The Skills Imperative 2035: Occupational Outlook – Long-run employment prospects for the UK

Working Paper 2c: Technical report on sources and methods

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The responsibility for the views expressed and for any remaining errors lies with the authors.

The opinions expressed in this report are those of the authors and do not necessarily reflect the views of Nuffield.

Nuffield Foundation

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1 Introduction

This document provides a technical description of the sources and methods used to generate the set of employment projections by industry and occupation presented in the reports from the Nuffield funded research programme – *The Skills Imperative 2035: Essential Skills for tomorrow's workforce*.[1] These projections have been prepared by the Institute for Employment Research (IER) at the University of Warwick and Cambridge Econometrics (CE), on behalf of the Nuffield Foundation.

This *Technical report* provides details on the data sources, methods and assumptions used to generate the projections described in Working Paper 2.[2] These projections represent the latest in a series of quantitative assessments of the employment prospects in the UK labour market over a 10-15-year horizon. Previously these projections have been funded by the UK Government and published under the Working *Futures* banner.[3]

The prime focus is on the demand for skills as measured by employment by occupation and qualification, although the supply side is also considered. The prime objective is to provide a benchmark for thinking about the structure of employment in the UK economy in 2035. The results are intended to provide a sound statistical foundation for reflection and debate among all those with an interest in the demand for and supply of skills. The labour market information provided can help to inform policy development and strategy around skills, careers, and employment, for both policy makers and a much wider audience.

This document sets out the methodological approach used to generate the detailed historical employment ***Database***, as well as the models and procedures used to produce the projections.[4] This includes information about the main data sources used, as well as the working assumptions adopted. It also sets out the limitations of the estimates produced and comparisons with official estimates.

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[1] https://www.nfer.ac.uk/key-topics-expertise/education-to-employment/the-skills-imperative-2035/
[2] Wilson *et al*., (2022c)
[3] See https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/863506/Working_Futures_Main_Report.pdf
[4] The term Database is used throughout this document to refer to the time series data on employment and output, cross classified by detailed sector (and in the case of employment, also by gender, status and occupation). It is indicated using bold italicised script.

1.1 The new projections

The full results of the projections may be found in the following documents and files:

Working Paper 2 – henceforth referred to as the *Headline Report*.[5] This presents the main findings about the size and composition of the labour market in 2035. It draws on the *Baseline projections and Alternative scenarios* projections to describe the likely range of potential outcomes for the future labour market and considers what the implications of these changes will be.

Working Paper 2a – This summarises the main findings for the UK in the *Baseline projections*.[6] It presents *Baseline projections* for the macroeconomy, sectoral employment and the labour force, based on our assessment of the most likely path the economy will take over the next 15 years or so given what we know about changes to the future policy landscape. It includes tables of data for selected years, together with a written commentary explaining and interpreting the forecasts. It covers the whole of the UK and the constituent countries which make it up.

Working Paper 2b – This summarises the findings for the UK for some *Alternative scenarios* that we have considered.[7] These build on our *Baseline projections* but consider other possible outcomes such as a more rapid adoption of technology, greater focus on green initiatives and the provision of better-quality education, health and care services.

Working Paper 2c – The main *Technical report* (this present document). This describes the detailed data sources and methods used to generate the results, including the models and methods used to develop the estimates of the demand for and supply of skills (as measured by qualifications).

[5] Wilson *et al*., (2022) op cit.
[6] Wilson *et al*., (2022a)
[7] Wilson *et al*., (2022b)

1.2 Structure of this document

The remainder of the present document is structured as follows:

- Section 2 outlines, in general terms, the models used to develop the employment scenarios
- Section 3 describes, in more detail, the methods used to model the UK economy, including detailed sectoral prospects
- Section 4 deals with shift from the SOC2010 method of classifying occupations to the use of SOC2020
- Section 5 covers the projections of labour supply by age and gender
- Section 6 presents the categories and classifications used for defining industries and sectors, including those used for reporting
- Section 7 covers the treatment of employment by gender and status
- Section 8 deals with occupational employment structure, including development of views about the likely nature of projected structural changes and new results developed at a 4-digit level of detail (the 412 unit groups of SOC2020)
- Section 9 deals with the methods used to generate replacement demands for occupations (covering losses due to retirements, etc.)
- Section 10 describes the main Employment and Output Database, including how these have been developed
- Section 11 describes, in more general terms, the data sources and methods used to produce the historical Database
- Section 12 covers issues relating to statistical precision and the robustness of the estimates
- Section 13 presents some warnings about confidentiality and statistical reliability when accessing the more detailed data. It also covers general caveats on the employment estimates produced, including issues related to comparison with official estimates
- Section 14 covers the methods used to deal with the demand for and supply of skills as measured by the highest qualifications held
- Section 15 explains how the *Alternative scenarios* have been developed, focussing on the macroeconomic model and related assumptions
- Section 16 provides a brief outline of the adjustments made to occupational employment shares in the *Alternative scenarios*.

The various sections of this report are designed to be read independently. They have therefore been written so that they can stand alone, with only limited cross-referencing. Inevitably this leads to a certain level of duplication and repetition. The authors hope that the benefits outlined above will outweigh any disadvantages that the latter may bring.

2 The Models used

2.1 The need for a macroeconomic model

Best practice worldwide suggests that labour market projections should be firmly grounded in an understanding of how the economy as a whole is changing. Changes in employment structure are intimately tied up with the development of the economy more generally. This has been operationalised in the form of the regional Multi-sectoral Dynamic Model of the UK economy (MDM-E3) developed by CE.

MDM-E3 has a Keynesian structure incorporating an input-output system and concentrates on the determination of changes in the real sector of the economy. Each region is modelled separately, with (for many variables) regional results being scaled to UK results. The level of disaggregation of commodities and industries is considerable by the standards of other models of the UK economy: at the UK level 87 sectors are distinguished, and disaggregation at the regional level is 46 sectors. Primarily because of the degree of disaggregation, the model is a large one and comprises over 5,000 behavioural and technical relationships (excluding accounting identities). Its main components are equations explaining consumption, investment, employment, exports, imports, and prices. At its heart is an input-output matrix, which deals with the flows of goods and services between industries and determines total industrial outputs. These equations are all solved together so that the final results are consistent with the various identities required by the national accounts.

2.2 The employment output relationship

A key relationship is that between industry employment and output. Employment is treated as a demand for labour, derived from the demand for goods and services. UK employment equations are estimated, relating industrial (headcount) employment in each industry to its gross output, and the relative wage costs as measured by industry wages relative to industry prices. In most cases the results suggest that an 'error correction' formulation can be applied, so this model was imposed in all industries. In this form, the residuals from the first stage 'co-integrating regression' (which represents the long-run relationship between employment and its determinants) are used in a 'second stage' dynamic specification, which incorporates various lagged terms to reflect adjustment lags. The inclusion of the residuals from the 'first stage' ensures that the long-run solution, given by the co-integrating regression, is imposed. To complement the employment equations, a set of hours equations by industry have also been estimated, which relate average weekly hours worked by industry to normal hours and capacity utilisation.

As a macro-econometric model, most of the relationships in MDM are driven by a continuation of historical patterns of behaviour and performance, subject to supply assumptions. Shocks to the economy that disrupt these trends are not automatically dealt with and often accounted for by changes to assumptions designed to specifically capture them. The post-Keynesian theoretical background of the model means that the economy is not assumed to completely return to an equilibrium growth path after a shock but rather adjusts and stabilises on a post-shock trajectory.

In MDM-E3 there are currently 87 main employing activities distinguished at the UK level (and 46 for the regions), defined using the Standard Industrial Classification 2007 (SIC2007). These categories are based on the limitations of available data.

At its greatest level of sector disaggregation, results are presented for 75 sectors defined by SIC2007. Using methods described below, the UK 87 sectors from MDM-E3 have been aggregated to the 75 sectors, and the model’s regional results (by 46 sectors) are disaggregated up to the level of the 75 sectors.

3 Modelling the UK economy

3.1 Introduction

As outlined above, the macroeconomic model used to develop the underlying employment projections is based on a detailed analysis of economic and other behavioural relationships, statistically estimated using robust econometric methods. The model offers a combination of great detail and a high level of sophistication. The use of a fully specified, formal macroeconomic regional multi-sectoral model provides a number of advantages over more ad hoc extrapolation methods. These include enforcement of logical and accounting constraints, and emphasis on making explicit the underlying assumptions built into the projections. The importance of using such methods, and further information about the approach, are set out in Barker and Peterson (1987)[8] and Wilson (1994)[9].

The forecasts were prepared using the latest version of the Cambridge Econometrics Multi-sectoral Dynamic Model (MDM-E3 Revision 13547 which is based on SIC2007). National Accounts data (with chained volume measures, with reference year 2018), along with a consistent input-output table and classification converters, have been incorporated into this revision of MDM-E3. All the main equation sets in the model, including the regional equations, were re-estimated on the latest data using a standard co-integrating technique. The estimation and model solution procedures were programmed in a common framework, with software facilities incorporated for checking the results and identifying errors.

Finally, the results of the model were translated into 75 industries defined in SIC2007 divisions for presentational purposes.

3.2 Impact of European System of National and Regional Accounts 2010

The MDM-E3 database is constructed using the Office for National Statistics (ONS) National Accounts, Regional Accounts and other key ONS statistics. The statistics conform (since 2014) to the European System of National and Regional Accounts (ESA 2010), with a methodology consistent with the System of National Accounts 2008 (SNA 2008).

3.3 Incorporating National Accounts data in a chained volume measure form

The 2003 National Accounts saw the introduction of 'annual chain-linking', a method for constructing aggregate chained volume measure (CVM)[10] of economic growth, which better reflect the changing structure of industry and patterns of expenditure. The latest version of MDM-E3 incorporates CVM data from the National Accounts 2020.

Using the 'annual chain-linking' method, the detailed estimates for growth for different industries are summed using information for the price structure updated every year to give

[8] Barker, T., and Peterson, W. (1987). (eds.) The Cambridge Multi-sectoral Dynamic Model of the British Economy. Cambridge University Press: Cambridge.
[9] Wilson, R, A. (1994). 'Modelling and Forecasting the Structure of Employment in the United Kingdom', in H. Heijke (ed.) Labour Market Forecasts by Occupation and Education. Massachusetts: Kluwer Academic, pp.9-35.
[10] Chained volume measure (CVM) is used in the UK National Accounts publications to describe volume measures derived by chain-linking in either index form (that is, set to be 100 for reference year) or in £million form (that is referenced to the current monetary value in the reference year).

each industry the most relevant weight which can be estimated. CVM indices are referenced to the most recent year for which a price structure is available; later years are compiled in the same way as constant-price data (using fixed weights from the most recent year for which a price structure is available).

The move to annual chain-linking has produced some loss of additivity in the components of aggregate totals in the years prior to the reference year. For example, if Gross Value Added (GVA) for each industry is summed through simple addition the total across the industries will not correspond to the CVM estimate of total GVA. A more complex method of weighting the series together is required to correct for this discrepancy.

3.4 Constructing a time series of input-output tables

Input-output supply and use tables (SUTS) provide a framework to make consistent estimates of economic activity by amalgamating all the available information on inputs, outputs, GVA, income and expenditure. For a given year, the input-output framework breaks the economy down to display transactions of all goods and services between industries and final consumers (e.g. households, government) in the UK. Since 1992, ONS has used the input-output process to set a single estimate of annual GDP and ONS has published the detailed analyses in the SUTS.

The information from the regular releases of SUTS are used in conjunction with the more detailed analytical tables to construct the inputs that are required for the MDM-E3 model. A time series of input-output tables has been estimated from official data to provide the detail needed to model inter-industry purchases and sales. The work required to adjust the original ONS input-output supply and use tables (which are in purchasers' prices) mainly entails (1) the reallocation of the duties on alcohol, tobacco and petrol to final consumers and (2) the reallocation of distribution and other margins from the valuation of each commodity's demand to wholesale and retail distribution commodity output. Associated classification converters have been constructed using the available ONS data.

3.5 ONS gross output and value added data

The forecast also incorporates data from the ONS on gross output and value added. CVMs of value added by industry are constructed from ONS SIC2007 indices of output data. Input-output balances provide data for gross output by SIC2007 in the reference year 2018. A time series for gross output has been constructed based upon updated gross output data in SUTs 2020, originally collected at the 105-industry level of detail, which have been aggregated to the MDM-E3 industry definitions. To extend the series further back from 1997 (for which SIC2007 data are not available) gross output data at the 123-industry level of detail corresponding to that of the 2005 input-output analytical tables (SIC2003) was aggregated and reclassified to the MDM-E3 industry definitions (see Table 3.1). These data have been updated in line with short-term indicators for more recent years.

MDM-E3 incorporates investment data by 88 investing sectors (corresponding to the 87 industry sectors, plus dwellings), based on the ONS's detailed data on investment by 82 industries and 44 products.

Household final consumption expenditure classified by 51 categories of purpose (which includes final consumption expenditure of non-profit institutions serving households) has been incorporated into MDM-E3, corresponding to the National Accounts. Historical data published in detail in the UK National Accounts and Consumer Trends are used to construct the data.

Table 3.1 Classification of Industries in MDM-E3 (SIC2007) – UK

MDM-E3 Industries	SIC2007 Division
UK87	
1. Crop and Animal Production, Hunting and related Service Activities	1
2. Forestry and Logging	2
3. Fishing	3
4. Coal	5
5. Oil	6.1
6. Gas	6.2
7. Other Mining and Quarrying	8
8. Mining Support Service Activities	9
9. Manufacture of Food	10
10. Manufacture of Drinks	11
11. Manufacture of Tobacco	12
12. Manufacture of Textiles	13
13. Manufacture of Wearing Apparel	14
14. Manufacture of Leather and Related Products	15
15. Manufacture of Wood and Wood Products, etc.	16
16. Manufacture of Paper and Paper Products	17
17. Printing and reproduction of recorded media	18
18. Manufacture of Coke and Refined Petroleum Products	19
19. Manufacture of Chemicals	20
20. Manufacture of Pharmaceuticals	21
21. Manufacture of Rubber and Plastics Products	22
22. Manufacture of Other non-metallic mineral products	23
23. Manufacture of Basic Metals	24
24. Manufacture of Fabricated Metal Products	25
25. Manufacture of Computer, Electronic and Optical Products	26
26. Manufacture of Electrical Equipment	27
27. Manufacture of Machinery and Equipment N.E.C	28
28. Manufacture of Motor Vehicles	29
29. Manufacture of Other Transport Equipment	30
30. Furniture	31
31. Other Manufacturing NES	32
32. Repair and installation	33
33. Electricity supply	35.1
34. Gas, heat and cooling supply	35.2-35.3
35. Water supply	36
36. Sewerage	37
37. Waste disposal activities	38

MDM-E3 Industries	**SIC2007 Division**
38. Waste management activities	39
39. Construction of buildings	41
40. Civil engineering	42
41. Specialised construction activities	43
42. Wholesale and retail trade of motor vehicles	45
43. Wholesale trade	46
44. Retail trade	47
45. Land transport	49
46. Water transport	50
47. Air transport	51
48. Warehousing/storage	52
49. Postal and courier services	53
50. Hotels and other accommodation	55
51. Catering	56
52. Publishing	58
53. Media	59
54. Broadcasting	60
55. Telecommunications	61
56. Computer services	62
57. Information services	63
58. Financial services	64
59. Insurance and pension funding (excluding compulsory social security)	65
60. Other financial and insurance support services	66
61. Real Estate	68
62. Legal and accounting activities	69
63. Management consultancy and other professional outsourcing activities	70
64. Architectural and engineering activities	71
65. Scientific Research and Development	72
66. Advertising and market research	73
67. Other professional services	74
68. Veterinary activities	75
69. Rental and leasing activities	77
70. Employment activities	78
71. Travel agencies	79
72. Security and investigation activities	80
73. Services to buildings and landscape activities	81
74. Office administrative and business support activities	82
75. Public administration and Defence	84
76. Education	85

MDM-E3 Industries	SIC2007 Division
77. Human health activities	86
78. Residential care activities	87
79. Social work activities without accommodation	88
80. Creative, arts and entertainment activities	90
81. Library, archives, museums and other cultural activities	91
82. Gambling and betting services	92
83. Sport and recreational activities	93
84. Activities of membership organisations	94
85. Repair of computers and personal household goods	95
86. Other personal service activities NES	96, 97
87. Unallocated	

The latest data from the ONS for exports and imports have also been incorporated into this forecast. These use the detailed data from the SUTS available at 105 sector detail, which is mapped to the MDM-E3 87 industries. The time-series data for years after 1997 were reconciled at an aggregate level with data from the ONS's Blue Book and more recent press releases.

