National Foundation for Educational Research

Nuffield Foundation

Rethinking skills gaps and solutions

Technical Supplement Part A to Working Paper 4 of The Skills Imperative 2035

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The Skills Imperative 2035

An analysis of the availability of Essential Employment Skills and the gaps between workers' skills and the skills their jobs require.

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Contents

The Nuffield Foundation is an independent charitable trust with a mission to advance social well-being. It funds research that informs social policy, primarily in Education, Welfare, and Justice. It also funds student programmes that provide opportunities for young people to develop skills in quantitative and scientific methods. The Nuffield Foundation is the founder and co-funder of the Nuffield Council on Bioethics and the Ada Lovelace Institute. The Foundation has funded this project, but the views expressed are those of the authors and not necessarily the Foundation. Visit www.nuffieldfoundation.org

Table of Figures

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Glossary

Term	Definition
Essential Employment Skills (EES)	The six skills that are anticipated to be most heavily utilised across the labour market in 2035. These are transferable skills, specifically: communication, collaboration, problem-solving, organising, planning and prioritising work, creative thinking and information literacy.
Skills Supply	The level of EES that people – specifically workers, the long-term unemployed and young people – possess across the six skill domains, derived from self-assessments of their behaviours, on a scale of 0-100.
Skills Requirements	Refers to the EES people need to do their jobs, across the six skill domains, on a 0-100 scale, according to the results of our survey. They are calculated using people's self-assessments of the level and importance of each skill required to do their job.
Skills Gaps	Refers to the skills gaps calculated based on responses to our survey, from Skills Requirements minus Skills Supply for each skill domain.
Skills deficiencies	Where a worker (or group of workers) has a Skills Gap, and the Skills Requirements for their jobs are greater than their Skills Supply, according to workers' self-assessments.
Skills under-utilisation	Where a worker (or group of workers) has a Skills Gap, and their Skills Supply is greater than the Skills Requirements of their jobs, according to workers' self-assessments.
Standard Occupational Classification (SOC)	The SOC system is the main system for classifying occupational information in the UK. Jobs are classified by their skill level and context. The UK introduced this classification system in 1990 (SOC90). It has been revised every ten years, with the latest update taking place in 2020.
Occupational hierarchy	At its highest level of classification, the SOC (2020) classifies occupations into nine 'major' groups, based on skill level and skills specialisation. Occupations in SOC1 (Directors, managers and senior officials) typically require the highest skill levels, followed by SOC2 (Professional occupations) whereas occupations in SOC9 (Elementary occupations) typically require the least.

Higher skill-level occupations	These are occupations in the first three broad occupational groups (SOC1 to SOC3) in the SOC, specifically: 1. Directors, managers and senior officials (SOC1) 2. Professional occupations (SOC2) 3. Associate professional occupations (SOC3).
Mid- and lower-skill-level occupations	These are occupations in the bottom six broad occupational groups (SOC4 to SOC9) in the Standard Occupational Classification, specifically: 4. Administrative and secretarial occupations (SOC4) 5. Skilled trades occupations (SOC5) 6. Caring, leisure and other service occupations (SOC6) 7. Sales and customer service occupations (SOC7) 8. Process, plant and machine operatives (SOC8) 9. Elementary occupations (SOC9).

Purpose of this report

This report is designed to be read after *Rethinking skills gaps and solutions, Working Paper 4 of The Skills Imperative 2035: Essential skills for tomorrow's workforce.* Its purpose is to give further depth and weight to the key findings and recommendations reported in Working Paper 4 by describing the analyses that were conducted using data from the NFER Essential Employment Skills Survey and the results that were obtained. The results are proceeded by a brief summary of the background context to the research and the research design and methodology. They are followed by a summary of the key findings.

1 Background context

- Previous research for The Skills Imperative 2035 has identified a set of six 'Essential Employment Skills' that are going to be most heavily utilised across the labour market in 2035.
- Job growth is anticipated to be concentrated in higher skill level occupations that most intensively utilise these skills. Continued adoption of Automation and AI are also likely to mean that people need higher levels of essential employment skills across the labour market.
- Shortages of essential employment skills are likely to cost employers, hold back social mobility and increase the costs of disruption to the labour market.
- Whilst 'skills shortages' have been the focus of much recent research, 'skills gaps' in the current workforce are a research gap. This stage of The Skills Imperative 2035 seeks to address this gap.
- Assessments of skills gaps have tended to rely solely on employer perspectives, with skills gaps attributed to the lack of skills employees possess rather than to under-utilisation of skills by employers. Our focus is gathering the missing worker perspective.
- Research comparing employers' perceptions of skills gaps with those of employees is severely limited. However, the dyadic research that has been done suggests there are perception gaps between employers and workers. The causes and consequences of these perception gaps has important implications for how skills gaps are addressed.

Our previous research has identified a set of 'essential employment skills' that will be most heavily utilised across the labour market in 2035.

Previous stages of *The Skills Imperative 2035* have projected the future distribution of employment and identified the skills that are likely to be in greatest demand across the labour market in 2035. Our analysis of the demand for skills in 2035 (Dickerson *et al.*, 2023) identified a set of skills that are used most intensively in employment today and which are anticipated to be in even greater demand in 2035. Based on projections of the skills that will be required in 2035, together with the findings of an earlier literature review, we identified six 'Essential Employment Skills' (EES):

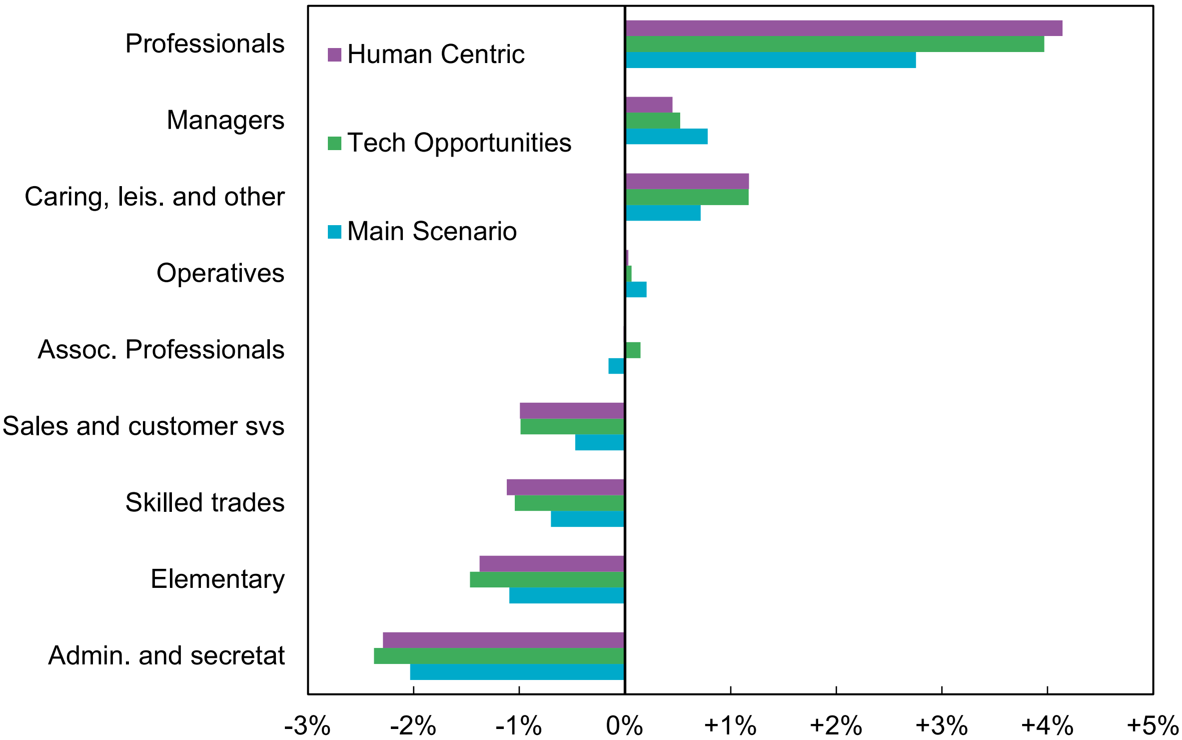
- Collaboration
- Communication
- Creative thinking
- Information literacy
- Organising, planning and prioritising
- Problem solving and decision making.

