UK Skills Mismatch in 2030

Industrial Strategy Council

Technical Appendix

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About the Industrial Strategy Council

The Industrial Strategy Council ('the Council') is an independent non-statutory advisory group established in November 2018. It is tasked with providing impartial and expert evaluation of the government's progress in delivering the aims of the Industrial Strategy. Its membership is comprised of leading men and women from business, academia and civil society.

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1. Introduction to Approach

This appendix provides details in the following sections on the methodology employed in our research:

1. **Introduction to modelling approach** – A high-level description of the modelling approach.
2. **Skills taxonomy for occupations** – The definition of 'skills' used for the purpose of this paper and the sources leveraged.
3. **Skills demand in 2030** – The methodology used to estimate the types of skills and the number of occupations required in the UK in 2030, given trends such as automation, an ageing population, and the shift away from non-renewable energy sources.
4. **Skills supply in 2030** – The methodology used to project the skills that workers will hold in 2030 given the skills in the workforce today, on-the-job training and the inflows and outflows of workers.
5. **Calculating the baseline 2030 skills mismatch** – An explanation of the 'market clearing' model created for the purposes of this paper, including how skill mismatch scores were calculated.
6. **Sensitivity testing** – An explanation of the sensitivities tested on the baseline model, including the impact of immigration and regional immobility.

This paper draws conclusions on 'skills' but it is based on data for 'occupations'. Occupational data is a useful descriptor of different skill 'bundles'. According to Office for National Statistics (ONS) categorisation, there are 369 occupations in the UK. Every job in every firm for every individual is slightly different, but occupations are the common unit of currency with which it is possible to compare different jobs across different firms performed by different individuals. Consequently, each of the 369 occupations is sufficiently different from the others to be distinct. It is clearly possible for the same person to fill roles in different occupations, either directly by deploying their existing skills, or after an amount of reskilling. However, there are significant limits to the workforce's fluidity across occupational boundaries.

Using occupations as a unit of currency gives us an indication into what skills are required in the economy, but it does not give us perfect information on the individuals who hold those occupations. Occupations require a 'package' of skills for individuals to be able to perform them effectively. An individual may fill a role without being 100% proficient in all the skills that the occupation requires. On the other hand, an individual may be able to perform that skill to a higher level than the occupation allows. Or a person may have a number of other skills that they are not able to apply in that occupation.

This paper seeks to measure 'skills mismatch'. In its simplest form, a skills mismatch is the difference between a worker's 'skills bundle' and the skills that are required to perform their job effectively. Skills mismatch includes both under-skilling and over-skilling, and a person can be both at the same time. A worker could be over-skilled relative to requirements in some areas, yet under-skilled in other areas.

There are many reasons why such mismatches might occur, such as the following:

- demand for skills increases faster than supply, or skills supply falls faster than demand
- the rate of return on investment in training is low or unclear
- companies have difficulties attracting and retaining staff
- imperfect labour mobility and/or imperfect information hampers job matching
- labour market regulations make hiring and firing hard in instances of poor job match

Figure 1 provides an overview of the basic modelling approach. Broadly, the model operates by doing the following:

1. Estimating the demand for skills in 2030
2. Estimating the supply of skills in 2030
3. Creating a ‘mismatch score’ for every potential transition between source occupation and target occupation
4. Allocating workers to target occupations based on a ‘market clearing’ model that optimises for the lowest possible total mismatch in the economy

The model assumes full employment, so all workers are allocated to a job regardless of the scale of the mismatch. The modelling approach and assumptions mean that the estimated skills mismatch is incremental to the current (2017) skills mismatch.

Figure 1: Overview of modelling approach

Methodology: The 'market-clearing' model attempts to quantify an overall measure of skills mismatch in the economy in 2030

Skills demand

- For workplace skills, we use MGI data on **the likely change in skill requirements based on several trends**:
  - automation adoption
  - rising incomes
  - an ageing population
  - increasing technology spend
  - transition to renewable energy sources
  - infrastructure spend
- For knowledge and qualifications, we assume demand will remain constant between 2017 and 2030

Skills supply

- For workplace skills, we assume workers have the level of skill required by their occupation in 2017:
  - We apply an **uplift in 'basic digital skills'** to account for improvement in existing workforce and the fact that incoming workers will be more proficient than retirees
- For knowledge and qualifications, we assume the level of workers is consistent with the level *required* by occupations in 2017 (such that the 2030 skills mismatch is incremental to 2017)

Measuring 'mismatch'

- We create a **composite score for skills mismatch** that takes the average mismatch for **qualifications, knowledge, and workplace skills**
- The mismatch score for each element is calculated as:

*(under-skilling score – over-skilling score) * (under-skilling score + over-skilling score)*

Market-clearing model

- Our model **compares the mismatch score for every possible transition** from source job to target job (385,000 in total)
- It then optimises the best possible combination of transitions such that the **overall mismatch for the economy as a whole is minimised**
  - For example, it may be optimal for the economy that worker A moves to job B, and worker B moves to job C, *rather than* worker A moves to job C and worker B 'remains' in job B

Source: MGI

2. Skills taxonomy for occupations

2.1. Explanation of taxonomy

The modelling uses a bundle of three different types of skills:

- **Knowledge** – content or subject matter knowledge required to perform an occupation, for example, economics and accounting.
- **Qualifications** – typical level of qualification required by an occupation as defined in one of five 'zones' used by O*NET[1] to classify qualification level, for example, zone 2: occupations that require a high school diploma.
- **Workplace skills** – learned capabilities that are applicable in a workplace setting, for example, problem-solving skills, basic digital skills.

This taxonomy differs from that used by O*NET, which focuses on knowledge, abilities (enduring attributes of the individual that influence performance), and skills (developed capacities that facilitate learning). This is because O*NET provides this data at the occupation level, but our demand forecasts rely on skill and ability data at the task level. Rather than using the occupation-level skills and abilities data from O*NET, this paper uses McKinsey Global Institute (MGI) classification of each task into one of 25 'workplace skills' (see below).

A taxonomy of 25 workplace skills provides sufficient granularity of skills mismatch to policy makers and also avoids double-counting – and therefore over-weighting – of certain O*NET skills and abilities that are very closely matched. For example, our taxonomy would highlight under-skilling in 'basic literacy and numeracy' for one occupation transition. However, if our model were based on all 86 O*NET skills and abilities, it would cause us to overstate the under-skilling gap, given that there are at least 7 skills and abilities related to basic literacy and numeracy (reading comprehension, writing, written comprehension, written expression, information ordering, mathematical reasoning and number facility).

The other benefit of using workplace skills (as opposed to O*NET's 'skills' or 'abilities') is that they are all actionable by employers, individuals, or policymakers. For example, O*NET abilities include inherent capabilities such as 'night vision', which arguably cannot be learned. It also includes enduring attributes that can only be influenced indirectly, for example, 'speed of closure' (the ability to combine

[1] The Occupational Information Network (O*NET) database is a comprehensive set of information on key attributes and characteristics of workers and occupations. It was developed under the sponsorship of the US Department of Labor/Employment and Training Administration (USDOL/ETA) through a grant to the North Carolina Employment Security Commission. See https://www.onetonline.org/

information into meaningful patterns) can best be influenced through improving the workplace skill (from our taxonomy) of ‘problem-solving’.

2.2. Methodology of taxonomy

2.2.1. Knowledge

For knowledge, we have used data from O*NET which classifies knowledge into 33 different types. For every occupation within its database, O*NET assigns (i) a level score, and (ii) an importance score.

O*NET defines the scores for each occupation using survey data. It asks respondents within that occupation to define the level required and the importance of each knowledge type to complete their occupation. Level is scored between 1 and 7, and importance is scored between 1 and 5.

For example, an actor has a mathematics level of 1.38 and a mathematics importance score of 1.7. An actuary has a mathematics level of 6.66 and a mathematics importance score of 4.97.

Box 1: O*NET knowledge types

- Administration and Management
- Psychology
- Clerical
- Sociology and Anthropology
- Economics and Accounting
- Geography
- Sales and Marketing
- Medicine and Dentistry
- Customer and Personal Service
- Therapy and Counselling
- Personnel and Human Resources
- Education and Training
- Production and Processing
- English Language
- Food Production
- Foreign Language
- Computers and Electronics
- Fine Arts
- Engineering and Technology
- History and Archaeology
- Design
- Philosophy and Theology
- Building and Construction
- Public Safety and Security
- Mechanical
- Law and Government
- Mathematics
- Telecommunications
- Physics
- Communications and Media
- Chemistry
- Transportation
  Biology

2.2.2. Qualifications

For qualifications, we have used data from O*NET for qualification 'zones' which define the qualification requirement for each occupation. O*NET uses 5 zones of qualifications and bases its data on level of education required, typical level of on-the-job training, and related experience required to do the work.

We have used O*NET zones rather than ONS qualification levels because both the workplace skills and knowledge skills are based on O*NET. O*NET zones also include a measurement of on-the-job training/preparation, unlike the ONS classification which mainly relies upon qualification levels.

