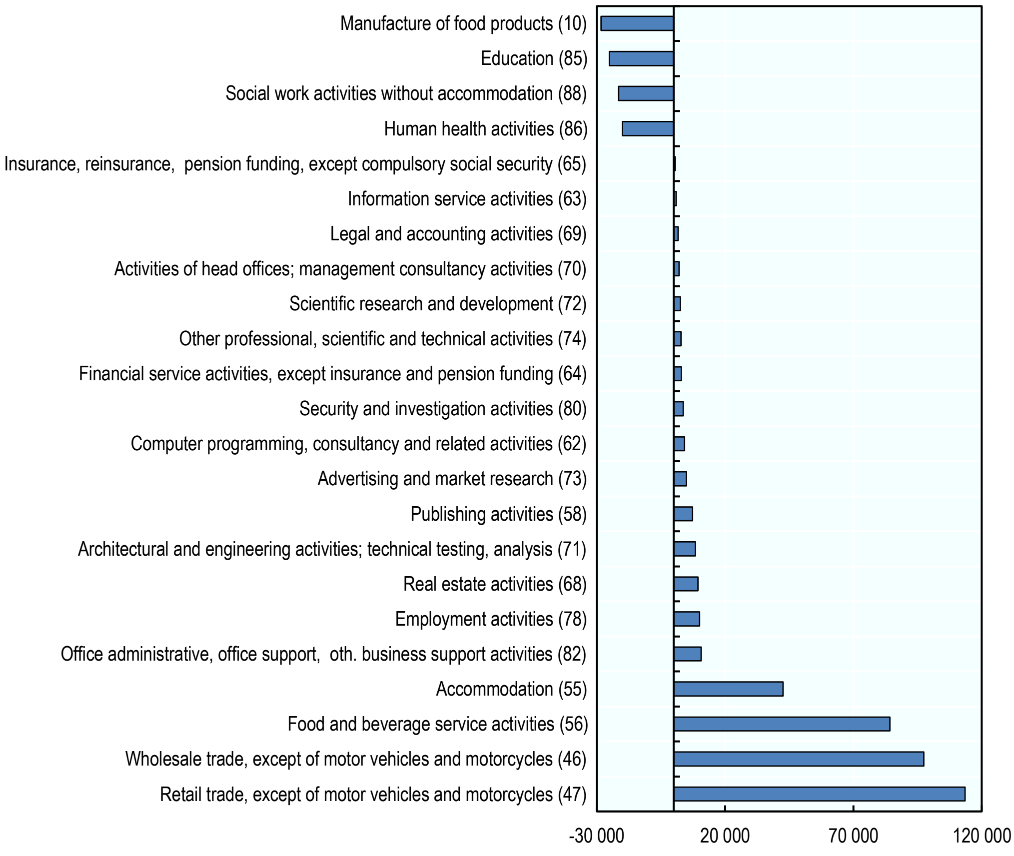
Source: Authors' own compilation based on OECD ENV-Linkages model, Lightcast™ (April 2023) and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

58. Blue collar workers are the only category of workers that are projected to experience an absolute contraction in employment opportunities. Figure 3.3 shed light on the overall share of employment of blue collar and farm workers in different clusters of sectors with similar skills requirements in 2019 and indicated if employment is projected to increase or decrease between 2019 and 2030. However, it does not indicate the extent to which such increase/decrease will result in an overall expansion of employment opportunities – a necessary condition of within cluster transitions – or a net loss or gain of employment.

59. Figure 3.4 illustrates absolute employment losses and gains for each of the sectors in the first cluster (from the left) presented in Figure 3.3, one of the largest clusters in terms of overall employment in 2019. Within this cluster a positive net employment gain across European Union countries of around 315 000 people is projected between 2019 and 2030. That means for blue collar and farm workers in this cluster, transition opportunities are available that require a relatively small difference in skills requirements because projected employment creation in this cluster exceeds projected employment destruction.

Figure 3.4. Sectors with several within-cluster transition opportunities

Absolute employment gains and losses by sector

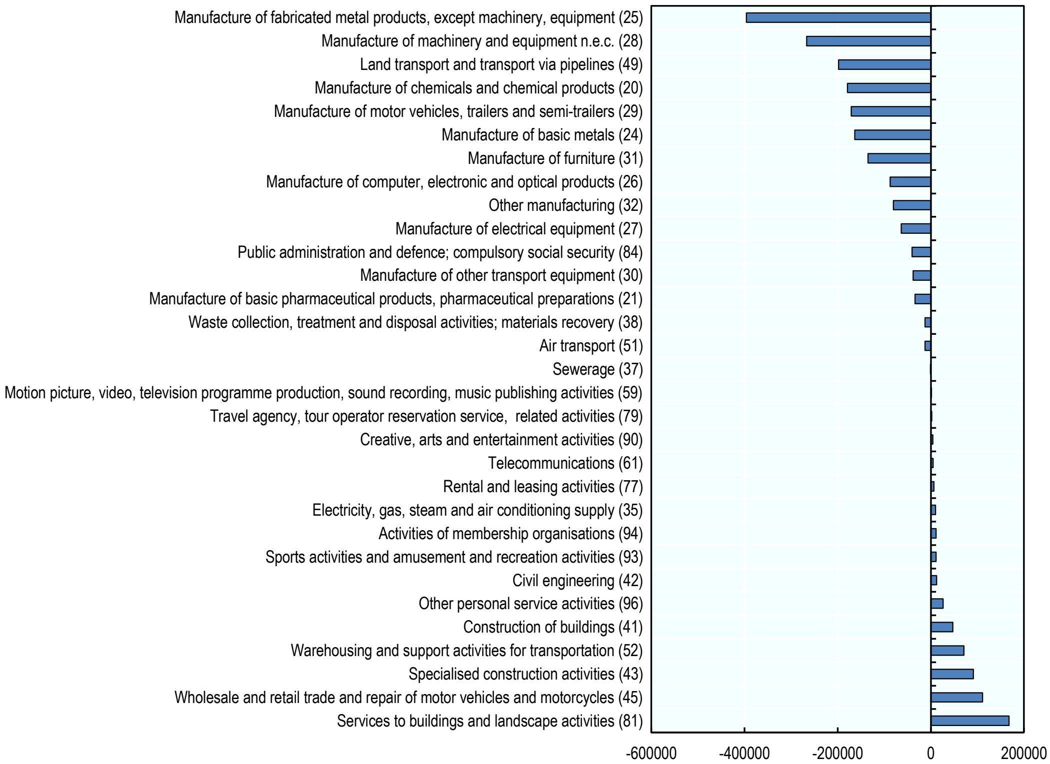


Note: The figure shows the absolute employment gains and losses for the cluster on the left in Figure 3.3. NACE sector numbers are provided behind sector names (
Table A B.2 provides an overview of NACE sector numbers and sector names). Sectors are sorted in descending order from sectors with highest employment gains to sectors with highest employment losses.
Source: Authors' own compilation based on OECD ENV-Linkages model and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

60. By contrast, in Figure 3.5, which illustrates absolute employment losses and gains for the second cluster presented in Figure 3.3, total employment gains are smaller than total employment losses. Overall, approx. 1 300 000 jobs are projected to be lost within this cluster between 2019 and 2030. Therefore, blue collar and farm workers in sectors in this cluster will not enjoy sufficient transition opportunities involving redeployment in jobs with similar skills requirements and will have to consider transitions into sectors with higher dissimilarity in skills requirements in other clusters, a likely indication of longer and more intense training requirements.

Figure 3.5. Sectors with limited within-cluster transition opportunities

Absolute employment gains and losses by sector

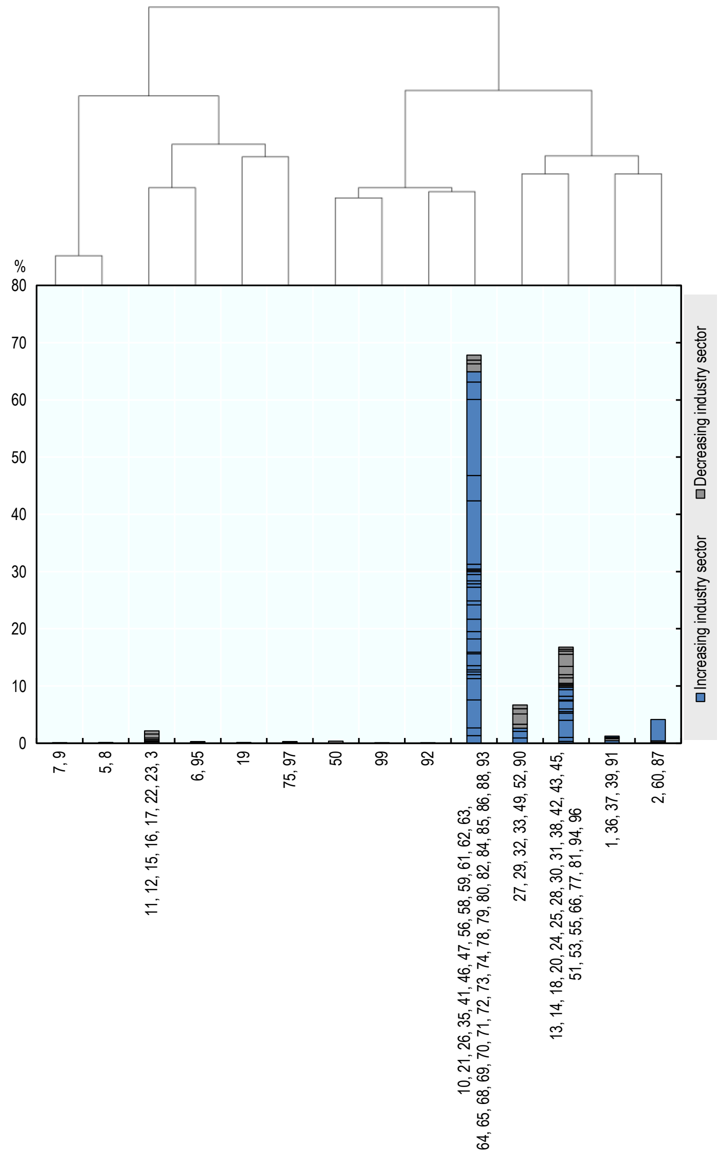


Note: The figure shows the absolute employment gains and losses for the second cluster from the left in Figure 3.3. NACE sector numbers are provided behind sector names (
Table A B.2 provides an overview of NACE sector numbers and sector names). Sectors are sorted in descending order from sectors with highest employment gains to sectors with highest employment losses.
Source: Authors' own compilation based on OECD ENV-Linkages model and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

61. However, workers in sectors that are projected to shrink employment following the Fit for 55 implementation will also be required to transition into new roles. Figure 3.6 illustrates transition opportunities based on skills similarity for professionals whereas Figure A B.1, Figure A B.2 and Figure A B.3 illustrate opportunities for managers, clerical workers and sales and service workers.

Figure 3.6. Skills similarity of employment opportunities for professionals

Dendrogram illustrating sectors based on skills similarity for professional workers, employment shares in 2019 and projected growth/decline between 2019 and 2030 under the implementation of Fit for 55



Note: The top part of the dendogram illustrates the degree of similarity in the skillset needed in jobs performed by workers in different sector: sectors that share the same tree of the dendogram are closest in terms of skills requirements, as estimated through cosine distance and hierarchical/agglomerative clustering, followed by sectors belonging to the same level one branch, followed by those belonging to the same level two branch etc. The bottom part identifies the share of professionals employed in each sector in 2019 (vertical axis, with stacked bar reflecting the size of sectors in increasing NACE code numbering). Each sector bar is colour coded to reflect if the sector is projected to increase or decline in demand between 2019 and 2030 under the Fit for 55 scenario. Sectors represented in blue are sectors for which the demand of professionals is projected to increase in demand between 2019 and 2030 whereas sectors in grey are sectors for which the demand of professionals is projected to decline.
Table A B.2 provides the sector names associated with the 2 digit sector codes shown in the figure. Underlying data are available upon request.
Source: Authors' own compilation based on OECD ENV-Linkages model, Lightcast™ (April 2023) and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

62. Contrary to blue collar and farm workers, overall employment for other occupations is projected to expand between 2019 and 2030. At the same time, in some sectors, opportunities are projected to decline over the same period, requiring transitions as for blue collar and farm workers. For example, employment opportunities for professionals are projected to decline (Figure 3.6) in sectors 10 (‘Manufacture of food products’), 21 (‘Manufacture of basic pharmaceutical products and pharmaceutical preparations’), 26 (‘Manufacture of computer, electronic and optical products’) (these sectors are shown in the fifth cluster from the right). These sectors are also close to each other in skills requirements for professional workers. Sectors that are projected to grow in demand for which employers require a relatively similar skillset for professionals include, for example, sector 35 (‘Electricity, gas, steam and air conditioning supply’), 41 (‘Construction of buildings’), and 46 (‘Wholesale trade, except of motor vehicles and motorcycles’).

4 Distributional implications and the organisation of training: The case of blue collar workers in the mining of coal and lignite sector

Estimating distributional implications from employment projections

63. Developing effective upskilling and reskilling initiatives to facilitate the redeployment of workers from shrinking sectors and occupations into increasing ones and integrating skills policies with social protection and social assistance policies requires to consider the distribution of projected employment trends in different countries and different groups in the population. If, for example, shrinking sectors were to be concentrated in certain countries or geographical areas and expanding sectors in others, skills policies would only play a partial role, alongside mobility initiatives, in facilitating a direct redeployment of workers across the two sets of sectors. Upskilling and reskilling could remain important to facilitate a more general shift of employment opportunities for workers in different countries and regions away from shrinking sectors, but social assistance and social protection policies would need to play a stronger role in countries and regions with a high concentration of workers employed in shrinking sectors and occupations.

64. Blue collar workers in 'mining of coal and lignite' are one group of workers that will be severely hit by the structural transformations to meet the Fit for 55 policy targets. This section analyses country-level differences in employment and socio-economic profiles of blue collar workers in 'mining of coal and lignite' based on information from the European Labour Force Survey (EU-LFS) to show distributions in employment in European Union countries in 2019 in combination with projected changes from the ENV-Linkages model.[20]

65. Many blue collar workers may have started their careers very young – a period that is especially salient for the development of identity and affiliation – and may have learnt their trade not only in training programmes but on the job whether through formal apprenticeship programmes or informal mentorships. Even if the reallocation of workers across sectors and occupations were to be achieved without the creation of short-, medium- or long-term unemployment, for some workers changing sector, industry, or occupation might lead to a sense of anomie. Such reallocation may in fact severe existing bonds between co-workers, disrupt networks of peer support, and require a change of identity of the self-based related to employment.

66. Employment of blue collar workers working in 'mining of coal and lignite' is projected to shrink by as much as 89%. Because the distribution of workers in different sectors and occupations differs across

[20] Annex C describes the procedure used to match projections in different sectors based on the ENV-Linkages model and sectors identified in the EU-LFS.

countries, some countries are projected to be especially hard hit by job losses. Therefore, the distribution of workers by sector and occupation both across countries and within countries should be evaluated in the development of policy responses.

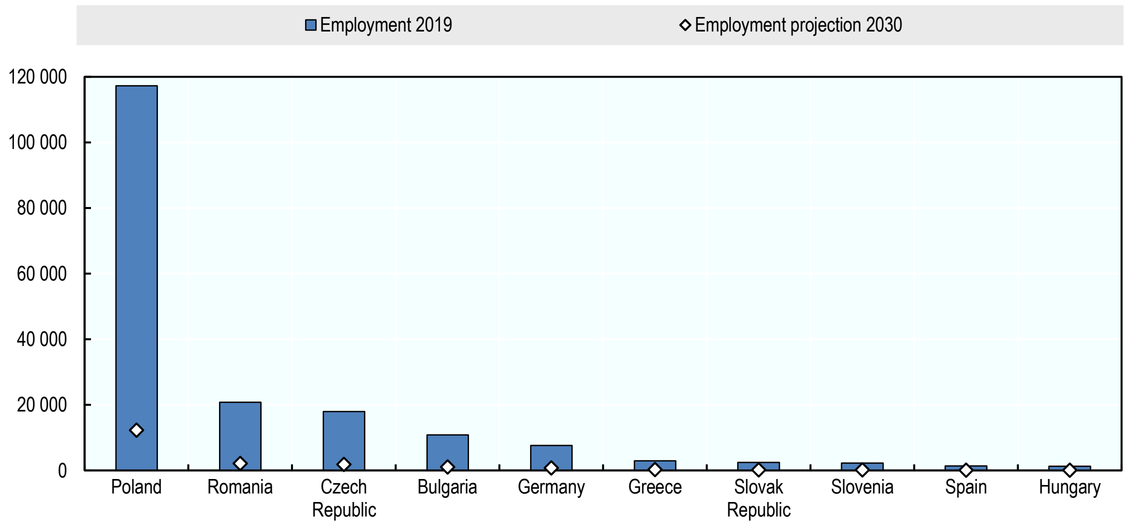
Projected distributional implications of Fit for 55 for blue collar workers in the mining sector

Country-level differences

67. Under the assumption of homogeneous effects of the Fit for 55 scenario in different countries, countries with the largest employment of blue collar workers[21] in 'mining of coal and lignite' in 2019 will be most affected. These are: Poland, Romania, the Czech Republic, Bulgaria and Germany, as illustrated in Figure 4.1.[22] For example, estimates indicate that in Poland in 2019 almost 120 000 individuals were blue collar workers working in 'mining of coal and lignite' whereas in 2030, under the Fit for 55 scenario, slightly more than 12 000 individuals would be similarly employed. In the Czech Republic in 2019 almost 18 000 individuals were blue collar workers working in 'mining of coal and lignite' whereas in 2030 under the Fit for 55 scenario around 1 900 individuals would be similarly employed.