Shifts in the distribution of employment are increasing the demand for these skills.

Over the past half century, there have been significant shifts in both the sectoral and occupational distributions of employment in the labour market, driven largely by the effects of technological change and globalisation. On the sectoral side, manufacturing has declined, and various service sectors and parts of the public sector (particularly health and education) have risen. Between 1970 and 2021, the proportion of jobs in professional services, education and health rose from 14% of the total share of jobs to 31% of the total (Cominetti *et al.*, 2021). This has increased the demand for EES, which are relatively more intensively utilised in these sectors. The decline of manufacturing and expansion of service sectors is likely to have increased the demand for EES given softer interpersonal skills are essential across service organisations, especially in customer facing roles (Payne, 2017; Bryson, 2017; (Hurrell, 2016). The pace of sectoral change has now slowed, but the pace of occupational change has not.

On the occupational side, the trend has been one of growth in higher paying, higher skilled professional occupations. Changes in the occupational distribution of employment have increased demand for EES because professional occupations utilise non-routine cognitive skills more intensively (Cominetti *et al.*, 2022). Employment projections for The Skills Imperative 2035 suggest this trend is going to continue. Almost all the growth in jobs between now and 2035 is projected to be in higher skilled, higher paid occupations that make the most intensive use of EES.
Figure 1 below shows the results of employment projections produced earlier in The Skills Imperative 2035 for the 'Main scenario' as well as two alternative scenarios (a 'Technological Opportunities Scenario' and a 'Human Centric Scenario') which model the effects of a more rapid uptake of automation-related technologies, including AI, on job displacement. These two scenarios make the same assumptions about job displacement but different assumptions about job creation. The consequence of these anticipated structural changes will be that EES continue to become ever more important across the labour market.

Figure 1 Percentage Growth (Change) in Employment Share, across the UK, 2020-2035, by broad occupational category (SOC major groups)



Source: Occupational Outlook - Long-run employment prospects for the UK, produced by Warwick IER for an earlier stage of The Skills Imperative 2035.

Continued adoption of Automation and AI are also likely to mean that people need higher levels of EES across the labour market.

Technology changes have reduced the demand for humans to perform routine tasks, especially routine manual tasks. They have also led to the creation of new roles to perform non-routine cognitive tasks that augment the role of technology (Acemoglu and Restrepo, 2022). Skills projections produced for The Skills Imperative 2035 (Dickerson *et al.*, 2023) reinforce the findings from previous studies that have highlighted increasing demand for non-routine cognitive and analytical skills (like decision making & problem solving, and creativity) and non-cognitive socio-emotional skills (like communication and collaboration) (e.g., Deming, 2017; Schanzenbach *et al.*, 2016). This trend is anticipated to continue, which has implications for the skills that people in the labour market will require in the future.

Evidence suggests shortages of EES cost employers, hold back social mobility and increase the costs of disruption to 'at risk' groups resulting from anticipated changes in the structure of the labour market.

Around two-thirds of employers (66% in the 2019 Employer Skills Survey) indicate that skills gaps are already impacting their institutional performance, for example by increasing workload for other staff, higher operating costs and difficulties meeting quality standards. If skills gaps grow, this is likely to increase the costs to employers.

Shortages of EES are also likely to increase the costs of disruption resulting from projected changes in the structure of the labour market. More of the workers in occupations that are projected to decline need to be able to transition into growing occupations, but these jobs typically utilise EES far more intensively. Prior research has shown proficiency in 'softer' transferable skills is essential for moving into higher-skilled roles (e.g., Laker and Powell, 2011). Increasing average levels of EES is, therefore, likely to be vital for cushioning the impact of anticipated changes on the groups likely to be most adversely affected.

EES are also important determinants of social mobility. People's levels of EES in childhood vary depending on their socio-economic background (de Vries and Rentfrow, 2016) and are associated with their broader job and life outcomes thereafter (e.g., Gutman and Schoon, 2013). This might be because they affect their aspirations, self-efficacy beliefs, motivation and persistence. Inequalities in the Supply of EES are, therefore, likely to hold back social mobility if not effectively addressed.

'Skills gaps' are a research gap.

Most of the recent focus has been on skills shortages not skills gaps. Increasingly, this has involved parsing the text in job advertisements associated with skills shortages, clustering the skills that are referenced and identifying the skills most frequently mentioned in industries or occupations with high densities of skills shortages (e.g., Nesta's Open Jobs Observatory, Lightcast's Open Skills and Faethm by Pearson). This has huge advantages for identifying the skills that employers are looking for, but the skills employers most frequently reference in job advertisements are not necessarily the skills they consider most important, or which are most intensively utilised in jobs. Employers may be more likely to treat some skills as implicit or to focus on 'top of-mind' skills, with the assumption that other skills are covered elsewhere in the application and assessment process (Popov, Snelson and Baily, 2022). Moreover, job advertisement data offers comparatively little insight into how skills are distributed across the population or into the scale and scope of skills gaps in the *current workforce*.

Skills under-utilisation represents another under-explored aspect of the skills challenge. Employers report that a higher proportion of their staff (8.1%) have qualifications and skills more advanced than are required for their current job role, compared to the proportion that are not proficient (5.7%) in the skills they need to do their jobs (IFF Research, 2023). This suggests there are pockets of latent skills in the labour market that are not being used by employers. This helps explain the focus of this research on measuring and explaining Skills Supply and Skills Gaps (both deficiencies of skills and under-utilised skills) in the current workforce.

Understanding the missing worker perspective.

Assessments of skills gaps have tended to rely on employer perspectives, with skills deficiencies attributed to the supply-side (i.e. the lack of skills employees possess) rather than the demand-side (i.e., under-utilisation of skills by employers, or withdrawal of skills by employees that are disaffected with their employer). Assessments of skills gaps that rely on employer perspectives are unlikely to deepen our understanding of how skills are distributed across the population, which is a vital prerequisite for identifying effective solutions to skills challenges, particularly in occupations with high skills gaps.

