

2025 Skills Forecast Technical Report

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Foreword

This document is the Technical Report accompanying the 2025 Skills Forecast. It outlines the key assumptions adopted and data utilised in preparing the 2025 release. Full details on the methodological framework applied and the various modules developed for producing the Skills Forecast can be found in the dedicated Methodological Report.

Table of contents

TABLE OF CONTENTS	3
LIST OF TABLES, FIGURES AND BOXES.....	4
Tables	4
Figures	4
Boxes Error! Bookmark not defined.	
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CHAPTER 1. INTRODUCTION	5
CHAPTER 2. DEVELOPMENT AND REFINEMENT OF THE METHODOLOGY.....	7
2.1. Introduction.....	7
2.2. Macroeconomic modelling.....	7
2.2.1. Population projections.....	7
2.2.2. GDP projections.....	9
2.2.3. Assumptions underpinning the European Green Deal.....	10
2.3. Expansion demands for occupations and qualifications (EDMOD and QUALMOD)	19
2.4. Replacement demand (RDMOD)	26
2.4.1. Adjustments to the RDMOD.....	26
2.5. Modelling qualification supply (QMOD)	29
CHAPTER 3. DATA UPDATE AND PREPARATION	32
3.1. Introduction.....	32
3.2. E3ME update.....	32
3.3. LFS update of Modules 2-5	38
LIST OF ABBREVIATIONS.....	40
REFERENCES	41

List of tables, figures and boxes

Tables

Table 2.1 Assumptions used in the E3ME model	13
Table 3.1 Description of updated variables.....	33
Table 3.2 Main data inputs from EU-LFS microdata	38

Figures

Figure 1.1 Cedefop Skills forecast modelling forecast.....	6
Figure 2.1 EU-27 Population projections, thousands.....	8
Figure 2.2 EU-27 short-term population scenarios, thousands.....	8
Figure 2.3 Ameco's 2023 Autumn Economic Projections	10
Figure 2.4 EU27 final energy demand in 2030, million tonnes of oil- equivalent (mtoe)	16
Figure 2.5 EU27 power generation allocation, 2030	17
Figure 2.6 Main greening assumptions and how they are reflected in E3ME 18	
Figure 2.7 Comparisons with EU-LFS estimates	22
Figure 2.8 Comparisons with EU-LFS estimates	23
Figure 2.9 Adjustments to occupational employment shares for 2035	24
Figure 2.10 Implementation of automation.....	28

Introduction

Cedefop's skill supply and demand projections provide comprehensive information about the current structure, and future trends, in the labour market. This technical report accompanies the release of the 2023 update to the projections.

The methodology¹ uses a modular approach, with the following main elements:

- (a) the demand side (skill needs), focusing on employment (jobs);
- (b) the supply side, focusing on available skills in the labour market, such as the number of people economically active and the qualifications they hold;
- (c) imbalances, comparing the results from the demand and supply side modules.

All modules adopt common data, methods and models for all countries (EU + the Republic of North Macedonia, Iceland, Norway, Switzerland and Turkey) to produce a comprehensive and consistent set of skill projections. The database draws primarily on Eurostat sources, including demographic data, both historical and projections, national accounts (NA) and the labour force survey (LFS).

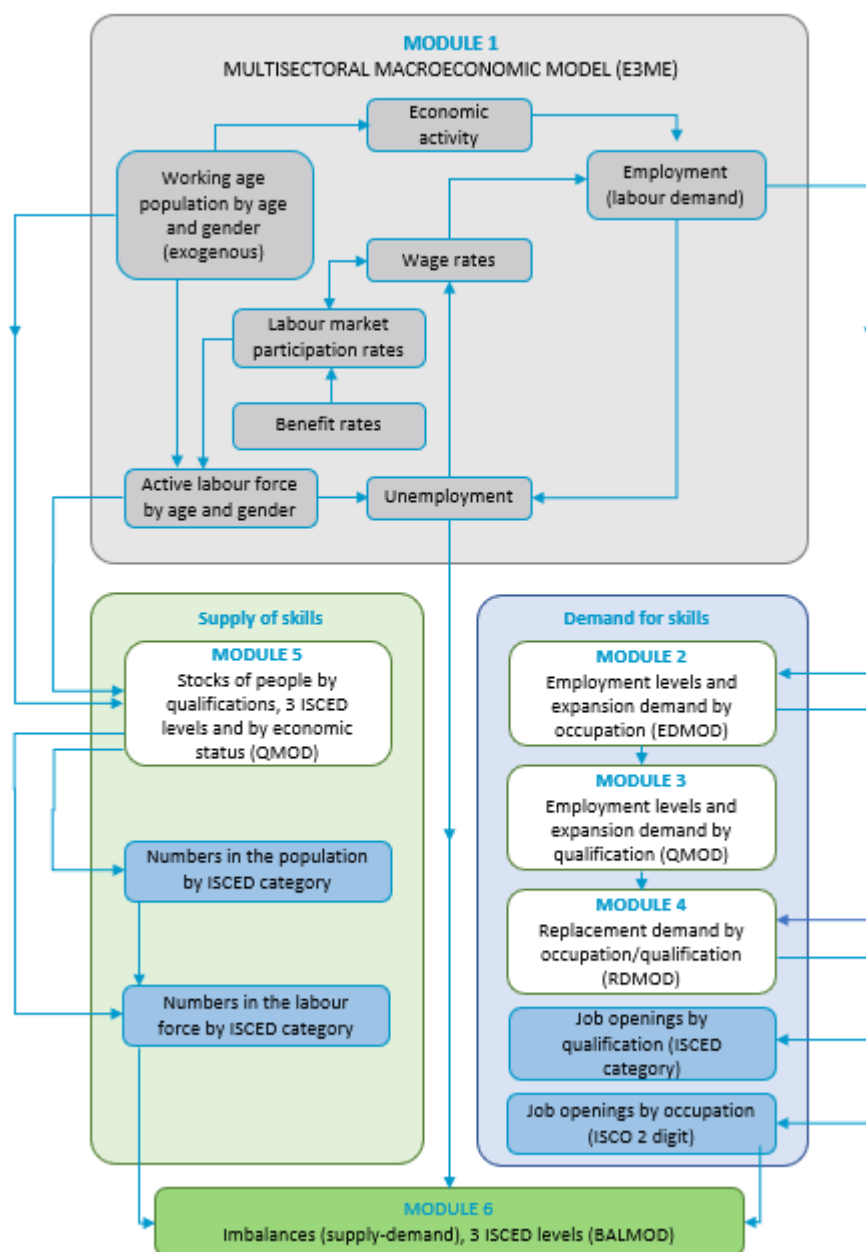
Individual country experts are involved in peer review and results validation. However, the use of common models and assumptions does not always allow incorporation of local data and factors that may affect skill supply and demand. Therefore, other country-specific information might be needed to complement the results.

Figure 1.1 presents the Cedefop Skills Forecast methodological framework. Module 1 of the methodology contains the Cambridge Econometrics' E3ME (macroeconomic) model. This is used to form projections of labour demand (employment) at sectoral level and labour supply (the economically active labour force) by demographic group.

Modules 2 and 3 cover employment levels and expansion demand (i.e. new jobs created over time) for occupations and qualifications. Module 4 covers replacement demand (i.e. job openings resulting from people exiting the labour market or changing jobs). Modules 5 focus on the supply of skills as measured by the highest qualification held, analysing stocks and flows. Module 6 reconciles skill demand and supply.

¹ https://www.cedefop.europa.eu/files/skills_forecast_methodological_framework.pdf

Figure 1.1 Cedefop Skills forecast modelling forecast



CHAPTER 1. Development and refinement of the methodology

1.1. Introduction

This chapter describes the development and refinement of the Cedefop Skills Forecast methodological framework. Section 3.2 describes the macroeconomic modelling and its underlying assumptions such as greening of the EU economy. Section 3.3 describes the changes to the replacement demand methodology. The final section discusses the changes to the other modules of the Cedefop Skills Forecast.

1.2. Macroeconomic modelling

This section outlines the main macroeconomic assumptions underlying the Cedefop projections. They cover:

- (a) Population projections,
- (b) GDP projections, both short and long-term,
- (c) Incorporation of part of the EU Green Deal, in particular the new emission reduction target (55% GHG reduction compared to 1990 levels by 2030) and improved resource efficiency by increasing recycling rates.

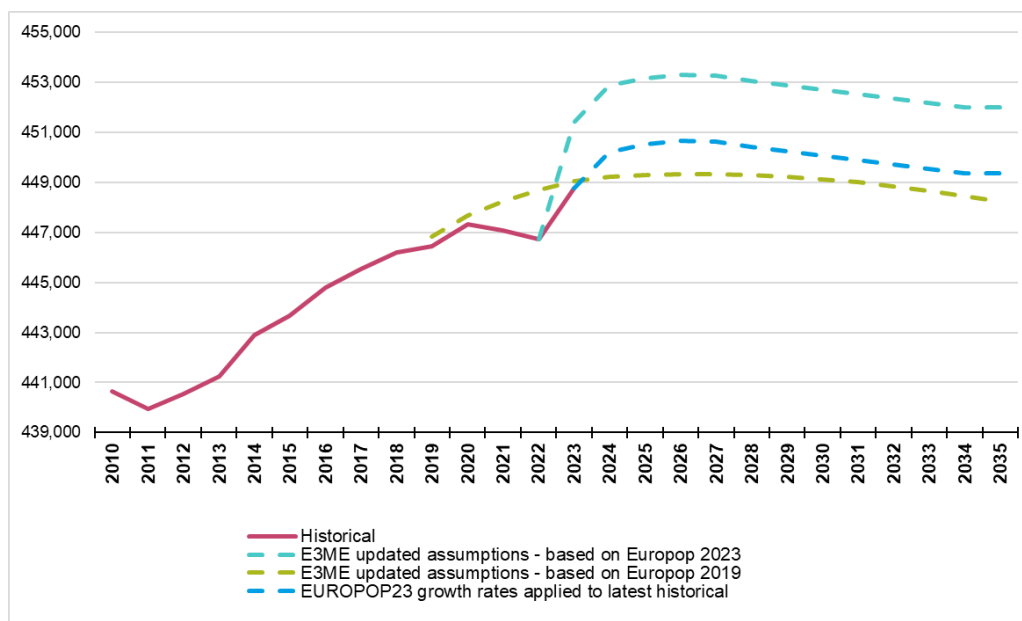
The forecast horizon has also been expanded from 2030 to 2035. These assumptions are discussed in further detail below.