Figure 4.1. Blue collar workers in 'mining of coal and lignite' in 2019 and 2030 in the European Union, by country

Total number of blue collar workers being employed in 2019 and projected employment in 2030 in 'mining of coal and lignite' following the implementation of Fit for 55



Note: The figure shows total employment among blue collar workers in 'mining of coal and lignite' in 2019 based on data from the EU-LFS and projected employment in 2030 which are estimated using EU-LFS employment numbers in 2019 and employment projections based on the OECD ENV-Linkages model. The figure shows only European Union countries with employment among blue collar workers in 'mining of coal and lignite' in 2019 based on data from the EU-LFS.
Source: Authors' own compilation based on OECD ENV-Linkages model and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

[21] The official aggregated occupational category is blue collar and farm workers but no farm workers are employed in 'mining of coal and lignite'.

[22] The estimates are based on the assumption that the structural transformations needed to meet the Fit for 55 policy targets will have equal effects on employment changes in different countries.

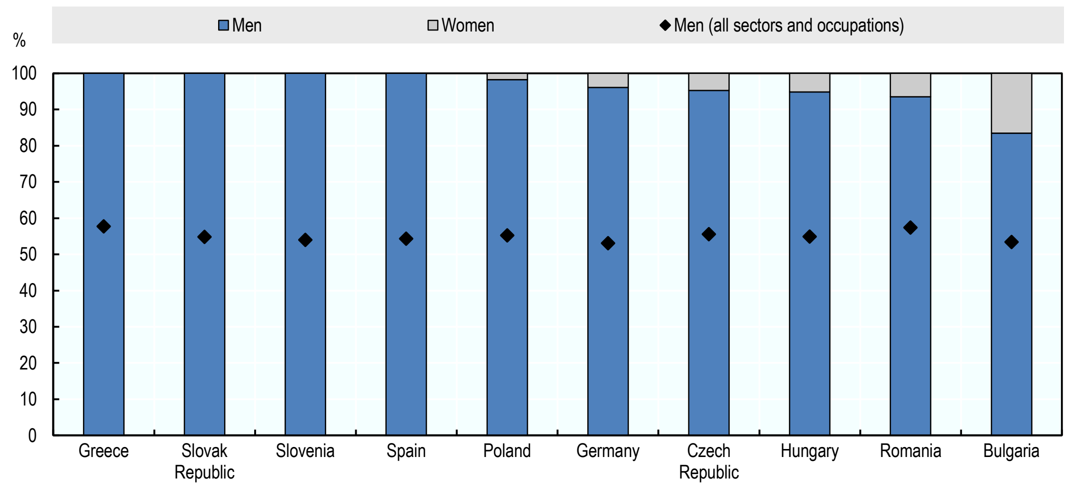
Inclusivity and gender differences

68. Men are over-represented in blue collar jobs in 'mining of coal and lignite', which is the most affected group by the structural transformations that will need to be implemented in order to meet the Fit for 55 policy targets. For example, they are overrepresented among blue collar workers in 'mining of coal and lignite' not only compared to women but also compared to the average share of men represented across all sectors and occupations in each country (Figure 4.2). In 2019 in all countries with employees in 'mining of coal and lignite', over 83% of individuals employed as blue collar workers were men. Data for Greece, the Slovak Republic, Slovenia and Spain show that blue collar workers in the sector of 'mining of coal and lignite' were entirely male.[23] The highest share of women is observed in Bulgaria, where female blue collar workers made up 17%, followed by Romania with 7% and Hungary with 5%.

69. Previous large-scale structural changes affecting sectors in which men were primarily employed, such as the phasing out of coal mines in the United Kingdom, spilled over to other sectors, such as manufacturing, in which women made up a large share of workers (Aragón, Rud and Toews, 2018[43]). Therefore, the evolution in the overall effect on the employment of men and women of the transition should be adequately and continually monitored to ensure that policies aimed at supporting displaced workers both directly – through social assistance – as well as indirectly – through upskilling and reskilling – will reach all those made vulnerable by the green transition. Equally important will be to ensure that the education and training will not only be of high quality and suited to the development of skills that will be in high demand but will also be organised to facilitate access and participation of a diverse group of learners and structured in ways that will reduce gender stereotypes leading to the segregation of men and women in different sectors and occupations.

Figure 4.2. Gender distribution among blue collar workers in 'mining of coal and lignite' in 2019 in the European Union, by country

Percentage of men and women working as blue collar workers in 'mining of coal and lignite' and percentage of men across all sectors and occupations



Note: The figure shows the percentage of men and women working as blue collar workers in 'mining of coal and lignite' in European Union countries. Countries are ordered in descending order according of the percentage of men. The figure shows only European Union countries with employment among blue collar workers in 'mining of coal and lignite' in 2019 based on data from the EU-LFS.
Source: Authors' own compilation based on European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

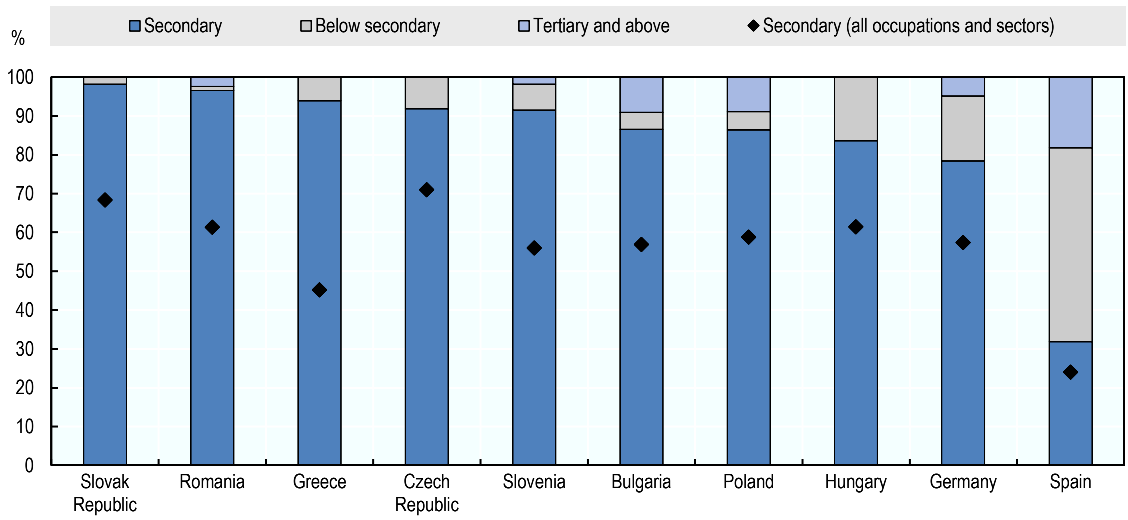
[23] The estimates are based on the assumption that changes in employment in different sectors and occupations estimated in Section 2 will be the same across all countries and that differences in changes in overall employment of men and women across countries will be determined solely by the relative distribution of men and women in different sectors and occupations across countries.

Educational profiles

70. In the majority of countries, workers with a secondary education degree represented the largest share of blue collar workers employed in ‘mining of coal and lignite’ in 2019: this share ranged between 98% in the Slovak Republic to 78% in Germany (Figure 4.3). In Spain, blue collar workers who were working in ‘mining of coal and lignite’ who did not obtain a secondary school degree (50%) outnumbered workers who obtained a secondary education degree (32%). In general, educational attainment of blue collar workers in the sector was significantly below the average educational attainment of workers employed in other economic sectors and occupations. To the extent that educational qualifications will remain a pre-requisite for entrance in certain professional activities, upskilling and reskilling efforts to help workers move across sectors and occupations may not be able to effectively facilitate transitions.

Figure 4.3. Education distribution among blue collar workers in ‘mining of coal and lignite’ in 2019 in the European Union, by country and by education

Percentage of blue collar workers with below secondary, secondary more than tertiary education working as blue collar workers in 'mining of coal and lignite’ and percentage of people with secondary education across all sectors and occupations



Note: The figure shows the percentage of blue collar workers with below secondary (ISCED level 0-2), secondary (ISCED level 3-4) and more than tertiary education (ISCED level 5-8) working in 'mining of coal and lignite’ in European Union countries. Countries are ordered in descending order according of the percentage of workers with secondary education. The figure shows only European Union countries with employment among blue collar workers in 'mining of coal and lignite’ in 2019 based on data from the EU-LFS.
Source: Authors’ own compilation based on European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

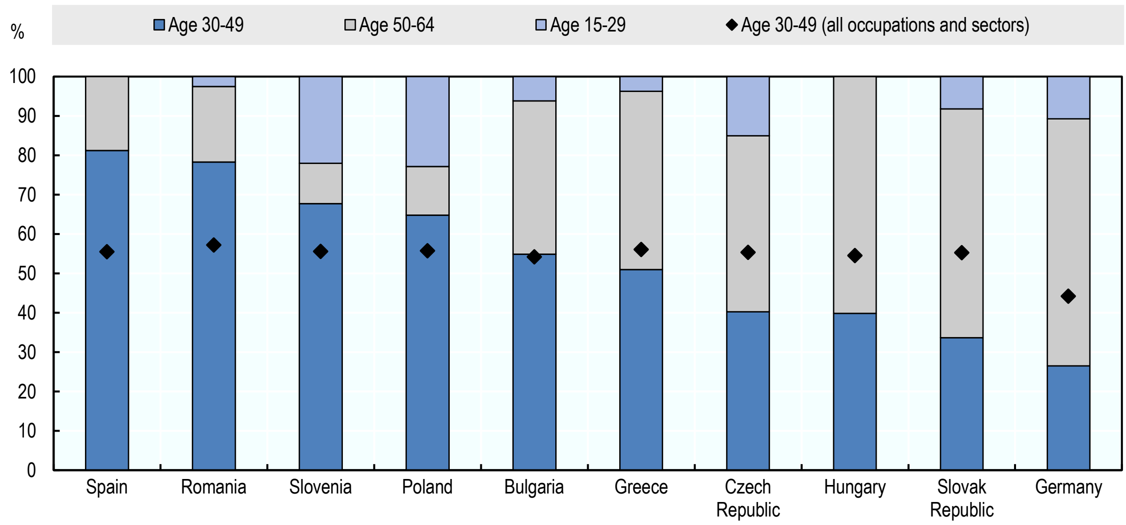
Age profiles

71. The age distribution of current workers is a critical factor to evaluate the relevance of education and training policies to upskill and reskill workers *vis-à-vis* the provision of social assistance and early retirement. There are strong regional differences in the age profiles of blue collar workers in 'mining of coal and lignite’, with a prevalence of workers in their prime (30-49 year-olds) in half of the countries and a prevalence of older workers (50-64 year-olds) in the other half, as illustrated in Figure 4.4. Specifically, 30-49-year-olds made up the largest share of blue collar workers in 'mining of coal and lignite’ in six out of the ten countries – Spain, Romania, Slovenia, Poland, Bulgaria and Greece – while in the Czech Republic, Hungary, the Slovak Republic and Germany 50-64 year-olds did. In Spain for example, 81% of individuals who were employed as blue collar workers are between 30-49 years old whereas only 19% were between

the ages of 50 and 64. By contrast, in Germany, only 27% of workers were between the ages of 30 and 49, 63% were between 50 and 64 and 11% were under the age of 30.

Figure 4.4. Age distribution among blue collar workers in 'mining of coal and lignite' in 2019 in the European Union, by country and by age

Percentage of blue collar workers aged 15-29, 30-49 and 50-64 working in 'mining of coal and lignite' and percentage of 30-49 year olds across all sectors and occupations



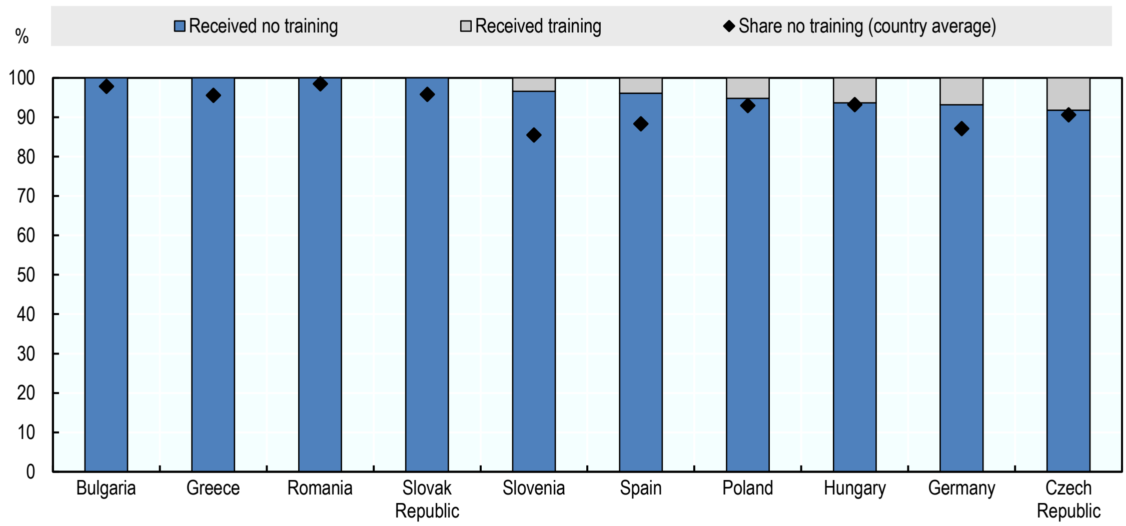
Note: The figure shows the percentage of blue collar workers in the age groups 15-29, 30-49 and 50-64 working in 'mining of coal and lignite' in European Union countries. Countries are ordered in descending order according of the percentage of workers between age 30-49. The figure shows only European Union countries with employment among blue collar workers in 'mining of coal and lignite' in 2019 based on data from the EU-LFS.
Source: Authors' own compilation based on European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

Participation in training

72. Participation in training is low among workers in general but appears to be especially low among blue collar workers in 'mining of coal and lignite', as illustrated in Figure 4.5. The low level of participation in training opportunities reveals that engaging workers in training to facilitate their redeployment in upskilling and reskilling is important but may be a challenge because many of the workers most in need of engaging in training may not be used to do so. Among blue collar workers employed in 'mining of coal and lignite', in 4 out of 10 countries, no respondent reported having participated in any form of formal or non-formal training in the four weeks preceding the interview. In the Czech Republic for example, 8% of workers participated in formal or non-formal training.

Figure 4.5. Distribution of training participation among blue collar workers in ‘mining of coal and lignite’ in 2019 in the European Union, by country and by training

Percentage of blue collar workers who did and did not receive training in 'mining of coal and lignite’ and percentage of workers not having received training across all sectors and occupations



Note: The figure shows the percentage blue collar workers who received no training and who received training in 'mining of coal and lignite’. Countries are ordered in descending order according of the percentage of workers who did not receive training. The figure shows only European Union countries with employment among blue collar workers in 'mining of coal and lignite’ in 2019 based on data from the EU-LFS.
Source: Authors’ own compilation based on EU Labour Force Survey 2019, ad hoc data extraction (for the year 2019).

5 Conclusions and implications for skills policies

Key results

73. The COVID-19 pandemic gave new impetus to the implementation of climate change mitigation policies worldwide. In the aftermath of the pandemic, European Union governments recognised the short-, medium- and long-term potential threat for public health posed by environmental degradation. Moreover, given the severity of the economic crisis induced by lockdowns, many countries adopted stimulus packages to promote economic growth. In many countries, such investments were tied to the achievement of reductions in greenhouse gas emissions and ambitious structural investments in digital infrastructures. Because past waves of structural transformation led to job losses and long-term vulnerability for some groups of workers, governments further recognised that any efforts to promote environmental sustainability should ensure that the green transition will be a just and inclusive transition, leading to improvements in working conditions rather than widespread job losses and contractual instability.

74. This paper emphasises that taking into account the distributional implications of the European Union's Fit for 55 policy targets is of paramount importance for the design of skills policies, social assistance policies, labour market policies, and local economic development policies. The modelling analysis applied in this paper relies on the OECD ENV-Linkages dynamic global Computable General Equilibrium (CGE) model and indicates that overall employment is projected to grow by 1.3% between 2019 and 2030 in a scenario in which equally stringent policy measures will be implemented in countries outside the European Union and the reallocation of workers in the economy will be without frictions, whereas it would have been 3% had the Fit for 55 policy package not been implemented. Even under these assumptions, in some sectors and for some workers employment is projected to shrink considerably. Overall, employment opportunities for blue collar workers are projected to shrink between 2019 and 2030 by 3% in the Fit for 55 scenario (whereas it is projected to decrease by 2% in a Baseline scenario in which the policy was not implemented), while for other occupations, employment is projected to increase by 4-5% under the Fit for 55 scenario (5-6% in the Baseline scenario).