Research by Hurrell suggests employers' biases can also result in them blaming employees for gaps in 'soft skills', when in reality many people may possess these skills but decide to withdraw them because of disaffection with their employer (Hurrell, 2016). Other organisational biases, for example assumptions about gender, have also been shown to influence how organisations understand and respond to skills shortages (e.g., Bryant and Jaworski, 2011). HR departments may also manipulate the reporting of organisational skills shortages to draw attention to future skills shortages and strengthen the case for investment in training and recruitment (Watson, Webb and Johnson, 2006). It is important that our understanding of skills gaps is not solely reliant on employer perspectives.

Minimal attention has been paid to the possibility that there may be a perception gap between workers and employers, or to the interplay between supply-side and demand-side factors. There have been almost no attempts to quantify the supply of EES or skills gaps from self-assessments of people's behaviours and efficacy beliefs. A notable exception is Skills Builder's annual Essential Skills Tracker (e.g. Seymour and Craig, 2023), which measures people's levels of 'essential skills' and the returns to these skills. However, this has not stretched as far as gathering data on people's 'Skills Requirements' or measuring workers' 'Skills Gaps'.

We supplement this existing knowledge base by developing and utilising a novel, first-of-its-kind instrument for measuring both people's Skills Supply and the importance and level of these skills required by their jobs. By using Rasch measurement theory, we account for differences in the probability of selecting statements at the top of the rating scale of each of our items. We put individuals' Skills Supply scores for each domain on a common scale, enabling us to compare them across domains, individuals and groups. We also equate individuals' Skills requirement scores with their Skills supply scores on a common latent scale, enabling us to compare Supply with Requirements and quantify Skills Gaps. Finally, we forecast how Skills Requirements, Skills Supply and Skills Gaps are likely to change between 2023 and 2035, exploring the impact of projected changes in the population, in employment, and in the skills that each occupation will require workers to utilise.

Skill perception gaps between employers compared with workers and students.

Prior research comparing employers' perceptions of skills gaps with those of employees are severely limited. However, the dyadic research that has been done has identified perception gaps between employers and workers, with greater misalignment between low-skilled workers and their employers (McGuinness and Ortiz, 2014; Hurrell, 2016; Tsirkas, Chytiri and Bouranta, 2020). There is also some evidence of perception gaps between employers, students and Higher Education Institutions (e.g. Pereira, 2013; Wesley, Jackson and Lee, 2017; Wickramasinghe and Perera, 2010; Wolff and Booth, 2017; Matsouka and Mihail, 2016). The scale, scope and causes of these perception gaps has important implications for the solutions and policy responses for closing skills gaps.

The remainder of this report starts by providing an overview of the research design and methodology (Section 2), before summarising the results (Sections 3-7). The results are split into:

- Differences in Skills Supply and Skills Gaps between sub-populations, occupations and industries (Section 3)
- The distribution of Skills Supply and Skills Gaps across the population (Section 4)
- Projected changes in Skills Supply and Skills Gaps between 2023 and 2035 (Section 5)
- The benefits associated with higher levels of EES (Section 6)

2 Research design and methodology

- We have developed a novel, first-of-its-kind instrument for measuring people's Skills Supply, Skills Requirements and Skills Gaps, in relation to Essential Employment Skills.
- We used this instrument to collect self-assessment data from around 12,000 people aged 16-65 in summer 2023.
- We define people's skills as the patterns of thoughts, feelings and behaviours individuals are able to exhibit in response to their environments *when their situation demands it*. Consequently, our survey asks people to self-report their behaviours, focusing on behaviours that are reflective of different levels of EES. We also ask respondents to self-assess the Skills Requirements of their jobs.
- Our measurement scales for each EES domain utilise both newly developed items and a range of existing self-report measures that have previously been piloted and validated. We rigorously validated our measurement scales through a large-scale pilot.
- The development of our instrument was underpinned by a conceptual framework that drew on relevant descriptions of skills from established skills frameworks, our earlier literature review for The Skills Imperative 2035 and the skills descriptors from O*NET (which is the primary database of occupational information in the United States).
- To examine the distribution of skills across the population we collect information from respondents on their background and the jobs they work in. Specifically, we gather data on individuals' demographic characteristics, industry, occupation, qualifications, employment status, socio-economic status, health status and training participation. We also collect data on individuals' salary, managerial status, and job and life satisfaction in order to explore how people's Skills Supply relates to these outcomes.
- Rasch measurement theory was used to transform respondents' raw ratings into meaningful measures of their skills that account for differences in the difficulty of agreeing with each statement in our instrument. This enables us to compare Skills Supply between people, and to compare individuals' Skills Supply with their Skills Requirements (to quantify Skills Gaps).
- We have also projected how Skills Supply and Skills Gaps might change between 2023 and 2035. To project future Skills Gaps, we first re-weight our survey data to account for projected changes in the population and in the composition of employment. We then also adjust workers' Skills Requirements to account for projected changes in EES utilisation within each occupational group (without adjusting workers' Skills Supply, which may, in reality, be responsive to increased utilisation of these skills). We use our 2035 projections to examine how Skills Gaps may over the next 10 to 15 years.

This section summaries information in an accompanying Technical Supplement on the development, piloting and validation of our instrument.

We utilise responses to the NFER Essential Skills Survey from around 12,000 people aged 15-65 in England to examine:

- **Differences in Skills Supply and Skills Gaps between sub-populations, occupations and industries**: We examine how the Supply of EES and Skills Gaps vary between adults in the workforce, young people and the long-term unemployed, and how Skills Supply and Skills Gaps among workers vary by occupation and industry.

- **The distribution of Skills Supply and Skills Gaps across the population:** We examine the relationships between people's Skills Supply and Skills Gaps and their demographic characteristics, childhood socio-economic status, employment and managerial status, health status, highest qualification achieved, training participation and personality traits.
- **Projected changes in Skills Supply and Skills Gaps between 2023 and 2035:** We project how Skills Supply and Skills Gaps may change between 2023 and 2035 as a result of anticipated changes in the composition of the population, the distribution of employment, and the skills requirements of occupations.
- **The benefits associated with higher levels of EES:** We examine the relationship between people's Skills Supply and their salary, likelihood of being in a managerial position, job satisfaction and life satisfaction.

The NFER Essential Employment Skills Survey measures respondents level (or 'Supply') of EES based on their responses to six scales of Likert-style items about their behaviours and attitudes. For each of the six skills, respondents were presented with statements which solicited their degree of frequency or agreement about the extent to which behaviours applied to them. Responses were weighted to account for compositional differences between the sample and the population. Rasch measurement theory was used to transform respondents' raw ratings into meaningful measures of their latent skills, accounting for differences in the ease of agreeing with each statement. This enables us to make valid comparisons between individuals' skills. The items used in the final instrument are provided in the accompanying Technical Supplement on the development, piloting and validation of our instrument. Workers' perceptions of the Skills Requirements of their jobs are measured using validated survey items and their anchors from questionnaires developed by the Occupational Information Network (O*NET). O*NET is the primary source of occupational information in the United States. Rasch techniques are used to transform respondents' raw ratings into meaningful measures and equate Skills Supply and Skills Requirements scores onto a common latent scale. This enables us to calculate Skills Gaps and explore how they vary by occupation, industry and by other individual characteristics.