3.6 Reconciling final demand time series with ONS National Accounts

MDM-E3 incorporates investment data by 88 investing sectors (corresponding to the 87 industry sectors, plus dwellings), based on the ONS's detailed data on investment by 82 industries and 44 products.

Household final consumption expenditure classified by 51 categories of purpose (which includes final consumption expenditure of non-profit institutions serving households) has been incorporated into MDM-E3, corresponding to the National Accounts. Historical data published in detail in the UK National Accounts and Consumer Trends are used to construct the data.

The latest data from the ONS for exports and imports have also been incorporated into this forecast. These use the detailed data from the SUTS available at 105 sector detail, which is mapped to the MDM-E3 87 industries. The time-series data for years after 1997 were reconciled at an aggregate level with data from the ONS's Blue Book and more recent press releases.

3.7 Intermediate demand

Intermediate demand is the monetary value of the goods and services used as inputs in production by other industries. The input-output coefficients derived from the input-output tables allow intermediate demand to be derived from each product given the final demand at the product level of disaggregation.

3.8 Detailed employment data consistent with BRES

Detailed UK Employment data by gender and status were derived from ONS Labour Market Statistics, which provides quarterly employees (1992Q4-2020Q3) by gender and status, and self-employment data (1996Q1-2020Q3), by gender, for 82 sectors based on an aggregation of 2-digit SIC2007.

The results were then converted to CE's MDM87 classification by splitting some of the 82 sectors further using a converter derived from the share of the more detailed sectors in the full 2-digit sector, using employment data from the Business Register and Employment Survey (BRES).

The quarterly data were then converted to an annual basis by taking the Q2 (June) observation for each year. This annual series was then extrapolated back to 1971 using growth rates from CE's own, consistent, earlier historical dataset, which is based on previously published ONS data.

3.9 Analysing and forecasting changes in economic structure

The economic model is designed to analyse and forecast changes in economic structure. To do this, it disaggregates industries, commodities and household and government expenditures, as well as foreign trade and investment. MDM-E3 disaggregates all of the main variables that are treated as aggregates in most macroeconomic models. The detailed variables are linked together in an accounting framework based on the United Nations System of National Accounts. This framework ensures consistency and correct accounting balances in the model's projections and forecasts.

The model is a combination of orthodox time-series econometric relationships and cross-section input-output relationships. Although it forms aggregate demand in a Keynesian manner, with a consumption function and investment equations, it also includes equations for average earnings by industry. Other aspects of the supply side come in through the export and import equations, in which capacity utilisation affects trade performance, as well as a set of employment equations which allow relative wage rates and interest rates to affect employment and therefore industry-level productivity growth.

The main exogenous variables of the model are as follows:

- world growth in GDP
- world inflation in GDP deflators and in prices of traded goods such as crude oil
- UK and regional population, labour force and natural resources (the main natural resources being coal, oil and natural gas)
- current and capital spending of the UK government
- UK tax rates and allowances
- the sterling-dollar and other exchange rates
- UK and US interest rates.

3.10 Adjustments made to MDM-E3

The main adjustments made to the model to produce a forecast were as follows:

- Recent data on outcomes and short-term industrial forecasts for 2021-23 are included directly in the model solution with multiplicative errors between model calculations and actual values being estimated.
- Time trends are not included in the long-term component of the equations unless based on theoretical grounds. Constants are included in the dynamic components of

the equations, so that the forecast will settle down to a steady growth path, unless there are long-term effects, such as the effect of accumulated investment.

- Cyclical variables were phased out by holding the variables constant at 'normal' values after the first year or so of the forecast.
- Special assumptions are made for forecasts of investment in the coal, oil and gas, electricity, gas and water industries, and public sector investment. These include:
  - Assumptions about global coal, oil and gas prices, which drive costs of production (given the current energy mix of most industries in the UK) and demand for UK exports, are based on short-term projections by the International Monetary Fund (IMF) for commodity prices.
  - Demand for the electricity, gas and water industries (major utility services) are driven by overall growth of the economy, due to their role in serving households and most other industries.
  - Assumptions for public sector investment are developed in consultation with the government's spending plans and statements and the OBR's forecast.

The multiplicative errors from the co-integrating equations and most of the other estimated residuals in the model are held constant at values for the last year for which data or short-term forecasts and estimates were available unless they are changed to allow the model to incorporate expert views or updated forecasts.

3.11 The reliability of the forecast

The reliability of the forecast partly reflects the reliability of the data. In recent years, the implementation of ESA2010 has been an important driver of improvements to the National Accounts. Resources have been invested in the production of annual input-output supply and use tables and these tables, and the associated analyses, are now incorporated in the annual estimates of the National Accounts published in the Blue Book.

The measurement of economic growth has been improved by the introduction of chain-linked estimates of GVA and its components since the 2003 National Accounts. These changes have improved the international comparability of UK data and reduced the size of revisions that occur when data are rebased to a new reference year.

The forecast should be seen as providing a reasonably consistent, comprehensive and sustainable view of the development of the economy which is built up from projections of individual industries. Part of the plausibility comes from the fact that strong trends over history, such as the extraordinary growth in household expenditure in the run-up to the 2008 recession, have not been thought to be sustainable because of their implications for the balance of payments and for inflation. Assumptions are made in the projections about changes in policy or behaviour, which produce changes in such trends and credible outcomes for both the macro economy and the individual industries.

The forecasts for individual industries are much less certain than those for the aggregates. Some indication of the errors involved is given by the residuals. These are the industrial counterparts to the ONS's residual errors for the whole economy, published in the Blue Book.

4 The switch from SOC2010 to SOC2020

4.1 Introducing SOC2020

The UK Standard Occupational Classification (SOC) is a framework used to group jobs based on the tasks and duties undertaken in the job. This classification is a critical input for conducting standardised statistical labour market analysis in the UK since it allows study of the labour supply and demand by the task complexity required to carry out a particular job. With the introduction of new technologies and changes in knowledge and expertise requirements, SOC2010 has increasingly become an outdated tool for classifying a wide range of occupations in the UK labour market. In 2020, the Office for National Statistics (ONS), as the agency responsible for maintaining the occupational classification, introduced SOC2020 to replace the old SOC2010 system (see ONS, 2021a for more details)[11].

4.2 Main improvements introduced in SOC2020

In summary, SOC2020 introduced three main improvements (see ONS, 2021b for more details)[12]:

1. a review of the classification of roles as *Professional or Associate professional*. A considerable number of jobs are progressively involving the application of knowledge and skills that are obtained via the higher education. Given this phenomenon, an increasing number of roles in SOC2010 major group 3, and to a smaller extent some occupations in major groups 4 to 9, require a degree-level qualification for the performance of their associated tasks.
2. the reclassification of occupations associated with information technologies (IT). Given the relatively high impact of technological changes in job requirements and the way IT occupations are being organised, it was necessary to revise different occupational groups, primarily within major group 2 (*Professional occupations*).
3. disaggregation into less heterogeneous unit groups. A general revision was conducted to assess whether unit groups could be disaggregated into less heterogeneous groups. All unit groups were considered for disaggregation, but the assessment focused on the 'not elsewhere classified' unit groups.

As pointed out by ONS, 2021b, these changes affected the employment distribution by major occupational groups. The increase in the share of *Professional occupations* is the most notable change. This increase was due to the redefinition of occupational categories from major group 3 (*Associate professional occupations*) to major group 2 (*Professional occupations*). From 2021, the ONS has implemented these changes by replacing the SOC2010 variable in the LFS data with the SOC2020 at four-digit level.

[11] (ONS, 2021a) https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/standardoccupationalclassificationsocextensionproject

[12] (ONS, 2021b) https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2020/soc2020volume1structureanddescriptionsofunitgroups

4.3 Updating the projections using SOC2020

As SOC2020 will be the principal classification in use in the next decade, the current projections have therefore adopted this renewed classification. This involved:

- using the ONS mapping of SOC2010 to SOC2020 at 4-digit level[13] to convert the historical *Working Futures* database from SOC2010 to SOC2020
- applying this mapping to the entire *Working Futures* database at 2-digit SOC to convert the previous round of projections on to a SOC2020 basis
- LFS data from 2001 to 2020 were converted to SOC2020 using the ONS mapping and then used to constrain the occupational shares.

Using the revised database new projections on a SOC2020 basis were developed.

As previously mentioned, the SOC update has some impact on occupational trends. It is clear that the share of occupations such as *Professional occupations* has increased compared with the projections made in 2017 using SOC2010. For instance, at the 1-digit level, using SOC2010 the employment level of Professional occupations was around 6,500,000 people in 2015. This figure rises to 6,885,000 when reclassified using SOC2020. These differences are relatively small for most of the other major occupational groups. Differences at more disaggregated levels (e.g. at 2-digit level) also arise due to the classification update.

[13] This mapping was developed by the ONS. It consists of a matrix containing the probabilities a certain SOC2010 unit group belongs to a SOC2020 unit group.

5 Labour supply

5.1 Introduction

This section describes the specification used in CE's Multi-Sectoral Dynamic Model of the UK economy (MDM-E3) to provide detailed projections of economic activity rates, labour supply and unemployment, for each of the Countries and Regions of the UK. The projections provide an aggregate analysis, focusing upon total labour supply by gender and age-band.

5.2 Specification of the regional model

A set of stochastic equations is used to forecast economic activity rates for the UK by age-band/gender in MDM-E3. The remainder of the model required to construct the projections of labour supply indicators consists of several accounting equations to derive labour supply and unemployment from the existing labour market and demographic projections in MDM-E3.

The key stages to determine the labour supply indicators can be summarised as follows:

- UK activity rates (by age-band/gender) are modelled as a function of unemployment and lagged activity rates
- regional activity rates are projected forward using the growth in the equivalent UK age-band/gender group
- the regional labour force is determined by activity rates multiplied by the population (by age-band/gender) – this is then scaled to UK labour force and the final regional activity rates are calculated
- workplace-based employment (jobs) is (are) determined using the existing MDM-E3 equations
- the LFS measure of employment (employed residents) is determined from workforce employment minus a labour market residual (note that one element of the residual is net commuting)
- regional LFS employment is taken away from regional labour force to determine regional unemployment (using the International Labour Organisation (ILO) definition).

As noted above, the difference between the LFS measure and the workforce measure of employment is accounted for in the labour market residual. As the LFS is a survey of private households, employment estimates reflect the area of residence of people with jobs. The surveys used to compile the workforce estimates of employment are surveys of employers, and so the figures at a regional level reflect the location of workplace and jobs, not the place of residence of the worker. One element of the labour market residual is therefore net commuting, which results from people travelling from their place of residence, across regional boundaries to their place of work. Both the LFS and the workplace measures of employment are determined in the model and the labour market residual is calculated as the difference. Differences between the labour supply and labour demand pictures are taken up in the labour market accounts residuals, including net commuting across geographical boundaries and 'double jobbing'.

ONS projections of population by region, gender and age-band are taken as exogenous inputs to MDM-E3.

Box 1.1: Definitions of employment and related labour market indicators

Alternative definitions

There are various ways of looking at employment. For example, a distinction can be made between the number of people in employment (head count) and the number of jobs. These two concepts represent different things, as one person may hold more than one job. In addition, a further distinction can be made between area of residence and area of workplace.

Similarly, there are various definitions of unemployment, the labour force, workforce and population. In this study, the following definitions are used:

Residence basis: measured at place of residence, as in the Labour Force Survey (LFS).

Workplace basis: measured at place of work, as in the Business Register and Employment Survey (BRES).

Workplace employment (number of jobs): these are typically estimated using surveys of employers, such as BRES, focusing on the numbers of jobs in their establishments. In this report references to employment relate to the number of jobs unless otherwise stated.

Employed residents (head count): the number of people in employment. These estimates are based primarily on data collected in household surveys, e.g. the LFS. People are classified according to their main job. Some have more than one job.

ILO unemployment: covers people who are out of work, want a job, have actively sought work in the previous four weeks and are available to start work within the next fortnight (or out of work and have accepted a job that they are waiting to start in the next fortnight).

Claimant Unemployed: measures people claiming Job Seeker's Allowance benefits. This is also referred to as the 'claimant count'.

Workforce: the size of the workforce is obtained by summing workplace employment (employee jobs and self-employment jobs), HM Forces, government-supported trainees and claimant unemployment.

Labour Force: economically active (employed residents plus ILO unemployed) aged 16+.

Labour market participation or Economic activity rate: the number of people who are in employment or (ILO) unemployed as a percentage of the total population aged 16 and over.

Labour Market Accounts Residual: workplace employment minus residence employment. The main cause of the residual at national level is 'double jobbing'. At a more disaggregated spatial level, net commuting across geographical boundaries is also very significant. The difference will also reflect data errors and other minor differences in data collection methods in the various sources.

Total Population: the total number of people resident in an area (residence basis).

Population 16+: the total number of people aged 16 and above (residence basis).

Working-age Population: the total number of people aged 16-64 (residence basis). The State Pension age of females was 60 years in 2011, increasing to 65 years in 2018. The State Pension age for all (both males and females) increased again to 66 years in October 2020. For the purpose of this analysis, the definition of working-age population is fixed at 16-64 years old for all periods in this study for consistency with the definition used by most major sources of historical data and given uncertainty about further changes to the pension age in the future.