75. A key feature of structural transformations aimed at reducing CO_2 emissions is that they will have substantial negative and positive effects on employment in sectors that currently employ few people – such as in mining (-89% projected employment loss, employing less than 0.5% in 2019) and the wind and solar energy generation sectors (+245% projected employment gain, employing less than 0.1% in 2019). This means that estimated projected changes in skills demands differ depending on whether one takes an absolute approach – based on overall projected changes in employment – or a relative approach – based on percentage changes compared to the status quo. Using skills information provided by the job postings database for the 2019-2022 period assembled by Lightcast combined with employment projections derived by the OECD ENV-Linkages model, findings indicate that economy-wide changes in the demand for skills will be driven mostly by small relative changes in the distribution of employment in sectors and occupations that employ many workers rather than large relative changes in the number of jobs that are especially well/or not well aligned with the achievement of green objectives.

76. Many of the skills that are projected to increase in demand between 2019 and 2030 relate either to the development and use of digital tools and applications or to interpersonal communication, management and leadership. This is because most employment growth will occur in service sectors and technology adoption is widely used in these sectors. Moreover, technology is a key driver of growth, and therefore is a key reason why the achievement of green objectives under the implementation of Fit for 55 can be achieved while sustaining employment. By contrast, many of the skills that are projected to decline in demand relate to the use of tools and machinery. This is because the implementation of Fit for 55 will accelerate the existing trend leading to structural reallocation of employment opportunities from blue collar and manual jobs to jobs in the service economy. These results, alongside results indicating higher employment projections had Fit for 55 not have been implemented, point to the critical role of technological adoption in general and the digital transition in particular for the green transition. Successfully achieving decarbonisation, economic and job growth depends on ensuring the adoption of digital technologies and on improvements in labour productivity related to technology use.

77. This paper further exploits European Labour Force Survey information to shed light on distributional impacts. Results presented in this work and the broader literature suggest that the green transition may have a marked gender dimension, which, in turn, will interact with social class and educational opportunities. Men are in fact considerably over-represented among workers in sectors and employment categories that will be especially exposed to structural transformations related to the green (and digital) transitions. For example, employment opportunities for blue collar workers are projected to shrink substantially between 2019 and 2030, among them a high share of men who did not complete secondary level qualifications, many in their prime and low propensity to engage in adult education. By contrast, men working in professional occupations, with high levels of educational attainment and strong digital skills will be positively affected by the twin green and digital transitions. All these factors pose a challenge for the design and delivery of effective upskilling and reskilling interventions aimed at facilitating the redeployment of workers from jobs that are projected to decline in demand into jobs that are projected to grow in demand. Many of the skills that are projected to grow the most in demand and that are required in jobs that might be relatively easy to delocalise through remote working arrangements, thus easing geographical and mobility constraints to the deployment of workers, pertain to the use of digital tools and applications.

Assumptions and limitations

78. Results identified in the paper in terms of employment and skills projections rely on a number of assumptions and, as such, suffer from limitations related to how much such assumptions reflect real world phenomena. Three sets of assumptions underpin the modelling and empirical analyses: 1) assumptions related to the estimation of employment projections between 2019 and 2030 at Baseline and following from the implementation of the Fit for 55 policy targets; 2) assumptions related skills requirements; and 3) assumptions related to the matching of employment projections data with skills requirement data.

Employment projections

79. While CGE models are a great tool to understand changes in the structure of the economy that follow the implementation of specific policies, they do not easily capture transition effects and abrupt changes. The employment results outlined in the paper need to be considered in this context. While they reflect the reallocation of employment across economic sectors, they cannot reflect abrupt changes in employment, such as those resulting from unexpected crises or booms.

80. The modelling results also depend on the scenario design, including the assumptions underlying the baseline calibration and assumptions on technological change and availability. For instance, the

baseline scenario does not fully take into account recent advances in the development and use of artificial intelligence tools and systems, which are likely going to affect structural change and technologies.

81. Finally, the regional and sectoral aggregation of the model also does not allow to capture granural effects, such as those for specific geographical areas. As the model focuses on aggregate regions (i.e. aggregating multiple countries), it cannot differentiate the effects of the policy-induced structural transformations across countries or reflect specific national policies and sectoral plans, which can differ substantially, such as in the case of mining. Furthermore, the model cannot capture the effects of the Fit for 55 package on the within-sector distribution of skills and occupations. One prominent example is vehicle manufacturing, where a rapid shift of the production from internal combustion engines to electric vehicles may have important labour market implications in the near term (Tamba, 2022[44]).

Skills projections

82. The demand for skills is derived from combining online vacancy information by Lightcast between 2019 and 2022 with employment projections from the OECD ENV-linkages model. Because employment projections are derived for five occupational categories, skills requirements for sector-by-occupation categories are inevitably aggregate. Moreover, they rely on the assumption that within each sector-by-occupation category the distribution of employment opportunities of specific jobs identified in online vacancies reflects the actual distribution in the labour market. A second key assumption is that the only driver of changes in skills demands in the economy is the change in employment numbers for different occupations and sectors, but that skills requirements for different occupations and sectors will not change over time. Should the employment mix in different occupations and sectors change or should the skills content of a job change over time, this assumption would be violated.

83. The analysis estimates skills requirements using information contained in online vacancies to be able to consider emerging skills needs and the likely evolution in employment characteristics since vacancies generally reflect the set of tasks and skills employers expect their employee to perform in the future. Data from a number of years were also used to smooth out idiosyncratic fluctuations in certain occupations and sectors. At the same time, all data used in this work predates the launch of generative AI applications and therefore do not reflect changes in skills requirements resulting from the potential wide-scale deployment of generative AI in labour markets and society. Although many analysts expect generative AI to have important implications for labour markets worldwide, it is difficult to pinpoint the scale of such effects and how quickly they will take place.

Taxonomies and classifications

84. In this work data from European online vacancies was used to identify European-wide distributions, but an important limitation is that online vacancy data are poor proxies for sectors and occupations that are shrinking in demand, such as mining and coal extraction. Since an important effect of the green transition will be the reorganisation of production to reach green objectives and the fact that countries might follow different trajectories, it will be important to ensure that adequate data will be collected to support evidence-based policy making.

85. The analyses presented use various data sources which required harmonisation across different taxonomies and classifications. In particular, the analyses required combining results obtained from a macro-modelling approach, big data analyses of online job postings, and household survey information. A number of challenges had to be overcome to produce estimates using European-specific data, since existing data collection instruments in Europe are not well-suited to map economic activities and employment distribution on estimates arising from international efforts estimating greenhouse gas emissions generation. In particular, the classification of employment in the European Labour Force Surveys into different sectors (NACE) and occupations (ISCO) is not easily matched with sectoral

classification used in the OECD ENV-Linkages model (Chateau, Dellink and Lanzi, 2014[24]), which allow to identify sectors depending on their CO_2 emission potential. An important example is NACE sector 35, a sector that is projected to be strongly affected by the green transition and for which cross-walks between different sectoral taxonomies are poor.

Discussion and implications

86. Skills policies, which comprise education and training policies targeted at both young people and adults, can play an essential role alongside other policy interventions to achieve the twin objectives of greening the economy and ensuring that the benefits of new investments do not lead to new forms of vulnerability and deprivation. Skills policies can facilitate the reallocation of workers away from sectors that will shrink because they are responsible for a large share of CO_2 emissions, such as 'mining of coal and lignite', into sectors that will expand because they can sustain the production of energy without emitting large quantities of CO_2, such as wind and solar energy production or in sectors that will expand because of the new demands induced by the demographic transition (to care and support rapidly ageing populations) (OECD/ILO, 2022[45]) or the digital transition (to work alongside digital tools and applications performing tasks that will not be automatable) (Lassébie and Quintini, 2022[46]). They are therefore important both because they can guarantee an adequate supply of workers in sectors that need to develop if CO_2 emission reductions are to be met while maintaining current levels of overall consumption, and because they can ensure that workers who previously worked in sectors that will decline or disappear will be able to find employment in other sectors of the economy. Education and training policies are also critical in ensuring continuous political support to reach a carbon neutral economy, since poor macroeconomic conditions – such as high levels of unemployment – could reduce support for policies that prioritise the environment over the economy, whenever these two objectives are not aligned (Asai, Borgonovi and Wildi, 2022[47]).

87. In order to minimise the economic and social cost of the green transition, it is essential that the workers' skills are aligned with the skills demanded in the economy. Skills-mismatches have large economic and social costs at both the individual and societal level: when individuals are engaged in tasks that require different and fewer skills than the skills they possess they are less productive than what their human capital could allow them to be. This leads to lower personal incomes and lower economic output (Quintini, 2014[48]; Adalet McGowan and Andrews, 2015[49]). Moreover, they may become demotivated with further negative implications for productivity and well-being. Similarly, productivity suffers when individuals are engaged in tasks that they cannot effectively perform because they lack the necessary skills. Given the negative relationship between skill mismatches and labour productivity, reducing skill mismatches emerges as a new channel through which well-designed framework policies can boost labour productivity.

88. Skills policies include various levers to promote engagement in adult education and training, ensure upskilling and reskilling efforts provide appropriate skills and facilitate the reallocation of workers. Among these, important strategies include the i) adjustment of hiring practices to include not only hiring decisions based on formal education qualification requirements but also skills-based hiring; ii) career guidance to navigate people successfully from education to employment; iii) remove barriers to and improving the flexibility of adult learning; vi) and recognising resistance to participation in training is connected with workers strong sense of identity and community they may have; v) providing adequate skills aligned with demands of the twin transitions and environmental awareness about climate change.

89. In order for efforts and investments in building skills through formal, non-formal and informal education and training to be effective, changes in hiring practices will also have to materialise. Formal educational qualifications and occupational licensing remain a key criterion guiding employers in hiring decisions. Although this may be changing due to large and persistent skills shortages employers face in some sectors, **skills-based hiring** will have to become more widespread and accepted if the deployment

of workers across sectors and occupations following engagement in training courses is to be successful. This paper found that in 2019, formal educational qualifications remained a clear marker of employment in different sectors and occupations. Although qualifications and degrees from initial education and training will continue to play a key role, alternative credentials (including digital badges, microcredentials, nanocredentials, minor awards, etc.) bear the promise of making existing qualifications and credentials systems better fit for purpose providing incentives for adults to engage in adult learning opportunities and adequate information on workers' skills and abilities to prospective employers.

90. A growing body of international evidence suggests that career guidance had the potential to support successful employment transitions: not only from the education system to the labour market, but also from unemployment to employment, and from declining to growing sectors. Career guidance and educational orientation programmes can assist individuals of all ages in making well-informed educational, training and occupational choices and in managing their careers. There is a growing body of evidence, indicating that high-quality career guidance can have a positive impact on short-term learning outcomes of individuals, such as decision-making skills, self-awareness or job search skills, that it can strengthen confidence and motivation and improve adults' attitudes towards learning; that it can increase adults' participation in education or training and that it can improve employment outcomes, in particular supporting the job placement of unemployed adults as part of active labour market programmes [see OECD (2004[50]; 2021[51]) (2022[52]) for extensive reviews].

91. As the twin digital and green transition emphasize the importance of individuals to up- and reskill, it is of important to **remove barriers to and improving the flexibility of adult learning** by recognising individuals diverse learning pathways and increased transparency in adult learning systems (OECD, 2023[40]). Flexible learning systems for example take into account the diverse pathways learners can take for example by breaking down a learning programme into a number of discrete modules (modularisation) or the validation of individual's existing knowledge and skills, which may have been acquired through formal, non-formal or informal learning (recognition of prior learning). Increasing transparency entails for example to organise, recognise, and assign value to qualifications via establishing National Qualification Frameworks and facilitating the transfer of acquired knowledge and skills between programmes and providers through Credit transfers systems. As adults' participation in training rate varies substantially across EU countries, policies that remove barriers to participation are crucial. Effective policies include among others statutory education and training or financial incentives (e.g. wage or training subsidies, co-financing of training costs) (OECD, 2019[41]).

92. For some workers the perspective of change may entail high psychological costs and ultimately lead to resisting participation in upskilling and reskilling opportunities. If education and training programmes are to be successful in promoting the reallocation of workers, they will not only have to help workers build the set of skills they will need to be able to perform new tasks in different sectors and industries, but they will also have to accompany workers build a new sense of **identity and community**. The fact that the green transition will align with other megatrends such as the demographic transition and the digital transition in shaping the demand for workers may prove to be an opportunity to reduce the persisting segregation of men and women in different sectors and activities, a segregation that ultimately reduces economic efficiency and weighs especially heavily on the labour market outcomes of women. However, unless it will be successfully managed, it could lead to the perpetuation of gender segregation, especially in jobs that are expected to benefit especially from the green and digital transitions, such as those in the tech sector.

93. As AI technologies mature and become widely adopted, it will be important to continuously monitor the evolution of AI and its application alongside changes in **skills demand** related to decarbonisation efforts to ensure that orientation programmes, education and training system consider broad structural transformations in labour markets due to the **twin digital and green transitions**. Given recent advances in AI development and adoption, it is possible that more tasks currently performed in labour markets – and associated skills – will become automatable in the medium term. Equally important will be to monitor the

environmental impact of the use of artificial intelligence systems, ensure that this is adequately assessed and integrated in broader efforts aimed at decarbonising the economy, and to ensure that energy to operate such systems comes from renewable sources. Rapid developments in AI systems highlight the need for skills systems to keep abreast of innovations and anticipate, rather than simply react to emerging trends.

94. Results presented in this work should be evaluated alongside results from other studies that map how the green transition will change the tasks workers will be required to perform in existing jobs to reduce greenhouse gas emissions or in new jobs that will emerge to promote the green transition. In particular, changes in the task content of occupations will change the bundle of skills individual workers and/or that teams of workers will need to possess to successfully carry out their jobs with important implications for the development and implementation of education and training programmes.

95. Finally, individuals are not only workers but also consumers, living creatures that consume energy to sustain life and can do so in ways that are more or less aligned with environmental preservation depending on their actions and behaviours. How individuals use their skills to preserve the environment in their work and in their daily life depends on the **level of awareness** they have about climate change, declining biodiversity, air and water pollution and the state of the environment more generally and their willingness to act on such knowledge. Education and training systems have a key role to play in building environmental sustainability competence in both youngsters and adults, to ensure that they have the skill as well as the will to act in ways that preserve the environment. Although detailing such role is beyond the scope of this work, education and training systems worldwide are considering how best to embed the promotion of environmental sustainability competence in their curricula and how best to monitor progress in this direction (Borgonovi et al., 2022[53]; Borgonovi et al., 2022[54]; OECD, 2022[55])

96. Efforts should be made to evaluate the effects of artificial intelligence on employment in different sectors and occupations so that upskilling and reskilling efforts would be directed at building the set of skills that will be needed in jobs not at high risk of automation. Equipping societies and economies with the skills needed to support green economic growth in the future is key and skills intelligence monitoring and anticipation systems can play a crucial role in this respect.

97. Virtually all human activities can create different levels of greenhouse gas emissions depending on how they are carried out, i.e. changes in how tasks are performed and how skills are used can help lead to different levels of CO_2 being emitted as a result of performing a given task or activity. For example, it has been estimated that train drivers on high speed trainlines can reduce energy consumption by optimising braking and the engine’s automatic stop/start system (SNCF, 2020[56]). This example does not imply a change in the reallocation of workers across sectors and occupations, or a difference in the skillset that are needed to perform a given job but, rather, that achieving green objectives will require a change in how individuals use their skills due to their awareness of and commitment to the goal of environmental protection.

Annex A. ENV-Linkages model

Model description

98. The ENV-Linkages model is a global recursive-dynamic computable general equilibrium model that describes economic activities in different sectors and regions and how they interact. It is based on the GTAP 10 database (Aguiar et al., 2019[35]) and GTAP-Power satellite account (Chepeliev, 2020[57]). In this paper, the GTAP database has been aggregated to 26 regions (Table A A.1) and 37 sectors Table A A.2.

99. Production in ENV-Linkages is assumed to operate under cost minimisation and constant returns-to-scale technology. The production functions are specifically tailored to agricultural sectors (intensification vs. extensification), and electricity production (cost-minimizing decision by representative agent based on available technologies: coal, oil, gas, nuclear, hydro, wind, solar and other).

100. The production structure of ENV-Linkages is based on constant elasticity of substitutions (CES) that determine the ease with which the different inputs in production can be used. The production structure represents the different substitution (and complementarity) relations across the various inputs in each sector. Each sector uses intermediate inputs – including energy inputs – and primary production factors (labour and capital). Agricultural sectors also need land input while in some sectors, primary factors also include a sector-specific natural resource factor, e.g. trees in forestry.

101. In the ENV-Linkages production structure, labour contributes to the creation of value-added along with a composite capital-energy bundle. For this project, the labour force has been differentiated in five occupational categories (‘Professionals’, ‘Managers and officials’, ‘Service and sales workers’, ‘Clerical workers’ and ‘Blue collar and farm workers’). The set-up of the model implies market clearance in all markets (goods, primary production factors, etc.), including in the labour market so that demand and supply for labour are equal.