We compare Skills Supply between and within three specific sub-populations:

1. ***Workers* (sample size (N) = 8,569)**: Adults aged 19-65 who are either currently in paid work or who have been in work at any point in the previous five years, and young people aged 16-18 who are in work-based training or employment 20+ hours per week.
2. ***Young people* (N = 1,889)**: 15-18 year olds who are not in work or who are working less than 20 hours per week[1].
3. ***Long-term unemployed* (N = 649)**: Adults aged 19 or over that have never worked or who have been unemployed for 5 or more years.

2.1 Essential Employment Skills: Definitions and concepts

Whilst there is agreement about the importance of 'soft' or 'transferable'/ 'transversal' skills in almost every job and at every level, there is conversely no consensus on which skills are most important, or even what attributes constitute skills. Skills are often conflated with personality traits, habits, attitudes, and commitment, obscuring the differences and interdependencies between them. Terms such as employability skills, essential skills, soft

[1] We assume that young people working under 20 hours per week (p/w) are involved in 'casual work' alongside their studies, whereas those working 20 plus hours p/w are involved in work-based learning such as an apprenticeship or have left education to enter the labour market.

skills, life skills, citizenship skills and socio-emotional skills are defined inconsistently and used interchangeably, obscuring nuanced differences in the aptitudes, attitudes, traits, values and behaviours to which they refer.

This terminological menagerie complicates efforts to distinguish and measure a set of 'essential employment skills'. We took a data-driven response to this challenge. Our earlier skills projections for *The Skills Imperative 2035* identified the skills that are likely to be most heavily utilised across the workforce in 2035, forecast changes in the relative importance of 161 different skill descriptors in O*NET (https://www.onetcenter.org/content.html). Using our projections of the top skills in 2035 from O*NET, together with the findings of an earlier literature review (Taylor *et al.*, 2022), we identified six Essential Employment Skills.

Initial definitions of our six EES drew on the relevant O*NET descriptors and the skills definitions in our literature review. To add depth to our definitions, we incorporated other relevant descriptions from skills frameworks such as the Skills Builder Universal Framework, UNICEF's Life Skills and Citizenship Education (LSCE) framework and the Australian Core Skills Framework (ACSF). This enables us to break each skill down into its constituent attributes and develop sets of survey items to measure each attribute.

Our six EES are:

1. Collaboration – Developing constructive and cooperative working relationships with others, maintaining them over time and utilising them to work towards a common purpose or goal(s).

2. Communication – Providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person'. This involves speaking, listening, writing, and presenting effectively to share meaning and build a common understanding with others.

3. Creative thinking – Developing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions. This relates closely to critical thinking and problem solving and is the ability to generate, articulate, and apply innovative ideas, techniques, and perspectives, often in a collaborative environment in response to a challenge or issue.

4. Information literacy – Getting, appraising, dissecting, synthesising, analysing and interpreting information to identify the strengths and weaknesses of options, reach conclusions, and approach problems. This involves accessing and examining data or facts to determine appropriate actions or recommendations, discerning and evaluating arguments, and making and defending judgements based on internal evidence and external criteria.

5\. Organizing, planning and prioritising – Developing specific goals and plans to prioritise, organise, and accomplish your work. This involves developing specific goals, plans and schedules to prioritise, organise and accomplish work, and directing and coordinating the activities of groups and individuals to complete these objectives on time and within budget.

6. Problem solving and decision making – Analysing information and evaluating results to choose the best solution and solve problems. This involves diagnosing problems, identifying solutions to address these problems, choosing between the alternative courses of action available, planning and carrying out the solution(s) and monitoring and evaluating the progress of the solution(s).

2.2 The NFER Essential Employment Skills Survey: A new source of evidence

The NFER Essential Skills Survey is a new instrument designed to measure the Supply of EES in the population aged 16-65, and to compare workers' Skills Supply with their Skills requirements, in order to quantify Skills Gaps.

Scales are used to measure people's Supply of each skill based on their self-reported behaviours and attitudes, and an additional pair of items is used to measure the 'Level' and 'Importance' of each EES required by people's jobs (with 'Level' added to 'Importance' to calculate overall Skills Requirements). Our instrument also includes background questions on respondents' demographic characteristics, industry, occupation, qualifications, employment status, socio-economic status, health status, training participation, and personality traits, as well as their salary, managerial status, and job and life satisfaction.

2.2.1 Measuring respondents' levels of essential employment skills.

We define people's skills as the patterns of thoughts, feelings and behaviours individuals are able to exhibit in response to their environments, i.e. the behaviours they are able to exhibit *when their situation demands it*, which can differ from the behaviours they typically exhibit. There are no existing datasets that provide comprehensive information about people's level of EES. There are a number of potential methods that could be used for collecting information about people's behaviours, for example situational judgement tests and game-based assessments. Our survey relies on *self-assessment* methods. This methodological choice was driven by a desire to collect quantitative data, at scale, on both people's Skills Supply and Skills Requirements (enabling us to equate and compare the two, to measure Skills Gaps).

Self-assessment methods have been used to establish individuals' type and level of skills in large international studies such as the Survey of Adult Skills (PIAAC) (OECD, 2013). They are also frequently used in the field of personality psychology, one example being the 'Big Five' self-report personality questionnaire NEO-PIR (Costa and McCrae, 1992). Self-report measures can be a very useful way of establishing participants' perceptions and reflections of their own Skills Supply, especially where the evaluation of skills is inherently subjective (see Lucas, 2018). A range of existing self-report measures have previously been piloted and validated, which contributed to the items used in our scales, where appropriate.

However, whilst the majority of published studies are based on self-reports, there are known shortcomings to this approach. Self-reported attitudes or behaviours may not completely correspond with how participants would react, or feel, in reality and the measures may be prone to a range of biases, for example reference bias (Lira *et al.*, 2022) and social desirability bias (Sayer, 2007). Further detail on the rationale for selecting self-assessment methods and the alternative methods that were considered can be found in the accompanying Technical Supplement. Our intention is not to suggest that workers' self-assessments are more valid than employers' perspectives - our aim is to gather the missing worker perspective to add depth to our understanding of Skills Supply and Skills Gaps.

2.2.2 Measuring workers' skills requirements.

Whereas no existing instruments have been designed to measure the ESS people possess, survey items for measuring the Skills Requirements of people's jobs have already been used at scale by the Occupational Information Network (O*NET) in the US. O*NET profiles the tasks that are utilised in each of 964 occupations, and scores are provided for the 'level' and ‘importance’ of each skill utilised in that occupation, based on employers’ and employees’ assessments and expert assessor judgments. This metadata has been widely used by economists to understand how the demand for skills varies by occupation (e.g., Autor, Levy and Murnane, 2003; Deming, 2017). In the last stage of The Skills Imperative 2035, we mapped information from O*NET to the UK Standard Occupational Classification (SOC2020) and projected the future utilization of skills within each occupation using historic data from O*NET combined with our own employment projections (Dickerson *et al.*, 2023).

To measure Skills Requirements, we use the ‘level’ and ‘importance’ self-assessment questions developed and used at scale by O*NET. Minimal changes were made to these items to make them suitable for an English audience. Questions ask respondents to rate the level and importance of each skill required in their current job. If they are not currently employed but have worked in the previous five years, they are asked to reflect on their last job. Skills Requirements are calculated by summing importance and level. We utilise the level scale anchors as O*NET to provide respondents with common reference points when rating their Skills Requirements. These anchors increase the objectivity of ratings. We equate respondents’ Skills Supply and Skills Requirements scores onto a common latent scale using Rasch measurement theory, enabling valid comparisons between Skills Supply and Skills Requirements (and hence the calculation of Skills Gaps).