6 Detailed industry categories and choice of sectors for reporting

6.1 Background

The sectoral analysis derives directly from the regional Multi-sectoral Dynamic Model of the economy (MDM-E3). MDM-E3 was used to generate estimates for output and productivity for the main industrial sectors and projections of total employment by industry at a regional level. The industries used for modelling are based on the 2007 Standard Industrial Classification (SIC2007). In all, 87 (UK) and 46 (regions) industries are distinguished in the standard version of MDM-E3, as set out in Table 3.1. For reporting, however, these are translated to the 75 industries, also defined on a SIC2007 basis.

The estimates and projections of employment produced are consistent with official data published by the ONS.

6.2 Extension of the number of industries in the models

The standard version of MDM-E3 provides forecasts for 46 industries, covering the Regions of England, as well as Wales, Scotland and Northern Ireland. These were extended to form the basis for a disaggregated set of projections of sectors at the detailed SIC2007 industries for this study. These detailed 75 industries are shown in Table 6.1 Detailed Industries (SIC2007). This was achieved using a sub-modelling approach, as described above. The methodology ensures that the results of the sub-model of 75 industry outcomes are consistent, both with existing historical data and the forecast results for the regional 46 industries produced by the MDM-E3. Regional output series for 75 industries were created consistent with the UK data and using available information for the regions. The remainder of this section presents the various industrial and sectoral classifications used for reporting.

6.3 Choice of sectors for analysis and reporting

The detail provided in the reports reflects various considerations: confidentiality; statistical robustness and precision; and practical considerations, including transparency and digestibility.

Table 6.1 Detailed Industries (SIC2007)

Industry (75)	SIC2007 Section	SIC2007 Division	Industry full name	Ind 6	MDM-E3	Industry (75)
					87 Ind	
1. Agriculture etc.	A	01-03	Agriculture, forestry and fishing	1	1-3	1
2. Coal, oil & gas, mining & related	B	05-09	Coal, oil and gas, other mining and quarrying	1	4-8	2
3. Food products	C	10	Food products	2	9	3 (part)
4. Beverages & tobacco		11-12	Beverages and tobacco products	2	10-11	3 (part)
5. Textiles		13	Textiles	2	12	4 (part)
6. Wearing apparel; leather etc.		14-15	Wearing apparel, leather and related products	2	13-14	4 (part)
7. Wood etc.		16	Wood and cork products	2	15	5 (part)
8. Paper etc.		17	Paper and paper products	2	16	5 (part)
9. Printing & recording		18	Printing and reproduction of recorded media	2	17	6
10. Coke & petroleum; chemicals etc.		19-20	Coke and refined petroleum products, chemicals and chemical products	2	18-19	7-8
11. Pharmaceuticals		21	Pharmaceutical products	2	20	9
12. Rubber & plastic		22	Rubber and plastic products	2	21	10 (part)
13. Other non-metallic		23	Other non-metallic mineral products	2	22	10 (part)
14. Basic metals		24	Basic metals	2	23	11 (part)
15. Metal products		25	Metal products except machinery and equipment	2	24	11 (part)
16. Computers, etc.		26	Computer, electronic and optical products	2	25	12
17. Electrical equipment		27	Electrical equipment	2	26	13
18. Machinery etc.		28	Machinery and equipment n.e.c.	2	27	14
19. Motor vehicles, etc.		29	Motor vehicles, trailers and semi-trailers	2	28	15
20. Other trans. Equipment		30	Other transport equipment	2	29	16

Industry (75)	SIC2007 Section	SIC2007 Division	Industry full name	Ind 6	MDM-E3	Industry (75)
					87 Ind	
21. Furniture		31	Furniture	2	30	17 (part)
22. Other manufacturing		32	Other manufacturing	2	31	17 (part)
23. Repair & installation		33	Repair and installation of machinery and equipment	2	32	17 (part)
24. Electricity, gas, etc.	D	35	Electricity, gas, steam and air conditioning supply	1	33-34	18
25. Water	E	36	Water collection, treatment and supply,	1	35	19 (part)
26. Sewerage		37	Sewerage	1	36	19 (part)
27. Waste management		38-39	Waste and waste management services	1	37-38	19 (part)
28. Construction	F	41	Construction of buildings	3	39	20 (part)
29. Civil engineering		42	Civil engineering	3	40	20 (part)
30. Specialised construction		43	Specialised construction activities	3	41	20 (part)
31. Motor vehicle trade	G	45	Wholesale and retail trade or motor vehicles and motorcycles	4	42	21
32. Wholesale trade		46	Wholesale trade	4	43	22
33. Retail trade		47	Retail trade	4	44	23
34. Land transport, etc.	H	49	Land transport and transport via pipelines	4	45	24
35. Water transport		50	Water transport	4	46	25
36. Air transport		51	Air transport	4	47	26
37. Warehousing, etc.		52	Warehousing and support activities for transportation	4	48	27 (part)
38. Postal & courier		53	Postal and courier services	4	49	27 (part)
39. Accommodation	I	55	Accommodation	4	50	28
40. Food & beverage services		56	Food and beverage service activities	4	51	29
41. Publishing activities	J	58	Publishing activities	5	52	30 (part)

Industry (75)	SIC2007 Section	SIC2007 Division	Industry full name	Ind 6	MDM-E3	Industry (75)
					87 Ind	
42. Film & music		59	Motion picture, video and music publishing	5	53	30 (part)
43. Broadcasting		60	Programming and broadcasting activities	5	54	30 (part)
44. Telecommunications		61	Telecommunications	5	55	31 (part)
45. Computer programming etc.		62	Computer programming, consultancy and related activities	5	56	31 (part)
46. Information services		63	Information service activities	5	57	31 (part)
47. Financial services	K	64	Financial service activities	5	58	32 (part)
48. Insurance & pensions		65	Insurance and pension funding	5	59	32 (part)
49. Auxiliary financial services		66	Activities auxiliary to financial services and insurance	5	60	32 (part)
50. Real estate	L	68	Real estate activities	5	61	33
51. Legal & accounting	M	69	Legal and accounting activities	5	62	34
52. Head offices, etc.		70	Activities of head offices; management consultancy activities	5	63	35
53. Architectural & related		71	Architectural and engineering activities	5	64	36
54. Scientific research		72	Scientific research and development	5	65	37 (part)
55. Advertising, etc.		73	Advertising and market research	5	66	37 (part)
56. Other professional		74	Other professional, scientific and technical activities	5	67	37 (part)
57. Veterinary		75	Veterinary activities	5	68	37 (part)
58. Rental & leasing	N	77	Rental and leasing activities	5	69	38 (part)
59. Employment activities		78	Employment activities	5	70	38 (part)
60. Travel, etc.		79	Travel agency and tour operator activities	5	71	38 (part)
61. Security, etc.		80	Security and investigation activities	5	72	38 (part)
62. Services to buildings		81	Services to buildings and landscape activities	5	73	38 (part)

Industry (75)	SIC2007 Section	SIC2007 Division	Industry full name	Ind 6	MDM-E3	Industry (75)
					87 Ind	
63. Office admin		82	Office administrative; office support activities	6	74	38 (part)
64. Public admin. & defence	O	84	Public administration and defence, compulsory social security	6	75	39, 46*
65. Education	P	85	Education	6	76	40
66. Health	Q	86	Human health activities	6	77	41
67. Residential care		87	Residential care activities	6	78	42 (part)
68. Social work		88	Social work activities without accommodation	6	79	42 (part)
69. Arts & entertainment	R	90	Creative, arts and entertainment activities	6	80	43 (part)
70. Libraries, etc.		91	Library, archives, museums and other cultural activities	6	81	43 (part)
71. Gambling		92	Gambling and betting activities	6	82	44 (part)
72. Sport & recreation		93	Sport activities, amusement and recreational activities	6	83	44 (part)
73. Membership organisations	S	94	Activities of membership organisations	6	84	45 (part)
74. Repair of goods		95	Repair of computers and personal household goods	6	85	45 (part)
75. Other personal service		96	Other personal services activities	6	86	45 (part)

7 Modelling gender and status

7.1 Historical estimates

Most official data on employment include breaks by gender. ONS estimates, based on the BRES, include a distinction between full and part-time status for employees. However, the published information, including such breaks, is much more limited for self-employment than for all employees. Self-employment estimates are available from the LFS and the Census of Population. The former is the main source of time series information, although the latter is crucial for benchmarking. Given the much smaller numbers involved compared to employees, together with the much smaller sample size of the LFS compared with the BRES, there are real problems in trying to obtain comprehensive and consistent estimates of self-employment across all the dimensions needed.

7.2 Method of projection of gender and status shares

Forecasts of total employment by (MDM-E3 87) industry were produced for the UK using econometric equations and disaggregated to regions (by 46 industries) using logical forecasting rules. Changes of employment by gender and status were projected by extrapolating recent trends. First, at the UK 87 industry level, the trend changes over the last whole economic cycle (1997-2007) studied by HM Treasury in the shares of employment by gender and status was calculated.[14] For some of the individual 87 industries, the volatility of data resulted in infeasible trends; in these cases trends were used from the corresponding broad sector, e.g. trends for the Transport, storage and communication sector used for the Water transport industry. These trend changes were then applied to current shares to generate projections of shares of employment by gender and status. The projected shares were then applied to the forecasts of total employment to calculate levels of employment by gender and status, by 87 industries in the UK. For the regions, by 46 industries, the trend changes in the shares of employment by gender and status are assumed to follow those at the UK level.

Employment forecasts by type (gender/status) for the 75 sectors were formed by:

- Using historical trends in proportions (using a functional form which reduces the rate of decline as the proportion approaches zero, or the rate of increase as the proportion approaches 1). This relationship was used to make initial estimates of employment by type over the forecast period.
- A RAS procedure was used to ensure consistency with total employment by MDM-E3 industry in the regions and total employment by gender and status for the UK (for each year a matrix of 75 industries by 6 gender/status categories, using the RAS procedure in blocks).[15]

[14] http://news.bbc.co.uk/1/shared/bsp/hi/pdfs/24_11_08_pbr_economiccycle.pdf
[15] RAS is a widely used iterative technique, which ensures that elements in a two-dimensional data array match target row and column totals. In many of the examples quoted, multi-dimensional arrays are used but the principles are the same.

8 Occupational projections

8.1 Historical estimates

BRES, the Annual Business Inquiry (ABI) and its predecessors do not include information on occupational employment. Generating such estimates relies upon other sources such as the LFS. Because of the relatively small sample size of the LFS, such estimates are much less robust than those for industrial employment. The present results rely on the most up to date information on trends in recent years available from the LFS. These data have been used to calibrate recent historical trends and adjust the projected future trends.

Estimates from the LFS have been combined with industry employment data (distinguishing gender and status) to develop a comprehensive set of estimates. These are in the form of detailed industry (SIC) by occupation (SOC) matrices.

Previous projections in the *Working Futures* projections were based on classifying jobs using the 2010 version of the Standard Occupational Classification (SOC2010). The Office for National Statistics (ONS) have recently updated this to SOC2020. A revised historical database has therefore been developed for this project, reclassifying jobs using this new system for the classification of occupations. Tables 8.1, 8.2 and 8.3 provide details of the 2-digit occupational categories used in SOC2020, SOC2010, SOC2000 and SOC1990.

Effectively a new series of SIC-SOC employment matrices based on SOC2020 have been developed, the whole database being translated on to a SOC2020 basis using a detail mapping between SOC2010 and SOC2020 categories developed by ONS (see Section 4 for more details).[16]

The data for 2001-2020 have also been constrained to match the overall patterns of employment by occupations (by SOC2020 categories), as reported in the official estimates published by ONS in the LFS.

The main ***Database*** therefore provides breakdown for the 75 SIC2007 industry level as used in MDM-E3.

8.2 Projections of occupational structure at the 2-digit level

In theory it would be desirable to develop a full model of supply and demand for different occupations, considering the various behavioural factors which may influence future developments. In practice, severe data limitations preclude such an ambitious approach. Throughout the world, most occupational employment forecasts are based on simplistic extrapolation of past trends.[17]

The availability of time series data from the LFS offers the possibility of a more sophisticated approach, based on econometric analysis of occupational shares (see Briscoe and Wilson,

[16](ONS, 2021c). See: https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2020/therelationshipbetweenstandardoccupationalclassification2010andstandardoccupationalclassification2020

[17] For a review, see: Wilson, R. A. (2001) Forecasting Skill requirements at National and company Levels, in P. Descy and M. Tessaring (eds.) Training in Europe (2nd report on Vocational Training Research in Europe 2000: Background Report, Volume 2) CEDEFOP Reference Series, Luxembourg, Office for Official Publications of the European Communities, pp.561-609.

2003).[18] In practice, although this analysis offers some insight into the sensitivity of the projections to certain key economic indicators, the results suggest that underlying trends are dominated by technological and organisational shifts, which can best be proxied by simple time trends. Moreover, such an approach cannot easily be extended to the more detailed sectoral and spatial level required here due to data limitations. The present projections are therefore based on more conventional approaches, involving extrapolation of historical patterns of change at a very detailed industrial level.

The occupational employment projections are generated by linking the industry employment results from MDM-E3 to the IER's occupational models, which produce projections of occupational employment shares based on extrapolative methods. The historical occupational by industry employment share (SIC-SOC) matrices are used to develop projections of occupational employment share in all future years. The occupational shares in each industry were then applied to the industry forecasts from the macroeconomic model to obtain the occupational employment levels (expansion demands). Details of the basic procedures are described in Box 8.1.

Changes in occupational employment levels between years both historical and projected can be analysed using shift-share analysis. This assesses the effects of aggregate employment change, changes in the industrial mix and a residual effect reflecting shifts in occupational structure within industries due to organisational and technological change.

Projections of occupational shares at this level place considerable demands on the data available, and the situation on the ground can be changed rapidly and substantially by technological and other changes. It is important to appreciate the assumptions used and the range of factors which it is felt are likely to influence immediate future trends, including how these may diverge from previous patterns of change. These issues are discussed in more detail in Section 4 and 5 of the *Baseline projections*.

[18] Briscoe, G., and R. A. Wilson, (2003). 'Modelling UK Occupational Employment'. International Journal of Manpower. 24(5), pp. 568-589.

Box 8.1: The IER's Occupational Employment Model

The approach to projecting occupational employment structure involves two stages. First, projections of the likely changes in industrial employment are made using the Multi-sectoral dynamic macroeconomic model of the economy. Second, projections of the occupational structure of employment within each industry are made using estimates from the LFS (basically extrapolations of past trends). These occupational coefficients are then combined with the projected levels of industrial employment to obtain projected levels of employment by occupation for the 26 2-digit level sub-major groups in SOC2020.

The occupational employment projections are therefore based on a sub-model which takes as input the industrial projections produced by the macroeconomic model. It is a 'top-down' approach, the industrial and regional employment projections being disaggregated into the 26 2-digit level occupational categories for each industry.

The overall changes in aggregate occupational structure arise through a combination of shifting patterns of industrial employment structure and the changing occupational composition of employment within industries. The former can be regarded as primarily a reflection of the way in which the changing pattern of demands for commodities by consumers and companies impinges on occupational structure, while the latter is more a reflection of technological and organisational changes affecting the manner in which goods and services are produced and provided. The level of employment in a particular occupation can, therefore, change for two main reasons; either because the industries in which it is concentrated grow or decline, or because of changes in occupational composition within industries. The former may be termed the industrial effect, the latter the occupational effect.