The five O*NET job zones are:

- Zone 1: Occupations that need little or no preparation. Some require a high school diploma and no previous work-related skill
- Zone 2: Occupations that need some preparation. All usually require a high school diploma
- Zone 3: Occupations that need medium preparation. Most occupations require training in vocational schools, related on-the-job experience or an associate degree
- Zone 4: Occupations that need considerable preparation. Most of the occupations require a four-year bachelor's degree
- Zone 5: Occupations that need extensive preparation. Most of the occupations require post-graduate qualifications

2.2.3. Workplace skills

For workplace skills, this paper leverages the MGI skills taxonomy developed for *Jobs lost, jobs gained* and *A future that works: Automation, employment and productivity*.[2] MGI conducted an analysis of work activities for each occupation using data published by the World Bank and O*NET from the US Bureau of Labor Statistics. The O*NET database breaks down about 800 occupations into more than 2000 activities. MGI then classifies these activities into one of 25 'workplace skills' required by employees to perform that task.

[2] MGI (2017). *A future that works: Automation, employment, and productivity*. Retrieved from: https://www.mckinsey.com/featured-insights/digital-disruption/harnessing-automation-for-a-future-that-works; MGI (2017) Jobs lost, jobs gained: Workforce transitions in a time of automation https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages

Figure 2: Workplace skills used in the modelling

‘Workplace skills’ are defined by tagging occupational tasks into one of 25 categories

Category	Workplace skills	Description
Physical and manual skills	General equipment operation and navigation	Operating simple and familiar equipment, such as a car or a pneumatic press
	General equipment repair and mechanical skills	Being able to identify and fix issues related to simple and familiar equipment, such as a car or a pneumatic press
	Craft and technician skills	Performing any kind of a physical craft or manufacturing such as, carpentry or tailoring
	Fine motor skills	Manipulating objects and tools in situations where precision of movement is crucial for proper execution of the task
	Gross motor skills & strength	Lifting, moving, and manipulating objects in situations where precision of movement is not required
	Inspecting and monitoring	Using vision to monitor areas or activities, or to inspect good or products
Basic cognitive skills	Basic literacy, numeracy, and communication	Reading, writing, and mathematical abilities at the junior school level in one's native language
	Basic data input and processing	Carrying out basic data-related tasks such as sorting, processing based on a pre-defined sequence of steps, or converting from one medium to another
Higher cognitive skills	Advanced literacy and writing	Being able to comprehend and generate complex text
	Quantitative and statistical skills	Evaluating numerical data, producing summary reports, and calculating operational and financial metrics
	Critical thinking and decision making	Applying logical reasoning to assess a situation and decide on a sequence of steps to accomplish a given goal without a clear pre-determined procedure
	Project management	Ensuring projects meet deadlines and deliverables, prioritising next steps, and coordinating stakeholders
	Complex information processing and interpretation	Identifying, evaluating, and using multiple sources of quantitative and qualitative information to extract and interpret key insights
	Creativity	Developing novel solutions to problems or producing items and works of artistic value

SOURCE: MGI

‘Workplace skills’ are defined by tagging occupational tasks into one of 25 categories

Category	Workplace skills	Description
Social and emotional skills	Advanced communication and negotiation skills	Conveying one's thoughts in a structured manner in order to persuade or influence others
	Interpersonal skills and empathy	Being able to work effectively with others, including interpreting and reacting to others' unstated emotions
	Leadership and managing others	Inspiring and leading a group of people or an organisation to achieve a common goal
	Entrepreneurship and initiative-taking	Proactively taking action to identify and solve existing issues or to create new opportunities
	Adaptability and continuous learning	Personal initiative to keep updating one's skills and knowledge to keep up with changing requirements
	Teaching and training others	Helping others acquire or improve skills, abilities, and knowledge; and influencing their mindsets
Technological skills	Basic digital skills	Using computers to execute a limited set of pre-defined tasks such as operating basic applications and sending e-mail
	Advanced IT skills and programming	Installing and maintaining computer software and hardware, and using programming to automate repetitive tasks or enable new tasks
	Advanced data analysis and mathematical skills	Applying advanced methods of data analysis (statistics, machine learning) to extract insights from large amounts of quantitative data
	Technology design, engineering, and maintenance	Designing new technology based on existing scientific research; testing, implementing, maintaining, and using the technology
	Scientific research and development	Developing and testing specific hypotheses to further scientific research

Source: MGI.

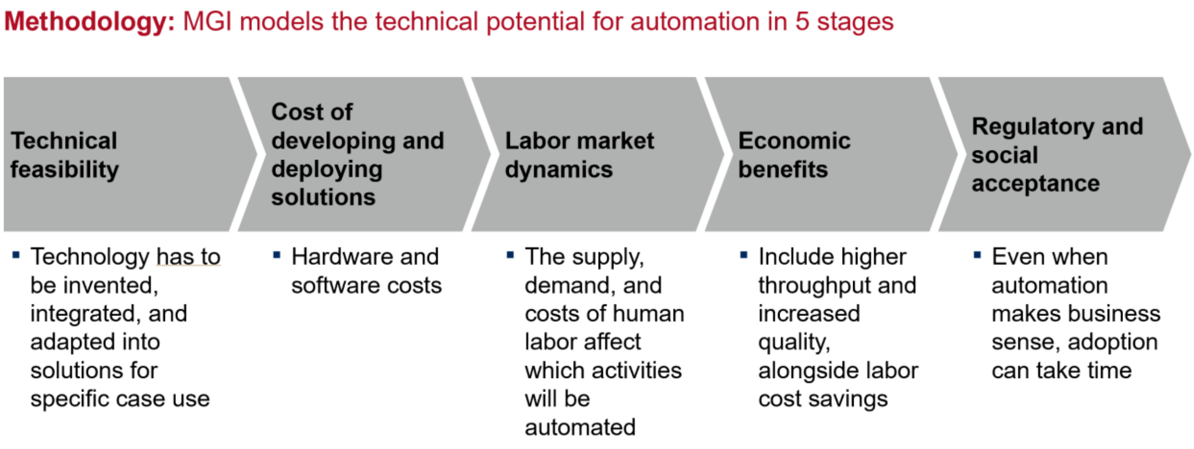
3. Skills demand in 2030

This adapts the methodology and findings in the MGI report *Jobs lost, jobs gained*.[3] A full methodology of that work is detailed in its technical appendix. In summary the modelling approach is to use macroeconomic trends, such as automation and an ageing population, to model shifts in the occupational mix and changing skill requirements within occupations.

3.1. Automation of tasks

MGI models the technical potential for automation in the global economy and projected adoption rates for the UK using databases published by the World Bank and O*NET. MGI has determined the performance capabilities needed for each activity based on the way humans currently perform them. The paper assesses the automation potential of each activity, then maps them into one of the workplace skills categories described above. ‘Automation potential’ is assessed not only as technical feasibility but also the likelihood of adoption by 2030. This is measured in five stage-gates (see Figure 3): technical feasibility, cost of developing and deploying solutions, labour market dynamics (for example, cost of labour), economic benefits, and regulatory and social acceptance. This framework is informed by academic research, internal expertise, and industry experts. This paper focuses on 2016–30, and thus takes the automation adoption percentage through to 2030.

Figure 3: Measuring automation potential



Source: MGI

[3] MGI (2017). *Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages*. Retrieved from: https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages

In *Jobs lost, jobs gained*, an assumption is made that each work task that could be automated will result in proportional job loss. For example, if 10% of current work hours in an occupation will be automated, then 10% of jobs in that occupation will be displaced. To calculate the work hours automated, the automation adoption percentage is multiplied by the size of the labour force in 2030. The size of the 2030 labour force is estimated using population projections from the United Nations, labour-force participation projections from the International Labour Organization, and the natural unemployment rate for OECD countries.

3.2. Other trends affecting the demand for jobs

Beyond automation, the MGI report also projects demand for jobs from other macro trends, on a country-by-country basis. These trends were selected from a shortlist of 20 after initial high-level sizing calculations. We have adapted the UK-specific projections for the purpose of this paper.

The trends are modelled independently. They are used to estimate potential labour demand, using estimated relationships with factors such as GDP per capita. Of course, whether this potential is captured depends on choices and investments made by economic agents.

The approach does not factor in supply and demand dynamics and feedback from factors such as changes in wage levels. The approach does not include new industries and occupations that could exist in the future, although studies have shown that, on average, 0.5% of the annual workforce has been working in ‘new jobs’ over the past couple of decades. Nor does the approach model changes in work structure, such as the growth of the ‘gig’ economy.

Where drivers include tradeable goods and services, MGI’s model uses data from the International Trade Organization and IHS Global Insight to model level of imports and exports. However, this is kept constant up to 2030 as shifts in globalisation are beyond the scope of the model.

Where trend projections include a per capita metric, population growth through to 2030 is based on projections from the United Nations. Where trends are modelled based on GDP growth, the McKinsey Global Growth Model (GGM) projections are used.[4]

Where changes in labour demand are generated by changing spending patterns, the general approach for the number of jobs created – incremental to 2014 levels – is captured by the following formula:

[4] The GGM is a global macroeconomic model that tracks long-term economic trends and generates projections under a range of scenarios. For the inputs to our labour-demand modelling, we use the GGM’s baseline scenario where available.

Net new jobs =

(2030 spend per capita x 2030 population x 2030 input–output multiplier)

- (2014 spend per capita x 2014 projected population x 2014 input–output multiplier)

Input–output multipliers are taken from McKinsey input–output tables based on source data from the World Bank Input–Output Database. Both direct and indirect job multipliers are used although, to avoid double-counting, indirect drivers are not considered on sectors that have been modelled as independent trends, for example, health care, education, and construction.