2.2.3 Validating the scales used to measure levels of essential employment skills.

We utilise Rasch measurement theory (RMT) to make valid comparisons of Skills Supply between people, and of Skills Supply and Skills Requirements within people. Rasch analysis is a psychometric technique that can facilitate the development of valid and reliable instruments, and which can provide researchers with more meaningful outcome measures (Royal *et al.*, 2010). People’s raw scores on the rating scales in our instrument are nonlinear and differences between any two consecutive categories of a rating scale cannot be assumed to represent equal intervals. Using Rasch techniques enables people’s raw scores to be expressed on a logit (interval) scale and a ‘difficulty’ measure to be computed for each item on the same logit scale. Our resulting measures for Skills Supply and Skills Requirements are comparable between people and across items because they account for both individual differences in skills and differences between items in how easy / hard it is to select frequency or agreement responses at the top of the rating scale. Further detail on the development, piloting and validation of our instrument using Rasch techniques can be found in the accompanying Technical Supplement.

2.2.4 Sampling methodology.

The sample for the final survey comprised three sub-samples, each of which was weighted to ensure it was representative. These sub-samples (and sizes) were:

1. **General population sample of adults 18-65 (N = 7,550):** A general sample of people in England aged 18-65, drawn from Kantar’s Public’s random probability Public Voice panel, a general population sample of adults aged 18-65 in England.

2. **Youth ‘boost’ sample (Year 11 and Year 13s) (N = 1,916):** A survey of young people in Year 11 or Year 13 of state schools and colleges in England, drawn from the National Pupil Database (NPD) and Individualized Learner Record (ILR), with samples systematically drawn from within each stratum after the sample frame was sorted by a range of variables, including SEN provision, prior attainment, Free School Meal eligibility and a range of demographic characteristics. This ensured the sample was representative of the population on these variables.

3. **PIAAC recontact sample (N = 1,926):** A recontact survey of people who had previously participated in the Programme for the International Assessment of Adult Skills (PIAAC) between September 2022 and June 2023 and gave their permission to be recontacted.

All interviews were conducted in summer 2023 using a Computer Assisted Web Interviewing (CAWI) self-completion methodology. The median interview length was 19 minutes. The questionnaire for each of the three surveys had only minor differences. Further detail on the survey fieldwork is available in the accompanying Technical Supplement.

2.2.5 Weighting the sample.

Weighting the sample comprised three stages. In stage one, the data from each of the three sub-samples above was weighted separately. In stage two, the three weighted samples were combined, and an overall weight was generated. In the final stage, the weights were adjusted to ensure the sample was representative of three discrete sub-populations required for the analysis (as well as to ensure the representativeness of the combined sample). Further detail on the weighting specification is available in the accompanying Technical Supplement.

2.2.6 Examining the distribution of Skills Supply and Skills Gaps.

A key research objective was to examine how Skills Supply and Skills Gaps vary across the population, depending on individuals' occupation, industry, demographic characteristics, geography, employment status, health status, qualifications and training and childhood socio-economic index. This started by exploring average relationships between these individual characteristics and people's Skills Supply. For example, to explore the average relationship between individuals' highest level of qualification obtained and their Skills Supply, we estimated a simple linear model:

$$\text{Skills supply} = \beta_0 + \beta_1 \text{qualification} + \varepsilon$$

Of course, qualification levels are also likely to affect people's skills indirectly by influencing their ability to access higher skill level occupations that utilise EES more intensively. Consequently, we were also interested in whether the relationship between qualification levels and Skills Supply would remain statistically significant after netting out the effects of occupation and other relevant factors. Therefore, we estimated the following multiple regression model:

$$\text{Skills supply} = \beta_0 + \beta_1 \text{qualification} + \boldsymbol{\beta}_2 \text{occupation sector} + \boldsymbol{\beta}_3 \text{other variables} + \varepsilon$$

where the estimated coefficient β_1 measures the effect that can be uniquely attributed to people's qualification level after making individuals comparable on the other attributes in our model. This approach was replicated for each individual characteristic. Models were restricted to respondents without missing values for any of the covariates being conditioned out.

There is likely to be a web of complex causal relationships between people's EES and their individual characteristics, increasing the risk of effects being misattributed between variables depending on the order in which they were added to our models. To account for this, we perform a Shorrocks-Shapley decomposition to isolate the marginal effect of different sets of related variables. Skills Gaps are calculated by subtracting Skills Supply from Skills Requirements and again multivariate regression modelling was used to assess the relationship between specific individual characteristics and Skills Gaps.

2.2.8 Projecting future Skills Supply and Skills Gaps in 2035.

We examine the impact on Skills Supply and Skills Gaps of changes in i) the composition of the population, ii) the jobs that will be available in the future, and iii) the skills that will be needed to do those jobs. This comprises three stages. Stage one involved re-weighting our survey data to account for projected changes in the composition, health, education and working hours of the population to 2035. Stage two involved exploring the impact that projected changes in the occupational and industrial distribution of employment are likely to have on Skills Supply and Skills Gaps. The final stage involved anticipating the effects of projected changes in the demand for skills within occupations. Full details on each stage of this process can be found in the accompanying Technical Supplement. We categorise everyone with a projected skills deficiency in 2023 and 2035 as having either a 'minor' skills deficiency or a 'substantial' skills deficiency by standardising the distribution of Skills Gap scores in 2023 and identifying a threshold equivalent to 1 SD from the mean. We use this same threshold (from the distribution of 2023 Skills Gap scores) to categorise individuals as having either a 'minor' or 'substantial' skills deficiency in 2035 and explore the extent to which skills deficiencies change between 2023 and 2035. Our projections of potential Skills Gaps in 2035 should be treated as exploratory, and comparisons between Skills Gaps today and potential Skills Gaps in 2035 should be interpreted cautiously. While no one can be certain about the future, quantitative projections provide a foundation for thinking about how Skills Gaps may change over time and the collective response that may be required to close them.

3 Analysis of differences in Skills Supply and Skills Gaps between sub-populations, occupations and industries

- 'Young people' and the 'Long-term unemployed' have lower average levels of Essential Employment Skills than 'Workers'.
- Workers' EES do not vary significantly between industries, with the exception of finance and insurance professionals (who self-report behaviours that indicate higher average Skills Supply) and workers in wholesale and retail (who indicate below average Skills Supply).
- Workers' EES vary by occupation, with workers in occupations at the top of the occupational hierarchy self-reporting behaviours indicative of the highest average Skills Supply and workers at the bottom of the hierarchy reporting behaviours indicative of the lowest Supply of these skills.
- Skills gaps vary by occupation, with workers in high skill level occupations typically experiencing skills deficiencies, whereas workers in mid and low skill level occupations typically experience skills under-utilisation.
- This pattern in Skills Gaps by occupation somewhat contrasts with the pattern reported by employers. Employers indicate skills gaps increase as we move down the occupational hierarchy and that transferable EES are a large constituent of these skills gaps, whereas we find the opposite.

3.1 Differences in Essential Employment Skills by sub-population

We start by examining Skills Supply across the population and between the three specific sub-populations of 'Workers', 'Young people' and the 'Long-term unemployed'.