The so-called occupational effect may arise for several reasons. Medium-term developments in technology may affect the structure of demand for certain skills. Demand may also change in response to changes in the relative rates of pay associated with certain trades, which may in turn be affected by the supply side of the labour market. In the short term the level of employment in each industry may depend upon the cyclical position in which it finds itself. Certain skills may be regarded as 'fixed' rather than 'variable' inputs in the production process for technological reasons. Furthermore, it is apparent that the costs of hiring and firing (that is costs associated with changing the level of employment) differ considerably between different occupations. Finally, the actual levels of employment observed at any particular time will reflect the balance of supply and demand; shortages for certain skills may result in divergence from the long-run structure of employment desired by firms. This again will be dependent upon current rates of pay, the scope for substitution of one skill for another in the production process, and the flexibility of wages.

In the absence of a formal econometric model encapsulating these behavioural influences, they are built into the projections in a more *ad hoc* fashion, using professional judgement based on a reading of the most important current developments. A particularly important element here is the use of data from recent Labour Force Surveys. However, a variety of other sources are also used, including some more qualitative data.

This information is used to calibrate the occupational model over the recent past and to modify the projections. The LFS data are used to make an estimate of occupational structure in the base year. This is then compared with that emerging from the occupational model. The results of this exercise are used to modify the projected changes in the light of recent and current developments in occupational structure. The results should be regarded as indicative of general trends and not precise forecasts of what will happen in particular cases.

Table 8.1 Skill levels and sub-major group structure of SOC2010 and SOC2020

Skill	Sub-major groups of:	
Level	SOC2010	SOC2020
Level 4	11 Corporate managers and directors	11 Corporate managers and directors
	21 Science, research, engineering and technology professionals	21 Science, research, engineering and technology professionals
	22 Health professionals	22 Health professionals
	23 Teaching and educational professionals	23 Teaching and other educational professionals
	24 Business, media and public service professionals	24 Business, media and public service professionals
Level 3	12 Other managers and proprietors	12 Other managers and proprietors
	31 Science, engineering and technology associate professionals	31 Science, engineering and technology associate professionals
	32 Health and social care associate professionals	32 Health and social care associate professionals
	33 Protective service occupations	33 Protective service occupations
	34 Culture, media and sports occupations	34 Culture, media and sports occupations
	35 Business and public service associate professionals	35 Business and public service associate professionals
	51 Skilled agricultural and related trades	51 Skilled agricultural and related trades
	52 Skilled metal, electrical and electronic trades	52 Skilled metal, electrical and electronic trades
	53 Skilled construction and building trades	53 Skilled construction and building trades
	54 Textiles, printing and other skilled trades	54 Textiles, printing and other skilled trades
Level 2	41 Administrative occupations	41 Administrative occupations
	42 Secretarial and related occupations	42 Secretarial and related occupations
	61 Caring personal service occupations	61 Caring personal service occupations
	62 Leisure, travel and related personal service occupations	62 Leisure, travel and related personal service occupations
		63 Community and civil enforcement occupations[1]
	71 Sales occupations	71 Sales occupations
	72 Customer service occupations	72 Customer service occupations
	81 Process, plant and machine operatives	81 Process, plant and machine operatives
	82 Transport and mobile machine drivers and operatives	82 Transport and mobile machine drivers and operatives
Level 1	91 Elementary trades and related occupations	91 Elementary trades and related occupations
	92 Elementary administration and service occupations	92 Elementary administration and service occupations

Source: SOC2020: Volume 1: Structure and Description of Unit Groups, ONS.

Table 8.2 SOC2000 Classification (Sub-major Groups)

	SOC2000 Sub-major groups	Occupations	Occupation minor group number[a]
11	Corporate managers	Corporate managers and senior officials; production managers; functional managers; quality and customer care managers; financial institution and office managers; managers in distribution and storage; protective service officers; health and social services managers	111, 112, 113, 114, 115, 116, 117, 118
12	Managers/proprietors in agriculture and services	Managers in farming, horticulture, forestry and fishing; managers and proprietors in hospitality and leisure services; managers and proprietors in other service industries	121, 122, 123
21	Science and technology professionals	Engineering professionals; information and communication technology professionals	211, 212, 213
22	Health professionals	Health professionals, including medical and dental practitioners and veterinarians	221
23	Teaching and research professionals	Teaching professionals, including primary and secondary school teachers and higher and further education lecturers; research professionals (scientific)	231, 232
24	Business and public service professionals	Legal professionals; business and statistical professionals; architects, town planners, and surveyors; public service professionals; librarians and related professionals	241, 242, 243, 244, 245
31	Science and technology associate professionals	Science and engineering technicians; draughtspersons and building inspectors; IT service delivery occupations	311, 312, 313
32	Health and social welfare associate professionals	Health associate professionals, including nurses and other paramedics; therapists; social welfare associate professionals	321, 322, 323
33	Protective service occupations	Protective service occupations	331
34	Culture, media and sports occupations	Artistic and literary occupations; design associate professionals; media associate professionals; sports and fitness occupations	341, 342, 343, 344
35	Business and public service associate professionals	Transport associate professionals; legal associate professionals; financial associate professionals; business and related associate professionals; conservation associate professionals; public service and other associate professionals	351, 352, 353, 354, 355, 356
41	Administrative and clerical occupations	Administrative/clerical occupations: government and related organisations; finance; records; communications; general	411, 412, 413, 414, 415
42	Secretarial and related occupations	Secretarial and related occupations	421
51	Skilled agricultural trades	Agricultural trades	511

	SOC2000 Sub-major groups	Occupations	Occupation minor group number[a]
52	Skilled metal and electrical trades	Metal forming, welding and related trades; metal machining, fitting and instrument making trades; vehicle trades; electrical trades	521, 522, 523, 524
53	Skilled construction and building trades	Construction trades; building trades	531, 532
54	Other skilled trades	Textiles and garment trades; printing trades; food preparation trades; skilled trades n.e.c.	541, 542, 543, 549
61	Caring personal service occupations	Healthcare and related personal services; childcare and related personal services; animal care services	611, 612, 613
62	Leisure and other personal service occupations	Leisure and other personal service occupations; hairdressers and related occupations; housekeeping occupations; personal service occupations n.e.c.	621, 622, 623, 629
71	Sales occupations	Sales assistants and retail cashiers; sales related occupations	711, 712
72	Customer service occupations	Customer service occupations	721
81	Process plant and machine operatives	Process operatives; plant and machine operatives; assemblers and routine operatives	811, 812, 813
82	Transport and mobile machine drivers and operatives	Transport drivers and operatives; mobile machine drivers and operatives	821, 822
91	Elementary occupations: trades, plant and machine related	Elementary occupations: agricultural trades related; process and plant related; mobile machine related	911, 912, 913, 914
92	Elementary occupations: clerical and services related	Elementary occupations: clerical related; personal services related; cleansing services; security and safety services; sales related	921, 922, 923, 924, 925

Notes: (a) Standard Occupational Classification, ONS (2001).

Table 8.3 SOC1990 Classification (Sub-major Groups)

	Sub-major groups	Occupations	Occupation minor group number[a]
1.1	Corporate managers and administrators	General managers and administrators in national and local government, large companies and organisations; executive officers in the civil service; production managers in manufacturing, construction mining and energy industries; specialist managers; financial institution and office managers; managers in transport and storing; protective service officers; managers and administrators n.e.c.	10, 11, 12, 13, 14, 15, 19
1.2	Managers/ proprietors in agriculture and services	Managers and proprietors in service industries; managers in farming, horticulture, forestry and fishing	16, 17
2.1	Science and engineering professionals	Natural scientists; engineers and technologists.	20, 21
2.2	Health professionals	Health professionals, including medical and dental practitioners and veterinarians.	22
2.3	Teaching professionals	Teaching professionals, including primary and secondary school teachers and higher and further education lecturers	23
2.4	Other professional occupations	Legal professionals; business and financial professionals; architects and surveyors; professional occupations n.e.c.	24, 25, 26, 27, 29
3.1	Science and engineering associate professionals	Draughtspersons, scientific technicians, quantity and other surveyors; systems analysts and computer programmers; associate professional and technical occupations n.e.c.	30, 31, 32
3.2	Health associate professionals	Health associate professionals, including nurses and other paramedics.	34
3.3	Other associate professional occupations	Legal associate professionals; business and financial associate professionals; social welfare associate professionals; literary artistic and sports associate professionals; librarians and related associate professionals	33, 35, 36, 37, 38, 39

	Sub-major groups	Occupations	Occupation minor group number[a]
4.1	Clerical occupations	Administrative/clerical officers and assistants in the civil service and local government; numerical clerks and cashiers; filing and general clerks; clerks (not elsewhere specified); stores and despatch clerks, storekeepers; clerical and secretarial occupations n.e.c.	40, 41, 42, 43, 44, 49
4.2	Secretarial occupations	Secretaries, personal assistants, typists, word processor operators; receptionists, telephonists and related occupations	45, 46
5.1	Skilled construction trades	Building trades.	50
5.2	Skilled engineering trades	Metal machining, fitting and instrument making trades, electrical/electronic trades	51, 52
5.3	Other skilled trades	Textile, garments and related trades; printing and related trades; woodworking trades; metal making, welding and related trades; vehicle trades; food preparation trades; other trades n.e.c.	53, 54, 55, 56, 57, 58, 59
6.1	Protective service occupations	NCOs and other ranks, armed forces; security and protective service occupations (including the police and fire brigade)	60, 61
6.2	Personal service occupations	Catering occupations (including chefs); travel attendants and related occupations; health and related occupations; childcare and related occupations; hairdressers, beauticians and related occupations; personal service occupations n.e.c.	62, 63, 64, 65, 66, 67, 69
7.1	Buyers, brokers and sales representatives	Buyers, brokers and related agents; sales representatives and agents.	70, 71
7.2	Other sales occupations	Sales assistants and check-out operators; mobile, market and street salespersons; sales occupations n.e.c.	72, 73, 79

	Sub-major groups	Occupations	Occupation minor group number[a]
8.1	Industrial plant and machine operators, assemblers	Food, drink and tobacco process operatives; textiles and tannery process operatives; chemicals, paper, plastics and related process operatives; metal working process operatives; assemblers/line workers; other routine process operatives; machine and plant operatives n.e.c.	80, 81, 82, 83, 84, 85, 86, 89
8.2	Drivers and mobile machine operators	Road transport operatives; other transport, and machinery operatives.	87, 88
9.1	Other occupations in agriculture, forestry and fishing	Other occupations in agriculture, forestry and fishing	90
9.2	Other elementary occupations	Other occupations: in mining and manufacturing; in construction; in transport and in services; postmen/women, mail sorters, messengers; other occupations n.e.c.	91, 92, 93, 94, 95, 99
82	Transport and mobile machine drivers and operatives	Transport drivers and operatives; mobile machine drivers and operatives	821, 822
91	Elementary occupations: trades, plant and machine related	Elementary occupations: agricultural trades related; process and plant related; mobile machine related	911, 912, 913, 914
92	Elementary occupations: clerical and services related	Elementary occupations: clerical related; personal services related; cleansing services; security and safety services; sales related	921, 922, 923, 924, 925

Note: (a) Standard Occupational Classification. OPCS (1990).

8.3 Extension to 4-digit level of SOC2020

LFS data for the first three quarters of 2021 were used to compute shares of 4-digit occupations within 2-digit groups for all industries, and then applied to all industries and for all years (2022-2035). The latest ONS data using SOC2020 at the time the projections were prepared relate to the third quarter of 2021. The 2021 estimates are therefore based on just 3 quarters. In principle, LFS data prior to 2021 can be converted to SOC2020 using the crosswalk between SOC2010-SOC2020 developed by the ONS. This has been done for the main database at the 2 digit-level of SOC2020.

Around 220 occupations at 4-digit level (out of the full set of 369 SOC2010 categories) have a one-to-one match with a SOC2020 Unit Group. Nevertheless, the use of this crosswalk at the more detailed 4-digit level cross-classified by industry of employment and other characteristics of interest (such as gender and status) is limited by the data available in the LFS. This is patchy, with many cells being empty. It was therefore decided that for the *Baseline projections* employment shares of Unit Groups with 2-digit categories would be assumed to be fixed at the 2021 values.

Using the LFS data to compute shares of 4-digit occupations within 2-digit groups (regardless of whether it is SOC2020 or SOC2010) for all industries and subsequent years involves some issues that need to be addressed. Primarily, these methodological problems have to do with the fact that some 4-digit occupations are industry-specific. Applying the method above can results in anomalous outcomes in a few cases (e.g. the largest numbers of some textile operatives appearing in the industry Food drink and tobacco rather than in the Textiles industry). If industry specific shares are used instead of industry ones the problem is (in principle) resolved. However, there are at least two problems with this alternative:

First, using distinctive shares for (say) the 6 broad industry groups fails to resolve the problem since the differences above do not become apparent at this level (for example, applying shares based on the whole of *Manufacturing* instead of all industries will not make the differentiation between *Textiles and clothing* and *Food, drink and tobacco*). To avoid that problem a much finer industry differentiation is needed (ideally at the 75 industry level!).

But this raises a second problem, notably that the LFS sample size is inadequate to produce robust shares at the 75 industry level. The only way around this impasse is to generate a set of industry specific shares that is consistent (as far as possible) with the all the information available.

The ‘knowns’ that the final estimates need to be consistent with are as follows:

1. the 75 industry employment totals
2. the 2-digit occupational totals

and within those

3. the 75 industry x 2-digit occupational total.

They are also available:

i. by gender and status
ii. by region/country
iii. by qualification.

Ideally, the expansion to the 4-digit level needs to cover all these dimensions.

Extension to i. – iii. poses more problems, not least in terms of the scale of the computations and programming required. Such extensions are, however, desirable since the detailed occupational patterns are likely to vary across these dimensions (see below).

The other ‘known’ it is important to take account of (in principle at least) is information on the overall pattern of employment by 4-digit occupation (shares of 4-digit within 2-digit categories) when aggregated across all industries, all regions and all gender/status types.

This was the aggregate information used in the approach to developing 4-digit level projections in the *LMI for All* project[19]. In principle, this aggregate information could be extended to cover region and /or industry (for example the 6 broad sectors). Ideally, it can be further extended to differentiate the shares for each of the 75 industries. However, this results in a very sparse data set, with many 'gaps' where the LFS has no entries (yet it is almost certain that there are people employed in those categories).

A compromise solution has been adopted which computes more detailed shares than was done in the *LMI for All* project, but without trying to impose the final aggregate 4-digit level constraint (which requires a further RAS process).

The details of the algorithm developed to fill the gaps are summarised in Table 8.4. The main steps are as follows:

- Step 1 – using the LFS data (combining years) to generate a set of shares of 4-digit within 2-digit categories for each 75 industry category and covering dimensions i. – iii. above for categories where data are available
- Step 2 – where there are gaps, using the nearest equivalent (more aggregate category)
- Step 3 – applying the final shares to the existing *Working Futures* employment data to generate a full data array of employment levels – 4-digit occupation by 75 industries. Step 3 effectively constrains this array to match the 'knowns' in points 1 – 3, above.