102. Household consumption demand is the result of a static maximisation behaviour: a representative consumer in each region – who takes prices as a given – optimally allocates disposable income among the full set of consumption commodities and savings. Savings is considered as a standard good in the utility function and does not rely on forward-looking behaviour by the consumer.

103. International trade is based on a set of regional bilateral flows. The model adopts the Armington specification, assuming that domestic and imported products are not perfectly substitutable. Moreover, total imports are also imperfectly substitutable between regions of origin. Allocation of trade between partners then responds to relative prices at the equilibrium.

104. The model links economic activity to environmental pressures, including greenhouse gas emissions, air pollutants and materials. Greenhouse gas emissions in ENV-Linkages are quantified based on data from the GTAP (Aguiar et al., 2019[35]) and EDGAR (Crippa et al., 2021[58]) databases. CO_2 emissions from combustion of energy are directly linked to the use of different fuels in production using constant coefficients, while process CO_2 emissions are substitutes to production in sectors where they are generated. The modelling of process CO_2 emissions follows the seminal work by Hyman et al. (2002[59]) by introducing these emissions as a substitute to production.

Table A A.1. ENV-Linkages regional aggregation

Aggregated region	ENV-Linkages region	GTAP regions
OECD America	Canada (CAN)	Canada (CAN)
	Mexico (MEX)	Mexico (MEX)
	United States (USA)	United States of America (USA)
	Central and South America A (CSAMa)	Chile (CHL), Colombia (COL)
OECD Asia & Pacific	Australia and New Zealand (AUNZ)	Australia (AUS), New Zealand (NZL)
	Japan (JPN)	Japan (JPN)
	Korea (KOR)	Korea, Republic of (KOR)
OECD Europe	European Union A (EUa)	France (FRA), Germany (DEU), Italy (ITA)
	European Union B (EUb)	Austria (AUT), Belgium (BEL), Czech Republic (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), Greece (GRC), Hungary (HUN), Ireland (IRL), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), Netherlands (NLD), Poland (POL), Portugal (PRT), Slovakia (SVK), Slovenia (SVN), Spain (ESP), Sweden (SWE)
	Other OECD Europe (OEURa)	Switzerland (CHE), Norway (NOR), Rest of European Free Trade Association (XEF), Israel (ISR), Türkiye (TUR)
	UK (OEURc)	United Kingdom (GBR)
Africa & Middle East	Middle East (ME)	Bahrain (BHR), Iran, Islamic Republic of (IRN), Jordan (JOR), Kuwait (KWT), Oman (OMN), Qatar (QAT), Saudi Arabia (SAU), United Arab Emirates (ARE), Rest of Western Asia (XWS)
	North Africa (NAFR)	Egypt (EGY), Morocco (MAR), Tunisia (TUN), Rest of North Africa (XNF)
	South Africa (SAFR)	South Africa (ZAF)
	Other Africa (OAFR)	Benin (BEN),Burkina Faso (BFA),Cameroon (CMR),Côte d'Ivoire (CIV),Ghana (GHA),Guinea (GIN),Nigeria (NGA),Senegal (SEN),Togo (TGO),Rest of Western Africa (XWF),Rest of Central Africa (XCF),South Central Africa (XAC),Ethiopia (ETH),Kenya (KEN),Madagascar (MDG),Malawi (MWI),Mauritius (MUS),Mozambique (MOZ),Rwanda (RWA),Tanzania, United Republic of (TZA),Uganda (UGA),Zambia (ZMB),Zimbabwe (ZWE),Rest of Eastern Africa (XEC),Botswana (BWA),Namibia (NAM),Rest of South African Customs Union (XSC),Rest of the World (XTW)
Other Asia	China (CHN)	China (CHN), Hong Kong, Special Administrative Region of China (HKG)
	India (IND)	India (IND)
	Indonesia (INDO)	Indonesia (IDN)
	Other Asia (OASIA)	Rest of Oceania (XOC), Mongolia (MNG), Taiwan (TWN), Rest of East Asia (XEA), Bangladesh (BGD), Nepal (NPL), Pakistan (PAK), Sri Lanka (LKA), Rest of South Asia (XSA)
	Other Southeast Asia (OASEAN)	Brunei Darussalam (BRN), Cambodia (KHM), Lao PDR (LAO), Malaysia (MYS), Philippines (PHL), Singapore (SGP), Thailand (THA), Viet Nam (VNM), Rest of Southeast Asia (XSE)
Other Eurasia	Russia (RUS)	Russian Federation (RUS)
	Caspian (CASP)	Kazakhstan (KAZ), Kyrgyzstan (KGZ), Tajikistan (TJK), Rest of Former Soviet Union (XSU), Armenia (ARM), Azerbaijan (AZE), Georgia (GEO)
	European Union C (EUc)	Bulgaria (BGR), Croatia (HRV), Cyprus (CYP), Malta (MLT), Romania (ROU)
	Other Europe B (OEURb)	Albania (ALB), Belarus (BLR), Ukraine (UKR), Rest of Eastern Europe (XEE), Rest of Europe (XER)
Other Latin America	Brazil (BRA)	Brazil (BRA)
	Other Latin America (CSAMb)	Rest of North America (XNA), Argentina (ARG), Bolivia (BOL), Ecuador (ECU), Paraguay (PRY), Peru (PER), Uruguay (URY), Venezuela (Bolivarian Republic of) (VEN), Rest of South America (XSM), Costa Rica (CRI), Guatemala (GTM), Honduras (HND), Nicaragua (NIC), Panama (PAN), El Salvador (SLV), Rest of Central America (XCA), Dominican Republic (DOM), Jamaica (JAM), Puerto Rico (PRI), Trinidad and Tobago (TTO), Rest of Caribbean (XCB)

Source: OECD ENV-Linkages model.

Table A A.2. ENV-Linkages sector aggregation

ENV-Linkages sectors	GTAP sector
Primary	
Animal agriculture (AnimAgr)	Crops nec (ocr), Bovine cattle, sheep and goats, horses (ctl), Animal products nec (oap), Raw milk (rmk), Wool, silk-worm cocoons (wol)
Mining (Mining)	Other Extraction (formerly omn Minerals nec) (oxt)
Other agriculture (OthAgr)	Forestry (frs), Fishing (fsh)
Vegetal agriculture (VegAgr)	Paddy rice (pdr), Wheat (wht), Cereal grains nec (gro), Vegetables, fruit, nuts (v_f), Oil seeds (osd), Sugar cane, sugar beet (c_b), Plant-based fibers (pfb)
Animal agriculture (AnimAgr)	Crops nec (ocr), Bovine cattle, sheep and goats, horses (ctl), Animal products nec (oap), Raw milk (rmk), Wool, silk-worm cocoons (wol)
Energy	
Coal (coa)	Coal extraction (coa)
Coal power (clp)	Coal base load power generation (CoalBL)
Gas (gas)	Gas extraction (gas)
Gas manufacture and distribution (gdt)	Gas manufacture, distribution (gdt)
Gas power (gsp)	Gas base load power generation (GasBL), Gas peak power generation (GasP)
Hydro power (hyd)	Hydro base load power generation (HydroBL), Hydro peak power generation (HydroP)
Nuclear power (nuc)	Nuclear power generation (NuclearBL)
Oil (oil)	Oil extraction (oil)
Oil power (olp)	Oil base load power generation (OilBL), Oil peak power generation (OilP)
Other power (xel)	Other base load power generation (OtherBL)
Petroleum and coal products (p_c)	Petroleum, coal products (p_c)
Power transport and distribution (etd)	Power transport and distribution (TnD)
Solar power (sol)	Solar peak power generation (SolarP)
Wind power (wnd)	Wind base load power generation (WindBL)
Manufacturing	
Chemicals (Chemicals)	Chemical products (chm)
Electric equipment (ElecEqui)	Electrical equipment (eeq)
Food (Food)	Bovine meat products (cmt), Meat products nec (omt), Vegetable oils and fats (vol), Dairy products (mil), Processed rice (pcr), Sugar (sgr), Food products nec (ofd), Beverages and tobacco products (b_t)
Iron and steel (IronSteel)	Ferrous metals (i_s)
Non-metallic minerals (Minerals)	Mineral products n.e.s (nmm)
Other energy intensive industries (OthEITE)	Paper products, publishing (ppp), Basic pharmaceutical products (bph), Rubber and plastic products (rpp)
Other manufacturing (OthManuf)	Wood products (lum), Metal products (fmp), Computer, electronic and optical products (ele), Machinery and equipment nec (ome), Manufactures nec (omf)
Non-ferrous metals (OthMetals)	Metals nec (nfm)
Textiles (Textiles)	Textiles (tex), Wearing apparel (wap), Leather products (lea)
Transport equipment (TransEqui)	Motor vehicles and parts (mvh), Transport equipment nec (otn)
Services	
Air transportation (atp)	Air transport (atp)
Construction (cns)	Construction (cns)
Dwellings (Dwellings)	Dwellings (dwe)
Business services (FinInsBus)	Trade (trd), Warehousing and support activities (whs), Financial services nec (ofi), Insurance (formerly isr) (ins), Real estate activities (rsa), Business services nec (obs)
Land transport (otp)	Transport nec (otp)

ENV-Linkages sectors	GTAP sector
Other services (OthServ)	Accommodation, Food and service activities (afs), Communication (cmn), Recreational and other services (ros)
Public services (PubServ)	Public Administration and defense (osg), Education (edu), Human health and social work activities (hht)
Water and waste (wts)	Water (wtr)
Water transport (wtp)	Water transport (wtp)

Note: The table provides an overview on the ENV-Linkages sectors and corresponding GTAP sectors. The abbreviation 'n.e.s' in the GTAP sector 'Mineral products n.e.s' means "not elsewhere specified".
Source: OECD ENV-Linkages model.

Table A A.3. Aggregate ENV-Linkages sectors, with distinction between European Emissions Trading System (ETS) and Effort Sharing Regulation (ESR) sectors

Aggregate ENV-Linkages sectors	ENV-Linkages sectors
European Emissions Trading System (ETS)	
FF-powered electricity	combines: Coal power (clp), Gas power (gsp), Oil power (olp)
Air and water transport	combines: Air transport (atp), Water transport (wtp)
Non-ferrous metals	refers to: Non ferrus metals (OthMetals)
Non-metallic minerals	refers to: Non-metallic minerals (Minerals)
Other electricity	refers to: Other power (xel)
Other energy-intensive industries	refers to: Other energy-intensive industries (OthEITE)
Refining activities	refers to: Petroleum and coal products (p_c)
Effort Sharing Regulation (ESR)	
Agriculture and food	combines: Animal agriculture (AnimAgr), Vegetal agriculture (VegAgr), Other agriculture (OthAgr) and Food (Food)
Renewables and nuclear electricity	combines: Hydro power (hyd), Nuclear power (nuc) Solar power (sol), Wind power (wnd)
Transport and electric equipment	combines: Transport equipment (TransEqui), Electric equipment (ElecEqui)
Business services	refers to: Business services (FinInsBus)
Land transport	refers to: Land transportat (otp)
Fossil fuels extraction and distribution	combines: Coal (coa), Gas (gas), Gas manufacture and distribution (gdt), Oil (oil)
Other manufacturing	combines: Other manufacturing (OthManuf) and Textiles (Textiles)
Other	combines: Mining (Mining), Power transport and distribution (etd), Water and waste (wts) and dwellings (Dwellings)

Note: The table provides an overview on aggregate ENV-Linkages sectors, which are used for presentation purposes, and the corresponding ENV-Linakges sectors, as they are used in the model. The table also distinguishes sectors between European Emissions Trading System (ETS) and Effort Sharing Regulation (ESR) sectors.
Source: OECD ENV-Linkages model.

Modelling instruments in the Fit for 55 scenario

105. Based on previous modelling of net-zero emission scenarios (Fouré, Dellink and Lanzi, 2023[28]), the Fit for 55 scenario includes modelling of the following policy instruments:

- Carbon pricing
- Fossil fuel support removal
- Subsidies to decarbonise household consumption
- Regulations in the power sector to enforce a switch away from fossil fuels
- Regulations to stimulate investments to decarbonise building and transport emissions
- Policies to stimulate firms' energy efficiency improvement.

106. Instruments other than carbon pricing and fossil fuel support removal are calibrated using intermediate scenarios, because calibrating all the required endogenous variables is too complex in a large scale model like ENV-Linkages. Therefore, a total of 16 scenarios are implemented to calibrate the full set of instruments in the following consecutive steps:

1. For each of the four activities group (Power, Transport services, Other services, Households), a scenario calibrating energy efficiency or energy mix.
2. For each of the four activities group, and for each instrument type (regulation or subsidy), a scenario calibrating input efficiency or subsidies rate, on top of the same assumptions as step 1.
3. Four scenarios gathering the information from steps 1 and 2: regulation for households and regulation for firms, regulation for households and subsidies for firms, subsidies for households and regulation for firms, and finally regulation for households and regulation for firms.

107. The calibration steps 1 and 2 use information for the World Energy Outlook 2021 (IEA, 2021[23]), as described below. The 3rd step is used for the combination of policy instruments, other than carbon pricing.

Carbon pricing

108. Carbon pricing increases the price of carbon-intensive energy sources compared to other sources. This additional pricing based on the carbon content of production and consumption leads to higher prices of emission-intensive commodities, inducing (i) an increase in expenditures to improve energy efficiency, and (ii) a shift in demand away from these commodities towards less emission-intensive commodities.

109. For fossil fuel combustion emissions, the carbon price increases the price of energy depending on the CO_2 emission factor of the fossil fuel commodity: the additional cost is therefore the highest for coal, while it is lower for gas. For industrial process emissions, as well as for fugitive emissions, the emissions are linked to the production level instead of the fossil fuel content. The carbon price therefore acts as an incentive to deploy end-of-pipe type mitigation actions, where emissions per unit of output can decrease at the cost of a lower productivity (more inputs and factors are needed to produce the same amount of output). As such, mitigation actions are implemented as long as their productivity cost is lower than the carbon price. The relation between carbon price, emissions abated, and corresponding costs is calibrated based on the mitigation potentials in each sector responsible for process CO_2 emissions.

Fossil fuel support removal

110. The fossil fuel support data used in the ENV-Linkages model are mainly constructed from a sector-detailed version of the OECD Inventory of support measures for fossil fuels (the “Inventory”) (OECD, 2023[60]) (OECD, 2023[60]) for the years 2014 and 2019. This dataset contains information for two kinds of beneficiaries, producer (PSE) and consumer (CSE). Measures falling under the Inventory’s general services support (GSSE) are not included in this analysis. Several economic activities are mapped to ENV-Linkages through ISIC Rev.4 codes that were provided by both sources. When the classification codes are not available, the concordance is reached using the sectors’ description provided. When fossil fuel support inventory sectors or energy commodities are more aggregated than in the GTAP database, fossil fuel support is downscaled based on GTAP energy data.

111. Finally, the dataset is extended with additional data gathered from the IEA Fossil Fuel Support Database (IEA, 2021[61]) for the years 2014 and 2019. This is because the OECD Inventory currently covers fossil fuel support in 50 OECD countries, G20 and Eastern Partnership (EaP) economies. The IEA Database instead contains figures about consumer fossil fuel subsidies for around 40 emerging economies where there is an existence of a lower consumer end-use price of fossil fuels relative to the international reference price, particularly seen in major oil-producing countries.

112. The ENV-Linkages model assumes that all the support corresponds to a subsidy on production (for producer support) or on consumption (for consumer support). The corresponding tax rates are recovered in the model by splitting net production tax revenues and net consumption tax revenues between (i) negative revenues from fossil fuel subsidies and (ii) other (positive or negative) revenues.

Subsidies to decarbonise household energy consumption

113. For each household h, region r, energy e, and time t, the preference parameter $\lambda^{ce}_{r,e,h,t}$ is calibrated in step 1 so that energy demand by households follows the dynamics coming from the indicated external sources:

$$\lambda^{ce}_{r,e,h,t} : xa_{r,e,h,t} = xa_{r,e,h,t-1} \cdot \frac{EnergyDemand_{r,e,h,t}}{EnergyDemand_{r,e,h,t-1}}$$

114. The level of subsidy needed to achieve the required level of expenditure is modelled through a decrease in consumption taxes. For each commodity i, activity a (households) in region r at time t, the level of consumption tax $paTax_{r,i,a,t}$ is as follows:

$$paTax_{r,i,a,t} : paTax_{r,i,a,t} = paTax^{BAU}_{r,i,a,t} + paTax^{cost}_{r,i,a,t}$$

115. Where $paTax^{BAU}_{r,i,a,t}$ is the level of consumption tax in the Baseline, corresponding to a fixed tax rate between 2014 and t and $paTax^{cost}_{r,i,a,t}$ is the endogenous subsidy (negative tax) calibrated to trigger the required expenditure for households. The calibration of policy instruments in preliminary scenarios is done through a mixed complementarity problem (MCP). This corresponds to the following equations:

$$paTax^{cost}_{r,i,a,t} : xa_{r,i,a,t} \geq xa^{BAU}_{r,i,a,t} + Expenditure_{r,i,a,t} \quad \perp \quad paTax^{cost}_{r,i,a,t} \leq 0$$

116. Where $xa_{r,i,a,t}$ is the level of consumption, $xa^{BAU}_{r,i,a,t}$ the level of consumption in the Baseline scenario, $Expenditure_{r,i,a,t}$ the required cost for the transition. This formulation as an MCP problem allows for two different cases: (i) if expenditures are lower than the target value $xa^{BAU}_{r,i,a,t} + Expenditure_{r,i,a,t}$, then the endogenous tax $paTax^{cost}_{r,i,a,t}$ will be stricty lower than zero; (ii) if the level of expenditure is already sufficient without subsidy, then the endogenous subsidy remains at 0. This second case can happen when, for instance, the macroeconomic impact of the scenario lead to more revenues for households, who in turn increase their expenditure on vehicles or construction services.