As shown in Table 1 below, the 'Long-term unemployed' in our sample were more likely (compared to 'Workers') to be female, at either end of the age distribution (either 15-24 or 55-65), non-white, to have no or low-level qualifications, and to have a long-term health condition or illness. 'Young people' were also more likely than Workers to be non-white. Our combined weights correct for departures between the sample and actual populations.

Table 1 Overview of the composition of each sub-population (%)

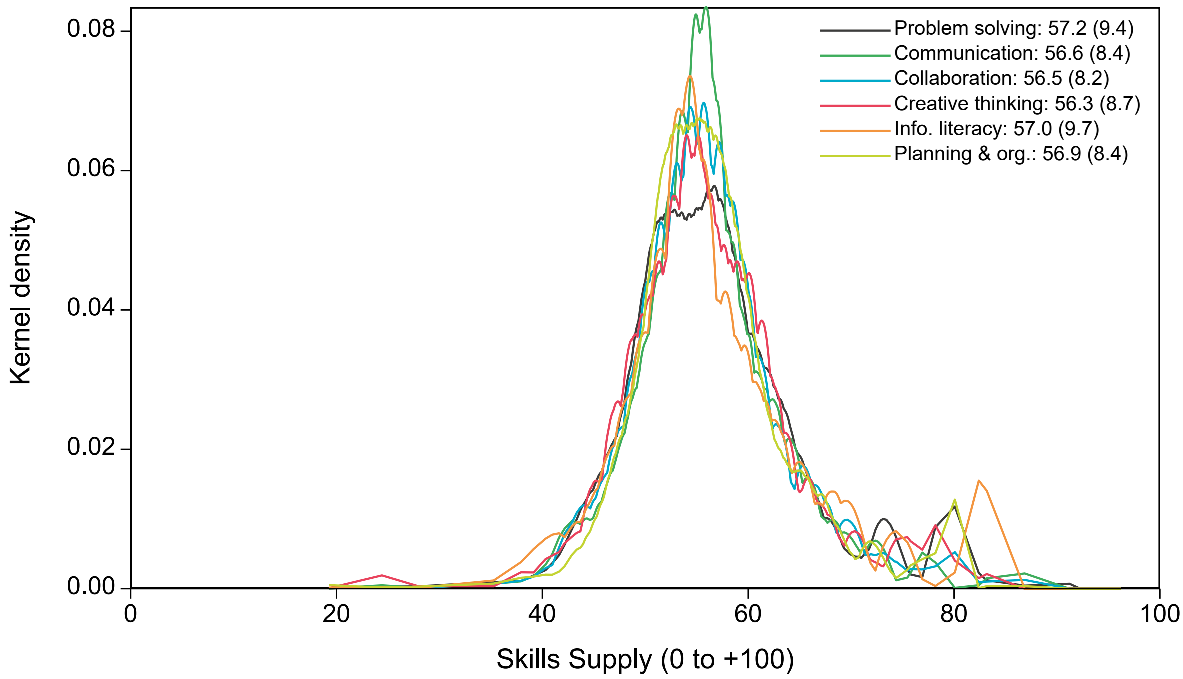
	Workers	Young people	Long term unemployed	Overall
Demographic variables				
Gender				
Male	51.4	50.7	37.4	49.7
Female	48.6	49.3	62.6	50.3
Age groups				
15-24	11.2	100.0	20.0	15.6
25-34	23.1	0.0	13.6	21.1
35-44	22.8	0.0	15.8	21.1
45-54	22.0	0.0	20.0	20.9

55-65	21.0	0.0	30.5	21.3
Ethnicity				
White	84.2	74.7	75.3	82.8
Non-white	15.8	25.3	24.7	17.2
Highest educational level				
No qualification	3.4	26.1	15.8	5.6
Low (Level 1-3)	43.8	72.2	57.6	46.3
Mid (Level 4-5)	10.3	1.3	9.7	9.9
High (Level 6-8)	42.5	0.4	17.0	38.2
Health condition				
No	81.4	83.1	45.5	77.2
Yes	18.6	16.9	54.5	22.8

Rasch techniques were used to transform respondents' raw ratings into meaningful measures of their Skills Supply and Skills Requirements, which were put on a scale of 0-100. Scores of 55-60 were broadly average, scores over 65 reflect particularly high skill levels, and skills under 50 reflect low skill levels. We compare the distribution of Skills Supply within and between our three subpopulations, both overall and by EES domain.

Our results indicate only marginal differences in average Skills Supply by domain in the overall population. Average Skills Supply scores range from 56.3 for Creative Thinking to 57.2 for 'Problem solving and decision making'.

Figure 2 Distribution of Skills Supply in the overall population, by domain



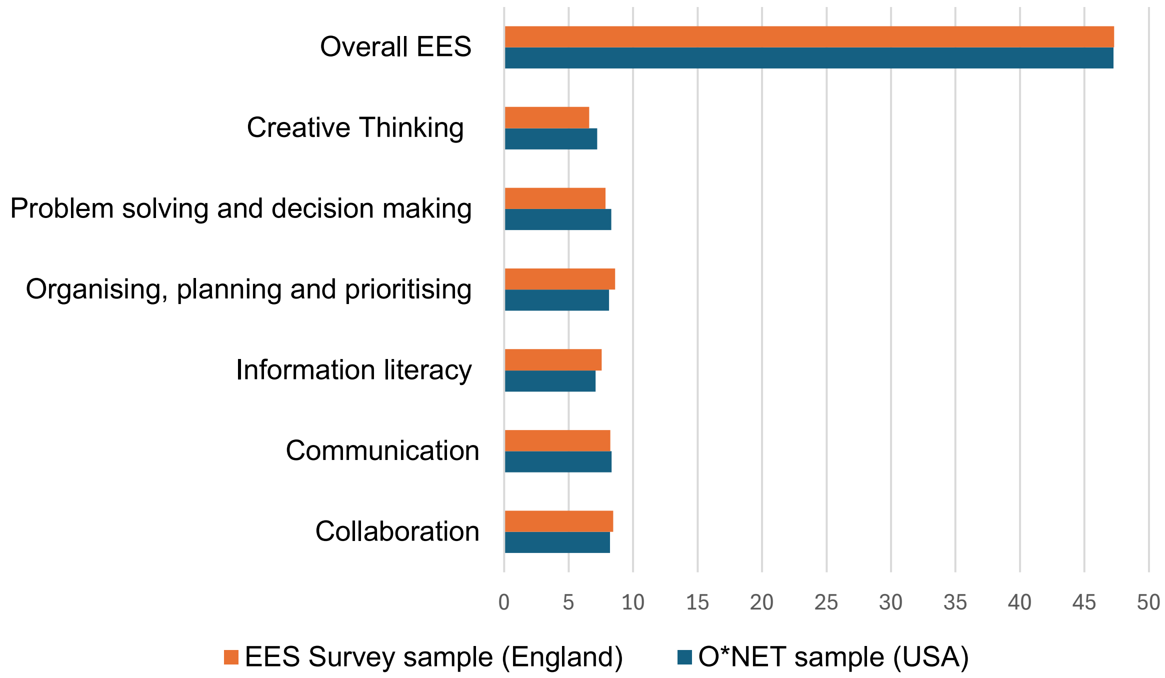
Note: The legend shows the mean and the standard deviation (in parentheses) of the Skills Gap for each domain. The y-axis shows the density of the population with each score for Skills Supply.