3.3. Methodology for calculating each labour demand driver

- **Rising incomes and consumer spending.** A cross-sectional univariate regression is applied using GDP per capita in 2014 as the independent variable, and 2014 consumption per capita by category (consumption of: accommodation, food services, automobiles, clothing, financial services, food, household goods, leisure goods, leisure services, and utilities) as the dependent variable, and estimated across the sample of 46 countries used in the MGI Future of Work model. Coefficient estimates are used to project consumption spending per capita by category in 2030, based on GDP per capita projections. This per capita projection for 2030 is then multiplied by a 2030 job multiplier, along with projections for the 2030 population, to calculate the number of jobs in 2030.

  The 2030 job multiplier is calculated by adjusting the 2014 job multiplier for projected productivity gains from factors other than automation. As well as using direct job multipliers, indirect multipliers are used to capture demand created in other sectors that supply to the sectors in question. Drivers related to education spend are sized separately from the rest of consumer spending, given the differences between countries in funding models for these sectors. For instance, for the trend in education jobs, MGI models the relationship through univariate regressions on student–teacher ratios and gross enrolment rates across different education levels, using 2014 data across the sample of 46 countries. Coefficient estimates are used to project jobs in 2030, and indirect job multipliers are used to capture jobs created indirectly in other sectors.

- **Ageing population.** A bivariate linear regression is applied to each of the 46 countries sampled using (i) GDP per capita in 2014 and (ii) share of population over 65 in 2014 as the independent variables, and health care professionals per 1000 people in 2014 as the dependent variable. The coefficient estimates are used to predict the number of health care professionals per 1000 of the UK population in 2030. A productivity-adjusted indirect job multiplier is then applied to estimate the job creation in sectors other than health care.

- **Development and deployment of new technology.** A univariate linear regression is applied using GDP per capita in 2014 as the independent variable and each category of IT spend per capita (includes consumer and enterprise spending) in 2014 as the dependent variable. The resulting spend per capita is then multiplied by productivity-adjusted direct and indirect job multipliers to calculate the impact of rising technology spend on the number of occupations.

- **Infrastructure investment**. A univariate linear regression is applied to GDP per capita as the independent variable and infrastructure spend per capita as the dependent variable. The estimated spend per capita in 2030 is then multiplied by productivity-adjusted direct and indirect job multipliers to calculate the effect on number of occupations.

- **Residential and commercial buildings**. A similar approach is taken to that for infrastructure investment. A univariate linear regression is applied to GDP per capita as the independent variable and per capita spending on residential and commercial buildings as the dependent variable. The estimated spend per capita in 2030 is then multiplied by productivity-adjusted direct and indirect job multipliers to calculate the effect on number of occupations.

- **Energy transitions and efficiency.** This driver captures job creation caused by the shift in mix of electricity generation. The increase in jobs due to overall increase in demand for power is already captured in the consumer spending driver. Here, MGI focuses only on the former, using McKinsey-modelled scenarios for gigawatt capacity in 2030 in each country. These were multiplied by a jobs-per-gigawatt multiplier across manufacturing, decommissioning, fuels, construction and installation, operations and maintenance by energy type.

3.4. Impact of each driver

- **Rising incomes and consumption** – UK consumption is forecast to grow by about 2% a year between 2014 and 2030 from £1.3 trillion to £1.8 trillion, driven by rising incomes. This is in line with historical growth of about 2% a year between 2000 and 2016. Consumers are projected to spend more on all categories and their spending patterns will shift, creating more jobs in areas such as consumer durables, leisure activities, financial and telecommunication services, housing, health care, and education. Accordingly, **rising incomes could create 2.6 million new jobs in the UK by 2030.**

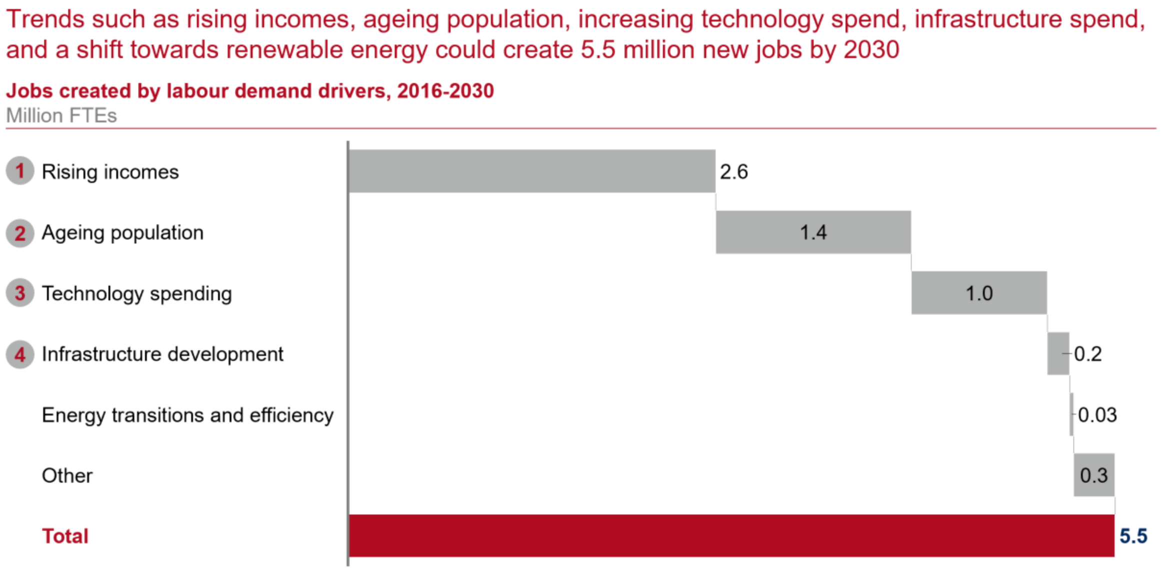
- **Ageing population**. By 2030, there will be at least 4.1 million more people aged 65 years and over in the UK than there were in 2014. This means that the percentage of people aged 65 years or older will increase from 17.5% to 22% between 2014 and 2030. Spending patterns shift with age, causing an increase in spending on health care and other personal services. This will create significant demand for occupations such as doctors, nurses, and health technicians, but also home health aides, personal care aides and nursing assistants. It will also reduce demand growth for paediatricians and primary-school teachers. Given the correlation of both rising incomes and share of the population over 65 on the number of health-care professionals, MGI estimates that the **number of jobs in health care and related services could increase by 1.4 million by 2030.**

- **Development and deployment of technology**. Both individuals and enterprises are projected to spend more on technology by 2030, which will impact on the demand for jobs like computer scientists, engineers, and IT administrators. Overall spending on technology in the UK could increase by 28% between 2014 and 2030 from £197 billion to £252 billion. About 61% of total technology spend is projected to be on enterprise information technology services. **MGI estimates that this trend could create one million jobs in the UK by 2030.**

- **Investment in infrastructure and buildings** –Rising incomes may also create demand for more and higher-quality buildings, and a part of the resulting higher tax revenues (assuming no policy changes) is likely to be channelled into government-funded infrastructure. UK infrastructure spending is projected to grow by 41% between 2014 and 2030, from £31 billion to £43 billion. **These factors could create 160,000 jobs by 2030**, including both skilled tradespeople (for example, architects, engineers, carpenters) and jobs with lower skill requirements (for example, construction workers, and machinery operators).

- **Investments in renewable energy, energy efficiency, and climate adaptation** – The UK will get an estimated 58% of its electricity production and about 54% of its total energy-generating capacity from renewables by 2030. The UK's energy and climate policy intentions will also require investments in renewable energy, energy-efficiency technologies and mitigation of climate change. **This may create 29,000 jobs in occupations such as energy-related manufacturing, construction, and installation.**

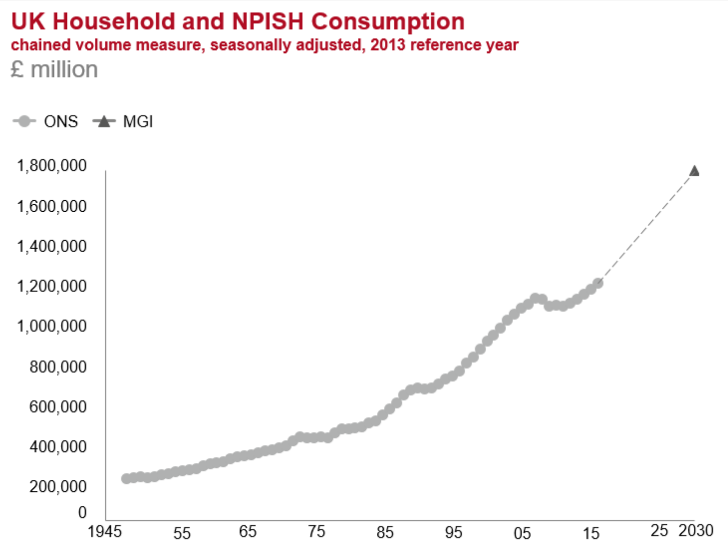
Figure 4: Jobs created by labour demand drivers[5]



Source: 2030 Skills Mismatch model

These estimates are in line with historic trends, both in terms of underlying trends in consumption and ageing demographics, but also in terms of employment trends in the relevant sectors (see Box 2).