1.2.1. Population projections

The latest population projections from Eurostat EUROPOP2023 have been used in this forecasting exercise. Figure 2.1 shows how, compared to the projections used in the previous forecasting exercise, EUROPOP2023 projections are slightly more optimistic in terms of population growth. Indeed, by 2035 EUROPOP2023 forecast that total population in EU-27 would be 0.8% higher compared to the previous 2035 outcome (around 3.7 million people more). In terms of the working-age population (15-64), EUROPOP2023 forecasts a 1.7% increase in 2035 compared to the previous population projections. The population data were updated at the end of 2023, when historical data for that year were not yet available. Historical population data for 2023 was later published, and showed a lower value compared to what was projected by EUROPOP23 as can be seen from

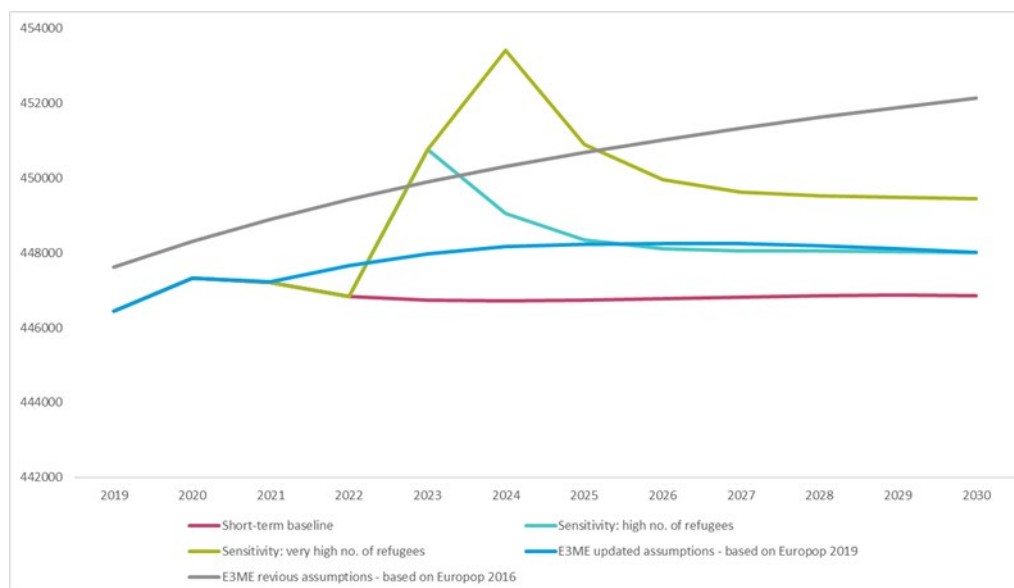
Figure 2.1. Applying EUROPOP23 growth rates to the 2023 historical data yields a projection which is closer to EUROPOP19. The difference between the historical 2023 population data and the EUROPOP23 projected 2023 value that was used in the forecast is unlikely to alter the results in any meaningful way, given the small magnitude of the discrepancy.

Figure 2.1 EU-27 Population projections, thousands



Source(s): E3ME and Eurostat [proj_esms]

Figure 2.2 EU-27 short-term population scenarios, thousands



Source(s): E3ME and Eurostat [proj_esms, proj_stp22]

1.2.2. GDP projections

The short-term GDP projections are in line with Ameco's Autumn 2023 Economic Forecast², while the long-term projections are in line with the GDP projections used in the EUROPOP2023 population projections, as detailed in the 2024 Ageing Report³. Since the 2024 Ageing Report does not contain assumptions about the European Green Deal⁴, the long-term GDP projections have been adjusted to reflect the implementation of parts of the Green Deal, based on information from the European Commission Fit-For-55 Impact Assessment⁵. These adjustments are discussed in more detail in Section 2.2.3. The decision to include the Green Deal reflects the recent response to the difficulties in the global energy market and disruptions caused by Russia's invasion of Ukraine. This has led the EU to accelerate the plans for the green energy transition and thus decrease the region's energy dependence on fossil fuels and unreliable supply sources.

The short-term GDP projections from Ameco's 2023 Autumn Economic forecast include assumptions on monetary tightening on phasing out of fiscal support. The EU-27 GDP is projected to grow by 0.6% in 2023 and to accelerate in the following to years, growing by 1.7% in 2025(see Figure 2.3).

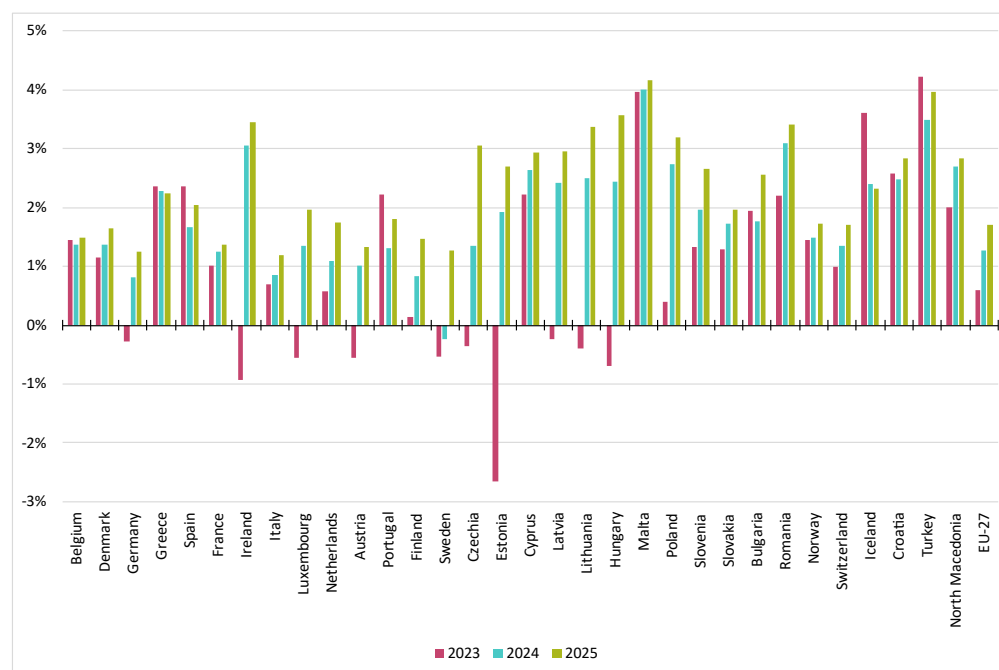
(²) Autumn 2023 Economic Forecast: A modest recovery ahead after a challenging year - European Commission (europa.eu).

(³) 2024 Ageing Report. Underlying Assumptions and Projection Methodologies - European Commission (europa.eu).

(⁴) https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en

(⁵) EU economy and society to meet climate ambitions (europa.eu).

Figure 2.3 Ameco's 2023 Autumn Economic Projections



Source(s): Ameco 2022 Spring Economic Forecast

The long-term GDP projections from the 2024 Ageing report mainly reflect assumptions about future labour working hours and labour productivity, as well as budgetary issues arising from changes in population structure (e.g. pension payments). The labour market assumptions (working hours as a measure of how much people work and; labour productivity how well people work) are used in the 2024 Ageing report to estimate labour's contribution to GDP growth, compared to capital.

1.2.3. Assumptions underpinning the European Green Deal

This section details the assumptions used in integrating part of the European Commission Green Deal policies into the Cedefop Skills Forecast. The European Green Deal (EGD) covers a significant portfolio of policy areas, such as agriculture, energy and climate, environment and research and innovation, to name a few. As there is limited quantifiable information to implement changes in all these policy areas and the E3ME model captures some of these policy areas more explicitly than others, only some of the EGD measures will be explicitly integrated in the Cedefop Skills Forecast. For example, the Green Deal envisages changes to the Common Agricultural Policy with policies looking at organic farming, animal welfare, and biodiversity, and these types of policies are beyond the scope of the E3ME model. It also looks at Horizon Europe, which can cover a broad range of

research and thus very difficult to make assumptions on and capture their economic impact in the E3ME model.

What will be explicitly integrated in the Cedefop Skills Forecast are the Fit-For-55 trends, for which detailed information exists in the “Commission Staff Working Document Impact Assessment Accompanying the Document Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: Stepping up Europe’s 2030 climate ambition. Investing in a climate-neutral future for the benefit of our people”⁶ (hereafter Impact Assessment). The Fit-For-55 trends cover developments in electricity supply, energy efficiency and other sectors (e.g. transport). Generally, the trends show an increased use of renewables, increased electrification and higher energy efficiency. In terms of sectoral implications, these trends would translate into lower activity in some energy-related sectors and increased economic activity in sectors manufacturing renewable and energy-efficient equipment. Explicit assumptions on circular economy (e.g. recycling rates) have also been included in the Cedefop Skills Forecast (see European Green Deal skills forecast scenario⁷).

These assumptions and methodology are specific to the E3ME model. The E3ME modelling framework which was used in the 2020 Cedefop Skills Forecast reflects the “at least 40% cuts in greenhouse gas emissions (from 1990 levels)”, i.e. the previous ambition from the 2030 climate and energy framework⁸ before the EGD was announced (hereafter called the baseline). The assumptions discussed in this section specifically outline the move from 40% to 55% emission reduction by 2030 in the EU MS. The 2020 E3ME baseline discussed above is consistent with the baseline used in the Impact Assessment to assess the impacts of the transition from a 40% cut in greenhouse gas emissions to a 55% cut.