The detailed occupational shares are extracted and applied as in the *LMI for All* project to the 2-digit occupational totals (but now differentiated for each of the 75 industries (as well as by region, gender/status and occupation)).

The final RAS process did not reach a unique solution due to irreconcilable differences between the aggregated summary of 412 4-digit occupations on the one hand and the detailed allocation of these within all the 48,600 categories/dimensions (industries in particular). The final set of results is fully consistent with all the other dimensions used in the published *Working Futures* estimates (region/country; industry (75 level) gender, status, SOC 2-digit occupational category and qualification level). The final discrepancies at the 4-digit level were small and concentrated in just two sub-major groups.

[19] The LMI for All portal provides high quality, reliable labour market information (LMI) to inform careers decisions. For details see https://www.lmiforall.org.uk/

Table 8.4 Algorithm for developing the 4-digit occupational database

Expanding the 26 SMGs in *Working Futures* to 412 SOC Unit groups			
Working Futures data		Labour Force Survey data	
1990-2024		10 quarters combined	
2	genders	2	genders
3	statuses	3	statuses
75	industries	75	industries
9	qualifications	6	qualifications
26	SMGs	412	SOC unit groups
12	regions		

From the LFS data, the shares for each unit group within each SMG is calculated. The *Working Futures* employment level for that SMG is shared out to the Unit groups. The share is applied to each nation/region and year.

Where the LFS has is no value in a cell, aggregations are tried in order:

- all statuses
- both genders
- both genders and all statuses
- all industries (by gender and status)
- both genders and all statuses all industries.

Shares are calculated separately within the six qualification categories and applied to the appropriate more detailed 9 qualification categories in the *Working Futures* data.

9 Replacement demands

9.1 The importance of replacement demands

Net changes in occupational employment (or expansion demand as they are referred to in the *Baseline projections* and *Alternative scenarios* reports) are only one indicator of future changes in the pattern of demand for skills. Another measure, which is equally important for assessing education and training provision, is the replacement demand needed to offset outflows due to retirements, occupational mobility, etc. Estimates of replacement demands have been a key feature of IER occupational projections for many years.

The analysis of occupational trends and prospects provides predictions of the changes in the number of people employed in particular occupational categories. However, education and training requirements are not simply dependent on which occupations are growing rapidly. The projected net change in employment (expansion demand) tells only a part of the story in terms of future skill requirements. It is crucial to recognise that there will be many job openings and important education and training requirements for many occupations where employment levels are expected to fall. These arise because of the need to 'replace' the existing skills that will be 'lost' as a result of retirements and other aspects of the normal process of labour turnover. Even in those occupations where employment levels are expected to decline substantially, there may be a need to train, simply to maintain the existing stock of skills at the required level. In addition to examining likely net changes in the numbers in each occupational category, it is also important, therefore, to assess replacement demands. These represent the numbers needed to maintain the existing stock of skills due to losses resulting from retirements and other outflows.

The scale of replacement demand typically outstrips the scale of expansion demand, in the present projections by a factor of around seven to one. This varies across occupations and sectors but, even where substantial job losses are projected, the replacement demand elements are usually more than sufficient to offset this. It is essential, therefore, for employers, education and training providers, and public agencies to recognise the different characteristics and requirements of these two different components of future skill needs.

9.2 Methods of estimating replacement demands

IER has developed procedures to produce such estimates, linked to the main occupational projections. These are summarised in Box 9.1. The various elements of replacement demand depend upon the rates of flows from employment due to factors such as retirement and occupational and geographical mobility, as set out in Box 9.1. The main source of information on the various flows (as well as information on age structure), which are used to generate replacement demand estimates, is the LFS. This is used to generate information on outflows over the past 12 months. Such estimates account, therefore, for some, but not all labour turnover (since many jobs are filled within a 12-month period). The total number of job openings is likely to be substantially greater than the estimates developed here. Nevertheless, they provide a useful benchmark for thinking about the number of new entrants to jobs that will need to be found.

While the LFS can provide useful information across all sectors and regions combined, its sample size is inadequate to provide specific data for particular sectors and regions at a detailed level. The Census of Population offers the potential for obtaining more robust estimates, at a much more detailed level. However, these results are already becoming somewhat dated. The present analysis draws upon both sets of data, using the more robust

Census data for 2011 to get a better fix on different patterns at a point in time while relying more upon the LFS to reveal how these patterns are changing over time.

In principle, there is no problem in providing such estimates in considerable detail, distinguishing sector, gender/status and geographical area. It is possible to generate customised estimates of replacement demand for any industry or spatial area, recognising unique features, including the age structure of the workforce and rates of flow. Such estimates are likely to vary significantly, depending upon these factors.

In practice, it is very difficult to obtain reliable data on these factors, which would enable such customised estimates to be produced. The current analysis is based on LFS data on labour market flows at national level. Attempting a breakdown for the countries and English regions within the UK, or for broad sectoral groups at a UK level, faces problems of empty cells in the LFS data. The LFS, even with its enhanced size, does not provide a sufficiently large sample to generate sensible estimates for individual sectors at a rather broad level, let alone breaks by region or LEP area. Indeed, as noted below, the estimates of occupational mobility from the LFS proved inappropriate for use at all but the most aggregate national level. The lack of availability of data from national sources therefore severely limits the extent to which such estimates can be customised for particular groups (sectors, geographical areas, etc.).

However, this should not be seen as an insurmountable problem. The key point in producing replacement demand estimates is to emphasise the importance of replacing those retiring, even in declining sectors and occupations. While these results are, of course, sensitive to the particular assumptions adopted, they can be regarded as indicative. Results are therefore provided at a considerable level of detail, based on a set of benchmark assumptions about age structures and flow rates. The main replacement demand estimates in the published reports use a ‘standard’ set of assumptions about flow rates, which are common to all sectors and geographies.

Occupational mobility estimates were used initially in calculating overall replacement demands at national level. However, when attempts were made to use the same assumptions about flow rates for individual sectors and regions, this led to implausible results. This is because of the very different occupational structures across sectors and the imprecision of some of the flow estimates, even at national level. To provide a comparable set of results at all levels, the occupational mobility estimates were therefore set by assumption to zero (as was the case for geographical mobility).

The estimates published in the various reports are therefore based on the heroic assumption that the general patterns of age structure and rates of flow are common across all sectors and regions. This enables a certain level of consistency. In particular, it ensures that disaggregated estimates will sum to more aggregate totals. These benchmark estimates provide a starting point for thinking about such issues. In particular, they emphasise the quantitative importance of replacement demands compared with the structural changes projected.

The estimates of replacement demands over the coming decade presented in the reports are generally over a third of the opening stock (employment levels at the start of the period under consideration).

This proportion depends on:

i. the length of period covered (the longer it is the greater the outflows)[20]

ii. the age structure in each occupation (older work forces will see greater outflows, all else equal)

iii. Outflow rates (these are age and gender specific but may also vary across other dimensions).

ii. and iii. are (initially) assumed to be common to all industrial and geographical categories although they might vary a lot in reality. The reasons for this are not that it is thought that such differences are unimportant. It is simply that the LFS data used to measure ii and iii are inadequate to measure these differences systematically and consistently across all the dimensions of the database.

In practice, it is likely that patterns of age structure and rates of flow will be very different for particular sectors or locations. The procedures and tools developed allow those with access to the more detailed data to explore alternative scenarios, by using industry specific or area specific assumptions about age structures or flow rates. These can draw on non-official data as well as the limited range of alternatives directly provided. In this manner users can, for example, explore alternative scenarios, based on 'local' knowledge about particular difficulties faced where a workforce is rapidly ageing.

9.3 Estimating replacement demands at the 4-digit level

Replacement demands at the 4-digit level are assumed to have the same outflow rates as the corresponding 2-digit category to which they belong. This is a strong assumption, unlikely to hold true in practice as the age structures of the 4-digit occupations are likely to differ significantly from their 2-digit averages. However, this assumption allows the presentation of an initial assessment of the potential scale of such effects.

[20] The present estimates are based on a 15-year period of outflows.

Box 9.1 Estimating Replacement Demand by Occupation

Measuring replacement demand

The projections of occupational employment focus on the total numbers of people that are expected to be employed in such jobs in the future. While such estimates can provide a useful indication of areas of change, highlighting the likely ‘gainers’ and ‘losers’, they can give a misleading impression of job opportunities and skill requirements. Even where the projections indicate significant employment decline over the medium term, there may nevertheless be quite good career prospects with significant numbers of new job openings. This is because, as long as significant numbers are still likely to be employed in the future, then employers will need to replace those employees who leave because of retirement, career moves, mortality or other reasons. This so-called ‘replacement demand’ may often dwarf any ‘structural demand’ resulting from growth in employment in a particular category and can easily outweigh any negative changes due to projected employment decline.

While the concept of replacement demand is simple enough to grasp, estimating it is a rather different matter. The main problem is that official statistics place much more emphasis on measuring stocks of people in particular states rather than flows from one state to another. Yet it is measurement of such flows which is essential to estimating replacement demands.

However, use can be made of readily available statistics in order to provide indicative estimates. Ideally, one requires a full set of demographic accounts which trace people’s movement from one socio-economic position (e.g. employment in a particular occupation) to another (e.g. retirement). In practice, such a complete set of accounts does not exist even at national level. However, the LFS now provides a sufficiently large sample to obtain rough estimates of the main elements at national level. The key components are:

- information on the age and gender structure of occupational employment
- information on rates of outflows due to:
    - retirement (and other reasons for leaving the workforce)
    - inter-occupational mobility
    - mortality.

Age structure

Data on age structure are required since many of the flows, especially retirements and mortality, are age specific. Age structures vary significantly by occupation. For some groups such as corporate managers and administrators, experience is a key requirement, and this is associated with age. The proportion in the 45-59 year old category is therefore relatively high. In contrast, in many other occupations the age structures are much more heavily biased to younger age groups. In sales occupations, for example, the age structure is much more heavily weighted towards younger age groups. Differences in age structure across occupations will clearly influence likely losses due to mortality and retirement which are age related.

Box 9.1 (continued) Estimating Replacement Demand by Occupation

Retirement rates

Retirement rates vary by gender and by age. By using data for the whole of the UK estimates of likely rates of outflow can be made. Data are not distinguished for different occupational groups since sample numbers are too small to allow for meaningful estimates. The estimates are based on data from the LFS, which show the % of those employed one year ago who have retired from employment, either temporarily or permanently. For males the main outflows are associated with retirement *per se*. For females, in particular, there is significant outflow for younger age groups associated with family formation.

Mortality

Another potential outflow is due to mortality. Information on mortality rates is available by age and gender from ONS. While losses due to death are not great for individual age groups up to the age of 65, they can cumulate to produce significant losses over an extended period of time. The rates used are again based on data for the whole of the UK. However, mortality rates are unlikely to vary very much across occupations.

Occupational mobility

Occupational mobility is an important source of loss for some occupations although not for all. The full occupational mobility flow matrix indicates that some occupations such as corporate managers and administrators tend to gain employment as people are promoted from other occupations. This means that many of the losses due to retirement are 'automatically' dealt with by the normal process of promotion and upward occupational mobility. However, for those occupational categories which provide the people who are promoted this means that losses due to retirement will understate the overall replacement demands. These data are based on an analysis of information for the whole of the UK.

Replacement demand

The overall scale of change is obviously dependent upon the length of period considered, as well as the opening stocks and the age structure of the current workforce. For the projections constant rates of flow are assumed. The tables in the main reports provide estimates of replacement demands over the forecast period. The projected net change in employment indicates the scale of structural or expansion demand (which in some cases may be negative). This is contrasted with estimated losses due to retirement and mortality (replacement demands). It is notable that the latter are substantial in comparison with the expansion demand element and that in most cases they offset any negative change.

10 Developing the employment database

10.1 Development of consistent sectoral and occupational estimates

The standard sectors used in MDM-E3 have been set out in Tables 3.1 and Table 6.1 Detailed Industries (SIC2007). These categories are based on data available from ONS in various official sources, especially those data relating to input-output information, which is central to MDM-E3. They are classified according to the 2007 Standard Industrial classification (SIC2007).

In the present exercise the main analysis is presented using 75 industries based on SIC2007. ONS have placed data at this level of detail into the public domain, so it is regarded by them as non-disclosive.

To this we have added an occupational dimension based on the latest SOC2020 classification.

The development of the Database has therefore involved a number of key elements:

- establishing consistent historical time series of sectoral employment within the UK
- expanding this to cover all 75-sector SIC categories
- development of occupational data relating to the new sectors.

In addition to this it was necessary to develop a number of related models and procedures, including:

- forecasting models and procedures to generate consistent projections across these various dimensions (described in Sections 2 and 4)
- a replacement demand module to generate replacement demand estimates across all the various dimensions (described in Section 9)
- treatments of Labour Supply (Section 5)
- qualifications (Section 15).

10.2 The core Database: employment by 75 industries

Historical estimates of employment by gender and status were based on various official sources, including quarterly workforce jobs (employee jobs and self-employment jobs) and BRES and ABI (for employees) data. These detailed employment data, covering all the main dimensions concerned, provide the core of the ***Database***.

Employment for 75 industries: The main MDM-E3 employment estimates are based on detailed SIC2007 categories used in the CE MDM-E3 model. This covers gender and status. These data series have been developed over many years and are as consistent as can be achieved with all the official published sources upon which they are based.[21]

For earlier time periods (before 1998), growth rates from the data from previous editions of *Working Futures*, which were based on previously released ONS data, were applied.

[21] Complete consistency is not possible since the various official sources are themselves inconsistent, not least because some have been subsequently revised and updated by ONS.

10.3 Occupations (26) within industries

The starting point for the occupational dimension is information from the LFS. Details of the occupational groupings are shown in Tables 8.2 to 8.3.

Sectoral data were based on the Census of Employment, the Annual Employment Survey (AES) and most recently the ABI and BRES. Together with information from the Census of Population and the LFS, these sources were used to generate a series of occupation by industry employment matrices to give the occupational categories shown in Tables 8.2 and 8.3.

Information classified using previous systems of classification used for both occupations and industries has been converted on to the latest systems (SOC2020 and SIC2007), based on matrices from the Census or LFS developed by IER in collaboration with ONS. These matrices also distinguish gender.

10.4 The detailed industrial estimates

The extension of the historical regional industrial employment elements from the 46 industries used originally in MDM-E3 to the 75 categories involved disaggregating each of the 46 industries. ONS currently publish sectoral employment data (employees) at this level of detail (based on the BRES) and ABI). The ABI data include breakdowns by gender and full-time /part-time status, but the latest BRES data only provide such breakdowns by full-time/part-time. Also, self-employment data are not available. Gaps in the official data were filled using various methods, as described elsewhere in this report. RAS procedures were used to ensure everything added up to the official published figures.