Box 2. Historic economic trends and MGI projections

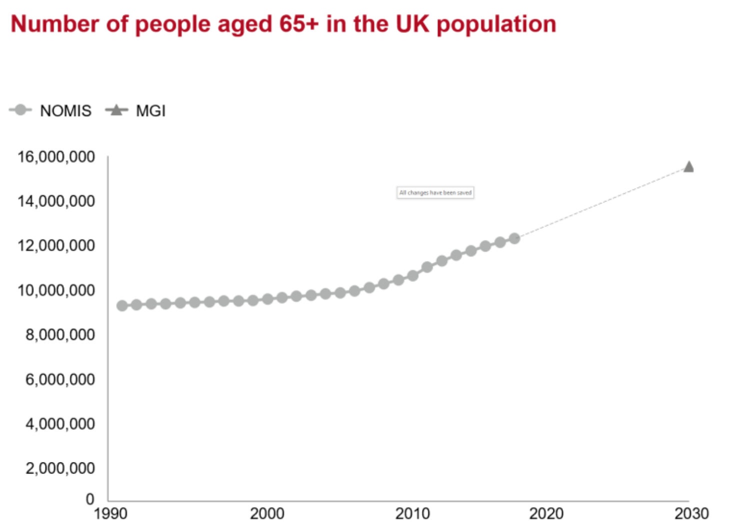


Rising incomes: UK consumption is forecast to grow by 36% between 2014 and 2030 from £1.3 trillion to £1.8 trillion, in line with historic trends.

*NPISH: Households and non-profit institutions serving households

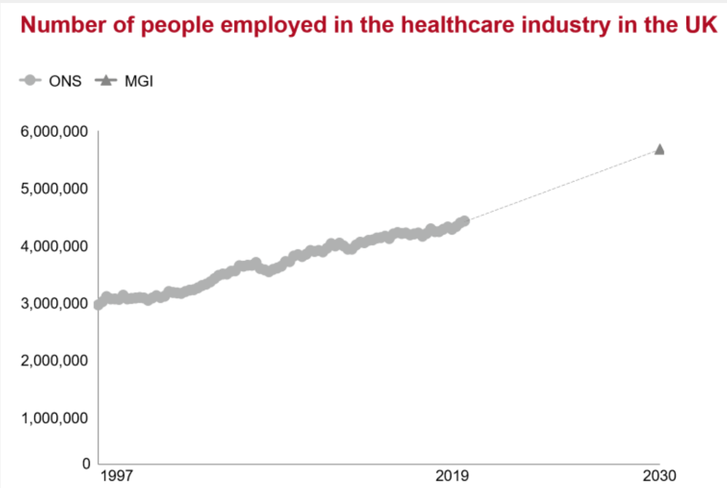
Source: Historic data: ONS Household and NPISH consumption sourced from the Bank of England Millennium dataset; 2030 projection: MGI

[5] Education falls into the 'Other' category (see graph). Given the discrepancies between countries in funding models for education and healthcare, these drivers have been sized separately from the rest of consumer spending, despite some proportion of education and health care spending being funded directly by consumers. For both these sectors, MGI model the full sector, which would include that funded by consumers as well as public and private sector funding.



Ageing population: By 2030, there are forecast to be at least 4.1 million more people aged 65 years and over in the UK than there were in 2014.

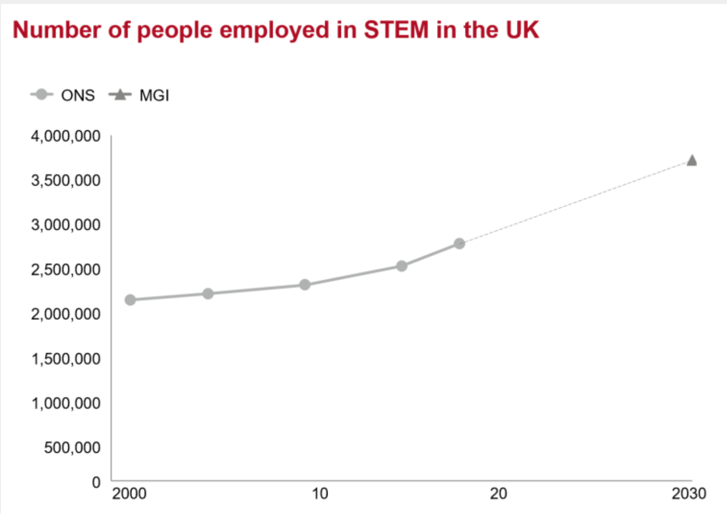
Source: Historic data: NOMIS population estimates; 2030 projection: MGI



Healthcare: MGI's estimated increase in the number of jobs in healthcare and related services as a result of ageing population and rising income, is in line with historic data.

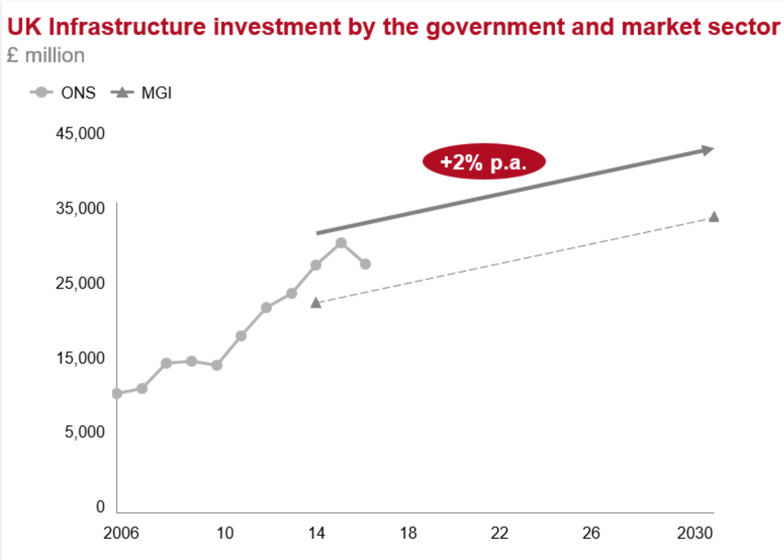
*SIC code Q: human health and social work activities

Source: historic data: ONS labour force survey: employment by industry



STEM: MGI estimated increase in the number of technology jobs is in line with historic data.

Source: historic data: ONS labour force survey; 2030 projections: MGI



Infrastructure: UK infrastructure spending is projected to grow by 2% p.a. to £43 billion by 2030.

Source: ONS Infrastructure experimental statistics

The list of trends that affect demand is not exhaustive. For example, the model does not consider the impact of the UK's departure from the European Union on skills demand and supply, given the uncertainty of the long-term impact. However, immigration is modelled as a sensitivity in section 5. The model also does not consider any other shocks to employment and the business cycle.

4. Skills Supply in 2030

In order to model the 'supply' of skills in 2030, our research paper uses the number of occupations and the skills required to perform them in 2017 to create a 'pool' of different 'bundles' of skills in 2030. Our paper makes a number of assumptions about, and adjustments to, this pool:

- First, it assumes that workers in 2017 are either a perfect match for their occupation as it stands, or will have acquired the necessary skills by 2030 through some endogenous training.[6] This is a generous assumption but one that is accounted for in the way the results are communicated. The aggregate 2030 skills mismatch (the composite score across all of knowledge, qualifications, and workplace skills) is described as incremental to the 2017 skills mismatch.

- Second, given that our estimate for skills demand assumes some population growth, we increase the number of workers in our pool (compared to 2017) to avoid creating false mismatches. Our skills demand forecasts a total 1.23% increase from 32 million workers in 2017 to 32.4 million jobs demanded in 2030. We therefore apply a 1.23% increase to the number of workers in each occupation in 2017 to create an equal ratio of workers to jobs in 2030. This is likely to be a conservative assumption compared to UN population projections, but, given that we are looking to find out the degree of under and over-skilling in the economy based on the 2030 demand for jobs, 2030 supply should be equalised. The alternative would give us a number of employed workers, but that would not inform us about the degree of mismatch.

- Finally, our model makes some adjustments to account for whether incoming workers will have a different skills bundle (knowledge, qualifications, and workplace skills) to that of outgoing workers, as detailed below. Our baseline model does not consider changes in the number of workers due to net migration, which is modelled as a separate sensitivity.

[6] Note the assumption is that workers acquire the necessary skills by 2030 for their current role as it stands, not for how the job might evolve by 2030.

Figure 5: Workforce supply trends[7]

Supply trends: The workforce in 2030 is likely to look slightly different to the workforce in 2017 as new cohorts are likely to have higher qualifications, higher basic digital skills and a larger number is likely to have STEM degrees

	Older cohort	Younger cohort
Qualifications	37% with a tertiary degree	52% with a tertiary degree
Knowledge	265 literacy and 257 numeracy PIAAC score	Gradual increase in those studying STEM subjects 266 literacy and 257 numeracy PIAAC score
Workplace skills	52% with basic or above basic digital skills	86% with basic or above basic digital skills

To reflect the difference in digital skills, we have uplifted each worker who has basic digital skills in 2017 by 15%. Research suggests qualifications and knowledge demand is likely to grow at the same pace as supply whereas the growth of basic digital skills demand is likely to outpace supply.