1.2.3.1. *Available information*

In terms of energy trends, we have detailed, publicly available, information on energy balances for both the 40% and 55% emission reduction pathways. The 40% emissions reduction pathway is referred to as the EU Reference Scenario

⁶ https://eur-lex.europa.eu/resource.html?uri=cellar:749e04bb-f8c5-11ea-991b-01aa75ed71a1.0001.02/DOC_2&format=PDF

⁷ <https://www.cedefop.europa.eu/en/publications/4206>

⁸ https://climate.ec.europa.eu/eu-action/climate-strategies-targets/2030-climate-energy-framework_en

2020⁹. The EU Reference Scenario 2020 includes EU level policies adopted by mid-December 2019 with respect to energy, transport and climate change. These include the “Clean Energy for All Europeans” package, the revised EU Emissions Trading System (EU ETS) Directive, transport policies such as the CO₂ standards for vehicles, the Directive on alternative fuels infrastructure, the Clean Vehicles Directive, for example. The Reference Scenario 2020 also includes national MS policies that were adopted as part of the National Energy and Climate Plans (NECPs). These plans include coal phase-out and nuclear-related policies (EU Reference Scenario 2020¹⁰).

Together with the EU Reference Scenario 2020, information on three policy scenarios is publicly available. The level of detail for the energy trends of the three policy scenarios is the same as the EU Reference Scenario 2020. The three policy scenarios build on the EU Reference Scenario 2020 to look at the impact of the European Green Deal policy package. These policy scenarios are:

1. MIX – the policy scenario relies on both ETS (carbon price signal) extension to road transport and buildings and strong intensification of energy and transport policies to achieve emission reduction targets.
2. REG – the policy scenario relies on very strong intensification of energy and transport policies/regulations in the absence of carbon pricing in road transport and buildings to achieve the emission target.
3. MIX-CP – the policy scenario represents a more carbon price-driven policy mix which includes a limited revision of the Energy Efficiency Directive and Renewables Directive, with more focus on the carbon price signals.

It is important to note that all policy scenarios have the same emission reduction target of 55% relative to 1990 levels. For this forecasting exercise, the MIX policy scenario was chosen among the three scenarios mentioned above since it provides a more balanced view of both regulation and carbon pricing.

Another relevant piece of information that will be used in this forecast is the Climate Target Plan Impact Assessment¹¹. This document includes information on the GDP and wider competitiveness impacts of implementing the policy scenarios starting from the EU Reference Scenario 2020 presented above. In particular,

⁹ https://energy.ec.europa.eu/data-and-analysis/energy-modelling/eu-reference-scenario-2020_en

¹⁰ <https://op.europa.eu/en/publication-detail/-/publication/96c2ca82-e85e-11eb-93a8-01aa75ed71a1/language-en/format-PDF/source-219903975>

¹¹ <https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52020SC0176&from=EN>

information on sectoral impacts, such as changes to output, changes to investment and consumer expenditure have been taken into account based on information from the Impact Assessment. The exact treatment of inputs is described in Table 2.1.

In summary, the following information from the MIX policy scenario is included in the Cedefop Skills Forecast:

- (a) Energy balances by sector, energy carrier and Member State
- (b) Power generation mix by technology by Member State
- (c) Emission results by Member State
- (d) Carbon pricing levels and coverage
- (e) Additional EU investment requirements (e.g. power plants, energy efficiency)
- (f) GDP impacts. Changes to consumer expenditure, investment and trade.

The energy balances, power generation, and emission results are available every 5-years to 2030. The economic information is mostly available for 2030.

1.2.3.2. *Modelling assumptions and implementation*

The implementation of the EGD assumptions is based on the information described above and is implemented with respect to the Reference Scenario baseline to maintain consistency with the Impact Assessment. Table 2.1 outlines how the information available and summarised in Section 2.2.3.1 translates to E3ME modelling inputs.

Table 2.1 Assumptions used in the E3ME model

Information taken from the EC Reference Scenario	What the information provides?	Where it will impact in the model?
--	--------------------------------	------------------------------------

Final energy demand	Use of different fuel (e.g. coal, gas) which will influence production of these fuels and/or imports. Changes to energy supply sectors.	Changes of energy trends. Changes in production and/or imports of fuel. Changes to economic production of energy supply sectors. Example 1: Coal is imported by most MSs. The decrease in coal use will also lead to a decrease in coal imports. Example 2: Increase in energy efficiency may lead to a decrease in gas use and thus decrease the gas imports and decreased activity in the gas supply sector.
Power sector technology changes	Changes in the power generation profile (e.g. solar, wind) lead to changes in investment made by the power generation sector.	Changes in investment made by the power generation sector, and subsequent changes its supply chain (e.g. different goods are needed to build a gas power plant compared to a wind farm). Some economic sectors (e.g. mechanical engineering, electronics) will benefit more from the transition.
Carbon pricing	Increase in fuel cost based on fuel use and carbon pricing	This affects the prices of different fuels, and therefore the costs of the sectors using these fuels. It impacts general price levels, based on fuel consumption levels.

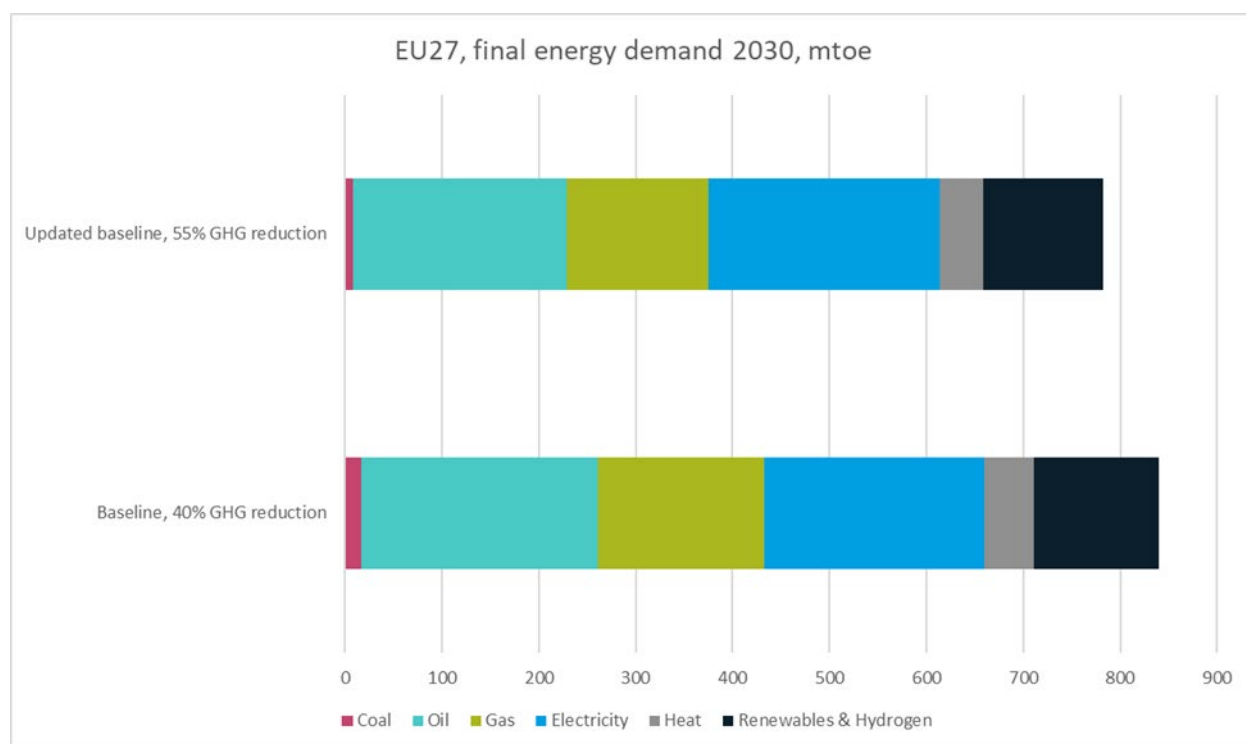
Additional investment requirement	Investment needed for energy efficiency (e.g. retrofitting), power grids, new fuel supply and storage (e.g. electricity storage or hydrogen).	Investment or expenditure needed by households to improve efficiency. (e.g. service sectors to improve office energy efficiency, new boilers). The increased investment activity is expected to lead to increased demand for investment goods.
GDP and components	How much GDP and components change compared to the baseline.	Not directly entered in the model. Used for comparison and fine-tuning after all of the above components have been added.

Changes in final energy demand compared to the baseline provide the energy use by sector and fuel type, and give us enough of information in terms of changes to economic production and imports of fuels, as well as the changes in purchases by different economic sectors of these fuel). What this means is that, based on the changes in fuel demand, the economic module in E3ME determines the new level of fuel needed to be extracted and/or imported. This leads to changes in domestic extraction which will lead to changes in employment in that sector. If there are changes in the supply, for example households and businesses demand less gas, then economic activity in the gas supply sectors is expected to decrease and as a result employment. The economic module also captures changes in intermediate demand, i.e. if a sector demands less gas and more electricity, then this is reflected in the purchases of intermediate goods of the respective sector.

The type of changes in final energy demand also have direct and indirect impacts on other sectors in the economy. For example, increased energy efficiency would lead to increased economic activity in construction and the sectors that provide services and materials to construction. A switch to electric vehicles, which are generally more fuel efficient than conventional vehicles, would impact retail activities (because petrol stations are accounted for under retail).

Figure 2.4 summarises the changes to the 2025 Cedefop Skills Forecast trends for final energy demand, which are: around 7% reduction in EU27 final energy demand, mainly from reduction in use of coal oil and gas and; a relatively large increase in electricity use.