117. Regulations targeting households also share the same principle, but due to structural differences in the way households final demand is implemented in the model, it is the level of minimal consumption $\theta_{r,k,h,t}$ that is determined endogenously by the model. $\theta_{r,k,h,t}$ corresponds to the subsistence minimum for consumer in region r, for commodity k (consumer commodities are mapped to standard commodities i on a one-to-one basis excepted for energy goods that are aggregated in a single consumer commodity but is not concerned by regulations) by household h (there is only one household per region). The level of minimal consumption becomes:

$$\theta_{r,k,h,t} : \theta_{r,k,h,t} = \theta^{BAU}_{r,k,h,t} + \theta^{cost}_{r,k,h,t}$$

118. The corresponding MCP is the following:

$$\theta^{cost}_{r,k,h,t} : xc_{r,k,h,t} \geq xc^{BAU}_{r,k,h,t} + Expenditure_{r,k,h,t} \quad \perp \quad \theta^{cost}_{r,k,h,t} \geq 0$$

where $xc_{r,k,h,t}$ is the level of consumption, $xc^{BAU}_{r,k,h,t}$ the level of consumption in the BAU scenario and $Expenditure_{r,i,a,t}$ the required cost for the transition.

Regulation in the power sector to enforce a switch away from fossil fuels

119. In the power sector, total power production is modelled as a Leontief function of all power generation technologies $elya$ (coal, oil, gas, nuclear, wind, solar, hydro, other) that are gathered into different power bundles pb (fossil, nuclear, hydro, renewables). The calibration step consists in setting

constant elasticity of substitution (CES) share parameters for each generation technology in power bundles $as_{r,elya,t}$ and the share of each power bundle in total power generation $apb_{r,pb,t}$ according to desired targets:

$$as_{r,elya,t} = \frac{PowerGeneration_{r,elya,t}}{\sum_{elya \in pb} PowerGeneration_{r,elya,t}}$$

$$apb_{r,pb,t} = \frac{\sum_{elya \in pb} PowerGeneration_{r,elya,t}}{\sum_{elya} PowerGeneration_{r,elya,t}}$$

Where $PowerGeneration_{r,elya,t}$ corresponds to the targeted power production coming from external sources.

120. Regulations follow the same modelling as subsidies for household energy demand and are calibrated in the preliminary step 1, but it is the input efficiency $\lambda^{io}_{r,i,a,t}$ that is endogenously determined by the model:

$$\lambda^{io}_{r,i,a,t} : \lambda^{io}_{r,i,a,t} = \lambda^{io,BAU}_{r,i,a,t} / \lambda^{io,cost}_{r,i,a,t}$$

Where $\lambda^{io,BAU}_{r,i,a,t}$ is the input efficiency in the Baseline, and $\lambda^{io,cost}_{r,i,a,t}$ is the endogenous efficiency modifier calibrated to trigger the required expenditure in sector a. The calibration of policy instrument is done through the following MCP:

$$\lambda^{io,cost}_{r,i,a,t} : xa_{r,i,a,t} \geq xa^{BAU}_{r,i,a,t} + Expenditure_{r,i,a,t} \quad \perp \quad \lambda^{io,cost}_{r,i,a,t} \geq 1$$

where, as in the previous case, $xa_{r,i,a,t}$ is the level of consumption, $xa^{BAU}_{r,i,a,t}$ the level of consumption in the BAU scenario, $Expenditure_{r,i,a,t}$ the required cost of transition.

Regulations to stimulate investments to decarbonize building and transport emissions

121. Energy efficiency changes follow a very different logic in the production function. The level of efficiency $\lambda^{e}_{r,e,a,t}$ is determined endogenously by the model in preliminary step 1 such that energy intensity demand follows the dynamics coming from external sources:

$$\lambda^{e}_{r,e,a,t} : \frac{xa_{r,e,a,t}}{xp_{r,a,t}} = \frac{xa_{r,e,a,t-1}}{xp_{r,a,t-1}} . \frac{EnergyDemand_{r,e,a,t} / Production_{r,a,t}}{EnergyDemand_{r,e,a,t-1} / Production_{r,a,t-1}}$$

Where $xa_{r,e,a,t}$ is the demand for energy e by sector a in region r in ENV-Linkages; $xp_{r,a,t}$ is the production of sector a ; $EnergyDemand_{r,e,a,t}$ is the energy demand coming from IEA and $Production_{r,a,t}$ is the production coming from the same external source.

122. Regulations for firms to decarbonise their transport and building emissions is identical to the regulations targeting the power sector.

Policies to stimulate firms' energy efficiency improvement

123. In other economic sectors, due to the lack of detailed external information, energy efficiency follows a simple constant-growth-rate path:

$$\lambda^{e}_{r,e,a,t} : \lambda^{e}_{r,e,a,t} = \lambda^{e}_{r,e,a,t-1} \left(1 + g^{\lambda^e}_{r,e,a,t}\right)$$

Where $g^{\lambda^e}_{r,e,a,t}$ is exogenous and is set in the Fit for 55 scenario to 3% per year in Services and 2% per year in Industry. As a comparison, the values for the *Baseline* scenario are 1.5% for both Services and Industry.

Annex B. Tables and figures: Supplementary analysis

Table A B.1. Projected absolute and relative changes in the demand for skills, by skill

		Absolute				Relative			
O*Net Level 1	O*Net Level 3	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)
Knowledge	Sales and Marketing	272	-30	154	96	3.978	-28	87	73
Knowledge	Computers and Electronics	252	-35	153	67	3.077	-32	51	48
Work Activities	Interacting With Computers	207	-40	152	48	2.692	-36	43	33
Knowledge	Language	153	-45	151	37	2.289	-42	33	29
Knowledge	Economics and Accounting	150	-29	150	106	4.050	-26	92	80
Work Activities	Thinking Creatively	137	-35	149	65	3.161	-31	54	49
Knowledge	Customer and Personal Service	135	-32	148	78	3.485	-31	61	53
Skills	Programming	132	-29	147	111	4.035	-26	90	86
Work Activities	Analyzing Data or Information	98	-28	146	116	4.281	-25	99	98
Knowledge	Administration and Management	97	-32	145	80	3.619	-29	65	63
Work Activities	Assisting and Caring for	86	-34	144	72	3.361	-32	58	47

		Absolute				Relative			
O*Net Level 1	O*Net Level 3	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)
	Others								
Knowledge	Medicine and Dentistry	85	-29	143	102	3.671	-26	68	89
Work Activities	Communicating with Persons Outside Organization	83	-31	142	85	3.914	-29	81	69
Work Activities	Performing General Physical Activities	75	-35	141	66	2.733	-34	44	39
Work Styles	Dependability	72	-43	140	38	2.337	-40	34	30
Technology Skills & Tools	Web platform development software	67	-28	139	115	4.668	-23	115	115
Work Activities	Provide Consultation and Advice to Others	62	-29	138	112	4.442	-25	108	94
Work Activities	Guiding, Directing, and Motivating Subordinates	62	-28	137	114	4.119	-26	93	83
Work Activities	Performing Administrative Activities	60	-27	136	120	4.466	-24	110	99
Knowledge	Production and Processing	57	-68	135	21	0.570	-71	14	10
Work Styles	Initiative	57	-37	134	59	2.952	-33	48	43
Skills	Time Management	57	-40	133	49	2.654	-37	39	32
Knowledge	Communications and Media	55	-31	132	84	3.674	-29	69	64
Work Activities	Establishing and Maintaining Interpersonal Relationships	54	-35	131	63	3.283	-31	57	50
Work Activities	Organizing, Planning, and Prioritizing Work	52	-42	130	41	2.371	-39	35	31
Work Activities	Selling or Influencing Others	51	-29	129	104	4.213	-27	95	77

		Absolute				Relative			
O*Net Level 1	O*Net Level 3	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)
Technology Skills & Tools	Operating system software	51	-27	128	117	4.610	-23	114	105
Abilities	Oral Expression	49	-33	127	76	3.660	-28	67	70
Knowledge	Personnel and Human Resources	47	-34	126	71	3.487	-30	62	55
Work Styles	Achievement/Effort	47	-39	125	51	2.684	-35	42	37
Work Activities	Monitoring and Controlling Resources	46	-41	124	46	2.873	-35	46	38
Technology Skills & Tools	Analytical or scientific software	45	-31	123	89	3.755	-27	71	75
Work Activities	Developing Objectives and Strategies	44	-30	122	95	3.906	-26	79	78
Knowledge	Food Production	44	-29	121	110	4.217	-26	96	82
Work Activities	Making Decisions and Solving Problems	42	-31	120	83	3.868	-30	78	58
Work Styles	Leadership	42	-37	119	58	3.109	-33	52	45
Knowledge	Law and Government	42	-41	118	47	2.670	-34	41	42
Technology Skills & Tools	Data base management system software	40	-22	117	142	6.209	-18	135	136
Knowledge	Chemistry	39	-41	116	43	2.757	-34	45	41
Technology Skills & Tools	Object or component oriented development software	37	-29	115	103	4.404	-24	107	102
Work Activities	Documenting/Recording Information	37	-35	114	64	3.383	-29	59	66
Work Activities	Communicating with Supervisors, Peers, or	35	-30	113	94	3.959	-28	85	72

		Absolute				Relative			
O*Net Level 1	O*Net Level 3	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)
	Subordinates								
Knowledge	Biology	34	-31	112	88	3.945	-25	83	90
Skills	Management of Financial Resources	28	-29	111	105	4.227	-26	97	88
Knowledge	Public Safety and Security	28	-30	110	101	4.332	-25	103	91
Knowledge	Engineering and Technology	28	-78	109	14	0.517	-75	12	9
Knowledge	Administrative	27	-32	108	77	4.016	-29	88	68
Technology Skills & Tools	Office suite software	26	-41	107	45	2.967	-36	49	35
Work Activities	Performing for or Working Directly with the Public	25	-27	106	118	3.777	-26	73	81
Work Activities	Judging the Qualities of Things, Services, or People	25	-34	105	73	3.638	-28	66	74
Work Activities	Staffing Organizational Units	25	-26	104	124	3.234	-30	55	60
Work Styles	Self Control	24	-34	103	69	3.609	-30	64	59
Knowledge	Mathematics	23	-33	102	74	3.762	-30	72	61
Work Activities	Monitor Processes, Materials, or Surroundings	22	-52	101	31	1.919	-45	30	25
Technology Skills & Tools	Configuration management software	22	-26	100	126	4.859	-21	121	121
Skills	Complex Problem Solving	22	-62	99	26	1.505	-52	25	21
Technology Skills & Tools	Development environment software	21	-30	98	98	4.519	-23	112	108
Work Activities	Resolving Conflicts and Negotiating with Others	21	-25	97	127	4.569	-23	113	116

		Absolute				Relative			
O*Net Level 1	O*Net Level 3	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)
Work Styles	Analytical Thinking	21	-31	96	92	4.307	-26	101	79
Technology Skills & Tools	Enterprise resource planning ERP software	20	-33	95	75	3.399	-30	60	57
Skills	Quality Control Analysis	20	-53	94	29	1.293	-52	22	22
Knowledge	Building and Construction	19	-53	93	28	0.916	-57	17	17
Technology Skills & Tools	Customer relationship management CRM software	17	-29	92	109	4.798	-23	119	112
Abilities	Originality	17	-36	91	62	3.260	-33	56	44
Knowledge	Psychology	16	-30	90	97	4.167	-23	94	110
Knowledge	Education and Training	16	-31	89	90	3.949	-25	84	92
Abilities	Fluency of Ideas	15	-31	88	86	3.858	-29	77	67
Knowledge	Geography	14	-31	87	81	3.924	-26	82	84
Technology Skills & Tools	Application server software	14	-27	86	121	5.155	-20	127	125
Work Styles	Adaptability/Flexibility	14	-74	85	17	1.340	-56	24	18
Technology Skills & Tools	Presentation software	14	-24	84	132	5.358	-21	129	123
Skills	Judgment and Decision Making	13	-31	83	82	5.134	-20	124	129
Work Activities	Inspecting Equipment, Structures, or Material	13	-46	82	36	2.657	-34	40	40
Skills	Management of Material Resources	13	-38	81	54	3.746	-31	70	52
Work Activities	Operating Vehicles, Mechanized Devices, or	13	-64	80	25	0.900	-63	16	13

		Absolute				Relative			
O*Net Level 1	O*Net Level 3	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)
	Equipment								
Work Styles	Stress Tolerance	12	-53	79	30	2.089	-43	31	26
Knowledge	Fine Arts	12	-29	78	107	3.913	-25	80	93
Knowledge	Transportation	12	-70	77	20	1.100	-62	20	14
Technology Skills & Tools	Graphics or photo imaging software	11	-37	76	56	4.049	-26	91	87
Work Activities	Scheduling Work and Activities	11	-30	75	99	4.360	-25	105	95
Skills	Management of Personnel Resources	11	-22	74	141	5.467	-20	131	131
Work Activities	Identifying Objects, Actions, and Events	10	-24	73	133	4.863	-23	122	111
Technology Skills & Tools	Data base user interface and query software	10	-27	72	122	4.773	-25	118	96
Knowledge	Philosophy and Theology	10	-34	71	68	3.520	-29	63	65
Work Activities	Training and Teaching Others	10	-39	70	52	2.624	-36	38	34
Work Styles	Concern for Others	10	-39	69	53	3.799	-28	74	71
Work Activities	Coaching and Developing Others	9	-28	68	113	3.813	-26	76	85
Technology Skills & Tools	Enterprise application integration software	9	-21	67	146	6.015	-18	134	137
Skills	Monitoring	8	-31	66	91	4.513	-23	111	114
Technology Skills & Tools	Web page creation and editing software	8	-30	65	93	4.356	-23	104	104

		Absolute				Relative			
O*Net Level 1	O*Net Level 3	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)
Work Styles	Attention to Detail	8	-36	64	61	4.313	-23	102	106
Work Styles	Cooperation	8	-79	63	13	1.175	-58	21	16
Skills	Systems Analysis	8	-30	62	100	4.397	-24	106	101
Technology Skills & Tools	Spreadsheet software	7	-61	61	27	1.823	-47	29	23
Work Styles	Innovation	7	-27	60	123	4.750	-22	117	118
Abilities	Mathematical Reasoning	5	-21	59	144	7.976	-13	150	154
Knowledge	History and Archeology	5	-27	58	119	5.479	-20	132	126
Work Activities	Getting Information	5	-70	57	19	1.022	-56	19	19
Work Activities	Evaluating Information to Determine Compliance with Standards	5	-42	56	42	3.144	-29	53	62
Knowledge	Telecommunications	5	-37	55	60	3.964	-22	86	117
Work Activities	Developing and Building Teams	5	-65	54	23	1.552	-53	27	20
Knowledge	Sociology and Anthropology	4	-24	53	129	4.681	-20	116	127
Technology Skills & Tools	Internet browser software	4	-66	52	22	2.231	-42	32	28
Work Activities	Updating and Using Relevant Knowledge	4	-32	51	79	4.828	-21	120	122
Technology Skills & Tools	Desktop publishing software	4	-24	50	131	5.148	-22	126	119
Technology Skills & Tools	Computer based training software	4	-37	49	55	3.023	-30	50	56
Technology Skills & Tools	Program testing software	4	-18	48	151	7.038	-15	145	147

		Absolute				Relative			
O*Net Level 1	O*Net Level 3	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)
Work Activities	Interpreting the Meaning of Information for Others	4	-41	47	44	4.284	-24	100	100
Knowledge	Therapy and Counseling	4	-43	46	40	4.233	-23	98	113
Skills	Systems Evaluation	3	-25	45	128	6.420	-19	137	134
Work Styles	Integrity	3	-49	44	34	2.534	-32	37	46
Technology Skills & Tools	Music or sound editing software	3	-26	43	125	5.456	-20	130	128
Technology Skills & Tools	Metadata management software	3	-24	42	130	7.693	-17	149	143
Work Activities	Processing Information	3	-72	41	18	1.818	-46	28	24
Technology Skills & Tools	Automatic teller machines ATMs	2	-37	40	57	1.323	-43	23	27
Technology Skills & Tools	Information retrieval or search software	2	-43	39	39	5.802	-19	133	132
Technology Skills & Tools	Cloud-based data access and sharing software	2	-31	38	87	5.137	-22	125	120
Abilities	Memorization	2	-21	37	147	8.020	-13	152	153
Skills	Service Orientation	1	-20	36	149	6.927	-14	143	149
Abilities	Written Comprehension	1	-46	35	35	2.874	-31	47	54
Work Activities	Repairing and Maintaining Electronic Equipment	1	-51	34	32	2.388	-36	36	36
Technology Skills & Tools	Business intelligence and data analysis software	1	-23	33	136	6.597	-20	140	130
Skills	Active Listening	1	-24	32	134	6.672	-16	142	144