Source: OECD employment by educational attainment level; Eurostat individuals' level of digital skills; PIAAC; HESA graduates by subject

4.1. Knowledge

O*NET provides the knowledge data by occupation for our base year, 2017. We do not make any adjustments for knowledge to change between 2017 and 2030 because of the evidence that supply and demand are likely to change at the same pace.

While average knowledge *required* by occupations has increased by approximately 13% since 2002 (based on historic O*NET data), Nesta finds that actual levels of knowledge in the population have been steadily approaching what it estimates will be required in the economy in 2030. Nesta finds that the prevalence of skills, knowledge and abilities has grown broadly in line with their increased importance from 2001 to 2017.[8]

[7] Older cohort: >55 years old, younger cohort: <25 years old. For tertiary degrees we have looked at those aged 25-34 years old as those under 25 may still be in education and those aged 55-64 years old. Gradual increase in those studying STEM subjects equals to 14% increase since 2013/14.

[8] Balhshi, H., Downing, J., Osborne, M. & Shneider, P. (2017). *The future of skills employment in 2030*. Retrieved from: https://media.nesta.org.uk/documents/the_future_of_skills_employment_in_2030_0.pdf

4.2. Qualifications

As with knowledge, the model does not make any adjustments to qualification level in the supply given the evidence that trends in supply and demand for qualifications in the workforce are likely to counteract one another:

- The OECD estimates that 27.5% of the UK workforce is already under-qualified. Therefore, using qualification levels *required* by occupations is already likely to over-estimate qualification level.[9]
- Qualification demand has stagnated in recent years. Until 2012, the number of jobs requiring a bachelor's degree increased by 3 percentage points every five years; since 2012, neither the proportion of jobs requiring higher education nor the proportion requiring no qualifications has changed significantly.[10]
- Meanwhile, *Working Futures* estimates that there could be a 30% increase in the number of people with bachelors and postgraduate degrees by 2024.[11] The average level of qualification in the workforce will also adjust with those leaving and entering the workforce: 37% of those aged 55–64 have tertiary education, compared with 52% of those aged 25–34 years.[12]

4.3. Workplace skills

For 2030 workplace-skills supply, we use the same level of workplace skills for each occupation as in 2017 but apply a 15% uplift for basic digital skills only. This is to reflect the fact that those workers entering the economy between 2017 and 2030 will have higher digital skills than the average in the workforce today (the level of basic digital skills among those aged 16–24 is 69% proficiency versus 30% proficiency for those aged 55–64). In addition, this uplift reflects the fact that those already in the workforce will be likely to increase their basic digital skills through on-the-job training.

[9] The OECD estimates that 28% of the UK workforce is underqualified for their occupations, while 13% are overqualified, based on educational attainment being higher or lower than that required for the job. Workers' views are more positive on them having the right qualifications for their job according to the OECD Survey of Adults Skills.

[10] Henseke, G., Felstead, A., Gallie, D. & Green, F. (2017). *Skills Trends at Work in Britain*. Retrieved from: https://www.cardiff.ac.uk/__data/assets/pdf_file/0011/1229834/2_Skills_at_Work_Minireport_Final_edit.pdf

[11] UKCES (2016). *Working futures 2014–2024*. Retrieved from: https://warwick.ac.uk/fac/soc/ier/wf6downloads

[12] OECD educational attainment; we have looked at those aged 25–34 years old as those under 25 may still be in education

We considered whether other workplace skills should also be uplifted but our analysis of Programme for the International Assessment of Adult Competencies scores showed that, for most other categories, workers over 55 years old (those likely to leave the workforce by 2030) had similar skills levels to those under 24 years old (those most similar to new workers entering the workforce by 2030). The only exception (other than basic digital skills) to this trend was ‘complex problem solving’. However, this difference is driven by age rather than by a trend in workforce capabilities, so young people today will experience a similar decline in cognitive function as they age.

5. Future Skills Mapping

To calculate the skills gap in 2030, we create a 'market clearing' model that allocates full time equivalents (FTEs) to an occupation in 2030 that is as close as possible a match to their package of workplace skills, knowledge, and qualifications.

This model optimises for the lowest possible skills mismatch for the economy as a whole. For example, if there were a shortage of doctors in the economy, it may be more optimal for the economy if a nurse becomes a doctor and a teacher becomes a nurse, rather than a teacher becoming a doctor.

5.1. Assigning a matching score

Our model operates by first assigning a matching score for every possible pair of occupations in our demand and in our supply. It calculates the match of a worker in the supply to an occupation in our demand, based on a composite matching score for knowledge, qualifications and skills. Note that a score of 0 represents a perfect match, and a score of 1 represents a completely imperfect match.

The matching score and threshold for each of these elements is calculated based on an assumption that all **knowledge** elements with a level greater than 4 are a requirement to complete that occupation (level is scored between 1 and 7). The cut-off point was level 4 because:

- Less than 30% of knowledge elements per occupation are above level 4[13]
- In the questionnaire that O*NET provides to respondents, level 4 is the point on the scale at which O*NET provides an example of an above-basic level of understanding (e.g. level 1 example for mathematics is 'add two numbers' level 4 example is 'analyse data to determine areas with highest sales').

In our model, the 'Biology' level for an accountant is less than 4 so this is not considered a requirement to perform the occupation, while 'Maths' has a level score of greater than 4 so is considered a requirement. The model calculates the percentage difference between the level required for each knowledge type in the target occupation, and the level held by the worker in the source occupation.

For example, if occupation A requires a level 5.2 in Maths and a level 6.1 in Economics, but the worker in occupation B has a level 4.0 in Maths and a level 5.0 in Economics then the Knowledge match score will be *((4.0-5.2)/5.2 + (5.0-6.1)/6.1) /2 = 0.2.*

[13] Handel M. J., (2016), *The O*NET content model: strengths and limitations*, Journal of Labour Market Research, Volume 49

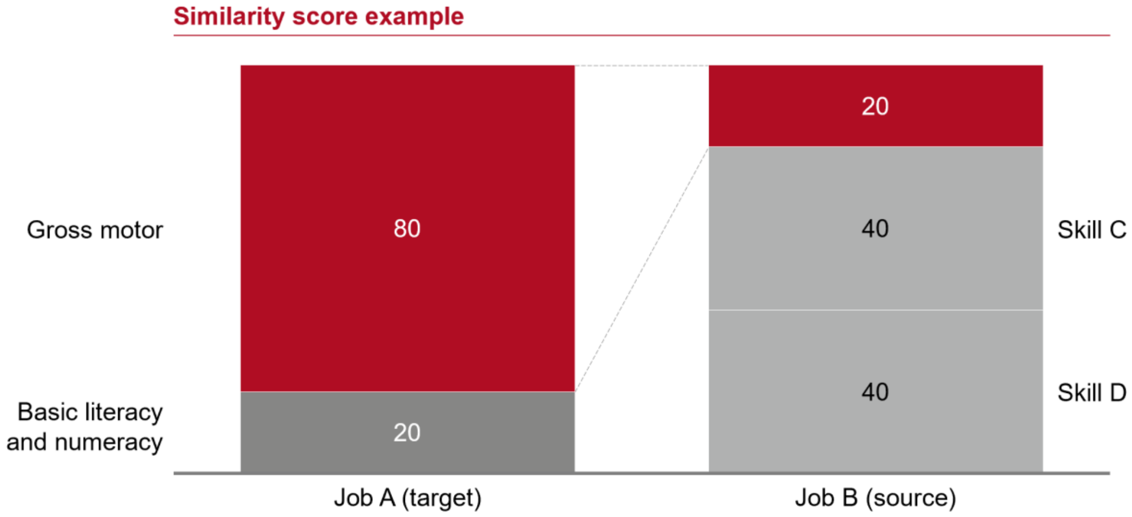
The model creates a similar score for **qualification** to that for knowledge. It calculates the number of zones difference between the target occupation's level of qualification and the source occupation's level of qualification.

For example, if occupation A requires a qualification in zone 5, but occupation B has a qualification in zone 3, the qualification match score will be *(3-5)/4 = 0.5*. If target occupation and source occupation have the same qualification level, this equals a 0 score.

To calculate the **workplace-skills** match score, the model calculates the percentage time spent in 2030 using that skill in the source occupation divided by the percentage time spent in 2030 using that skill in the target occupation. We sum this up across all the skills between occupations to calculate a percentage comparison in skills between each occupation.

For example, occupation A requires two skills: 80% of time is spent on gross motor skills, and 20% of time is spent in basic literacy and numeracy (see Figure 6). Occupation B uses two different skills (skill C and skill D) as well as 20% of its time spent on gross motor skills. The workplace-skills similarity score for a worker previously in occupation B moving to occupation A would be (20/80 + 0/20) /2 = 0.125. Note that skill C and skill D are not included in the mismatch score because these are not required by the target occupation.

Figure 6: Time spent in source occupation on skills of relevance to target occupation



$$\frac{\left(\frac{20}{80}+\frac{0}{20}\right)}{2} = 0.125\ (similarity\ score)$$

Source: 2030 Skills Mismatch model

5.2. Composite matching score

To calculate a total mismatch score, the model must use a composite of all three skills elements. Each element also has two dimensions: for each of knowledge, qualifications and workplace skills, each source occupation has (i) a relative under-skilling and (ii) a relative over-skilling score attached to it as compared to the target occupation. The model calculates a single score for each of the three elements through the formula:

(Under-skilling score – Over-skilling score) * (Over-skilling score + under-skilling score)

This method captures both the absolute amount of under-skilling and over-skilling of a source occupation to a target occupation but also the difference between the relative under-skilling and over-skilling.