Figure 2.4 EU27 final energy demand in 2030, million tonnes of oil-equivalent (mtoe)

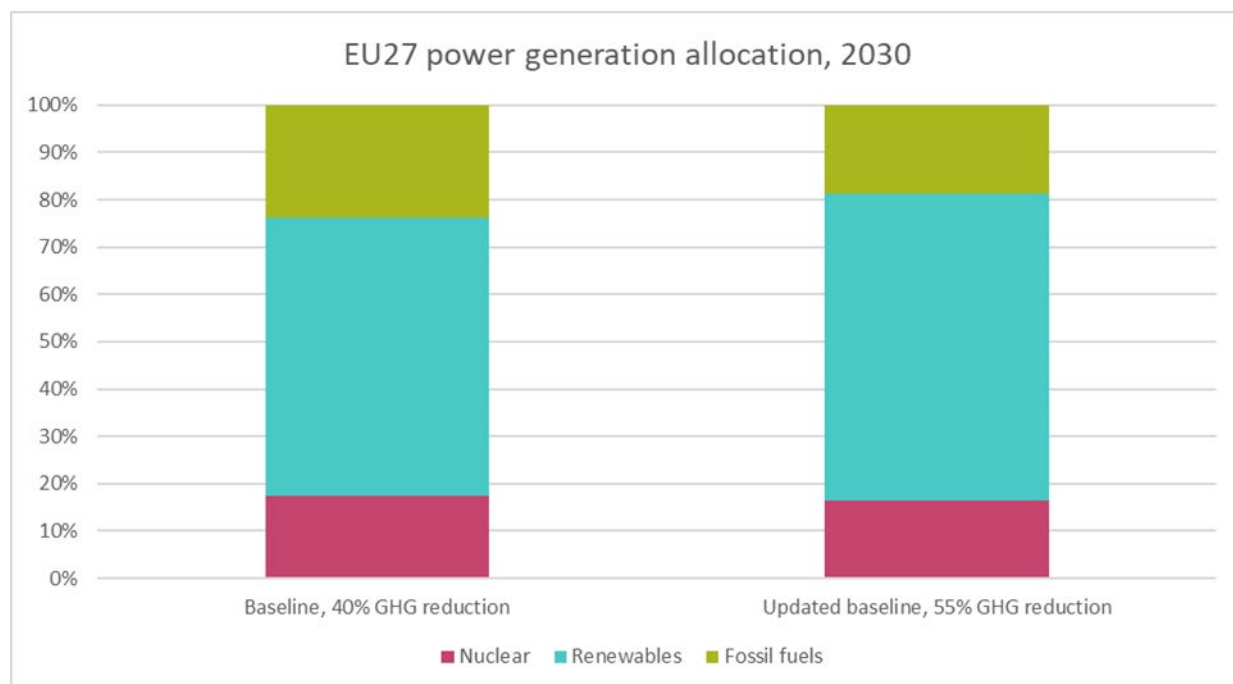


Sources: Impact Assessment

Power sector transition information is used to estimate the investment needed. For example, we have information on how much solar technology will be deployed, so we can use this information to calculate how much it will cost to build solar plants and how much it will cost to maintain them by using capital, and operation and maintenance unit costs already available in E3ME. Furthermore, different power sector technologies have different goods purchasing requirements. The building of a solar power plant will require goods from different sectors (e.g. mechanical engineering, electronics) than a gas plant and we can estimate these shifts in sectoral demand based on information available in E3ME (i.e. information on goods purchases required by different types of plants).

Figure 2.5 summarises the changes to the updated green assumptions; by 2030 an increase in renewable generation shares of about 6pp would be implemented. The increased renewable generation means that, compared to the 40% GHG reduction baseline, an increase in economic activity is expected in the sectors that manufacture renewable technologies (e.g. solar), such as electronics and electrical engineering, machinery and equipment, as well as sector that install them, such as construction and service sectors in their supply chain, for example, architecture.

Figure 2.5 EU27 power generation allocation, 2030

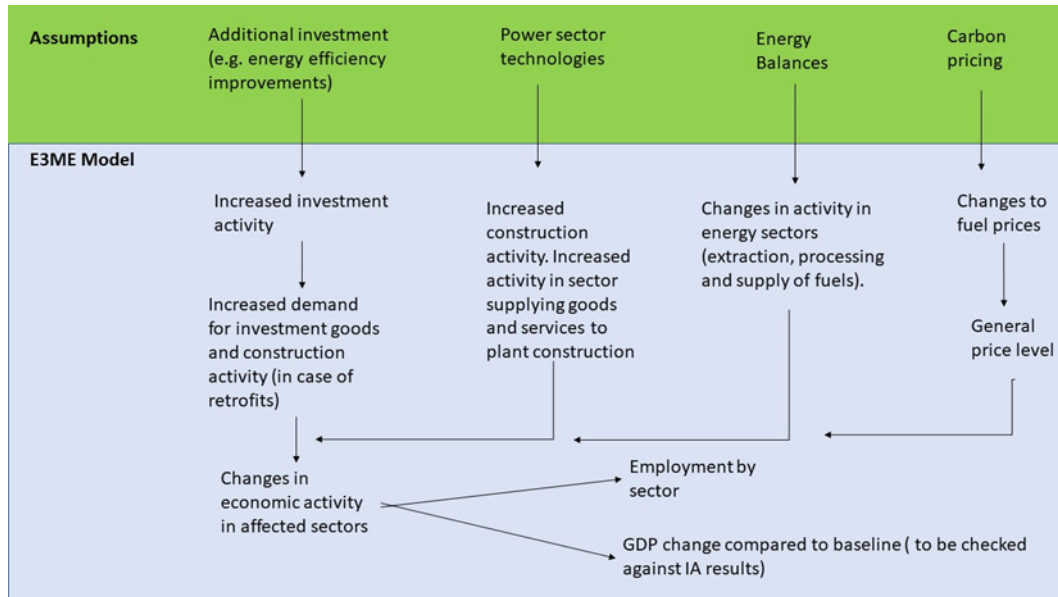


Sources: Impact Assessment

The exogeneous carbon pricing information taken from the Impact Assessment assumptions for the MIX policy scenario is used by the E3ME model to determine energy prices. The energy price level and energy use then feed through to the general price level.

The additional investment requirements mainly capture any energy efficiency investments and other infrastructure improvements needed to support the transition. The type of investment is determined by the sector making it (e.g. energy efficiency investment is mainly one by households and offices to improve building performance). The investment activity leads to increased demand for goods and services elsewhere in the economy, as shown in Figure 2.6 below.

Figure 2.6 Main greening assumptions and how they are reflected in E3ME



1.2.3.3. *Assumptions on automation/digitalisation*

For the purpose of this update, we are assuming the continuation of existing trends in automation and digitalisation, with increased capacity in advanced digital skills and technologies as well as increased automation. This approach is consistent with the one in the Impact Assessment of the Fit-for-55 policies. Furthermore, the assumptions used for the Impact Assessment are actually consistent with those outlined in Section 2.2.2 above (e.g. European Commission’s 2024 Ageing Report, the Autumn release of Ameco for the short-term GDP etc)¹².

1.2.3.4. *Impact on employment forecast*

The impact on sectoral employment in the forecast are directly linked to changes in sector activity and composition resulting from the implementation of the above assumptions. For example, changes to the use of gas by the economy have resulted in changes in economic activity in the gas extraction and gas supply sectors leading to a decrease in employment in these sectors. Another example is increased renewables uptake in power generation, which has resulted in increased activity in the sectors which supply components for the renewable power plants as

¹² <https://op.europa.eu/en/publication-detail/-/publication/96c2ca82-e85e-11eb-93a8-01aa75ed71a1/language-en/format-PDF/source-219903975>

well as construction. Increased activity in these sectors has resulted in increased demand for labour.

1.2.3.5. *Conclusions*

The integration of sectoral changes resulting from the European Green Deal implementation compared to the EU Reference Scenario 2020 baseline based on available information. The one shortcoming is that we could not capture the impacts of financing the transition (some financing options might lead to better employment outcomes, while others to worse).

1.3. Expansion demands for occupations and qualifications (EDMOD and QUALMOD)

General considerations

Previously detailed data on occupational employment structures as well as information on qualification patterns has been available from the EU-LFS. This enabled the development of models to explain and project expansion demands by occupation (EDMOD) and similar models for qualifications (QUALMOD). These models focus on the patterns of employment within sectors, which have been extrapolated forward to develop the projections.

Since 2015, concerns about confidentiality have led to significant restrictions on the level of detail that has been made available to researchers from the EU-LFS¹³. The much more limited information available since then severely restricts what is possible in terms of model development for EDMOD and QUALMOD. The existing methodology (see [Methodological Report](#)) is based on exploring the occupational and qualification structures of employment *within sectors* in considerable detail. This is no longer possible given the restrictions imposed.

Information on the latest ISCO and ISCED classifications is therefore much more limited than was available when the original versions of EDMOD and QUALMOD were developed. We have information on the latest ISCO for just a few years, and with much less detail on patterns within industries than was previously made available.

The existing methodological framework is described in detail in the [Methodological Report](#). The general approach is based on the idea that occupational and qualification demands are driven by changes in the industrial employment structure. Technological change, demography, as well as other factors, help to determine the overall patterns of employment by industry/sector.

¹³ See details on the data used in Section 33.

This, in turn, drives the demand for different occupations and qualifications, which are often industry specific.

Technological changes, as well as digitalisation, for example, also influence the patterns of employment *within* sectors. Technological developments result in shifting demands for occupations as employers find new ways of doing things (for example the impact of information technology on the demand for secretaries and clerical workers). These patterns are also affected by factors such as changing relative wage levels in different occupational and qualification groups (as employers substitute more expensive inputs for cheaper ones).

In an ideal world, it would be possible to model these influences econometrically. In practice, there is limited information on wages and technological indicators available to develop such models. The existing EDMOD and QUALMOD modules therefore rely upon a simple analysis and extrapolation of trends in such patterns over a relatively short timescale. The data no longer enable us to analyse and update trends within sectors. Our approach to dealing with this is to use the data which have been made available to adjust our previous projections to take account of what information is available on recent trends. This will inevitably reflect recent events such as the Covid-19 pandemic and current responses. However, recent developments in communications with Eurostat may enable the team to access more detailed data and, subject to data checks, include more information in the projections. The following sections outline this in more detail.