Our findings indicate that average Skills Supply is lower amongst ‘Young people’ (53.5) and the ‘Long-term unemployed’ (54.2) compared to ‘Workers’ (56.9). However, these differences in average Skills Supply between sub-populations are modest given that ‘Workers’ tend to be more educated and have more opportunities to develop their EES in work.

‘Young people’ and the ‘Long-term unemployed’ have higher levels of ‘Creative thinking’ than they have of the other five EES domains, whereas this is not true of ‘Workers’. This might be because Creative Thinking is less intensively utilised in work than the other five EES (Dickerson *et al.*, 2023), and therefore least developed in a work context.

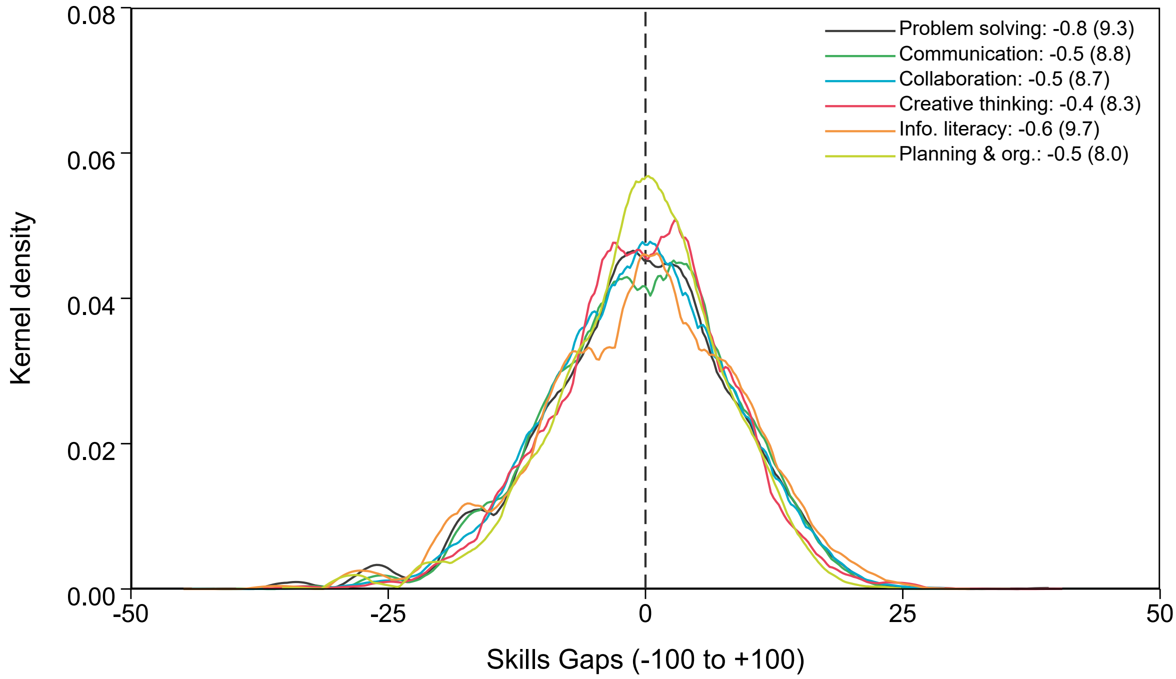
The average Skills Requirements across our weighted sample look very similar to the Skills Requirements reported by workers in O*NET’s sample of US workers, as show in Figure 3 below.

Figure 3 Average Skills Requirements (level + importance) across our weighted survey sample vs. the O*NET's sample in the US, using raw scores



Skills Gaps are calculated by subtracting Skills Supply from Skills Requirements, with positive gaps reflecting *skills deficiencies* and negative gaps reflecting *skills under-utilisation*. Our results indicate that Workers’ average Skills Supply (56.9) is very similar to average Skills Requirements (56.7), as shown in Figure 4 below. The mean skills gap is -0.1. However, this masks important variation in Skills Gaps across the population, particularly between occupations. Average Skills Gaps are similar across the six EES domains among ‘Workers’, albeit ‘problem solving and decision making’ skills are more likely to be under-utilised.

Figure 4 Distribution of Skills Gaps among 'Workers', by domain[2]



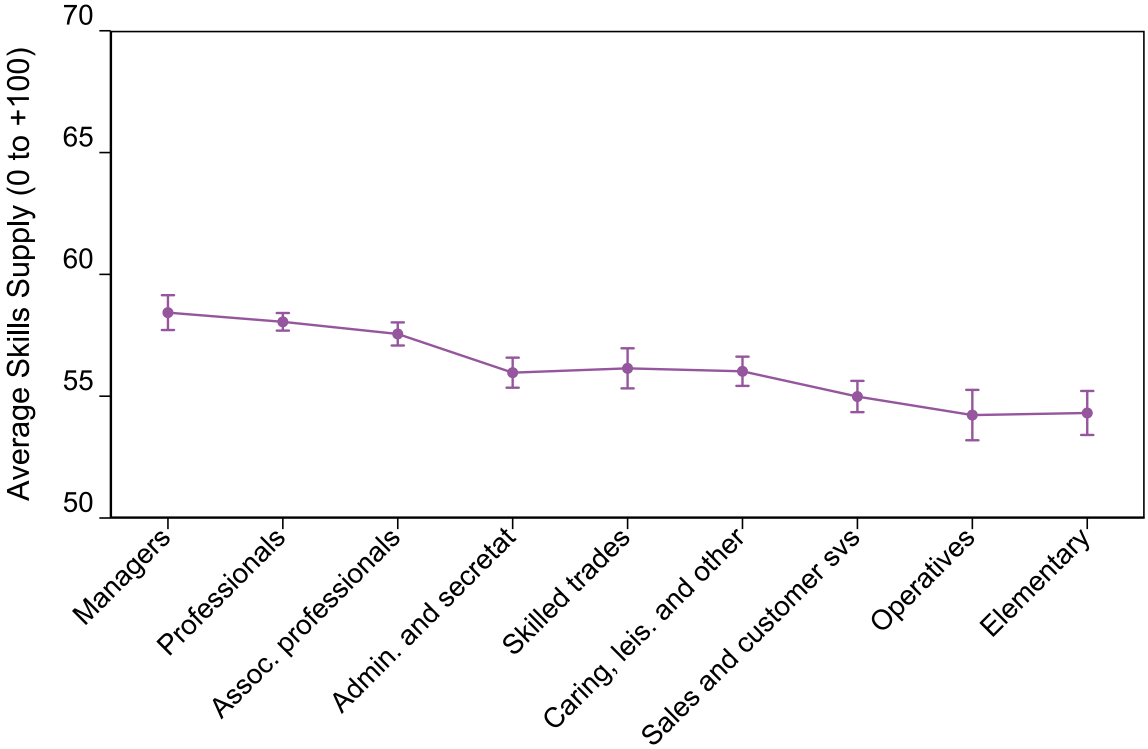
Note: Skills Gaps are calculated by subtracting Skills Supply from Skills Requirements and are on a scale of -100 to +100. The legend shows the mean and the standard deviation (in parentheses) of the Skills Gap for each domain. The y-axis shows the density of the population with each Skills Gap score.