For example, compared to target occupation A, source occupation B has a workplace skills over-skilling score of 0.35, and an under-skilling score of 0.20. By summing the difference, we get to 0.15 which is 0.15 over-skilled. However, given that some workers will have large degrees of under or over-skilling, and others will have only small amounts, we multiply by the sum of under and over-skilling to capture that magnitude:

$$(0.2 – 0.35) * (0.35 + 0.2) = 0.0825 \text{ in absolute terms}$$

To calculate a single composite score across all three skills elements, the model uses the average score between workplace skills, knowledge and qualifications.

This composite score can total any value between 0 and 1. The lowest possible score – or a ‘perfect match’ – in our model is 0.

5.3. Occupation matching

The model allocates workers based on the lowest possible total mismatch across the economy. In other words, the model minimises the total skill mismatch ($f^T x$) in the economy, where f^T is the vector of similarity scores, and x is the number of FTEs assigned to each occupation. Using the composite scores, it compares flows of occupations to calculate the optimal number of FTEs to assign to each occupation.

In some cases, it could be possible for an accountant to become an actuary, rather than to remain an accountant, if it minimises the total skill mismatch in the economy.

We include here the equation that describes the model solution method:

min fTx such that Aeq*x=beq and x<=ub

where

f^T = total skills mismatch in the economy

x = number of FTEs assigned to each occupation

Aeq = a matrix of 1s and 0s, such that supply of labour equals demand

beq = a vector of the supply of workers in the economy by occupation

ub = the upper bound of the supply of workers

beq is a vector of the supply of workers in the economy by occupation, and Aeq a matrix of 1s and 0s, such that the first constraint requires supply of labour to be equal to demand. The second constraint ensures that the solution x is less than the upper bound of 2030 workers, that is, no more than 100,000 accountants can change occupations if we have 100,000 accountants in the supply.

Although the model clears the market through using only positive numbers and minimising the difference from zero, we convert the composite score into a negative or positive number to assess the overall level of under- and over-skilling in the economy. This is simply done by removing the absolute clause from the formula for each of the three types of skills we consider.

6. Sensitivities

A series of sensitivity tests, controlling for changes in openness to migration, regional labour mobility and the speed of automation have been conducted. The only factor that changes the result in a significant way is a faster rate of automation.

We tested the model by limiting immigration and inter-regional worker mobility and found little change in our results. Both sensitivities were intended to see whether there would be a noticeable effect on the degree of under-skilling in the economy through immigration or regional mobility. As the charts below show, workplace skills mismatch is fairly uniform across all scenarios (Figures 7 and 9). This indicates that skills mismatch is mainly driven by within-job changes rather than exogenous factors such as inter-regional mobility or immigration.

6.1. Immigration

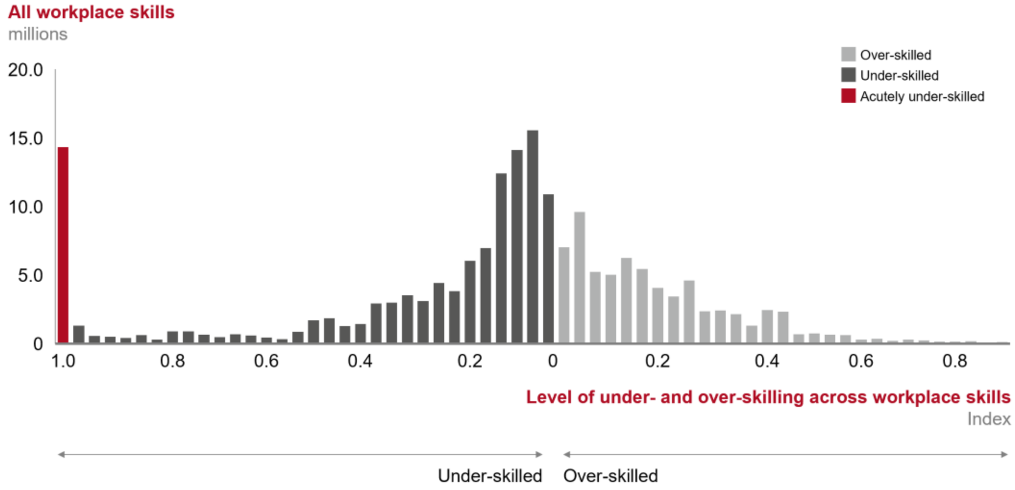
To test immigration as a sensitivity, we restricted the population to just include the skills bundles of UK-born nationals. We did this by inputting ONS data on employment by occupations and country of birth. Country of birth is the country in which the person was born and for the purposes of our modelling exercise has been used as a proxy for whether the person is a migrant. We have chosen country of birth rather than nationality as it gives a more robust estimate of the resident population change over time. It is possible that an individual’s nationality may change, but the person’s country of birth will not. Moreover, those born abroad that remain in the UK often apply to become British nationals. The downside of using country of birth is that it would exclude British nationals born abroad; for example, those born abroad if their British parents were in military services overseas.[14]

We found that restricting immigration did not materially change the results. When looking at UK-only population (the most extreme of our two immigration scenarios), extreme under-skilling does increase (14 million to 15 million). However, this under-skilling is unlikely to affect more than 125,000 people given that the chart shows the bundle of skills the population holds, not the number of people. Given this finding, we considered the model to be robust to sensitivities. It is worth noting, there are some occupations for which the UK is heavily reliant on immigration, for example, weighers and graders, packers and bottlers, and taxi drivers, but most of these occupations are projected to decline by 2030, according to MGI.

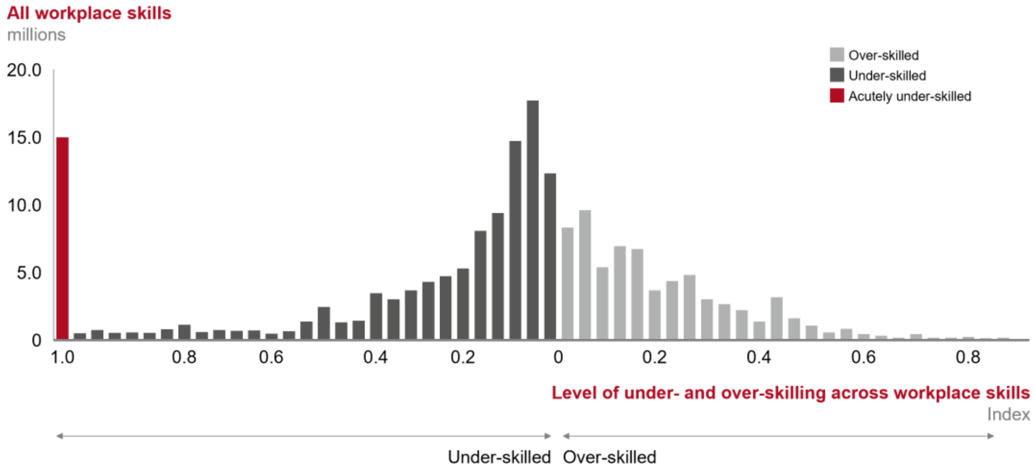
Figure 7: Workplace skills base case and migration scenario analysis

[14] ONS (2018). *Population by country of birth and nationality QMI*. Retrieved from: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/internationalmigration/methodologies/populationbycountryofbirthandnationalityqmi