		Absolute				Relative			
O*Net Level 1	O*Net Level 3	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)
Technology Skills & Tools	Geographic information system	1	-17	31	152	7.381	-14	147	150
Technology Skills & Tools	Access servers	1	-23	30	137	6.294	-18	136	138
Technology Skills & Tools	Word processing software	1	-51	29	33	6.458	-18	138	140
Abilities	Information Ordering	1	-20	28	148	7.102	-16	146	145
Work Activities	Estimating the Quantifiable Characteristics of Products, Events, or Information	1	-94	27	10	0.726	-68	15	12
Knowledge	Design	1	-97	26	8	0.322	-83	11	8
Technology Skills & Tools	Computer aided design CAD software	1	-87	25	11	0.544	-70	13	11
Technology Skills & Tools	Optical character reader OCR or scanning software	1	-39	24	50	6.957	-18	144	135
Technology Skills & Tools	Network monitoring software	0	-15	23	153	7.592	-14	148	151
Skills	Critical Thinking	0	-23	22	135	8.118	-17	153	142
Technology Skills & Tools	Transaction security and virus protection software	0	-23	21	139	7.979	-18	151	139
Technology Skills & Tools	Video creation and editing software	0	-18	20	150	6.651	-16	141	146
Skills	Resource Management Skills (general)	0	-85	19	12	4.028	-23	89	103
Technology Skills & Tools	Object oriented data base management software	0	-34	18	70	6.475	-18	139	141
Technology Skills & Tools	Safety harnesses or belts	0	-23	17	138	4.952	-23	123	107
Technology Skills & Tools	Blow molding machines	0	-65	16	24	3.801	-27	75	76

		Absolute				Relative			
O*Net Level 1	O*Net Level 3	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)	Absolute projected demand FF55 scenario	% change in demand due to FF55 relative to Baseline	Rank (Absolute projected demand FF55 scenario)	Rank (% change in demand due to FF55 relative to Baseline)
Technology Skills & Tools	Compliance software	0	-21	15	145	8.203	-15	154	148
Work Activities	Coordinating the Work and Activities of Others	0	-23	14	140	1.538	-25	26	97
Work Styles	Persistence	0	-22	13	143	5.276	-19	128	133
Technology Skills & Tools	Offset printing presses	0	-12	12	154	-12.842	-14	1	152
Technology Skills & Tools	Injection molding machines	0	-221	11	4	4.454	-23	109	109
Skills	Repairing	0	-220	10	5	1.011	-61	18	15
Skills	Equipment Maintenance	-1	-77	9	15	-0.047	-104	9	6
Technology Skills & Tools	Computer aided manufacturing CAM software	-2	-569	8	2	-1.689	-330	4	3
Work Activities	Handling and Moving Objects	-2	-103	7	7	0.002	-100	10	7
Technology Skills & Tools	Lasers	-3	-75	6	16	-3.620	-31	3	51
Technology Skills & Tools	Milling machines	-5	-29	5	108	-4.807	-21	2	124
Knowledge	Physics	-7	-124	4	6	-0.378	-137	8	5
Work Activities	Repairing and Maintaining Mechanical Equipment	-7	-97	3	9	-1.314	-813	6	2
Work Activities	Controlling Machines and Processes	-37	-241	2	3	-0.587	-172	7	4
Knowledge	Mechanical	-50	-2170	1	1	-1.552	-843	5	1

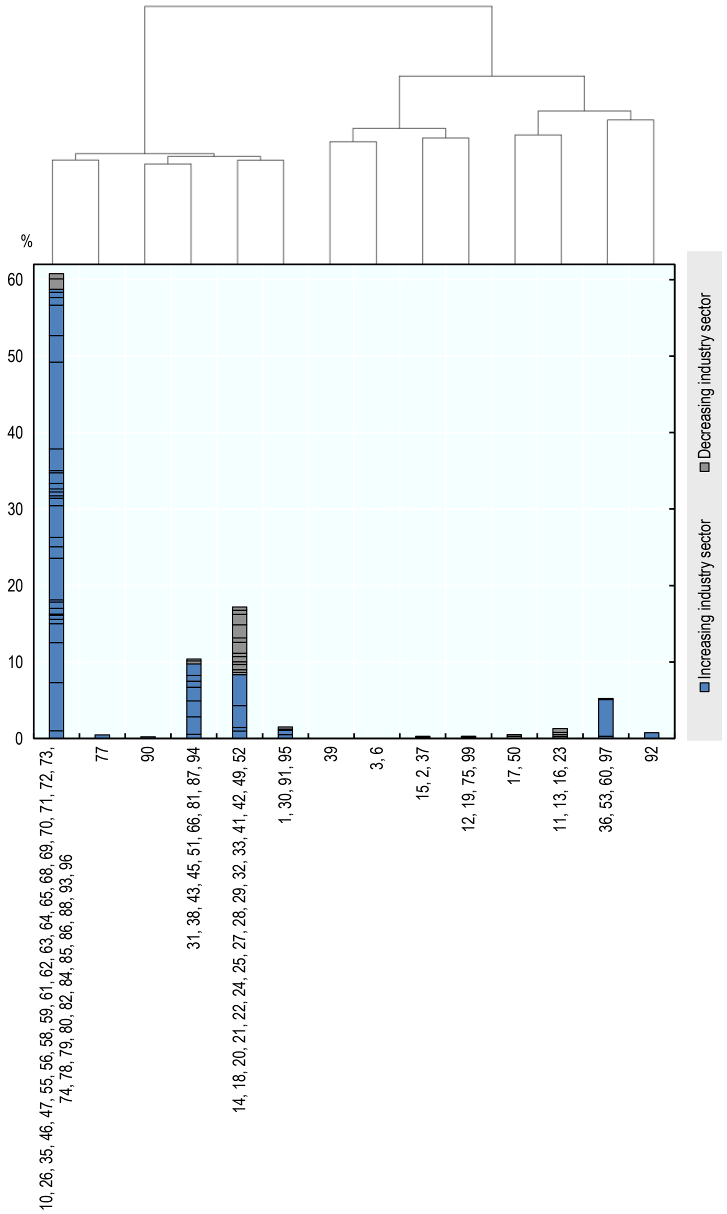
Note: The colour scheme reflects whether demand in skills depending on the relative or absolute scenario and whether based on absolute projected demand in the FF55 scenario or based on the % change in demand due to FF55 relative to Baseline is in the Top quartile (Quartile 1), Quartile 2 Quartile 3, Bottom (Quartile 3), and decreasing.

4. Quartile
3. Quartile
2. Quartile
1. Quartile
Decreasing

Source: Authors' own compilation based on OECD ENV-Linkages model, Lightcast™ (April 2023) and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

Figure A B.1. Skills similarity of employment opportunities for clerical workers

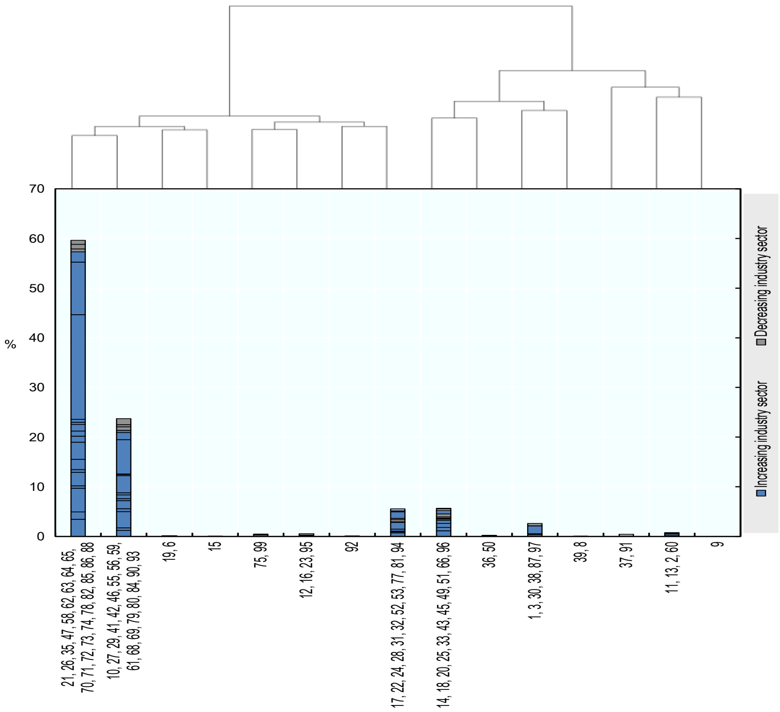
Dendrogram illustrating sectors based on skills similarity for clerical workers, employment shares in 2019 and projected growth/decline between 2019 and 2030 under the implementation of Fit for 55



Note: The top part of the dendogram illustrates the degree of similarity in the skillset needed in jobs performed by workers in different sector: sectors that share the same tree of the dendogram are closest in terms of skills requirements, as estimated cosine distance and hierarchical/agglomerative clustering, followed by sectors belonging to the same level one branch, followed by those belonging to the same level two branch etc. The bottom part identifies the share of clerical workers employed in each sector in 2019 (vertical axis, with stacked bar reflecting the size of sectors in increasing NACE code numbering). Each sector bar is colour coded to reflect if the sector is projected to increase or decline in demand between 2019 and 2030 under the Fit for 55 scenario. Sectors represented in blue are sectors for which the demand of clerical workers is projected to increase in demand between 2019 and 2030 whereas sectors in grey are sectors for which the demand of clerical workers is projected to decline.
Table A B.2 provides the sector names associated with the 2 digit sector codes shown in the figure. Underlying data are available upon request.
Source: Authors' own compilation based on OECD ENV-Linkages model, Lightcast™ (April 2023) and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

Figure A B.2. Skills similarity of employment opportunities for managers and officials

Dendrogram illustrating sectors based on skills similarity for managers and officials, employment shares in 2019 and projected growth/decline between 2019 and 2030 under the implementation of Fit for 55



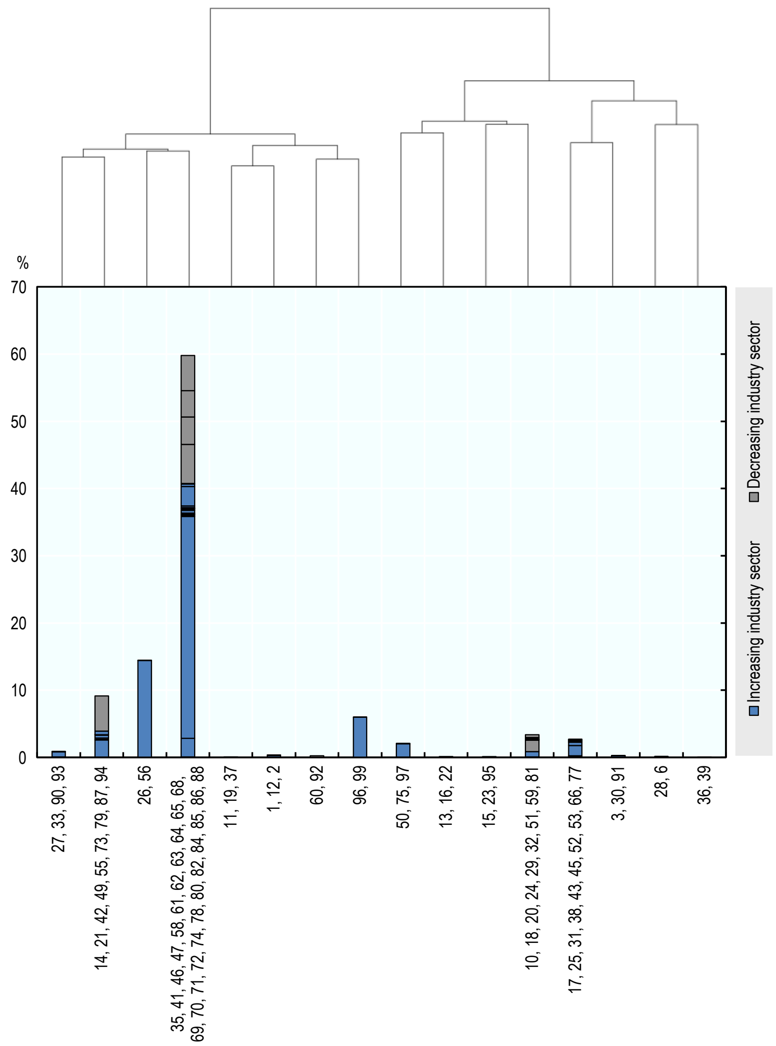
Note: The top part of the dendogram illustrates the degree of similarity in the skillset needed in jobs performed by workers in different sector: sectors that share the same tree of the dendogram are closest in terms of skills requirements, as estimated cosine distance and hierarchical/agglomerative clustering, followed by sectors belonging to the same level one branch, followed by those belonging to the same level two branch etc. The bottom part identifies the share of managers and officials employed in each sector in 2019 (vertical axis, with stacked bar reflecting the size of sectors in increasing NACE code numbering). Each sector bar is colour coded to reflect if the sector is projected to increase or decline in demand between 2019 and 2030 under the Fit for 55 scenario. Sectors represented in blue are sectors for which the demand of managers and officials is projected to increase in demand between 2019 and 2030 whereas sectors in grey are sectors for which the demand of managers and officials is projected to decline.

Table A B.2 provides the sector names associated with the 2 digit sector codes shown in the figure. Underlying data are available upon request.

Source: Authors' own compilation based on OECD ENV-Linkages model, Lightcast™ (April 2023) and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

Figure A B.3. Skills similarity of employment opportunities for service and sales workers

Dendrogram illustrating sectors based on skills similarity for service and sales workers, employment shares in 2019 and projected growth/decline between 2019 and 2030 under the implementation of Fit for 55



Note: The top part of the dendogram illustrates the degree of similarity in the skillset needed in jobs performed by workers in different sector: sectors that share the same tree of the dendogram are closest in terms of skills requirements, as estimated cosine distance and hierarchical/agglomerative clustering, followed by sectors belonging to the same level one branch, followed by those belonging to the same level two branch etc. The bottom part identifies the share of service and sales workers employed in each sector in 2019 (vertical axis, with stacked bar reflecting the size of sectors in increasing NACE code numbering). Each sector bar is colour coded to reflect if the sector is projected to increase or decline in demand between 2019 and 2030 under the Fit for 55 scenario. Sectors represented in blue are sectors for which the demand of of service and sales workers is projected to increase in demand between 2019 and 2030 whereas sectors in grey are sectors for which the demand of of service and sales workers is projected to decline.

Table A B.2 provides the sector names associated with the 2 digit sector codes shown in the figure. Underlying data are available upon request.

Source: Authors' own compilation based on OECD ENV-Linkages model, Lightcast™ (April 2023) and European Labour Force Survey (n.d.[39]), ad hoc data extraction (for the year 2019).

Table A B.2. Statistical classification of economic activities in the European Community, NACE 2 digit

Nr	Sector	Nr	Sector	Nr	Sector
1	Crop and animal production, hunting and related service activities	35	Electricity, gas, steam and air conditioning supply	73	Advertising and market research
2	Forestry and logging	36	Water collection, treatment and supply	74	Other professional, scientific and technical activities
3	Fishing and aquaculture	37	Sewerage	75	Veterinary activities
5	Mining of coal and lignite	38	Waste collection, treatment and disposal activities; materials recovery	77	Rental and leasing activities
6	Extraction of crude petroleum and natural gas	39	Remediation activities and other waste management services	78	Employment activities
7	Mining of metal ores	41	Construction of buildings	79	Travel agency, tour operator reservation service and related activities
8	Other mining and quarrying	42	Civil engineering	80	Security and investigation activities
9	Mining support service activities	43	Specialised construction activities	81	Services to buildings and landscape activities
10	Manufacture of food products	45	Wholesale and retail trade and repair of motor vehicles and motorcycles	82	Office administrative, office support and other business support activities
11	Manufacture of beverages	46	Wholesale trade, except of motor vehicles and motorcycles	84	Public administration and defence; compulsory social security
12	Manufacture of tobacco products	47	Retail trade, except of motor vehicles and motorcycles	85	Education
13	Manufacture of textiles	49	Land transport and transport via pipelines	86	Human health activities
14	Manufacture of wearing apparel	50	Water transport	87	Residential care activities
15	Manufacture of leather and related products	51	Air transport	88	Social work activities without accommodation
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	52	Warehousing and support activities for transportation	90	Creative, arts and entertainment activities
17	Manufacture of paper and paper products	53	Postal and courier activities	91	Libraries, archives, museums and other cultural activities
18	Printing and reproduction of recorded media	55	Accommodation	92	Gambling and betting activities
19	Manufacture of coke and refined petroleum products	56	Food and beverage service activities	93	Sports activities and amusement and recreation activities
20	Manufacture of chemicals and chemical products	58	Publishing activities	94	Activities of membership organisations
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	59	Motion picture, video and television programme production, sound recording and music publishing activities	95	Repair of computers and personal and household goods
22	Manufacture of rubber and plastic products	60	Programming and broadcasting activities	96	Other personal service activities
23	Manufacture of other non-metallic mineral products	61	Telecommunications	97	Activities of households as employers of domestic personnel
24	Manufacture of basic metals	62	Computer programming, consultancy and related activities	98	Undifferentiated goods- and services-producing activities of private households for own use
25	Manufacture of fabricated metal products, except machinery and equipment	63	Information service activities	99	Activities of extraterritorial organisations and bodies
26	Manufacture of computer, electronic and optical products	64	Financial service activities, except insurance and pension funding		

Nr	Sector	Nr	Sector	Nr	Sector
27	Manufacture of electrical equipment	65	Insurance, reinsurance and pension funding, except compulsory social security		
28	Manufacture of machinery and equipment n.e.c.	66	Activities auxiliary to financial services and insurance activities		
29	Manufacture of motor vehicles, trailers and semi-trailers	68	Real estate activities		
30	Manufacture of other transport equipment	69	Legal and accounting activities		
31	Manufacture of furniture	70	Activities of head offices; management consultancy activities		
32	Other manufacturing	71	Architectural and engineering activities; technical testing and analysis		
33	Repair and installation of machinery and equipment	72	Scientific research and development		

Note: The table shows the NACE 2 digit number and the sector name.
Source: Adapted from European Union (2023[62]), "Regulations: Commission Delegated Regulation (EU) 2023/137 of 10 October 2022", *Official Journal of the European Union*, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32023R0137&qid=1690274572441.