EDMOD

EDMOD deals with expansion demands (net projected employment levels) by occupation at the 2-digit level of ISCO. QUALMOD is the corresponding module that deals with expansion demands for the three broad educational levels.

In the existing models econometric and other techniques were used to identify trends in such patterns within industries and extrapolate them forward. The sectoral employment projections from the E3ME model then drive the projections of occupational employment and employment by qualification level.

As explained above, we have therefore adopted a pragmatic approach, which relies on the previously available detailed data by industry, being combined with more aggregate information now available.

For each country the latest EU-LFS information across all sectors is compared with the previous historical estimates. Adjustments are then made to the historical information on occupational and qualification employment shares to bring them into line with the EU-LFS estimates.

Figure 2.7 illustrates the process, with an example for Associate Professionals in Czechia. The figure has three panels. It shows employment shares for the selected occupations, aggregated across all industries. The left-hand panel presents the results based on the latest E3ME projections and extrapolating the previous trends within sectors without any additional adjustments to the projections. The historical data have been constrained to match the observed EU-LFS estimates.

The second panel shows the results of adjusting the overall occupational trends for 2020-35 based on the observed patterns in the EU-LFS until 2022. The final panel shows the most recent “raw” EU-LFS data, together with a linear trend line fitted to the data points. In this case, the projections have been adjusted quite significantly (compare Panel 1 and 2). In other cases, the EU-LFS trend line extrapolated to 2035 did not look plausible, so more modest adjustments have been imposed.

Figure 2.7 Comparisons with EU-LFS estimates

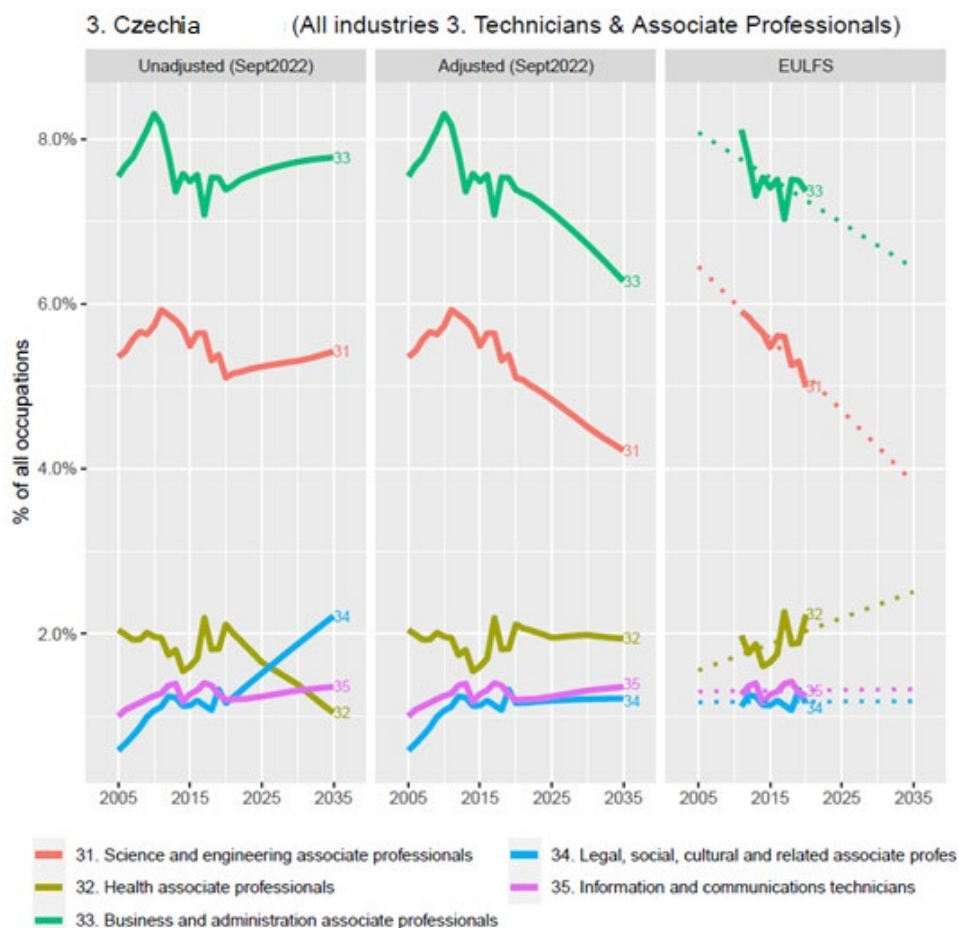
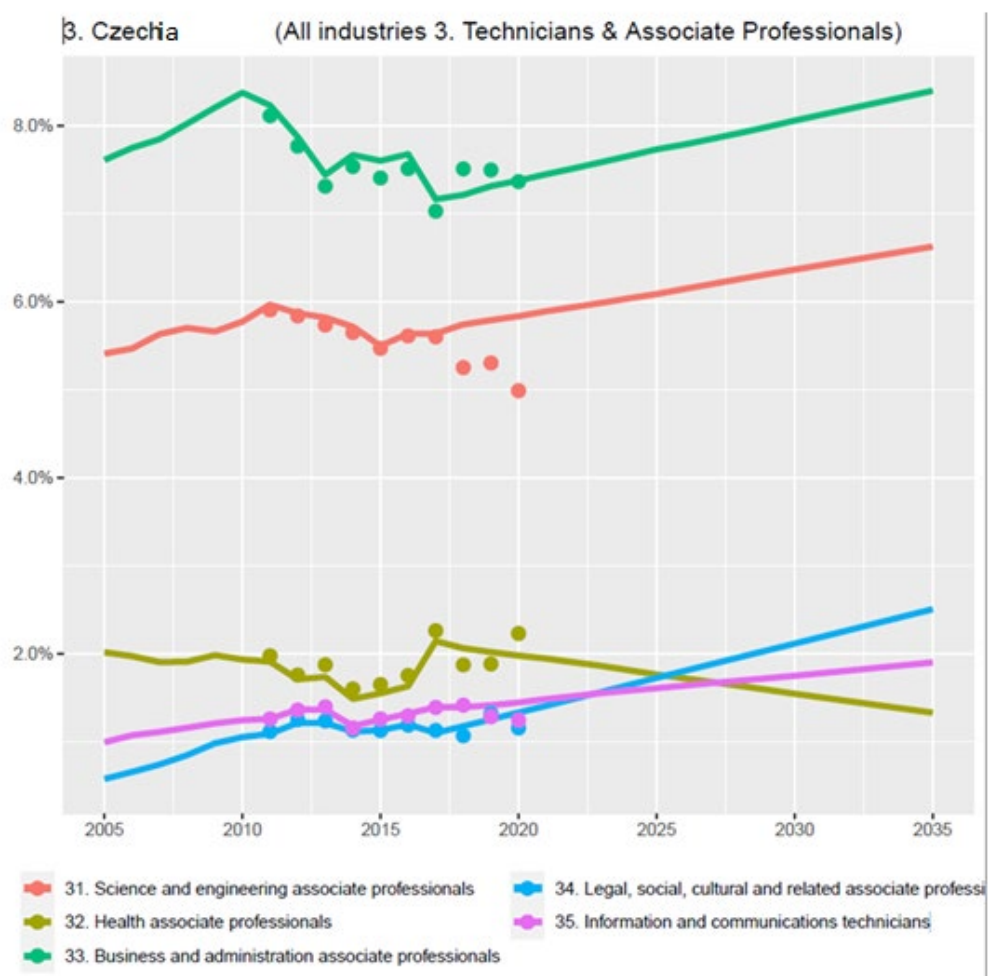


Figure 2.7 focuses on the results from the EU-LFS data. These have been applied on top of the left-hand panel. The dots are the estimates from the EU-LFS across all industries. Note that because the sectoral structure of employment in the EU-LFS does not match the National Accounts based employment used in E3ME model, we do not expect a perfect match. The solid lines show the unadjusted projections, again summed over all sectors.