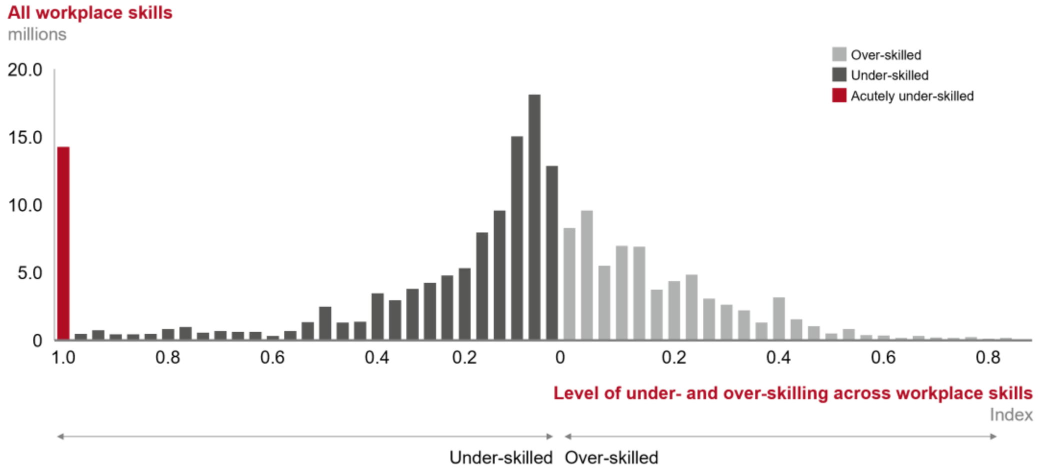
Base case: Workplace skills



Migration, UK-only population: Workplace skills

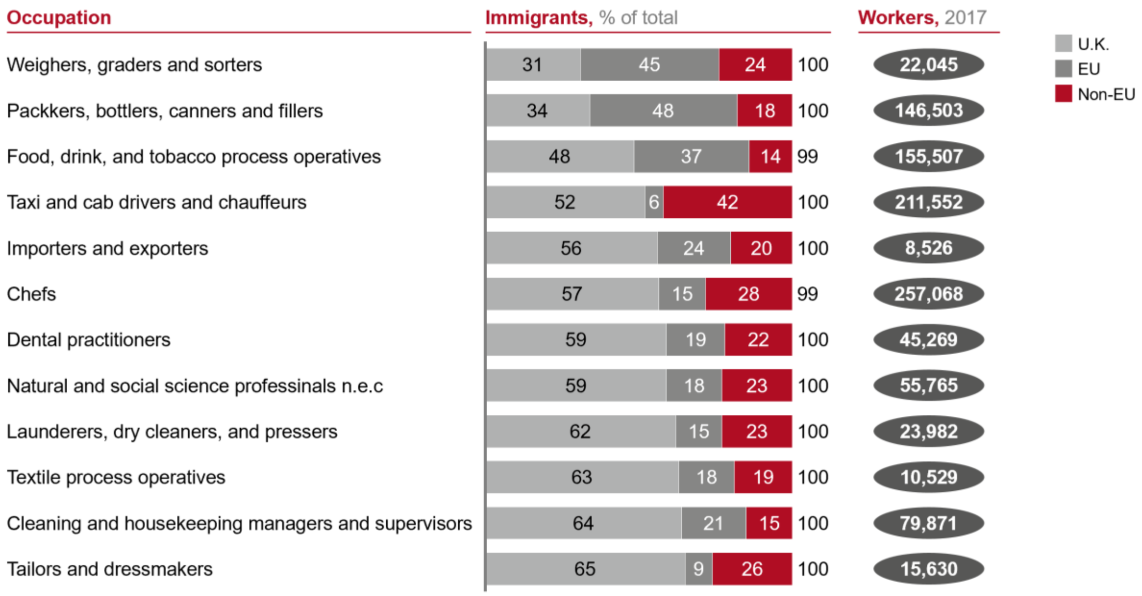


Migration, UK & Non–EU population: Workplace skills



Source: 2030 Skills Mismatch model

Figure 8: Workforce by region of origin



Source: 2030 Skills Mismatch model

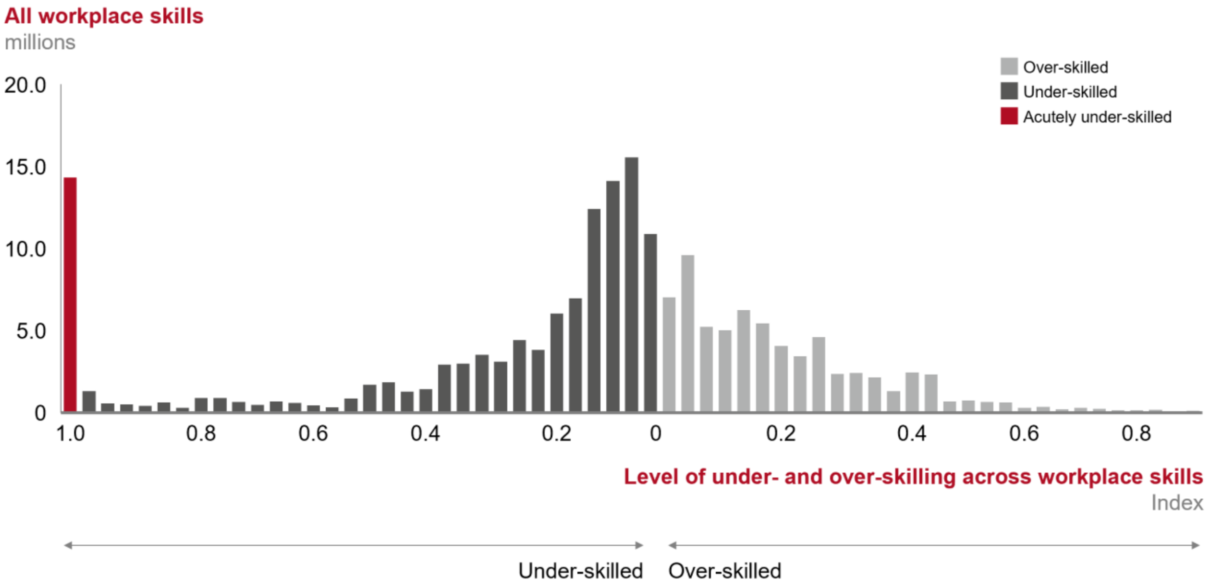
6.2. Regional mobility

In the baseline model, we assume that workers can transition to a new occupation anywhere in the UK. To better reflect the fact that only 0.6% of people move regions for an occupation, we restricted regional mobility by running our model for each individual region and then summing up the results for the UK. We did this by inputting ONS data on employment by occupation and region.

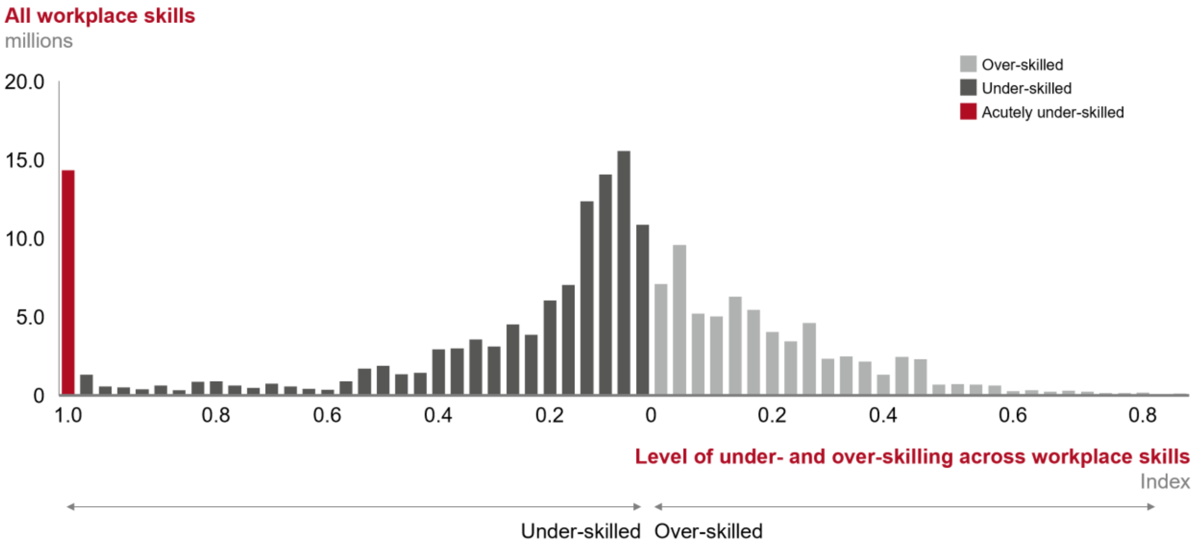
Our model finds that restricting regional mobility does not have a significant impact on skills mismatch. This is expected, given that the distribution of occupations (albeit not sectors) is similar across regions, apart from London (see Figure 10). London is an exception as it has a higher proportion of professional occupations (6 percentage points), but all other regions follow a similar distribution of occupations.

Figure 9: Workplace skills base case and limited regional mobility scenario analysis