Annex C. Online vacancy data and skills data collected by Lightcast

Lightcast data collection

124. Skills information was derived from data collected by Lightcast. Lightcast is a labour market analytics company that collects postings from over 80 000 online job sites to develop a comprehensive, real-time portrait of labour market demand (job vacancy information) including vacancies posted directly by employers and vacancies posted by agencies advertising temporary staffing needs thus covering a range of work opportunities available to freelance professionals. Lightcast identifies websites with employment-opportunity-related content using spider technology to search those sites for employment opportunities. Based on a retrieved list of job postings, job postings are deduplicated to avoid the same posting appearing multiple times. Data are extracted from job posting texts including company, industry, occupation, skills. Lightcast then uses natural language processing to identify what skills employers seek in their prospective employees based on information made available in the text of the posting. For each posting a number of skills demanded are identified. Comprehensive overviews of the data collection process, representativeness and limitations of Lightcast online job postings is provided in Brüning and Mangeol, (2020[63]), Samek, Squicciarini and Cammeraat (2021[64]), and OECD (2022[65]). Although the data provide rich information on vacancies and the perspective of employers, they identify job openings (labour market flows) rather than employment levels (stocks). Furthermore, they reflect the expectations of prospective employers and no information from existing employees on the set of tasks and skills they perform. They only contain qualitative information on the range of skills employers seek rather than quantitative information on the level of proficiency employers expect employees to possess.

Sample used in this work

125. The dataset used in the analysis includes information about the following European Union countries: Belgium, Germany, Denmark, Spain, Estonia, France, Croatia, Italy, Lithuania, Latvia, Luxemburg, Hungary, Malta, Netherlands, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden, Ireland, Austria, Czech Republic, Greece, Bulgaria. The time range of the data was 2019 to 2022.

126. The total number of postings over the January 2019 to December 2022 period for all countries was around 203 million. The data was not distributed equally for each year: around 28 million vacancies were collected in 2019, 35 million in 2020, 54 million in 2021, and 85 million in 2022. This difference reflects, to a large extent, the increasing use of online portals to advertise vacancies in European countries. In the analyses, data from the 2019 to 2022 period were pooled to increase the absolute number of vacancies for under-represented sector-by-occupation combinations and thus reduce variability. The unbalanced nature of the data means that data from more recent years weight more heavily in determining the skills profile of different sector-by-occupation combinations. This should be an advantage to the extent that such data are more representative and that postings in more recent years more accurately reflect the skills content of different occupations.

Linking ENV-Linkages projections and Lightcast data

127. Projections obtained using the ENV-Linkages model reflect changes in employment for relatively aggregated sector-by-occupation combinations and the skills profile of workers in these combinations can be heterogeneous. A key assumption underlying the skills analyses is that the number of vacancies posted online for workers in different sector-by-occupation combinations reflects the potential distribution of workers and their skills within each sector-by-occupation combination in the near future. Because of the complexity and timeline inherent in the development of official statistics, official statistics data are ill suited to capture rapidly evolving labour market trends such as trends in the demand for digital skills and professionals and workers in companies that will be heavily influenced by the green transition. By contrast, vacancy data provide information on the set of skills demanded by prospective employers seeking workers to take on existing and future assignments.

128. In order to link data on skills (Lightcast data) to data on changes in employment estimated using the ENV-Linkages model, information on industry sector and occupation that Lightcast assigned to postings, were used. Lightcast classifies industry sectors using the European classification of economic activities: the Nomenclature of Economic Activities (NACE). Occupations were classified using the European Skills, Competences, Qualifications and Occupations (ESCO).

129. The NACE sector taxonomy is structured around four hierarchical levels: sections (21 categories, alphabetical code), divisions (99 categories, numerical codes), groups (not used in the analysis), and classes (not used in the analysis). The structure of NACE allows for a detailed and comprehensive categorisation of economic activities and is comparable across European Union countries. The specific version of the NACE taxonomy used in the analysis is the NACE Rev.2. The second level (divisions) was used to match postings to the ENV-Linkages sectors. [24] Lightcast postings with either missing information on the industry sector (NACE) or occupation (ESCO) were dropped, as well as postings which only had industry information provided at the sections level.

130. Postings in the Lightcast data were assigned a unique NACE sectoral and a unique ESCO occupational classifier using information contained in the vacancy text, sectoral and occupational information could suffer from misclassification if the text contained information that did not allow machine learning algorithms to correctly predict industry and occupational categories. Moreover, for a number of postings, the vacancy text did not contain sufficient information to produce a sectoral or occupational prediction.

131. A limitation of the NACE sector taxonomy is that it may not accurately capture emerging or rapidly evolving industries, and that it captures only sectors in the formal economy and therefore may not reflect important economic activities in countries or contexts with a large informal section. Finally, the NACE sector taxonomy is specific to the European Union and may not be directly comparable to other regional or global taxonomies, which can limit its usefulness for cross-country or global analyses.

132. Across the 2019-2022 time period, on average 6% of all postings had missing industry information, and 2% had missing occupational information. Missing values were unevenly distributed: industry information was missing in 43% of postings advertised in Denmark and in 20% of the postings advertised in Bulgaria whereas less than 1% of all postings advertised in Slovenia and Sweden did not contain a valid sectoral classifier. For occupation, as many as 26% of all postings advertised in Estonia and 20% of postings advertised in Denmark did not contain a valid occupational classifier whereas almost all postings contained a valid occupational classifier in Ireland and Luxemburg. Table A C.1 illustrates the total number

[24] To merge NACE sectors to ENV linkages, a correspondence table was used as described in Annex C, Section 'Correspondence table between ENV-Linkages sectors and NACE 2 digit industry sectors'.

of online vacancies in each country and the share of vacancies that were not assigned a valid sectoral or occupational classifier.

Table A C.1. Number of online postings and description of missing information (2019-2022), by country

Country	Total number of postings	Percentage of NACE industry sections (alphabetical code) dropped	Percentage of postings dropped due to with missing industry information	Percentage of postings dropped due to missing occupation information
Austria	3 816 947	46	12	0
Belgium	8 884 397	30	3	2
Bulgaria	1 371 233	25	22	3
Croatia	767 349	13	4	2
Czech Republic	3 490 983	53	12	13
Denmark	1 005 784	16	35	3
Estonia	456 764	11	5	18
Finland	1 099 618	14	5	8
France	40 471 350	29	3	1
Germany	53 883 901	47	18	1
Greece	426 601	32	10	4
Hungary	1 398 909	52	4	3
Ireland	2 363 087	26	14	0
Italy	8 566 071	39	7	0
Latvia	467 256	27	8	3
Lithuania	725 864	16	3	7
Luxembourg	142 249	25	8	0
Malta	73 816	23	10	1
Netherlands	8 322 251	39	5	1
Poland	21 709 518	26	3	1
Portugal	2 583 893	30	11	2
Romania	1 529 205	33	4	1
Slovak Republic	908 531	31	7	3
Slovenia	342 573	48	1	1
Spain	5 915 174	26	5	2
Sweden	6 363 166	43	3	5

Note: Table shows the total number of postings pooled across 2019-2022 for each European Union country, the percentage of postings with missing industry information and the percentage of postings with missing occupational information.
Source: Authors' own compilation based on Lightcast™ (December 2022).

Lightcast skills taxonomy

133. Information on the skills content of jobs come from the text of the vacancies prospective employers posted online as they were looking to fill positions that became available in their company or institution during the 2019 to 2022 period either because of staff turnover or because of new job creation. Lightcast data include vacancies posted by recruitment and staffing agencies as well as those posted directly by employers. Lightcast first uses a language detection model to identify the language used in a specific posting. In a second step, it uses language-specific machine learning algorithms developed for different European languages to impute, for each posting, a set of word labels that could indicate skills demanded

by prospective employers. In a third step, such word labels were converted into a standard classification system of skills common to all countries in the European Union, namely ESCO skills taxonomy.

134. The skills pillar of ESCO contains almost 13 500 keywords structured around four concepts: 1) Knowledge, 2) Skills; 3) Attitudes and values, and 4) Language skills. Lightcast mapped language specific word labels extracted from the text of vacancies posted online into the European wide ESCO skills taxonomy, using the ESCO taxonomy version 1.0.8 until the end of the second quarter of 2022 and the ESCO taxonomy version 1.1.1 from the third quarter of 2022. Such taxonomy was augmented with word labels referring to digital and ICT skills (referred to STACK by Lightcast) which are referred to as “Digital +” in this work. The need to augment the ESCO taxonomy derives from the rapid evolution of the digital landscape and the fact that official taxonomies take time to be updated while new digital skills emerge all the time.

135. In the analyses presented in this work, ESCO level 3 skills were converted into higher order categories to aid interpretability of results. In particular, in order to align information contained in this work with information contained in the OECD' Skills for Jobs database and other publications on the green economy that employ the O*NET skills classification, skills information in the ESCO taxonomy is mapped onto the O*NET skills taxonomy. The conversion was developed by Cedefop and can be requested from Cedefop or the authors.

Obtaining skills distributions

136. In order to identify the overall demand for skills in the European labour market given the distribution of workers in different sectors and occupations in 2019 and the projected changes in employment estimated in Section 3, information on the skills required to perform specific jobs derived from online postings was matched to information on employment numbers in different sectors and occupations.

137. Postings were classified into different sector-by-occupation cells based on NACE sectors (99 industry sectors) and ESCO occupations (5 occupations). The distribution of postings in each cell is assumed to represent either the current or near future distribution of jobs in each cell (since postings contain information on job openings and desired skills). To ESCO level 3 and Digital + skill category, a relative comparative advantage (RCA) weight was assigned to reflect the importance of that skill in each sector-by-occupation cell. RCAs were then normalised such that within each cell the sum of all RCAs equal 1. RCA weights were then multiplied by employment numbers in each cell to derive a measure of the overall demand for different skills in each sector-by-occupation cell. The process was repeated three times. Once for the 2019 employment numbers, once for the employment numbers projected in the Baseline scenario (2030), and once for the employment numbers projected in the Fit for 55 scenario (2030). Because employment projections based on the ENV-Linkages model refer to a sectoral classification that does not map uniquely to NACE sectors at the two-level digit (99 codes). In order to estimate the overall demand for each ESCO3 and Digital+ skill in each country and each scenario, for each skill the overall demand across all sectors and occupation was computed.

138. For each skill and for each country the percentage change between 2019 and 2030 (Fit for 55) and between 2030 (Baseline) and 2030 (Fit for 55) was calculated to illustrate the change in the demand for skills over the period and the specific change attributable to the implementation of the Fit for 55 policy targets. Second, ESCO3 and Digital+ skills were grouped into O*NET level 2 skills categories (29 categories). Several ESCO3 and Digital+ skills map into one O*NET level 2 skills category. Since a different number of ESCO3 and Digital+ skill map into each of the O*NET level 2 categories weights were developed and applied to such that each percentage change in ESCO3 and Digital+ skill was multiplied by the employment share of each sector and occupational category.

139. In the following formulas, (s) represents ENV-Linkages sectors, (o) represents occupation groups, (i) represents NACE sectors, (l) represents ESCO level 3 skill groups, (n) represents O*NET level 2 skill categories, (c) represents countries.

140. The following describes the analytical steps of the skills analysis:

1. **RCA.** For each ESCO skill level 3 group (l) in country (c) within each sector (i) -by-occupation (o) cell the Relative Comparative Advantage weight was created as follows:

$$RCA_{loic} = \frac{\frac{Postings_{loic}}{\sum_{l=1}^{L} Postings_{loic}}}{\frac{\sum_{o=1}^{O}\sum_{i=1}^{I} Postings_{loic}}{\sum_{o=1}^{O}\sum_{i=1}^{I}\sum_{l=1}^{L} Postings_{loic}}}$$

   with $Postings_{loic}$ being the total number of postings within country (c) and within each sector (i) -by-occupation (o) cell. RCAs are adapted from Alabdulkareem et al., (2018[36]) and reflect the relative comparative advantage of a skill (l) in a sector (i) -by-occupation (o) cell. While the relative importance of skill (l) in a sector (i) -by-occupation (o) cell is assessed in the numerator, the relative importance of skill (l) in all other sector (i) -by-occupation (o) cells is assessed. Therefore, the ratio can be interpreted as a measure of relative importance of the skill category in an occupation, compared to the importance of the same skill category in all other occupations. RCAs range between 0 and +∞, with values larger 1 indicating that skill (l) is more important in a specific sector (i) -by-occupation (o) cell. As values are not bounded, values across sector (i) -by-occupation (o) cells are not comparable.

2. **RCAs were then normalised.** Normalised RCAs were created for each ESCO skill level 3 group (l) in country (c) within each sector (i) -by-occupation (o) cell by dividing the RCA of each ESCO skill level 3 group (l) in country (c) within each sector (i) -by-occupation (o) cell by the sum of RCAs in each sector (i) -by-occupation (o) cell. The normalisation process ensures that the total of the employment changes remain the same: RCAs add up to 1 within each sector (i) -by-occupation (o) cell.

3. **Quantification of skills demand at the granular level.** Skills demand/skills importance was estimated by multiplying the normalised RCAs by different employment scenarios for each country (c) and each sector (i) by occupation (o) cell. Estimates were obtained for each of the three employment scenarios: employment numbers (in millions of workers) in 2019, in 2030 under the Fit for 55 scenario and in 2030 in the Baseline scenario. Employment numbers in 2019 are based on estimates from the European Labour Force for each NACE sector identified in the Lighcast data. Employment numbers for the Baseline scenario and the Fit for 55 scenario were estimated by combining European Labour Force data (expressed in NACE sectors) and projected employment growth (expressed in ENV-Linkages agents). Annex C, Section 'EU-LFS data' illustrates the procedure used to identify projected employment trends of NACE sectors based on estimated employment growth under different scenarios in ENV-Linkages **Quantification of overall skills demand at the country level.** The overall demand for each skill for country and each skill was computed by summing each ESCO skill level 3 group across all sectors and occupations. **Identification of changes in demand for aggregated skill categories.** To aid interpretability ESCO skill level 3 group (l) were mapped onto O*NET level 2 categories (n). Since a different number of ESCO level 3 skills map onto each of the 29 O*NET level 2 categories, for each country, the weighted sum of ESCO level 3 skills that map into one O*NET level 2 categories was taken.

Annex D. EU-LFS data

Correspondence table between ENV-Linkages sectors and NACE 2 digit industry sectors

141. A correspondence table between ENV-Linkages agents and NACE sectors was created to identify employment projections in the Fit for 55 and Baseline scenarios in 2030.

142. The correspondence table maps 37 ENV-Linkages sectors to NACE 2 digit sectors and is available upon request from the authors. The correspondence was conducted by mapping ENV-Linkages sectors have been mapped to NACE industry sectors following the following steps:

a. ENV-Linkages sectors were mapped onto GTAP[25] (Link ENV-Linkages to GTAP see Table A A.2)

Sectors Food and Agriculture:

i. GTAP to CPC[26] (Link GTAP to CPC www.gtap.agecon.purdue.edu/databases/contribute/concordinfo.asp (accessed 22.03.2023)
ii. CPC to ISIC[27] 4 digits (Link CPC to ISIC correspondence: https://unstats.un.org/unsd/classifications/unsdclassifications/cpcv21.pdf (accessed 22.03.2023)
iii. ISIC 4 digits to ISIC 2 digits (Link ISIC https://unstats.un.org/unsd/publication/seriesm/seriesm_4rev4e.pdf) (accessed 22.03.2023)

Sectors Other than Food and Agriculture:

iv. GTAP to ISIC (Link GTAP to ISIC www.gtap.agecon.purdue.edu/databases/contribute/concordinfo.asp (accessed 22.03.2023)

b. ISIC Rev. 4 to NACE (Link to ISIC classification https://unstats.un.org/unsd/publication/seriesm/seriesm_4rev4e.pdf (accessed 27.03.2023)

EU-LFS data

143. Section 4 uses employment information from the European labour force survey (EU-LFS) in 2019.European labour force survey (EU-LFS) in 2019.Section 4 uses employment information from the European labour force survey (EU-LFS) in 2019.European labour force survey (EU-LFS) in 2019. Employment information are provided for each European Union country by occupation (International

[25] Global Trade Analysis Project (GTAP).