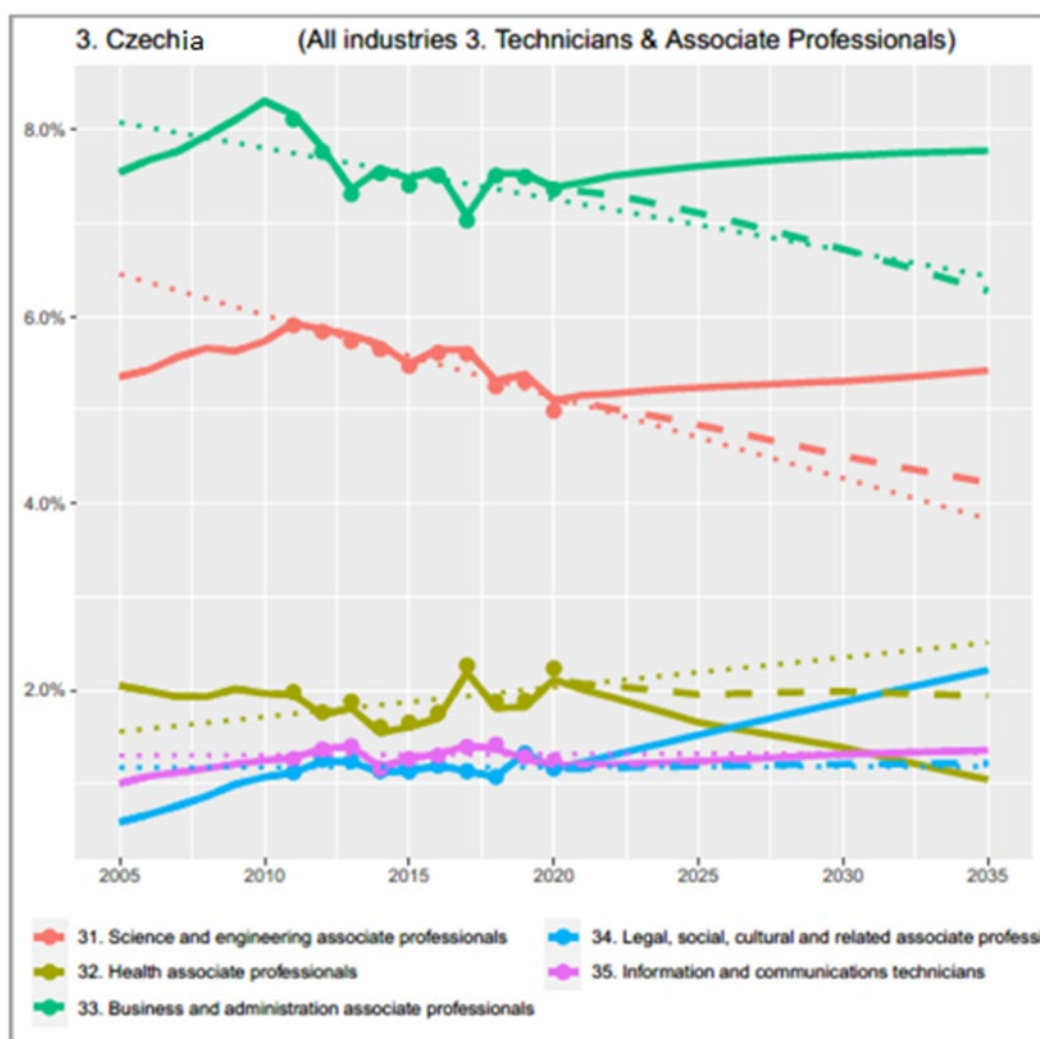
In this example, the database appears to be broadly consistent with the latest EU-LFS data. However, the projected trends appear to be out of line with the most recent historical trends.

Figure 2.8 Comparisons with EU-LFS estimates



We have therefore reassessed the projected occupational shares and, where the data suggest it is appropriate, adjusted these for 2035 to be in line with the latest EU-LFS trends. The values of the adjustments for earlier years are linearly interpolated back to zero in the last historical year (2021). The adjusted (solid line) and unadjusted (dashed line) projections are shown in Figure 2.8.

Figure 2.9 Adjustments to occupational employment shares for 2035



A revised projection of the shares to 2035 is made, based on the linear trend extrapolation of the historical EU-LFS estimates and professional judgment. This is shown as the dashed lines in

Figure 2.9. The values of the adjustments for earlier years are linearly interpolated back to zero in the last historical year (2020). Extrapolated trend shares are constrained to lie between 0 and 100%. The sum of shares across all occupations is constrained to be 100%.

In order to ensure that the data remain consistent with the other information in the E3ME database a RAS process is employed.¹⁴

¹⁴ RAS is a widely used iterative technique, which ensures that elements in a two-dimensional data array match target row and column totals. In our case, multi-dimensional arrays are used, but the principles are the same

Where specific adjustments for occupational shares have been provided by country experts these have been integrated into the forecast.

QUALMOD

Figure 2.9 focuses upon occupations. We are also interested in the qualification or educational levels that employers are looking for. Given the limitations of the EU-LFS we are only able to provide a broad breakdown into three levels. The highest is broadly equivalent to a university degree, while the lowest refers to those with the bare minimum of formal qualification or none at all. This is dealt with in the QUALMOD module. This is described in detail in the [Methodological Report](#). As with occupations, this focuses upon the patterns of employment within sectors/industries and occupations.

The more limited information now available from the LFS means that the EDMOD module cannot be updated as previously. A similar process is therefore adopted for qualifications/educational levels, which ensures the results from QUALMOD match up with the latest EU-LFS historical data and trends. The results by qualification/ educational level are then constrained to match the available supply as indicated by QMOD (as discussed in Section 3.5 below).

Impact of Covid-19

The most recent data from the EU-LFS are for 2022. This may not reflect the full long-term impact of the Covid-19 pandemic.

The sectoral employment data from E3ME model include the most up-to-date information on the general impact of Covid-19 on the labour market. The effects of the pandemic and the various lock-down measures introduced to deal with it on sectors such as hospitality are therefore taken into account. This includes the knock-on effect on occupations employed in such sectors. This includes information on both the immediate impact of the pandemic in 2020 and the eventual recovery as the economy and labour market returned to something like normality in 2021 and 2022.

However, with EU-LFS data only available for 2022, the long-term impact on occupational employment patterns cannot be clearly identified. The results therefore show the sectoral impact of the pandemic but without any special adjustment to take account of the pandemic on occupational employment patterns within industries.

1.4. Replacement demand (RDMOD)

Replacement demand focuses on what might be called “permanent or semi-permanent” withdrawals from the employed workforce. These include retirement, family formation or other reasons for leaving the workforce, and emigration. Previous replacement demand forecast using the RDMOD have used constant flow rates based on available EU-LFS data over 2010-14 as more recent data are not available anymore in the EU-LFS. However, since the period 2010-14, worker flows have changed due to (1) technological changes, (2) increasing job mobility and (3) pension reforms and increasing job mobility. Therefore, historical flow rates might not reflect the current state in the labour market. For this reason, we have conducted background research into ways to improve the replacement demand estimates for the current forecast.

1.4.1. Adjustments to the RDMOD

To adjust the RDMOD for reforms in pension age, we qualitatively adjust the final outflow which lies at 65 year-old to the effective retirement ages of individual countries. Based on the underlying datasets of the European Commission 2021 Ageing report (European Commission, 2024), we construct a more accurate age at which the final cohort of workers will all flow out of the labour market and need to be replaced.

For the adjustment to the outflow rates of the RDMOD due to technological changes and job mobility, we changed the method in which we quantitatively estimated whether the 2010-14 flow rates reflect current automation trends or not. If this is not the case, automation can be explicitly modelled within the RDMOD to correct for this. This background study for the RDMOD adjustment is based on the work of Hess and Montizaan (2022) for the Netherlands. They show that the estimation errors of replacement demand can be decreased when implementing an automation correction on the estimates of occupations measured at a very detailed level of granularity (114 occupations). We tested whether the mean absolute errors in the RDMOD for the Netherlands can be decreased using an automation correction. We compared estimates of the RDMOD using the 2010-14 flow rates, to estimates with the automation correction from Hess and Montizaan (2022) and compared them to the true values of the replacement demand as these are also known for the Netherlands over the period 2015-2021.

The change in methodology assumes that adjusting the Dutch outflow rates for automation does not improve the estimates of the replacement demand compared to the RDMOD with 2010-2014 flow rates. This is because at the aggregation level at which the replacement demand is estimated, the

improvements in the error terms do not hold. For some occupations, the error decreased, for others it increased without a qualitative pattern showing which occupations can be improved and which cannot be improved. Our conclusion therefore is that we cannot adjust the RDMOD for automation in a quantitatively estimated model. As we do observe that automation impacts the replacement demand and might increase estimation biases for specific occupations, we believe that the role of the Country Experts in assessing the RDMOD-results becomes more important with the decreasing quality of the available quantitative data from the EU-LFS. Any indication of policies affecting participation rates (e.g. retirement rates, increased engagement in education) has been taken into account both in the labour supply projections as well as in the replacement demand estimates. Limited feedback has been provided by ICEs on replacement demand, so no other adjustments have been implemented apart from those summarised above.

But why is it important to consider automation when forecasting replacement demand? First, automation has been shown to severely impact the labour market in general (e.g., (Acemoglu and Autor, 2010), Cedefop, 2021, among many others), and labour demand in particular (e.g., (Dixon, Hong and Wu, 2021)). Second, replacement demand estimates how many workers are replaced by other workers in an occupation. By reducing the number of workers to be replaced in an occupation, automation can have detrimental effects on the forecast accuracy. Thus, automation can potentially be the source of substantial forecast error.

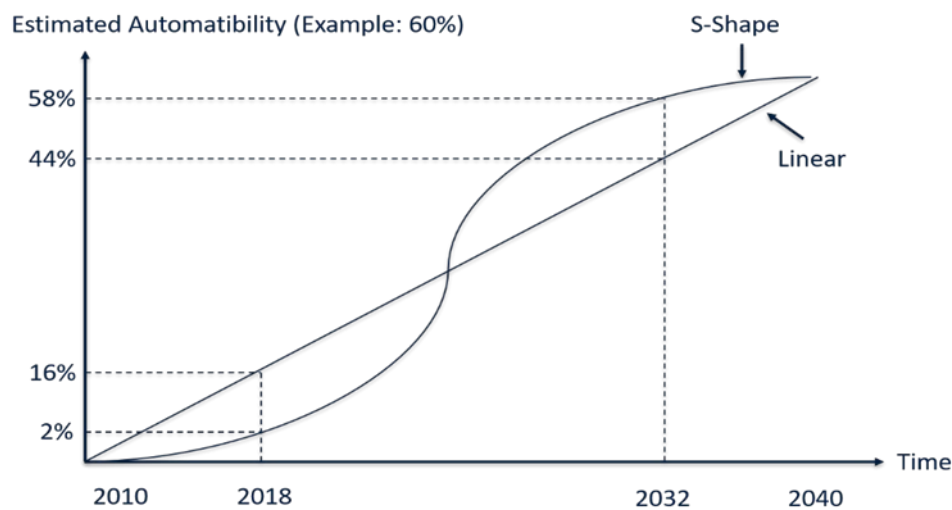
While the concern of forecast error must not be neglected, replacement demand already incorporates occupation-specific trends in several dimensions closely related to automation. Therefore, explicitly accounting for automation in the replacement demand does not necessarily improve its performance. However, if outdated flow rates do not account for the current pace or level of automation, we likely overestimate the replacement demand which in turn deteriorates the quality of the occupation-specific forecasts. Therefore, we want to know whether the replacement demand already sufficiently accounts for automation of job tasks in the labour market, or whether we need to re-adjust the replacement demand to better account for such automation. As research by Cedefop (2021) shows, automation reduces the replacement demand in European countries for professions that are easily automatable. This mostly holds for low qualified jobs.