Base case: Workplace skills

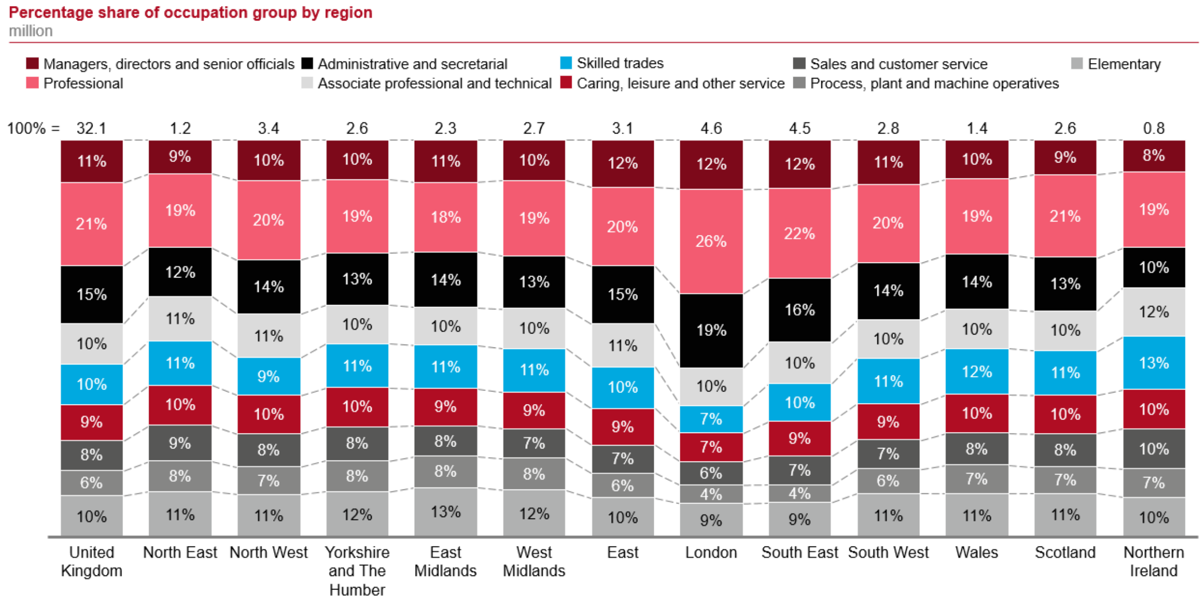


Limited regional mobility: Workplace skills



Source: 2030 Skills Mismatch model

Figure 10: Shares of occupations in employment by region



Source: ONS

6.3. Faster rate of automation

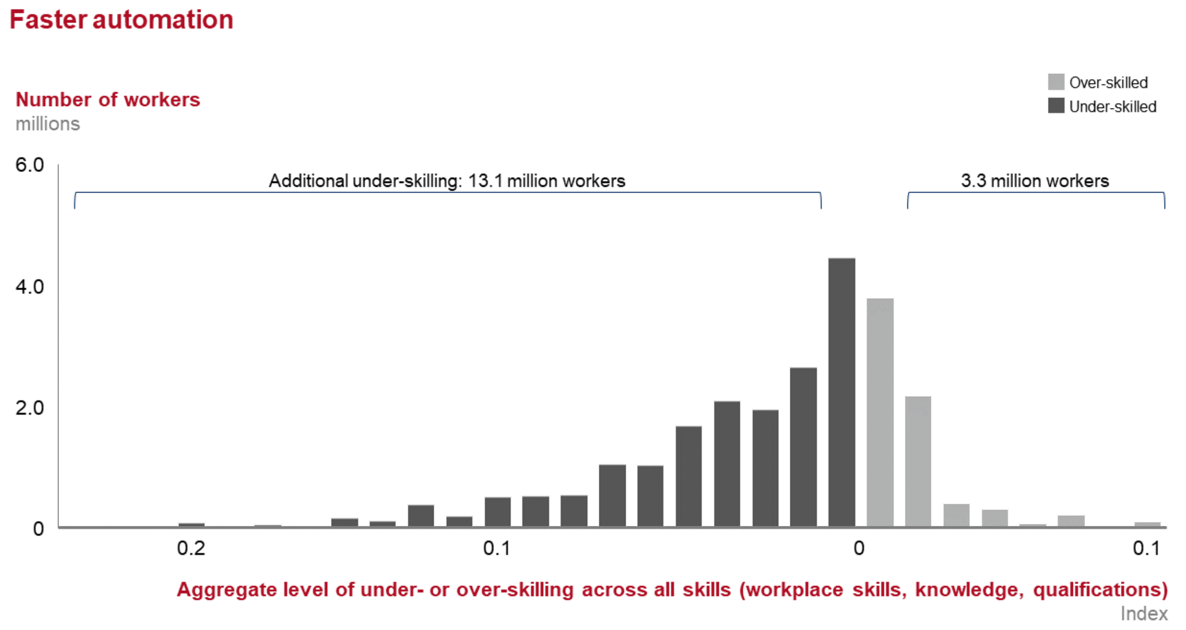
We also tested the pace of automation as an additional sensitivity to the model. For this, the model uses MGI estimates of the effect of faster automation on each workplace skill for a given occupation. Under the faster automation scenario, the number of jobs lost in the UK due to automation increases, thereby reducing the total to 24 million jobs (compared with 32.4 million in the base case).

To understand the skills mismatch in a faster automation scenario, we multiplied the 2017 supply of each occupation by a common factor to ensure that 2030 total supply equals total demand (24 million).

The results of the sensitivity show that faster automation could result in more extreme under-skilling in the UK economy. In this scenario, 13.1 million workers could be under-skilled in the UK by 2030, compared to 7.0 million in the base case. Similarly, 3.3 million workers could be over-skilled compared to 0.9 million in the base case. The number of extremely under-skilled workers also nearly doubles relative to the base case. This is driven by the higher number of occupation transitions predicted in the model, 14 million compared to 5.7 million in the base case.

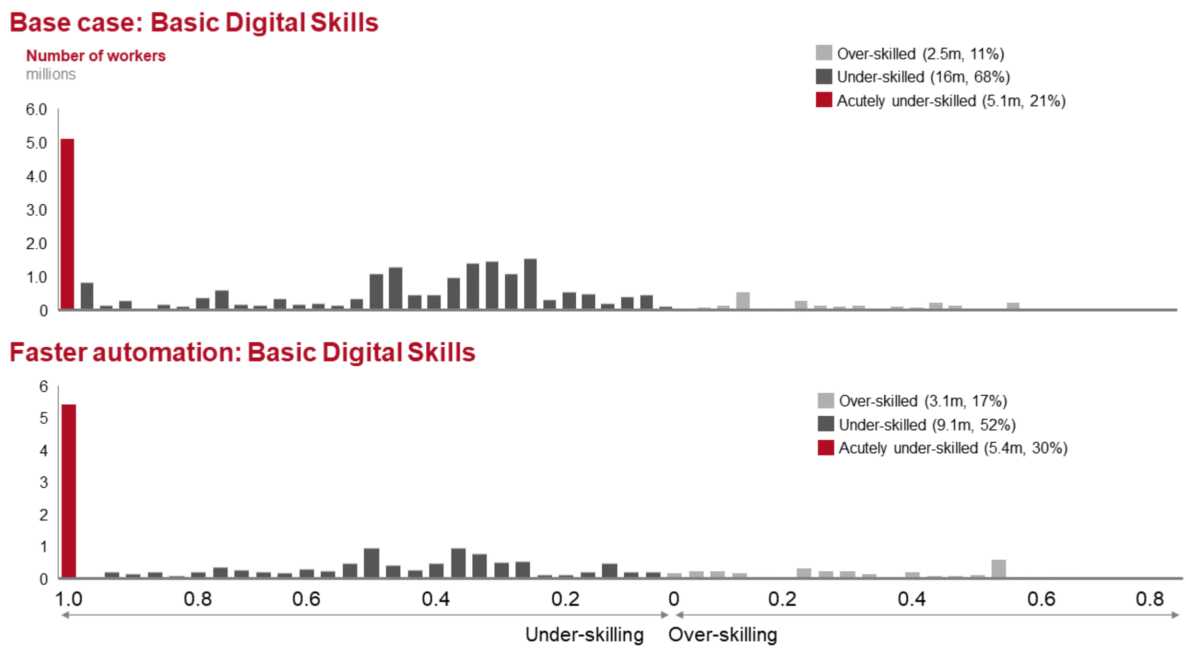
Faster automation would also likely cause more extreme under-skilling in basic digital skills and STEM workplace skills (see Figure 12).

Figure 11: Total number of under-skilled workers under faster rate of automation – scenario analysis



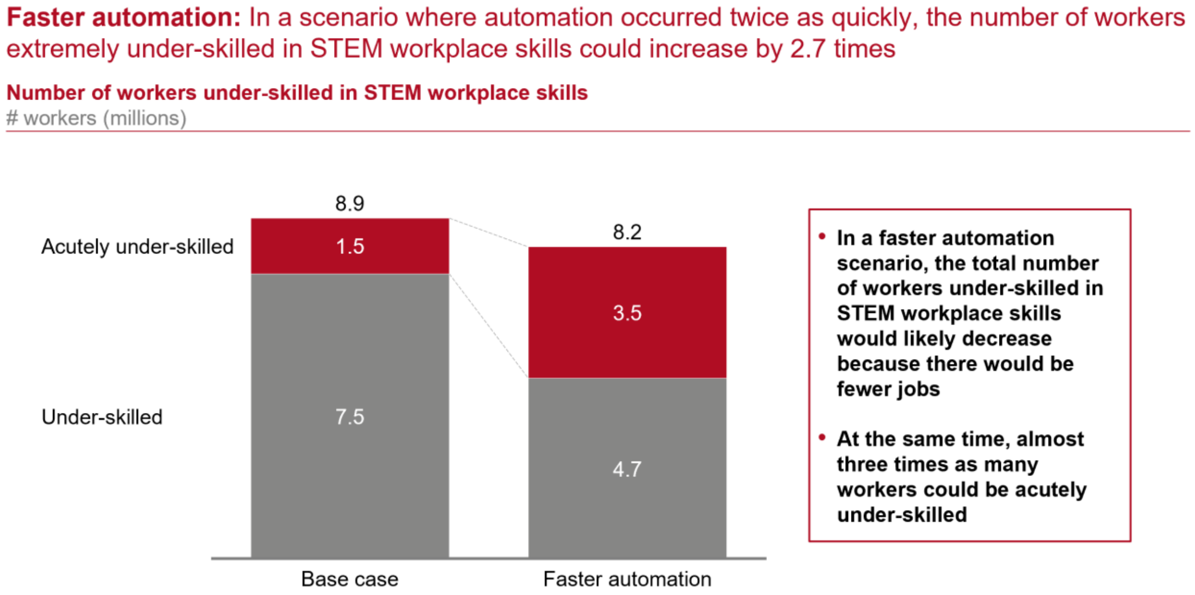
Source: 2030 Skills Mismatch model

Figure 12: Skills mismatch under faster rate of automation – Basic Digital Skills - scenario analysis



Source: 2030 Skills Mismatch model

Figure 13: Skills mismatch under faster rate of automation –STEM - scenario analysis



Source: 2030 Skills Mismatch model