10.5 Extending the occupational analysis to cover detailed industries

Extending the *historical data* on occupations to cover the 75 detailed industries was problematic for a number of reasons. Most importantly both SIC and SOC have changed significantly. In addition, the earlier data were only made available for 10 per cent (hard copy) or 2 per cent (electronic) sub samples, which makes obtaining robust estimates at this level of detail difficult, if not impossible, in many cases. The LFS sample size is only adequate to obtain reliable estimates at a UK level, and even here is not able to provide robust estimates for many of the detailed industries required, (which almost by definition tend to be small).

In the previous analysis for *Working Futures 2017-2027* historical figures for the additional (79/75) industries were estimated using information already to hand.[22] These historical series were then constrained to match the other estimates at more aggregate levels. Given that most of the new industries are normally small components of larger parts, this procedure generates reasonably plausible results. An RAS iterative procedure was then used to ensure that everything still adds up to the published headline totals by industry, occupation, region, etc. This RAS adjustment is not a trivial process. The software used to generate a consistent ***Database*** runs to thousands of lines of complex computer code. This procedure avoids the major inconsistencies that would otherwise emerge between the published headline figures reported by ONS and the sum of the detailed parts.

[22] A more comprehensive reassessment of the historical record, involving re-interrogation of old Census records could be undertaken. However, given time and resource constraints this was not feasible in this project.

11 Sources and general methods

11.1 Main sources

The Office for National Statistics (ONS) is responsible for most of the economic and labour market statistics upon which this analysis is based. Many of the data are made available via the National Online Manpower Information System (NOMIS).

ONS is responsible for most of the key economic statistics upon which MDM-E3 is based, including the UK National and Regional Accounts and the Input-output Tables. This includes indicators such as:

- output and related indicators
- wages and prices
- trade statistics
- UK Balance of Payments
- Regional Accounts

ONS is also responsible for workforce jobs (including employee jobs and self-employment jobs) data, and the BRES and ABI. BRES has replaced the ABI since December 2010 and provides annual employment figures on the 2007 Standard Industrial Classification (SIC2007) basis only. BRES and ABI are the most important sources of information on detailed industry employment levels at regional level.

ONS also undertakes the LFS, as well as the more infrequent Census of Population. These two sources provide information on key aspects of employment structure, such as occupational employment and the various information on flows and age structure needed for replacement demand estimates.

11.2 General approach and methods

The general approach adopted can be summarised in a few words:

- Underlying the whole set of projections is the use of a detailed multi-sectoral macroeconomic model. This is described in previous sections
- All published official data on employment have been used. The data within the models and database are constrained to match the official sources
- Where there are inconsistencies between official sources, the industrial information (currently from Workforce Jobs and BRES/ABI data) is given precedence
- All the employment data are constrained to match headline figures published by ONS through its website. This is achieved using so called RAS iterative methods, as described below
- Where no official data are published, estimates are generated by assuming common patterns to the next level of aggregation up at which official estimates are available
- Occupational estimates and self-employment estimates (where data are not available from the Workforce Jobs series) are based on information from the Census of Population and the LFS.

The sectoral and spatial level data are therefore consistent with ONS estimates available at the time the analysis was conducted. Information on occupations and qualifications is based on LFS data available at the same time. The latter is constrained to match the sectoral data, using the RAS process (described below) so the numbers will no longer match the original LFS information, although the general patterns are fully consistent. The detailed numbers may not match the latest ONS estimates for a number of reasons:

- revisions and changes made by ONS since the analysis was conducted
- modifications introduced as a result of the RAS process
- differences in classification – the published database is entirely on SIC2007.

11.3 The RAS Iterative Process

The detailed employment data can be conceived of in terms of multi-dimensional arrays with the following dimensions:

- industries (75 2-digit SIC2007 categories)
- geographical areas (9 English regions plus the 3 devolved nations within the UK)
- occupations (26 sub major groups)
- gender
- employment status (full-time, part-time, self-employment)
- time (years from 2001-2035).

ONS publish various headline statistics for certain aggregate elements of these arrays (typically sums across one or more dimensions).

An iterative process, based on the so-called RAS procedure,[23] is used to develop the detailed elements within the arrays in such a way that the various constraints are met. In two dimensions, a RAS procedure involves taking a two-dimensional matrix of numbers and progressively and alternatively:

- forming row or column totals
- calculating a ratio of these compared with some target values (typically provided by ONS figures)
- multiplying the rows or columns of the array by that ratio
- re-summing and repeating the process.

Typically, this process delivers a new array which matches the desired row and column totals within a comparatively few iterations (normally 20-30). In developing the database complex procedures have been developed which repeat this essentially simple process across all the dimensions above simultaneously.

[23] For a general discussion of RAS methods see: Lahr and De Mesnard, L. (2004); McMenamin and Haring (1974); Miller and Blair (2009); Toha (1998).

12 Statistical robustness

12.1 Background

The discussion in Sections 10 and 11 highlighted the problems raised by trying to develop an employment ***Database*** with so many dimensions, given the current data available from official sources. The main problems relate to:

- statistical precision and robustness; and to
- confidentiality.

The first issue is addressed here, the second in the following section.

12.2 Statistical robustness

Although it has been possible to develop a very detailed employment ***Database***, covering all the various dimensions of interest, it is important to recognise that this has its limitations. Given the various dimensions required (sector, gender, employment status, occupation and spatial areas), the full ***Database*** comprises huge numbers of time series.[24] Such detailed breakdowns can only ever be indicative, since they are based on survey estimates that were not designed to produce precise estimates at this level of detail.

The rules ONS adopt when publishing employment estimates are briefly summarised below. These can be used as guidelines in assessing the robustness and precision of the data in the ***Database***.

It is important to recognise that, without enormous resources, it is not possible to monitor and quality assure every one of these series. CE/IER have checked to ensure that the basic trends and structural features of the data are sound but it is impossible to check and validate every series.

Given the nature of the ***Database***, which has been constructed from a variety of different sources, it is not possible to attach precise margins of error to the estimates. In order to help users in deciding what weight to attach to the various estimates, some general 'rules of thumb' have been developed. These are based loosely on the statistical rules adopted by ONS when publishing employment estimates.

ONS recommend using minimum cell sizes of 10,000 (grossed up), when presenting data based on the LFS. This is relevant for the ***Database,*** since the occupation estimates and self-employed numbers are based primarily on this source. Given that there are 25 occupations to be distinguished in each sector, this suggests a minimum size for an industry of approximately 250,000 if occupational data are to be published.

These rules have been used to decide on the levels of detail which should be published and in indicating the reliability of the more detailed data.

[24] For example in *Working Futures 2004-2014* there were over half a million (that is: Sector (67) * occupation (25) *geographical area (47 local areas plus Scotland, Wales and Northern Ireland) * gender/status (6) = 512,550 separate time series). For *Working Futures 2017-2027* the main projections cover 135,000 series but this excludes qualifications, and the extension to 4-digit occupations as well as the sub-regional analysis.

12.3 ONS practice on release of employment data

ONS do not publish consistent time series information on employment cross-classified by region (let alone by sub-area) at a very detailed industry level. Detailed information on self-employment is regarded as even less reliable, being based on the LFS, the sample size of which is inadequate to provide the kind of detail required here. Because of differences in the way data are collected for Northern Ireland, information for the whole of the UK is not available on a consistent basis.

Nevertheless, it is possible to generate estimates at this level of detail, which are informative, and of use to labour market analysts. These can be constructed by using the information ONS are prepared to publish, including the raw BRES/ABI data (which have been subject to frequent revision).[25] This involves various procedures of interpolation and adjustment to fill in gaps and to ensure consistency with published headline figures. While not strictly precise in a statistical sense, such estimates can provide useful information and intelligence to users about detailed employment trends. However, the use of such data needs to be handled with care and, as noted above, there are strict limitations on what can be published due to concerns about confidentiality. The latter are discussed in more detail in the next section.

The employment estimates incorporate the quarterly Workforce Jobs and annual BRES. These data are also used to constrain the ***Database.*** The time series data currently made available by ONS for the UK are adequate to provide all of the 75 categories required.

At a regional level, the problems are more acute. ONS are not prepared to release data (the quarterly Workforce Jobs series) at anywhere near so detailed a sectoral level, when cross-classified by region. Apart from construction, the categories normally separated out by ONS all form part of the service sector. Only broad aggregates are made available for the other sectors. To provide the necessary sectoral detail, annual BRES data at 2-digit SIC07 is used and then scaled to the workforce jobs series.

When considering this question a distinction needs to be made between statistical reliability and the provision of useful LMI at a detailed level. If strict rules regarding statistical robustness are applied to decide what level of sectoral and occupational disaggregation can be provided at sub-area level, it would not be possible to provide much detailed data at all. The official surveys carried out by ONS are (with a few exceptions) not designed to provide statistically robust estimates at this level of detail. Following such rules would restrict what might be reported to very broad aggregates, which are not very helpful to those on the ground.

IER/CE have addressed this issue for a number of years in providing results based on their LEFM methodology. This is based on the notion of providing ‘benchmark’ estimates and projections, using the most detailed data where they are available for the local level, in combination with broader national and regional trends where they are not. While not subject to the normal tests of statistical precision, such estimates can provide useful and informative LMI for those operating at the local level. Other consultants have adopted similar solutions.

In providing such information it is important that users are aware of its limitations (as well as avoiding any problems of confidentiality). Nevertheless, IER/CE would argue that this is more useful than suppressing the detail at an early stage. This solution requires that such

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[25] The levels of detail which ONS typically provide for public dissemination are summarised in Section 13.

detailed information is only made available to a restricted audience. It is therefore necessary to restrict access to the more detailed results.

12.4 Margins of error

The employment estimates make use of a wide variety of sources, as described in more detail in Section 10. As a consequence, it is not possible to calculate precise margins of error. From an analysis of previous projections it is clear that these margins can be quite large. The results of this analysis are indicative:

Industry employment levels (at the 22 industry level) are typically projected within ±10 per cent over a 5-10 year horizon. The directions of change are projected correctly in around 90 per cent of cases. The errors in terms of annual percentage growth rates are usually of the same order of magnitude as the observed changes.

Occupational employment levels (at the 2r sub-major group level) are typically projected with ±7 per cent over a 5-10 year horizon. The direction of change is correctly projected in about 80 per cent of all cases. Occupational shares are usually projected within ±2 % points. (The typical share is around 4 percentage points).

Historical revisions to the data account for a very large part of the forecast errors. It is important to appreciate that the purpose of the projections is not to make precise forecasts of employment **levels**. Rather, the aim is to provide policy analysts with useful information about the general nature of **changing employment patterns** and their implications for skill requirements.

The results provide a useful benchmark for debate and policy deliberations about underlying employment trends. However, they should not be regarded as more precise than the general statements in the text. Many years of international research have demonstrated that detailed manpower planning is not a practicable proposition. The results presented here should be regarded as indicative of general trends and orders of magnitude, given the assumptions set out in detail in this *Technical report* and in the *Baseline projections and Alternative scenarios* reports, rather than precise forecasts of what will necessarily happen.[26]

Changing patterns of employment by sector and occupation (as represented by shares of total employment) are largely dominated by longer-term trends rather than the cyclical position of the economy. The results from the current set of projections can therefore be used as a robust guide to likely future developments in the structure of employment, even though the effect of the slowdown and subsequent recovery on employment **levels** may remain somewhat uncertain. The current *Working Futures* results present a plausible picture of future developments over the coming decade.

[26] For further discussion see: Briscoe and Wilson (2003).

13 General caveats on the employment estimates

13.1 Statistical matters

Some general caveats on the employment estimates are in order. When using data based on raw LFS data ONS recommend using minimum cell sizes of 10,000 (grossed up), in presenting employment estimates. Given that there are 26 occupations to be distinguished in each industry, this suggests a minimum size at UK level of at least 250,000. In a few cases the data reported below fall below this threshold. This is a particular problem in the Primary sector and utilities group. The results for individual occupations or other categories within these industries therefore fall well below the 10,000 guideline figure. They are included here in the absence of any better estimates. For further discussion on these issues see the more detailed discussion above, especially Sections 10-13.

This highlights that there are real problems in developing reliable data at the levels of detail that analysts and policy makers would ideally like to have access to. One response to this would be to limit the amount of detail at which the projections work is undertaken. This would be very restrictive and would severely limit the level of detail that could be made available. Instead, a less restrictive approach has been adopted. When generating the projections, full details have been maintained, while maintaining a strict control on the release of such data into the public domain to prevent misuse.

A clear distinction needs to be made between statistical reliability and the provision of useful labour market information at a detailed level. If strict rules regarding statistical robustness are applied to decide what level of sectoral and occupational disaggregation can be provided, it would not be possible to provide much detailed data at all. The official surveys carried out by ONS are not designed to provide statistically robust estimates at the level of detail required here, across all dimensions simultaneously. Following the ONS rules as described above would restrict what might be reported to very broad aggregates, which are not very helpful to most users. However, in providing such detailed information it is important that users are aware of its limitations (as well as avoiding any problems arising over confidentiality). This is more useful than suppressing the detail.

13.2 Comparison with official estimates

The estimates are all based on published official data on employment, but they have been adjusted to produce a consistent set of estimates across all the dimensions of interest (sector, occupation, qualification, gender, status (full-time and part-time employee or self-employed)) and region.

Where there are inconsistencies between official sources, the industrial information is given precedence. All the employment data are constrained to match headline figures published by ONS in the UK and regional labour market statistics bulletins and similar publications. This is achieved using so called RAS iterative methods, as described elsewhere in this *Technical report*. Where no official data are published, estimates are generated by assuming common patterns to the next level of aggregation up at which official estimates are available. Occupational estimates, information on qualifications and self-employment estimates are based primarily on information from the LFS.

The sectoral and spatial level data are consistent with ONS estimates available at the time the analysis was conducted (the summer of 2018). Information on occupations and qualifications is based on LFS data available at the same time. The latter are constrained to match the sectoral data, using the RAS process described above. One important point to note here is that the present estimates refer to June and the data for all areas are made consistent with the level above. The data for regions are consistent with the GB data but also with the ONS released data for the regions for aggregate sectors. All scaling is done by type. Local area data are scaled to the regional data which are for June, not for September.

As a result the numbers in the present database may no longer match the original information, although the general patterns are fully consistent. The numbers by sector, region, occupation and qualification may differ from the latest ONS published estimates for a number of reasons:

- revisions and changes made by ONS since the analysis was conducted
- inconsistencies in the various official estimates from different sources
- differences in classification – the present database is entirely on SIC2007 and SOC2020
- differences in timing (mid-year (June) as opposed to other periods)
- modifications introduced as a result of the RAS process (this affects only the occupational and qualification patterns).

The estimates from the present database provide a complete and consistent picture across all dimensions of employment that is not available from any other source.

14 Skill supply and demand projections

14.1 Conceptual issues

There are many conceptual difficulties in modelling labour supply by level of skill (as measured by qualifications held). Most occupations are undertaken by people with a bewildering range of formal qualifications. This is partly a function of age, with older workers generally relying more upon experience than formal qualifications. There are enormous differences even allowing for the age factor. This makes defining the supply of people into an occupation almost impossible. It is possible to identify some key elements, focusing on the flows of people through the education and training system, but boundaries are too blurred and transitory to enable quantitative modelling. Much the same is true for the concept of supply of labour to a sector.