Hess and Montizaan (2022) test for the Netherlands whether the predictive power of the labour market forecast model can be improved by testing automation-induced reductions in replacement demand. As the effects for individual industries and technologies are probably not uniform they perform the evaluation agnostically without expectations by using two functional forms of how automation affects labour demand to vary the impact in current years (see also Heald et al. for similar

assumptions with respect to the Cedefop Skills Forecasts).¹⁵ First, a linear development is assumed that produces a gradual introduction of automation technologies by using the estimated automatability index of occupations from Nedelkoska & Quintini (2018) and assuming that this automatability will be reached in 2040 with a starting point in 2010. Every year an increasing share of out rotating workers will be replaced by technologies. Figure 3.5 shows the idea of this type of implementation. Assuming an estimated automatability of 60%, each year an additional 2% of replacement demand will be deducted, so that we would observe a 60% decrease in replacement demand after 30 years due to automation.

Second, an s-shaped development is assumed (logistic function), starting with a low impact of technology in the first years, accelerating in the medium term and decelerating at the end again. The idea is to account for the often mentioned accelerating technological change (see, (Hershbein and Kahn, 2018)). The s-shaped function reduces replacement demand less than the linear function we implement.

Figure 2.10 Implementation of automation



Source: ROA (2022)

Following Bakens et al. (2021), Hess and Montizaan (2022) first examine bivariate correlations between different empirical measures that can resemble replacement demand, and automation (as measured by Nedelkoska and Quintini (2018) for OECD-countries). Then they perform a multivariate regression analysis

(¹⁵) Heald, S., Smith, A., & Fouarge, D. (2020). Labour market forecasting scenarios for automation risks: Approach and outcomes. ROA. ROA External Reports.

to understand which of the different variants of replacement demand can be best predicted by the model in step 1. Finally, the predictive power of the model for the different variants of replacement demand is evaluated by comparing the calculated replacement demand and the replacement demand predicted by the model. The results show that, adjusting for automation linearly over a 30-year period, the Mean Squared Error (MSE) is way below the MSE for the model without adjustment, or the MSE for the model with non-linear adjustment. As other correlations and measures of goodness of fit do not change much, the error produced by outliers can be reduced in the replacement demand of the Dutch labour market forecasts.

We used the linear automation multivariate regression analysis to predict replacement demand for the Netherlands within the RDMOD- framework, and the base RDMOD forecast, and compare them to the observed replacement demand for the Netherlands until 2018. Accounting for technology worsens the results of the RDMOD as the MSE does not decrease. This is because for some occupations the bias decreases and for others it increases. We correlated the estimated bias for occupations with different labour market variables such as share of temporary contracts or the development of the wages, but there is no strong predictor of whether occupations belong in the group of occupations for which the bias increases or decreases. Therefore, our conclusion is that there is no quantitative way to incorporate automation in the RDMOD that will improve the estimates. Expert knowledge on how automation impacts replacement demand in specific occupations in specific countries is a better way to deal with this issue. While some ICEs commented on how automation may play an important role in future developments in their country, no detailed information on trends was given with respect to replacement demand. As such, no further adjustments were made.

1.5. **Modelling qualification supply (QMOD)**

Unlike EDMOD and QUALMOD, the data now available from the EULFS were adequate to update the existing approach to modelling qualification supply in 2022/23. However, due to limited resources, these models were not updated in the latest round.

. As for the demand side we adopted a pragmatic approach of adjusting the detailed results to ensure that as far as possible they are consistent with the latest EU-LFS aggregate data.

In 2022/23 the QMOD stock-flow model was updated.¹⁶ This model is used for projecting the three levels of qualifications (low, medium and high) for the 32 countries for which data were available. Given the constraints imposed by the characteristics of the data, including the very small sample sizes for some countries, the model works well, although it is pushed close to its limits in making projections through as far as 2035.

The initial activity was to update the EU-LFS data within the stock-flow model, insofar as was necessary, bringing past data into line with the most up-to-date series. The projections are heavily dependent on the latest information and, in particular, the changes to qualifications amongst the younger age groups. Within the context of a stock-flow model, the outcomes for older individuals are more heavily dependent on earlier flows. Given that formal qualifications are largely determined before age 30, the earlier years of data do not play such an important role, but still determine the qualification levels of older individuals.

The work followed the normal course, in the first instance, that of establishing a satisfactory working model for one or two countries. Based upon this work, the Czechia was used to develop a template of the stock-flow model which was subsequently used for all the countries. Applying the model to the Czechia case first, allowed comparisons to be made with earlier work carried out for Cedefop. Most, although not all of the issues with the modelling were identified at this stage, prior to rolling out the model to other countries.

The model was estimated for the whole population and for the economically active population of the Czechia. Comparisons were then made between the two estimates and the associated activity rates were calculated. As with all elements of the estimation process, checks were made for accuracy and that the resulting outcomes were plausible.

Once the results were rolled-out, they were checked on a country-by-country basis to ensure that there were no previously unforeseen problems with the data or the modelling. The tests applied are mainly for internal consistency of the estimates, such as non-negative proportions and values, activity rates outside of the range zero to unity, that for most age groups activity rates are generally higher for more qualified than less qualified individuals, etc.

A number of issues in the latest data were investigated including: the small sample sizes in the EULFS for a number of the countries (and the associated very small cell sizes) and the treatment of the oldest individuals, when data are only available for an open ended, 65 and over age group. The first of these problems did not materialise in terms of the internal checks applied to the results. The latter

¹⁶ For details on the Stock-flow model see the [Methodological Report](#).

issue was limited to a small number of countries and was dealt with by the adoption of a slightly different treatment of the over-65 group for all countries. A.

Using this version of the model, the detailed results were then adjusted in aggregate based on the latest EU-LFS data to be consistent to EU country-level population projections.

CHAPTER 2. Data update and preparation

2.1. Introduction

This chapter presents the work on data update and preparation required in the modelling framework so as to produce the 2025 Cedefop Skills forecast. The chapter is structured as follows. The first section describes the update of the E3ME model. The second sections describe the data preparation for Modules 2-5 of the Cedefop Skills Forecast framework (as shown in Figure 1.1).

2.2. E3ME update

The historical and forecast database of the Cambridge Econometrics' E3ME model¹⁷ underpinning the sectoral employment and labour force projections was updated with the latest data available in November 2023. Table 3.1 shows in detail the model variables updated.

Information on short-term trends is used to assess current developments and incorporate the most recent developments into the forecast macroeconomic trends. We make the employment projections consistent with other forecasting exercises produced by the EC. For the short term (until 2025), we refer to the Autumn Economic Forecast (AMECO)¹⁸ of DG ECFIN. We applied the growth rates from the AMECO forecast to total employment and compensation of employees in each MSs. The AMECO employment forecast is used to inform short-term growth of employment projections, while information on the compensation of employees gives us more information on the average wage profile at the start of the projection period. These data are used to supplement the more detailed historical sectoral data and reflect recent developments as well as expectations. AMECO unemployment rate and real GDP were used to update both the short-term projections and historical values for these two variables. We also apply the AMECO projected growth rates of GDP components (i.e. consumption, investment and trade) to make them consistent with GDP growth. After 2025, we applied the annual percentage growth rates implied by the long-term GDP projections shown in DG ECFIN Ageing Report 2024 (which provides yearly projected GDP growth rates until 2070).

¹⁷ See <https://www.e3me.com/> for further details on this model.

¹⁸ https://ec.europa.eu/commission/presscorner/detail/en/ip_23_5743

Table 3.1 Description of updated variables

Variable	Source and variable code	Breakdown	Original source update date	Why we need it
Employment (000s persons)	Eurostat, National accounts (nama_10_a64_e)	Sector (2-digit NACE)	30/11/2023	Main variable projected in the forecasting exercise
Output (million EUR)	Eurostat, National accounts (nama_10_a64)	Sector (2-digit NACE)	30/11/2023	Measure of economic activity by sector
Employees (000s)	Eurostat, National accounts (nama_10_a64_e)	Sector (2-digit NACE)	30/11/2023	Used to calculate average wages
Compensation of employees (million EUR)	Eurostat, National accounts (nama_10_a64)	Sector (2-digit NACE)	30/11/2023	Used to calculate average wages
Consumption (million EUR)	Eurostat, National Accounts (nama_10_co3_p3)	Consumption categories (COICOP)	29/11/2023	Impacts economic activity
Investment (million EUR)	Eurostat, National Accounts (nama_10_a64_p5)	Sector (2-digit NACE)	29/11/2023	Impacts economic activity
Exports and imports (million EUR)	Eurostat, National Accounts (nama_10_gdp)	Sector (2-digit NACE)	28/11/2023	Impacts economic activity
Labour participation rates (%)	Eurostat, LFS (lfsa_agan)	Age groups (5-year bands)	27/04/2023	Using participation rates and population, labour force (000s) is calculated.
Population (000s)	Eurostat (demo_pjangroup)	Age groups (5-year bands)	28/09/2023	Used in calculating labour force
Population projections (000s)	Eurostat (proj_19np)	Age groups (5-year bands)	28/06/2023	Used in calculating labour force projections based on the participation rate projections
Employment projections (short-term, ,000s persons)	AMECO (Spring Forecast)	Total	15/11/2023	Short-term projections consistent with GDP projections