[26] Central Product Classification (CPC).

[27] International Standard Industrial Classification of All Economic Activities (ISIC).

Standard Classification of Occupations (ISCO), 1 digit level, major groups) and industry (Statistical classification of economic activities in the European Community (NACE), 3 digit level). Further employment information is used by sex, age (15-29, 30-49, 50-64), education ('below secondary' (ISCED level 0-2), 'secondary' (ISCED level 3-4), 'more than tertiary education' (ISCED level 5-8)), training participation (education and training received during the past four weeks (including the survey reference week) in formal and non-formal education).

144. To ensure comparability across occupation classifications used in the OECD ENV-Linkages model and EU-LFS, ISCO 1 digit level major occupations groups are combined to match OECD ENV-Linkages occupations in the shown in Table A D.1.

Table A D.1. Corresponding occupations groups between ENV-Linkages and EU-LFS

OECD ENV-Linkages occupations	EU-LFS occupations
Professionals	Technicians and associate professionals
Managers and officials	Managers; Professionals
Service and sales workers	Service and sales workers
Clerical workers	Clerical support workers
Blue collar and farm workers	Skilled agricultural; Forestry and fishery workers; Plant and machine operators, and assemblers; Elementary occupations; Craft and related trades workers

Note: The table shows which ISCO 1 digit level major occupation groups from the EU-LFS have been combined to correspond to OECD ENV-Linkages occupations.
Source: OECD ENV-Linkages model.

References

Adalet McGowan, M. and D. Andrews (2015), “Skill Mismatch and Public Policy in OECD Countries”, *OECD Economics Department Working Papers*, No. 1210, OECD Publishing, Paris, https://doi.org/10.1787/5js1pzw9lnwk-en. [49]

Aguiar, A. et al. (eds.) (2019), *Disaggregating Labor Payments*, Journal of Global Economic Analysis, https://jgea.org/ojs/index.php/jgea/article/view/77. [34]

Aguiar, A. et al. (2019), “The GTAP Data Base: Version 10”, *Journal of Global Economic Analysis*, Vol. 4/1, pp. 1-27, https://doi.org/10.21642/jgea.040101af. [35]

Alabdulkareem, A. et al. (2018), “Unpacking the polarization of workplace skills”, *Science Advances*, Vol. 4/7, https://doi.org/10.1126/sciadv.aao6030. [36]

Aragón, F., J. Rud and G. Toews (2018), “Resource shocks, employment, and gender: Evidence from the collapse of the UK coal industry”, *Labour Economics*, Vol. 52, pp. 54-67, https://doi.org/10.1016/j.labeco.2018.03.007. [43]

Asai, K., F. Borgonovi and S. Wildi (2022), “Understanding how economic conditions and natural disasters shape environmental attitudes: A cross-country comparison to inform policy making”, *OECD Social, Employment and Migration Working Papers*, No. 280, OECD Publishing, Paris, https://doi.org/10.1787/8e880ea2-en. [47]

Bontadini, F. and F. Vona (2022), *Anatomy of Green Specialisation: Evidence from EU Production Data, 1995-2015*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4140894. [12]

Borgonovi, F. et al. (2022), “The environmental sustainability competence toolbox: From leaving a better planet for our children to leaving better children for our planet”, *OECD Social, Employment and Migration Working Papers*, No. 275, OECD Publishing, Paris, https://doi.org/10.1787/27991ec0-en. [53]

Borgonovi, F. et al. (2022), “Young people’s environmental sustainability competence: Emotional, cognitive, behavioural, and attitudinal dimensions in EU and OECD countries”, *OECD Social, Employment and Migration Working Papers*, No. 274, OECD Publishing, Paris, https://doi.org/10.1787/1097a78c-en. [54]

Bowen, A. and B. Hancké (2019), *The Social Dimensions of ‘Greening the Economy’. Developing a taxonomy of labour market effects related to the shift toward environmentally sustainable economic activities.*, Publication Office of the European Union, https://doi.org/10.2767/448791. [16]

Brüning, N. and P. Mangeol (2020), "What skills do employers seek in graduates? Using online job posting data to support policy and practice in higher education", *OECD Education Working Papers*, No. 231, OECD Publishing, Paris, https://doi.org/10.1787/bf533d35-en. [63]

Cedefop (2021), *The green employment and skills transformation: insights from a European Green Deal skills forecast scenario*, http://data.europa.eu/doi/10.2801/112540. [22]

Chateau, J., R. Bibas and E. Lanzi (2018), *Impacts of Green Growth Policies on Labour Markets and Wage Income Distribution: A General Equilibrium Application to Climate and Energy Policies*, OECD Environment Working Papers, https://doi.org/10.1787/ea3696f4-en. [19]

Chateau, J., R. Dellink and E. Lanzi (2014), "An Overview of the OECD ENV-Linkages Model: Version 3", *OECD Environment Working Papers*, No. 65, OECD Publishing, Paris, https://dx.doi.org/10.1787/5jz2qck2b2vd-en. [24]

Château, J., A. Saint-Martin and T. Manfredi (2011), "Employment Impacts of Climate Change Mitigation Policies in OECD: A General-Equilibrium Perspective", *OECD Environment Working Papers*, No. 32, OECD Publishing, Paris, https://doi.org/10.1787/5kg0ps847h8q-en. [21]

Chepeliev, M. (2020), "GTAP-Power Data Base: Version 10", *Journal of Global Economic Analysis*, Vol. 5/2, pp. 110-137, https://doi.org/10.21642/JGEA.050203AF. [57]

Crippa, M. et al. (2021), "GHG emissions of all world countries 2021 Report", https://doi.org/10.2760/173513. [58]

Curtis, E. and I. Marinescu (2022), "Green Energy Jobs in the Us: What are They, and Where are They?", *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.4184319. [15]

EU Commission (2021), *'Fit for 55': delivering the EU's 2030 Climate Target on the way to climate neutrality,*, COM/2021/550 final, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52021DC0550&from=EN. [69]

European Council and Council of the European Union (2022), *Fit for 55*, https://www.consilium.europa.eu/en/policies/green-deal/fit-for-55-the-eu-plan-for-a-green-transition/ (accessed on 2 May 2023). [71]

European Labour Force Survey (n.d.), *ad hoc data extraction (for the year 2019)*, https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey. [39]

European Parliament and the Council (2018), *Directive (EU) 2018/410 of the European Parliament and of the Council of 14 March 2018 amending Directive 2003/87/EC to enhance cost-effective emission reductions and low-carbon investments, and Decision (EU) 2015/1814 (Text with EEA relevance.)*, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32018L0410&from=EN. [31]

European Parliament and the Council (2009), *Decision No 406/2009/EC of the European Parliament and of the Council of 23 April 2009 on the effort of Member States to reduce their greenhouse gas emissions to meet the Community's greenhouse gas emission reduction commitments up to 2020*, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32009D0406&from=EN. [30]

European Parliament and the Council (2009), *Directive 2009/29/EC of the European Parliament and of the Council of 23 April 2009 amending Directive 2003/87/EC so as to improve and extend the greenhouse gas emission allowance trading scheme of the Community (Text with EEA relevance)*, https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:140:0063:0087:en:PDF. [29]

European Parliament and the Council (2008), *Directive 2008/101/EC of the European Parliament and of the Council of 19 November 2008 amending Directive 2003/87/EC so as to include aviation activities in the scheme for greenhouse gas emission allowance trading within the Community (Text with EEA rel*, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32008L0101&from=EN. [33]

European Parliament and the Council (2003), *Directive 2003/87/EC of the European Parliament and of the Council of 13 October 2003 establishing a scheme for greenhouse gas emission allowance trading within the Community and amending Council Directive 96/61/EC (Text with EEA relevance)*, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32003L0087&from=EN. [32]

European Union (2023), *Regulations: Commission Delegated Regulation (EU) 2023/137 of 10 October 2022*, European Union, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32023R0137&qid=1690274572441 (accessed on 25 July 2023). [62]

Fouré, J., R. Dellink and E. Lanzi (2023), “Public finance resilience in the transition towards carbon neutrality”, *OECD Environment Working Papers*, No. 214, OECD Publishing, Paris, https://doi.org/10.1787/7f3275e0-en. [28]

Gathmann, C. and U. Schönberg (2010), “How General Is Human Capital? A Task-Based Approach”, *Journal of Labor Economics*, Vol. 28/1, pp. 1-49, https://doi.org/10.1086/649786. [5]

Georgeson, L. and M. Maslin (2019), “Estimating the scale of the US green economy within the global context”, *Palgrave Communications*, Vol. 5/1, https://doi.org/10.1057/s41599-019-0329-3. [8]

Guillemette, Y. and D. Turner (2021), “The long game: Fiscal outlooks to 2060 underline need for structural reform”, *OECD Economic Policy Papers*, No. 29, OECD Publishing, Paris, https://dx.doi.org/10.1787/2226583X. [27]

Hyman, R. et al. (2002), “Modeling non-CO 2 greenhouse gas abatement”, *Environmental Modeling and Assessment*, Vol. 8, pp. 175-186. [59]

IEA (2021), *Fossil Fuel Subsidies Database - 2021 edition*, https://www.iea.org/data-and-statistics/data-product/fossil-fuel-subsidies-database (accessed on 25 August 2022). [61]

IEA (2021), *World Energy Outlook 2021*, OECD Publishing, Paris, https://doi.org/10.1787/14fcb638-en. [23]

IMF (2020), *World Economic Outlook, October 2020: A Long and Difficult Ascent*, https://www.imf.org/en/Publications/WEO/Issues/2020/09/30/world-economic-outlook-october-2020 (accessed on 22 January 2021). [67]

International Labour Organization (2017), *Just Transition, Decent Work, and Climate Resilience*, International Labour Organization, Bangkok, https://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/documents/publication/wcms_589098.pdf. [4]

Kambourov, G. and I. Manovskii (2009), “Occupational specificity of human capital”, *International Economic Review*, Vol. 50/1, pp. 63-115, https://doi.org/10.1111/j.1468-2354.2008.00524.x. [6]

Lassébie, J. and G. Quintini (2022), “What skills and abilities can automation technologies replicate and what does it mean for workers?: New evidence”, *OECD Social, Employment and Migration Working Papers*, No. 282, OECD Publishing, Paris, https://doi.org/10.1787/646aad77-en. [46]

Lightcast (n.d.), *Lightcast website*, https://lightcast.io/about/company (accessed on 4 April 2023). [25]

O*NET (n.d.), *O*NET database*, https://www.onetcenter.org/database.html#individual-files. [38]

OECD (2023), *Flexible Adult Learning Provision: What it is, Why it Matters and How to Make it Work*, OECD, Paris, https://www.oecd.org/els/emp/skills-and-work/adult-learning/booklet-flexibility-2023.pdf. [40]

OECD (2023), *Job Creation and Local Economic Development 2023: Bridging the Great Green Divide*, OECD Publishing, Paris, https://doi.org/10.1787/21db61c1-en. [10]

OECD (2023), “OECD Inventory of Support Measures for Fossil Fuels: France (Edition 2022)”, *OECD Environment Statistics (database)*, https://doi.org/10.1787/c9ee3fcf-en. [60]

OECD (2022), *Are Students Ready to Take on Environmental Challenges?*, PISA, OECD Publishing, Paris, https://doi.org/10.1787/8abe655c-en. [55]

OECD (2022), *Career Guidance for Adults in Canada*, Getting Skills Right, OECD Publishing, Paris, https://doi.org/10.1787/0e596882-en. [52]

OECD (2022), *Global Plastics Outlook: Policy Scenarios to 2060*, OECD Publishing, Paris, https://doi.org/10.1787/aa1edf33-en. [68]

OECD (2022), *OECD Employment Outlook 2022: Building Back More Inclusive Labour Markets*, OECD Publishing, Paris, https://doi.org/10.1787/1bb305a6-en. [65]

OECD (2021), *Career Guidance for Adults in a Changing World of Work*, Getting Skills Right, OECD Publishing, Paris, https://doi.org/10.1787/9a94bfad-en. [51]

OECD (2021), *OECD Economic Outlook, Volume 2021 Issue 2*, OECD Publishing, Paris, https://dx.doi.org/10.1787/66c5ac2c-en. [66]

OECD (2020), “Making the green recovery work for jobs, income and growth”*, OECD Policy Responses to Coronavirus (COVID-19)*, OECD Publishing, Paris, https://doi.org/10.1787/a505f3e7-en. [20]

OECD (2019), *Getting Skills Right: Future-Ready Adult Learning Systems*, Getting Skills Right, OECD Publishing, Paris, https://doi.org/10.1787/9789264311756-en. [41]

OECD (2017), *Getting Skills Right: Skills for Jobs Indicators*, Getting Skills Right, OECD Publishing, Paris, https://doi.org/10.1787/9789264277878-en. [70]

OECD (2012), *What Green Growth Means for Workers and Labour Market Policies: An Initial Assessment*, OECD Employment Outlook 2012, OECD Publishing, https://doi.org/10.1787/EMPL_OUTLOOK-2012-5-EN. [18]

OECD (2004), *Career Guidance and Public Policy: Bridging the Gap*, OECD Publishing, Paris, https://doi.org/10.1787/9789264105669-en. [50]

OECD (n.d.), *Skills for Jobs Database*, https://www.oecdskillsforjobsdatabase.org. [37]

OECD/ILO (2022), *Equipping Health Workers with the Right Skills: Skills Anticipation in the Health Workforce*, Getting Skills Right, OECD Publishing, Paris, https://doi.org/10.1787/9b83282e-en. [45]

Peters, D., L. Eathington and D. Swenson (2011), *An Exploration of Green Job Policies, Theoretical Underpinnings, Measurement Approaches, and Job Growth Expectations*, https://edauniversitycenter.uic.edu/wp-content/uploads/sites/16/2018/09/Green_Jobs_USDA.pdf (accessed on 18 July 2023). [11]

Poletaev, M. and C. Robinson (2008), “Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000”, *Journal of Labor Economics*, Vol. 26/3, pp. 387-420, https://doi.org/10.1086/588180. [7]

Quintini, G. (2014), “Skills at Work: How Skills and their Use Matter in the Labour Market”, *OECD Social, Employment and Migration Working Papers*, No. 158, OECD Publishing, Paris, https://doi.org/10.1787/5jz44fdfjm7j-en. [48]

Samek, L., M. Squicciarini and E. Cammeraat (2021), “The human capital behind AI: Jobs and skills demand from online job postings”, *OECD Science, Technology and Industry Policy Papers*, No. 120, OECD Publishing, Paris, https://doi.org/10.1787/2e278150-en. [64]

Saussay, A. et al. (2022), *Who’s fit for the low-carbon transition? Emerging skills and wage gaps in job ad data*, https://www.lse.ac.uk/granthaminstitute/publication/whos-fit-for-the-low-carbon-transition-emerging-skills-and-wage-gaps-in-job-ad-data/ (accessed on 18 July 2023). [14]

SNCF (2020), *How taking a train can help save the planet*, https://www.sncf.com/en/commitments/sustainable-development/how-taking-train-can-help-save-planet (accessed on 18 July 2023). [56]

Tamba, M. (2022), “Economy-wide impacts of road transport electrification in the EU”, *Technological Forecasting and Social Change*, Vol. 182, https://doi.org/10.1016/j.techfore.2022.121803. [44]

United Nations (2018), *World urbanisation prospects: the 2018 revision*, https://population.un.org/wup/Publications/Files/WUP2018-Report.pdf (accessed on 18 July 2023). [26]

United Nations Framework Convention on Climate Change (2015), *Paris Agreement*, https://unfccc.int/files/essential_background/convention/application/pdf/english_paris_agreement.pdf (accessed on 14 February 2023). [1]

Valero, A. et al. (2021), *Are ’green’ jobs good jobs?*, https://cep.lse.ac.uk/_new/publications/abstract.asp?index=8581. [3]

von Rueden, C. and I. Bambalaite (2020), “Measuring occupational entry regulations: A new OECD approach”, *OECD Economics Department Working Papers*, No. 1606, OECD Publishing, Paris, https://doi.org/10.1787/296dae6b-en. [42]

Vona, F. (2021), *Labour Markets and the Green Transition: a practitioner's guide to the task-based approach*, https://doi.org/10.2760/65924. [2]

Vona, F. and F. Bontadini (2022), "Anatomy of Green Specialisation: Evidence from EU Production Data, 1995-2015", *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.4140894. [9]

Vona, F., G. Marin and D. Consoli (2019), "Measures, drivers and effects of green employment: evidence from US local labor markets, 2006–2014", *Journal of Economic Geography*, Vol. 19/5, pp. 1021-1048, https://doi.org/10.1093/jeg/lby038. [13]

Weitzel, M. et al. (2023), "A comprehensive socio-economic assessment of EU climate policy pathways", *Ecological Economics*, Vol. 204, p. 107660, https://doi.org/10.1016/j.ecolecon.2022.107660. [17]