For these reasons, the development of supply estimates and projections by occupation and/or sector are not regarded as a practicable proposition. As in previous *Working Futures* exercises, the approach adopted is to focus on general projections of population and overall labour supply (those economically active) by gender for each geographical area, and to then disaggregated these by the highest levels of qualification held using stock-flow modelling and other techniques.

The project updates the previous projections using the methodologies developed in previous *Working Futures* exercises. The first step was to produce projections of economic activity rates, labour supply and unemployment for each of the countries and English regions within the UK. The projections provided focus upon total labour supply by gender and broad age group. These reflect the move to 16-64 as the new official working age definition. The methodology is described in detail in Section 5 above.

14.2 Labour supply by age and gender

Labour supply projections are developed for the various geographical areas and include:

- total population
- population aged 16 and over
- working age population
- labour force
- workforce
- ILO unemployment
- claimant unemployment
- employed residents
- workplace employment
- labour market residual.

A set of stochastic behavioural equations to forecast economic activity rates by age-band/gender is incorporated into MDM-E3. These include a number of explanatory variables including unemployment. The remainder of the model required to construct the projections of overall labour supply indicators consists of a number of accounting equations to derive labour supply and unemployment from the existing labour market and demographic projections in MDM-E3.

The key stages to determine the labour supply indicators can be summarised as follows:

- UK activity rates (by age-band/gender) are modelled as a function of unemployment and lagged activity rates
- regional activity rates are projected forward using the growth in the equivalent UK age-band/gender group
- the regional labour force is determined by activity rates multiplied by the population (by age-band/gender) – this is then scaled to UK labour force and the final regional activity rates are calculated
- workplace-based employment (jobs) is determined using the existing MDM-E3 equations (see Section 4)
- the LFS measure of employment (employed residents) is determined from workforce employment minus a labour market residual (note that one element of the residual is net commuting)
- some adjustments to the labour market residual are made in the projections to account for trend changes
- regional LFS employment is taken away from regional labour force to determine regional unemployment (ILO).

The difference between the LFS measure and the workforce measure of employment is accounted for in the labour market residual. This includes net commuting which results from people travelling from their place of residence, across regional boundaries, to their place of work.

The analysis described above provides projections of labour supply, for each of the countries and regions of the UK, by gender. The modelling work is undertaken by detailed age-band[27] so also delivers projections disaggregated by age-band.

[27] The age-bands distinguished are 0-15, 16-24, 25-34, 35-44, 45-59, 60-64, 65+.

14.3 Labour supply by highest qualification held

With regard to qualifications held by the workforce, IER has built up considerable experience of working with the qualification data available in the LFS, including work for Dearing, Leitch and the UK Commission for Employment and Skills (UKCES). While a number of different approaches can be adopted to modelling qualifications, the present approach is intentionally pragmatic and eclectic, making the most of the limited data available. This section provides a brief overview, building upon the work for *Working Futures 2014-2024* and *Working Futures 2017-2027*. For more details readers are referred to Bosworth (2015a), which describes the detailed models and methods used to develop the estimates of the demand for and supply of skills (as measured by qualifications). The main difference from the previous projections is that the National Model results are now based on the times series alternative developed previously rather than the stock-flow model.

The results are internally consistent at the different levels of aggregation. The modelling of the supply side adopts the methodology previously carried out for the UKCES. It builds on the models developed for *Working Futures 2017-2027*, focussing upon both demand and supply. The present exercise focuses on the highest level of qualification held. The 'supply of qualifications' focuses on the future flows of individuals in the population with different qualification levels (based upon the Regulated Qualifications Framework (RQF) which superseded the Qualifications and Credit Framework (QCF)).

A number of the eight main levels of the RQF have relatively small numbers of individuals, which makes some of the cell sizes very small when disaggregated by gender and year of age, let alone by other dimensions in the projections. So, for the main part of the qualifications modelling, qualification levels are aggregated such that in the present work: the no qualification group comprises entry level and qualifications below level 1 from the RQF; level 1 contains low level GCSE (grade 3 and under) and equivalent; level 2 contains high grade GCSE (grade 4 and above); level 3 comprises A level and equivalent; level 4 is degree at undergraduate level and equivalent; and level 5 is postgraduate degree level and equivalent. The word equivalent means that vocational qualifications are included alongside the academic at that level.

The present work also considers the 'demand side'. This generates estimates and projections of population and active population rates by level of qualification, as well as the distribution of employment by sector, occupation and region.

This distinction between supply and demand is somewhat artificial, as the observed outcomes are the result of a combination of both demand and supply influences. The flow of individuals through qualification levels depends upon perceptions of current and future employment opportunities and wage rates, amongst other factors. Likewise, employment by qualification is the outcome of the interaction between supply and demand.

In previous rounds (e.g. *Working Futures 2012-2022*), comparisons were made between the results of this analysis and those based on the National model – a time series extrapolative approach (similar to models developed in earlier work by the authors for the Treasury (as part of the Leitch Review) and for the UKCES) – and a pseudo-cohort, stock-flow model. On balance the National model was preferred as giving more robust results. The stock-flow model although conceptually superior, appears to underestimate the possibilities for qualification acquisition for older people. The National (time series) model is the one used to generate the *Working Futures* results. For more details of the two forms of model see Bosworth and Wilson (2011a, 2011b).

The qualification data for migrants remain extremely weak despite the introduction of a separate question in the LFS about immigrant qualifications in 2011 (revised in 2014). The National model assumes, as a base line, that the reported qualifications of individuals who were not resident in the UK one year prior to the survey are representative of the flows of immigrants. Nothing is known about the qualifications of emigrants, so the qualification mix of emigrants are assumed to be the same as the UK population as a whole. While the migration data are weak, sensitivity tests in previous rounds of *Working Futures* suggest that the overall projections are not particularly affected by changes in the migration assumptions. Given the political sensitivity to the question of migration, while not as strong as it once was, it nevertheless remains an important issue which requires exploration in more detail. Separate results are produced for men and women, as well as all individuals combined (the latter can be useful where the cell sizes are small by gender).

Given that data for Northern Ireland and, to a slightly lesser extent, Wales, are subject to small sample size problems, results for the four nation states have been produced by disaggregation of the UK projections at broader age groups than for the UK as a whole. Further disaggregation of the results is made to regional level, for example, apportioning the results for England to the regions of residence. This is done by broad age group (rather than individual year of age), but small sample sizes for some regions still pose problems for the most detailed results.

As noted above, the regional qualification model produces equivalent regional results (including results all for the individual countries and regions within the UK). This model focuses upon the shares of the active population who are qualified to various levels. It covers the following main dimensions: country/region (12); gender (2); qualification level (6). The results are constrained to sum to the UK total from the national model.

The demand side results are generated through the macro model and related occupational modules, which gives benchmark information on future employment prospects by occupation. Occupation is one of the main drivers of changing patterns of employment by qualification, as different occupations tend to have very different requirements (e.g. most professional occupations require higher level qualifications as a matter of course, etc.). In addition there are often significant trends in these patterns within each occupational category which can be modelled and exploited to generate projections. The aggregate employment projections are then further disaggregated by a series of sub-models.

The occupational/qualification shares model (QUALSHARE) develops projections of qualification shares within occupations.

To reconcile the supply and demand sides, a sorting algorithm (SORT) sorts people into occupations such that the various results from the different parts of the modelling exercise are made consistent. In particular, this model is designed to reconcile the projections from the National model with those from QUALSHARE. The former can be regarded as essentially a view of supply side developments (the overall numbers of people acquiring qualifications), while the latter is more concerned with which occupations they end up in. The SORT model uses an iterative RAS procedure to reconcile the two sets of estimates, constraining the overall qualification shares from QUALSHARE to match those from STOCKFLOW, while maintaining the patterns of occupational deployment in QUALSHARE. The constraint is imposed at the 2-digit occupational level. The key dimensions are occupations (25); gender (2); qualification levels (6). SORT operates at a UK level.

Finally, there is an extended replacement demand module, which generates estimates of qualification numbers for detailed industries and geographical areas. This final module provides the mechanism whereby the implications for individual sectors and regions are developed, focussing on replacement needs. The overall results from this module are calibrated to match the main results from the benchmark projections for the UK and its constituent countries and regions which emerge from SORT and REGQUAL. Data and parameters are provided for individual sectors and regions which enable customised projections for these categories to be developed. These include aggregate qualification and age profiles for individual sectors and regions (but not cross-classified). While data limitations mean that it is not possible to ensure that these results are consistent in every respect with those from the national results, they provide reasonably robust and consistent implications at the more detailed regional and sectoral level. The key dimensions covered are occupations (25); gender (2); qualification levels (6); regions (25); sectors (22).

15 Alternative scenarios – MDM assumptions

15.1 Introduction

This chapter describes the methodology to produce alternative economic scenarios for the UK and its regions using CE's MDM-E3 model.

The purpose of the scenarios is to explore alternative macroeconomic futures and their potential to transform the labour market to 2035. The scenarios represent deviations from economic trends captured in the existing business-as-usual baseline. They operationalise assumptions about possible structural changes in the economy from an industrial perspective.

15.2 Scenarios

Three *Alternative scenarios* have been modelled. The first (*Automation*) scenario models the job losses from the adoption of labour-displacing/replacing technologies. The remaining two scenarios build on top of the first scenario, making use of identical assumptions about job destruction but differing in their assumptions about new job opportunities. For the purposes of the wider project, a further assumption/constraint in the modelling of these two later scenarios is that the effect of these transformations on the UK economy is distributional only. In other words, we assume that total demand for labour (measured by the total number of jobs) is relatively unaffected. Instead, there are, ultimately, only shifts of jobs from one sector or occupation to another. This allows us to highlight potential changes in the nature of work, with possible winners and losers from the transition. We thus produce scenarios that affect the composition of UK employment, rather than its size.

The rationale for this approach is that the evidence on jobs at risk of automation (i.e. potential losses) is reasonably well-explored, because it amounts to assessing the task/skills content of existing roles. On this evidence alone, the implication is of dramatic job losses with relatively little to say about the potential scale of new jobs created. However, historical experience suggests that economies and labour markets have usually been able to adjust to such technological shocks, which also offer many opportunities for job creation. For example, the process of investment in technology is itself likely to create more high skilled jobs, as will the operation and maintenance of these new technologies.

In the absence of evidence to say how large these opportunities might be, the scenarios impose the assumption of no net change in employment between the scenarios and the *Baseline projections* by 2035. In effect, this creates scenarios of how the UK economy (and, in turn, its demand for jobs and skills) might change focusing upon the implications for the structure/composition of employment in 2035 rather than how the overall size of the labour market may change. This provides results which emphasise, changing jobs *requirements* (re-composition/reorientation) rather than changes in the total *number* of jobs.

The three scenarios are as follows:

1. ***Automation scenario***, a scenario in which the adoption of automation technologies accelerates to reach its maximum potential. All activities performed by humans and feasibly replaced by technologies are automated. This involves investment in productivity-enhancing automation technologies. However, no intervention takes place to address the substantial scale of job losses, leading to high levels of technological unemployment. This scenario reveals the sectors in which jobs are most at risk across the economy, as the starting point for the other two scenarios.

2. ***Technological opportunities scenario***, a scenario with accelerated technological change also creating new jobs to support economic growth in the following ways:
    - improved management of technologies (such as data science, engineering and customer support for personal applications and technology solutions), leading the UK to reap various competitive advantages in core economic sectors[28]
    - the transition to a low-carbon economy (including increased investment in renewables and low-carbon or zero-emissions solutions, as well as stronger enforcement of regulations and standards to comply with climate commitments)
    - the provision of better-quality education, health and care services, in which workers are especially difficult to replace with technology or, in the case of education, critical to the development and transformation (reskilling) of the workforce
3. ***Human-centric scenario***, in which technological displacement places a relatively greater premium on non-cognitive or 'soft' skills, which are harder for automation to replicate and therefore less susceptible to replacement. In such a scenario, the UK places greater emphasis on high-quality provision of education, healthcare and residential and social care services, while still making some investment towards realising technological opportunities and environmental ambitions (albeit more modestly than in the *Technological opportunities scenario*). The intent behind this scenario is to provide a contrast to the *Technological opportunities scenario*. Rather than afford opportunities for technology to create/enhance jobs, this *Human-centric scenario* places more emphasis on the kinds of jobs that are less susceptible to technological change. The scenario thus represents a doubling down on skills unique to humans.

15.3 Impacts of automation

The motivation for the modelling exercise is the prospect of large-scale automation, to an extent and at a pace that could lead to widespread economic change. Automation puts certain jobs at risk, and this is modelled identically in all three *Alternative scenarios*. The *Technological opportunities scenario* and *Human-centric scenarios* then differ in how automation might create alternative employment opportunities in place of these lost jobs.

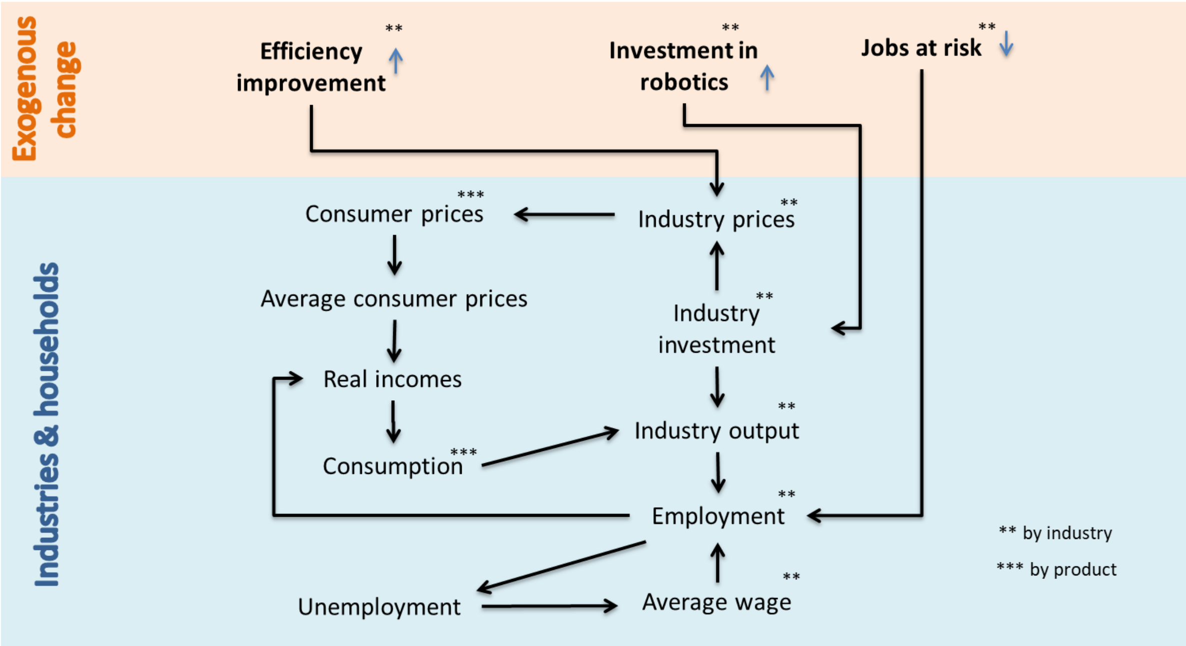
Drawing on the available evidence, we have considered the following direct impacts of automation:

1. automation renders at least some jobs obsolete, which reduces real incomes and thus consumption and output (further reducing employment)
2. new automation technologies require investment, which adds to aggregate demand
3. efficiencies (productivity improvements) arising from the new automation technologies alter production processes and prices

[28] OECD (2017, 2019) analysis identified various UK competitive advantages while noting that these may not be sustained in an age of increasing globalisation and international competition. With new technological opportunities, these advantages may be sustained over the longer term.