Variable	Source and variable code	Breakdown	Original source update date	Why we need it
				Used to inform recent developments.
Compensation of employees projections (short-term, million EUR)	AMECO (Spring Forecast)	Total	15/11/2023	As above
Compensation of employees projections (short-term)	AMECO (Autumn Forecast 2023)	Total	15/11/2023	Used to assess short term trends
Consumption (short-term)	AMECO (Autumn Forecast 2023)	Total	15/11/2023	Used to assess short term trends
Investment (short-term)	AMECO (Autumn Forecast 2023)	Total	15/11/2023	Used to assess short term trends
Unemployment rate (% , historical and short term projections)	AMECO (Spring Forecast)	Total	15/11/2023	As above
Real GDP (million EUR 2010 prices, historical and short-term projections)	AMECO (Spring Forecast)	Total	15/11/2023	Used to assess short term trends
Real GDP (million EUR 2010 prices, long-term projections)	Ageing Report 2024	Total	10/11/2023	Long-term economy trends
Commodity prices (indices)	World Bank commodities price forecast	Commodities	09/2023	Global commodity prices used to inform import prices
ECB inflation	ECB staff macroeconomic projections for the euro area	Total	09/2023	Inform price trends in the long term

Source(s): The Authors

Historical labour force data from the EU-LFS and population data are used to compute historical participation rates by age and gender, which are projected over

the forecast horizon through econometric equations¹⁹. The forecast participation rates are then multiplied with Eurostat population projections to obtain forecast of labour force. Eurostat data for labour force and population were available until 2022 for all MSs, except for a few gaps in the historical data that were interpolated. As shown in Table 3.1, historical data for employment, output, compensation of employees, number of employees and GDP components come from the Eurostat National Accounts database. The variables from the National Accounts are essential to the equations in the E3ME model. Employment by sector is their main variable of interest in the Cedefop Skills forecast. The historical employment data from the National Accounts are used as input in the model to produce the employment forecast by sector through econometric equations²⁰. In E3ME, employment is a function of output, real wage costs, hours worked and, capital and R&D expenditure as proxies for technological development. The equation set up is based on the representation of the theoretical optimisation problem in which firms try to minimise costs for a given level of output (i.e. it allows for the substitution of labour and capital based on cost pressures in the economy). While productivity is not explicitly featured in the equation determining employment, its impact is reflected through wages. Among the determinants of wage rates by sector and wages feed into the employment equation.

The availability of National Accounts historical data varies between Member States (MSs), both in terms of years and sectoral breakdowns. Most MSs have data until 2022, which can be considered the last historical year for the variables based on the National Accounts database. However, several exceptions are highlighted below:

- (a) Some MSs had data in 2022 only for 1-digit NACE sectors (e.g. Germany, Spain);
- (b) Some MSs had data for 2022 for only a subset of 2-digit NACE sectors (e.g. France, Italy);
- (c) Malta, Luxembourg and Switzerland do not have data for many 2-digit sectors due to confidentiality issues, and in the case of Malta there were some gaps in the series;

¹⁹ More information on the econometrics equations can be found in the E3ME Technical Manual (<https://www.e3me.com/wp-content/uploads/sites/3/2019/09/E3ME-Technical-Manual-v6.1-onlineSML.pdf>).

²⁰ More information on the econometrics equations can be found in the E3ME Technical Manual (<https://www.e3me.com/wp-content/uploads/sites/3/2019/09/E3ME-Technical-Manual-v6.1-onlineSML.pdf>).

- (d) Some sectors in certain MSs were not available due to confidentiality, such as R&D in Sweden;
- (e) Eurostat data for the Republic of North Macedonia and Turkey had to be complemented with data from the respective statistical offices to complete the series. Employment for Turkey came from the LFS instead of National Accounts.

In these instances, we used all available information to impute the missing sectors and obtain complete historical data series at the 2-digit NACE level until 2022:

- (a) In the cases where 2-digit NACE data was missing for 2022, we disaggregated 1-digit NACE values in 2022 using the shares of 2-digit NACE in 2021.
- (b) In some cases, it was possible to derive the missing 2-digit NACE sectors as the difference between the parent 1-digit NACE and the other 2-digit NACE.
- (c) In the case of Malta, Luxembourg, and Switzerland, the 2-digit NACE sectors were obtained by sharing updated 1-digit NACE figures with shares obtained either from the Structural Business Statistics (SBS) or OECD STAN database. For Malta, in some cases it was possible to fill individual yearly gaps in the series with shares from the closest available year.
- (d) Data from OECD STAN and SBS were used in other MSs in a few cases.

The mining and energy sectors are shown only at the 1-digit NACE level on Eurostat (sector B and D respectively). Shares derived from the SBS data were used to disaggregate those two sectors into the relative 2-digit NACE sectors. Data for consumption, investment, export and imports were updated as well based on National Accounts data extracted from Eurostat.

In the case of the Republic of North Macedonia, several assumptions were made:

- (a) No employment data were available for 2022 from the National Accounts (either the Eurostat or Makstat, North Macedonia statistical office), so we applied the total growth rate in 2022 from LFS data, and disaggregated into 2-digit NACE sectors using the 2021 sectoral employment shares.
- (b) Data for employees were not available from Eurostat National Accounts, so were taken from the National Statistical Office and are based on a survey of enterprises. Those data arrive only until 2020, so the figure for total employees was extended by applying the growth rate from the

updated total employment figures and shared with 2-digit NACE sectors shares from 2020.

- (c) Data for labour force in 2020-21 were extracted from Makstat.
- (d) Sectoral output was available only until 2020. Total output for 2021 was extracted from Makstat, and then extended to 2022 using the GDP growth rate from the AMECO 2023 Autumn Forecast. The 2-digit NACE sectors breakdown for 2021 and 2022 was obtained by sharing the totals with 2020 shares.
- (e) Data for compensation of employees for 2021 was extracted from Makstat. The total for 2022 was obtained by applying the total growth rate from total employees, and the breakdown by 2-digit NACE sector was obtained by applying 2021 shares.
- (f) Data for total consumption for 2020-22 was extracted from Makstat and share by consumption categories using 2019 shares.
- (g) Data for total investment in 2022 was obtained by applying AMECO growth rate to 2021 value. Since no data is available at the sectoral level for real investment, sectors were derived by sharing totals with output shares.
- (h) Population projections were not available from Eurostat. Hence, growth rates from the UN population projections were applied to historical data.

In the case of Turkey, the following assumptions were made:

- (a) No employment data were available from the National Accounts. Hence LFS data at 2-digit NACE sector breakdown were directly used until 2020. To fill data in 2021-22, total employment figures from Turkstat were shared with 2020 2-digit NACE sector shares.
- (b) No employees data were available from the National Accounts. Hence, LFS data at 1-digit NACE sector were disaggregated with 2-digit NACE sectors share from updated employment figures until 2020. To fill data in 2021-22, total employment figures from Turkstat were shared with 2020 2-digit NACE sector shares.
- (c) Data for labour force in 2021-22 were extracted from Turkstat.
- (d) Total output was taken from the National Statistical Office and disaggregated using 2-digit sectoral shares from previous version of the forecast.
- (e) Compensation of employees was available only at the 1-digit NACE, so each 1-digit NACE was disaggregated using 2-digit NACE shares from the updated employees shares.
- (f) Total investment was taken from AMECO and was disaggregated using output sectoral shares.

- (g) Population projections were not available from Eurostat. Hence, growth rates from the UN population projections were applied to historical data.

2.3. LFS update of Modules 2-5

Due to the restrictions on the release of confidential data from EU-LFS²¹, the research team mostly relied on the anonymised LFS microdata for Modules 2-5, which at the time the analysis is undertaken will go up only to 2020²² (see Table 3.2). The research team used the EU-LFS microdata for the previous update of the Skills Forecast. The procedure described in the [Methodological Report](#) for estimating occupational shares of employment by sector has been implemented for the current update. A summary of the approach can be found in Section 2.3.

Table 3.2 Main data inputs from EU-LFS microdata

	Variable	Breakdown
Demand	Employment	Sector (NACE 1-digit); occupation (ISCO 2-digit), qualification level (3 broad levels); gender
	Employment	Sector (NACE 2-digit); age; gender
Supply	Employment	Gender; age group; qualification level (3 broad levels); occupation (ISCO 3digit); ILOSTAT employment status (1,2,3,4)
	Population	E3ME age groups; qualification level (3 broad levels); gender
	Labour force	E3ME age groups; qualification level (3 broad levels); gender

Firstly, the data collection and update of the raw data were based on two datasets, both generally available until 2020:

- (g) a set of data have been provided from the LFS microdata including the dimensions: year, country, sex, education (Low/ Medium/ High), NACE Rev. 1 1-digit sector and ISCO-08 3-digit occupation; and
- (h) a set of data including the dimensions: country, year, sex, age (0-4,5-9,10-14, ..., 95-99), education (Low/ Medium/ High), labour market status and ISCO-08 3-digit occupations.

Second, to complement and cross-check the microdata an additional special request to Eurostat was made to also obtain data for additional countries (Turkey, North Macedonia) which are not available from the microdata. Eurostat provided these data at ISCO 1-digit occupation level only for the first set of data in Table 3.2. Similarly, another special request to Eurostat provided the data by NACE Rev.

²¹ Eurostat is no longer releasing in the scientific use files the matrix of employment by 2-digit ISCO occupation and 2-digit NACE sectors.

²² [Datasets-availability-table.pdf \(europa.eu\)](#).

2 2-digit sectors, age groups and gender according to the second set of data in Table 3.2. These data have also been made available by Eurostat including age groups 15-24, 25-54, 55-64, 64+. With respect to the supply side data (third set of data in Table 3.2) another special request to Eurostat was made to collect such data; again, age groups available are only 15-24, 25-54, 55-64, 64+. These data are generally available until 2020).

Third, data collected from Eurostat website²³ (on employment, population, labour force) are compiled complementing the ones from Eurostat special requests as these include more detailed age groups (15-19, 20-24, ..., 65-69).

All these data have been collected and prepared and made available as an input for Modules 2-5.

²³ [Database - Eurostat \(europa.eu\)](https://ec.europa.eu/eurostat).

List of abbreviations

LFS	Labour Force Survey
VET	vocational education and training

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