Figure 15.1 shows the logic of these impacts in MDM-E3, with the three initial impacts at the top of the diagram marked as exogenous changes to be inserted into the model. We discuss each of these assumptions in detail below.

Figure 15.1: Channels of automation impact



Source(s): CE

15.3.1 Jobs at risk

Previous CE modelling of automation relied principally on PwC (2017) to inform estimates of jobs at risk. In that analysis, PwC (2017) employed a task-based approach to identify jobs vulnerable to automation. PwC's analysis suggested that some 30% of UK jobs were at potential high risk of automation by the mid-2030s. This share is somewhat lower than those estimated for the US and Germany but higher than for Japan. This is mainly due to the UK economy being more services-based with fewer automatable jobs than other European countries but more than in Asian and Nordic countries (PwC, 2018). As PwC (2017) noted, this analysis still depends on what automation (AI/robotics) technologies might be capable of in the future.

PwC (2018) took this analysis further to consider this automation as occurring in three waves:

1. **Algorithms**: The first (and current) wave of automation that involves straightforward computational tasks on structured data. This wave also includes more recent commoditisation of big data and machine learning techniques.
2. **Augmentation**: This wave is expected to alter many tasks more drastically, especially those which are routine and repeatable. Information entry and exchange will be increasingly automated while advances in AI could lead machines to develop certain algorithms themselves. While robots are not expected to become fully autonomous during this wave, technological advances are expected to substantially augment the scale and efficiency of automated tasks.

3. **Autonomy**: The third and final wave is expected to emerge at an economy-wide level (some technologies are already in the pilot stage) in the 2030s, further automating tasks involving physical labour and significant manual dexterity. During this wave, computing will evolve from being able to analyse structured data (as in the first wave) to being able to respond and make decisions in the face of dynamic situations.

In the UK, 2% of jobs could be at potential high risk of automation from the first wave (algorithms). The augmentation wave will raise this share to 20%, while the final autonomy wave will increase this to 30%.

PwC's (2021) most recent estimates project that automation may displace a more modest 2-2.5 million jobs in the UK by the 2030s (compared to 10 million jobs suggested by PwC's earlier work in 2017 and 2018). Using this latest finding, we modelled the following (aggregate) pattern of initial job losses (as percentage reductions from the baseline):

- 2022: 0.5% (representing the algorithms wave)
- 2030: 4% (augmentation wave)
- 2035: 6% (autonomy wave)

The pattern of job losses by sector follows PwC's earlier (2017 and 2018) analyses.

15.3.2 Investment costs of new automation technologies

Automation technologies incur investment costs which must be borne by the sectors in which the automation occurs. This additional investment contributes to aggregate demand while the deployment of automation technologies is underway. Thereafter, firms within those sectors incur annual maintenance costs.

While there is substantial heterogeneity in technologies, and thus investment costs, our evidence review suggests the following purchase costs based on information from the International Federation of Robots (IFR) (2020) and Robotiq (2021):

- services automation: £50,689 per unit (in 2019 prices), derived by dividing the sales value by the number of units sold, as reported by the IFR (2020)
- industrial automation: £101,378 per unit (in 2019 prices), derived by applying a cost differential of two to the above cost of services automation, based on analysis by Robotiq (2021).

We assume that these costs will fall over time due to production efficiencies at a rate of 5 per cent pa over the forecast period. This is in line with short-term forecasts by the IFR (2020) which suggest implied unit costs falling over 2020-23 (the period covered by their analysis) at 3.5-5.8 per cent pa for different types of services automation. In comparison, an independent analysis by Statista (2021) estimated the cost of industrial automation to have fallen by about 5 per cent pa over 2014-17 and to be expected to fall more rapidly at 10 per cent pa over 2017-25. A 5 per cent pa rate is thus consistent with existing findings while being at the conservative end for future production/cost efficiencies.

A combination of diversity in future technologies (e.g. industrial robots versus AI) and uncertainty (about the future nature of these technologies) makes it difficult to establish a firm estimate of maintenance costs. Nevertheless, such an assumption is necessary as part of a macroeconomic modelling exercise. Here, we assume that annual maintenance costs of the new automation technologies will be 10 per cent of the purchase cost. This figure is broadly consistent with Kopacek (1993) and lies between implied figures of 20 per cent, as in Zhao *et al*., (2021), and of 4 per cent, as in Perzylo *et al*., (2019). The final results are not, in any case, sensitive to this assumption.

Based on Acemoglu and Restrepo (2020), we assume a replacement rate of 3.3 workers per unit.

15.3.3 Productivity improvements

The final input assumption to the job-replacement side of the *Automation scenario* is the additional productivity conferred on those who remain in the workforce. This reflects a potential increase in the economy's overall productive capacity due to technology uptake replacing the least productive workers and labour-technology complementarity which enhances the productivity of the remaining workers. It is to be distinguished from the real productivity of a unit of labour-replacing technology compared to a worker.

Here, we assume that the transformed workforce will become 50 per cent more productive by 2035 compared to a business-as-usual baseline. We consider this to be a conservative assumption given the replacement rate of 3.3 from Acemoglu and Restrepo (2020) and the fact that technologies do not have the same physical limits as humans.

15.4 Creation of new job opportunities

While automation is likely to lead to large-scale job displacement, it is also possible for new job opportunities to arise, either complemented by the technologies or because of a renewed emphasis on skills not (so) susceptible to replacement. In other words, technologies may not be entirely labour-replacing or direct substitutes for workers: they can be labour-augmenting or complementary to the human workforce.

The modelling assumptions concerning new job creation concern:

- how new jobs will be created
- the absolute number of new jobs
- the sectoral distribution of those new jobs

15.4.1 Support for job creation

This section describes our approach to generate the two scenarios under the aforementioned constraint that total UK employment is similar in the scenarios compared to the baseline. In doing so, we consider how the composition, rather than the size, of UK employment might change over time.

In contrast to the evidence base on jobs at risk, the potential for job creation through automation remains uncertain and under-explored. Automation could augment the existing labour force and/or increase the value and output of jobs that are more immune to automation.

We assume that new job opportunities are generated from new investments, in addition to investments in automation technologies.

New investment will be targeted at specific industries where new opportunities are expected to emerge, and the number of new jobs is determined by the industry-specific employment multiplier of investment (i.e. the number of jobs supported by each £1m of investment). These new jobs may be within the same industries where jobs are displaced by automation or in a different industry entirely.

In addition, investment could be in the form of direct investment by firms in equipment, recruitment and training or contribution to a government scheme to prepare workers with the right skills for the future of work.

We assume that investment is entirely funded by the private sector for market sectors, spurred by a combination of higher financial return (from the technologies/opportunities becoming viable) and policy/regulatory requirements (especially with respect to decarbonisation). For a small number of service sectors where provision is shared between the government and non-profit institutions serving households (NPISH), the funding contribution is determined by the current split in demand fulfilled by these providers.

15.4.2 New job opportunities

Considering the three major transformations described as part of the scenario narrative, we assume three corresponding types of new job:

- automation-driven: jobs in *Service industries*, especially *IT, Scientific research, Education*, and *Health* and *Social work*, to complement the deployment and use of technologies, in line with PwC (2021), WEF (2018) and McKinsey (2017)
- decarbonisation-driven: jobs in 'green' occupations such as scientific researchers, machine operators and repairers, agricultural producers and regulatory professionals, to support more concerted decarbonisation efforts, based on Sofroniou and Anderson (2021)[29]
- population-serving: jobs in services predominantly provided by the government to serve the population, i.e. *Healthcare* and *Residential and social care*, to provide greater provision for an ageing population, as well as education and training to help develop and retrain the future workforce with the necessary skills.

Table 15.1 shows the industries that emerge from this assessment, noting that some fall into more than one of the three groups mentioned above.

Table 15.1 Sectors with potential for new job opportunities

Broad sector	Industry	Automation-driven	Decarbonisation-driven	Population-serving
Primary sector & utilities	Crop & animal products		X	
	Forestry & logging		X	
	Mineral extraction		X	
Manufacturing	Food & drink products		X	
	Paper		X	
	Chemicals		X	

[29] For the modelling assumptions, we made a qualitative assessment of which industries these occupations most closely map to, based on whether they are likely to account for a large proportion of the workforce.

Broad sector	Industry	Automation-driven	Decarbonisation-driven	Population-serving
	Rubber & plastic		X	
	Metal products		X	
	Computers		X	
	Electrical equipment		X	
	Machinery		X	
	Other manufacturing & repair		X	
Construction	Construction		X	
Trade, accommodation & transport	Land transport		X	
Business & other services	IT services	X	X	
	Financial & insurance services	X	X	
	Legal & accounting	X	X	
	Architecture & related	X	X	
	Other professional services	X	X	
	Arts & entertainment		X	
Non-market services	Public administration & defence		X	
	Education	X		X
	Health	X		X
	Residential & social care	X		X

Source: CE's assessment

In the *Technological opportunities scenario*, the extent to which new jobs are created in an industry is determined by the following factors (with the outcome being equally influenced by each):

- industries in which the UK has a comparative advantage (as judged by higher projected future demand for their output in the baseline) are likely to see stronger job creation
- industries in which the UK is likely to develop a comparative advantage (as judged by higher future investment needs or ambitions in the baseline) are likely to invest in more jobs to reap these future gains
- industries at low risk of automation, requiring skills which are difficult to replace with technology, provide a new source of job opportunities, leading to growth in provision in these sectors.

In contrast to the *Technological opportunities scenario*, in which a third of the investment is expected in public service sectors, in the *Human-centric scenario*, 60 per cent of the investment is expected in *Public service sectors* (including *Education*, *Health*, and *Residential and social care*), which is then projected to bolster employment in those sectors. This proportion is similar to the current market share of private provision (by NPISHs) in these sectors, which serves as an upper limit for the assumption.

16 Alternative scenarios – Occupational adjustments

16.1 Data Issues

There are many conceptual challenges facing us when deciding what adjustments to occupational shares are appropriate in the *Alternative scenarios*. There are 412 occupational Unit Groups in the SOC2020 classification. Very little of the available evidence provides information at this level of detail. Clearly, not all these groups are expected to follow the same path. The evidence from socio-economic trends and other research suggests that the employment level of some occupations may be increased, whilst others will decline or not experience major changes.

To identify the occupations to be adjusted, first, it was necessary to conduct a review of international and updated sources to consider possible changes in occupational employment patterns. There is a wide range of forecasting exercises around the world that provide such evidence. We focus our analysis on well-known sources of information. These include the US O*NET system, recent labour market projections conducted by the World Economic Forum (2020) for a variety of countries, and numerous papers related to the future of work (Lund *et al*., 2021; Healy *et al.*, 2017; BLS 2022).

In addition, we have conducted a historical trend analysis for 2011-2021 based on LFS data, as well as considering the evidence on recent trends in employers' requirements. We have also drawn upon other work conducted as part of the present project.

A second issue arose once the main sources of information were selected. Each of these sources highlighted different occupations/roles which are expected to see significant increases or decreases in demand over the next decade or two. Most of these sources use very different occupational classifications and different disaggregation levels to the Unit groups of SOC2020. For instance, the O*NET uses a detailed occupational classification based on the US SOC. Consequently, it was necessary to standardise the different labour market projections to the SOC2020 at the four-digit level. To do so, we have mapped these occupations into the SOC2020 using CASCOT[30] and manual inspections. This enables us to identify those UK occupations that are likely to experience a significant change to the trends in their shares of employment over the period to 2035.

We have selected 44 occupations (out of the 412 occupations distinguished at the SOC2020 4-digit level) as likely to experience significant job losses between 2021 and 2035. We have also identified 52 other occupations which are expected to experience significant increases in employment share over the same period.

The rationale behind selecting the adjustments made for these occupations is based on the following considerations/drivers that were identified in the literature and empirical review:

- Occupations at risk of automatisation
- High-tech intensive occupations

[30] Computer Assisted Structured Coding Tool (CASCOT) was developed by IER. It is a computer program designed to make the coding of text information to standard classifications simpler, quicker and more reliable. Details can be found at: https://warwick.ac.uk/fac/soc/ier/software/cascot/

- Green occupations
- Ageing of the population and care and health related jobs
- Labour market flexibility
- Rising female labour market participation
- Trend analysis of LFS data for 2011-2021
- Trend analysis of vacancy data 2019 – 2021.

Further details are provided in the *Alternative scenarios* report. Once the occupational groups were selected, and to ensure intuitive results, we revised case by case (occupation by occupation) and made the corresponding adjustments manually.

A third issue arose when making these manual adjustments. The results of the adjustments for the *Alternative scenarios* need to be constrained to match the E3ME results by industry, gender, status and region. For this reason, it was necessary to manually evaluate each occupational group, since adjusting the share of one occupation will also affect the other occupational groups. In some cases, the initial output was not economically intuitive.

For instance, suppose we wished to increase the share of Health Professionals from 14 to 20 per cent. This means that we would need to reduce the share of other occupations by 6 percentage points. When we apply this decrease proportionally distributed across occupations, the results might be counterintuitive. Some occupational groups might end up with negative or very small values in the employment level. All these cases were evaluated, and corresponding manual adjustments were made.

Glossary

ABI	Annual Business Inquiry
ABS	Annual Business Survey
AES	Annual Employment Survey
BRES	Business Register and Employment Survey
CE	Cambridge Econometrics
CoP	Census of Population
CVM	Chained volume measure
DfES	Department for Education and Skills
DIUS	Department for Innovation, Universities and Skills
DTI	Department of Trade and Industry
ESA95	European System of (National) Accounts, 1995
GDP	Gross Domestic Product
GDPO	Gross Domestic Product (output)
GORs	Government Office Regions
GVA	Gross Value Added
IER	Institute for Employment Research
IoP	Index of Production
ILO	International Labour Organisation
LAD	Local authority district
LEC	Local Enterprise Council
LEFM	Local Economy Forecasting Model
LEP	Local Enterprise Partnership
LFS	Labour Force Survey
LLSC	Local Learning and Skills Council
LSC	Learning and Skills Council
MAFF	Ministry of Agriculture Food and Fisheries
MDM-E3	Multi-sectoral Dynamic Model
NES	New Earnings Survey
Nes	not elsewhere specified
n.e.c.	not elsewhere classified
NOMIS	National On-line Manpower Information System
ONS	Office for National Statistics
OPCS	Office of Population Censuses and Surveys

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