3.2 Differences in Essential Employment Skills by occupation

Workers' average Skills Supply decreases as we move down the occupational hierarchy from 'managers, directors and senior officials' at the top-end to 'elementary' occupations at the bottom-end, as shown in Figure 5 Average Skills Supply in the overall population, by occupation (SOC major group) below. This is perhaps unsurprising given higher-paid, higher skill level occupations typically require higher education levels and utilise Skills more intensively, affording more opportunities for the development of these skills (Dickerson *et al.*, 2023) However, compared to occupation-related differences in Skills Requirements, differences in average Skills Supply between occupations are fairly modest; the average skill level of 'Directors, managers and senior officials' is only four percentage points higher than workers in 'Elementary' occupations. Occupation-related differences in average Skills Supply are also very similar when comparing across the six EES domains measured by our instrument, as shown in Figure 6.

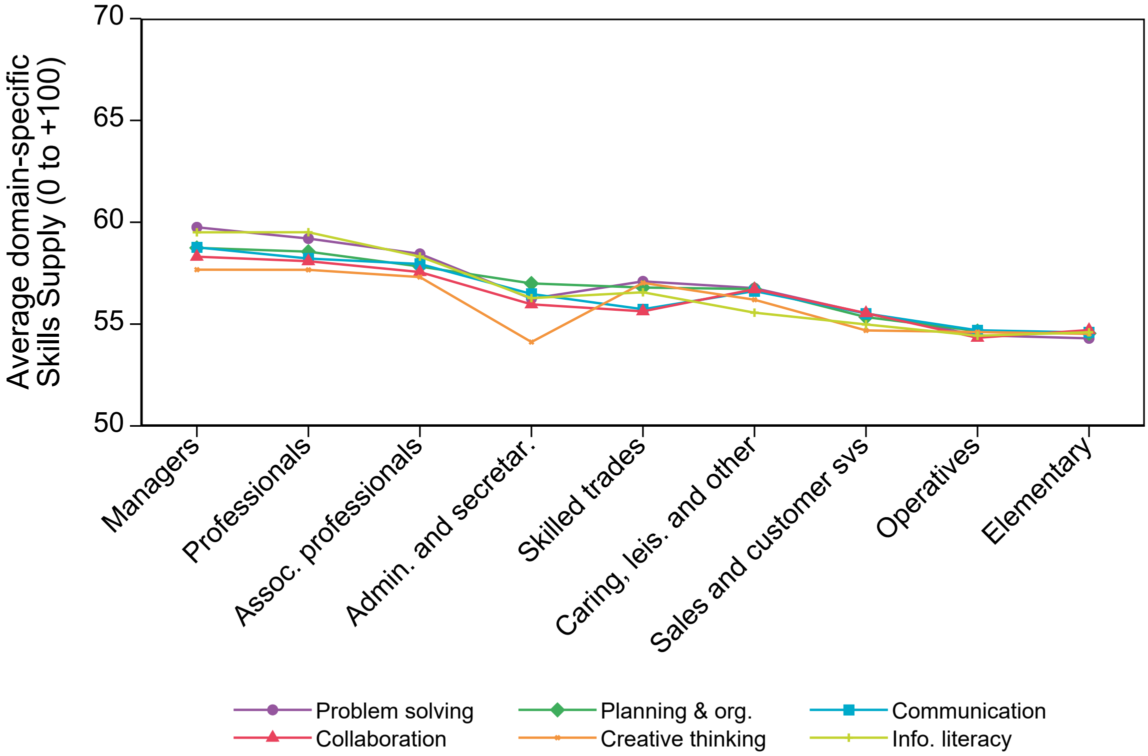
[2]The mean of the overall skill measure does not lie within the range of the means of the measures for each skill. This is because score-to-measure conversion is ogival rather than non-linear in Rasch analysis.

Figure 5 Average Skills Supply in the overall population, by occupation (SOC major group)



Note: Individuals' Skills Supply is calculated from their self-reported behaviours and put on a scale from 0-100, where larger numbers indicate higher skill levels.

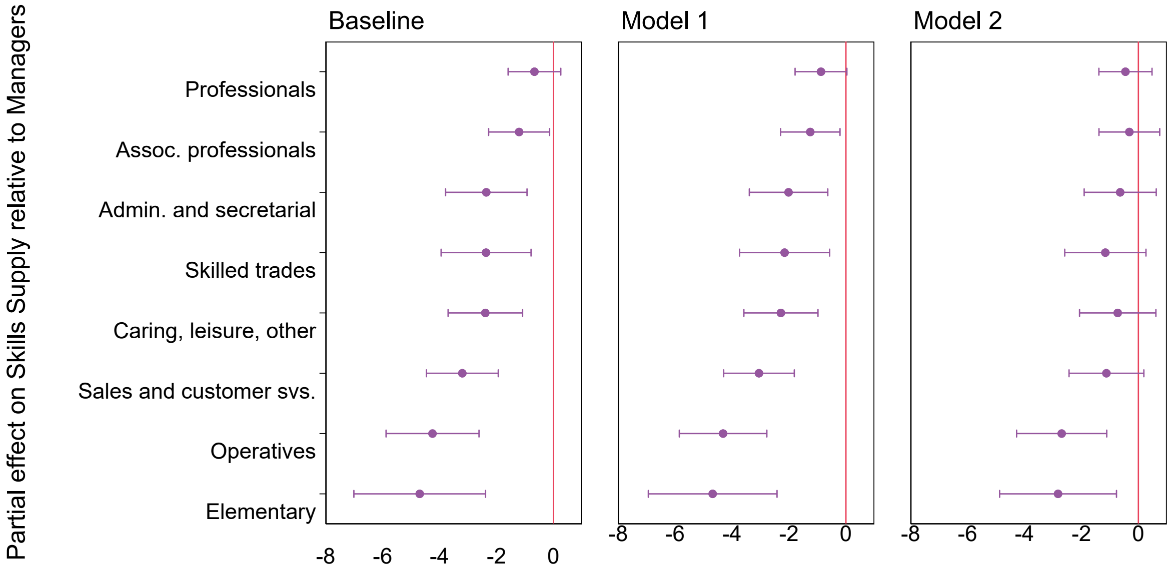
Figure 6 Average levels of Skills Supply in the overall population, by occupation (SOC major group), for each EES domain



Regression analysis indicates that a substantial share of the variation in Skills Supply between occupations among 'Workers'[3] is attributable to differences in other individual characteristics, as shown in Figure 7 below. 'Model 1' below controls for differences in demographic characteristics (gender, age, ethnicity, country of birth) and health status, and 'Model 2' adds further controls for differences in 'employment' (employment status and managerial status), 'geography' (region and local area deprivation), 'education and training' (highest qualification level and participation in off-the-job and on-the-job training) and industry[4]. These individual differences account for a large share of the relationship between occupation and Skills Supply, as is shown by the fact the dots representing the partial effects of each variable are closer to the red line in 'Model 2' below compared with the 'Baseline' model. However, the pattern remains one of Skills Supply declining as we move down the occupational hierarchy. The relationship between Skills Supply and occupation is similar across five of the six domains, but weaker for *communication*, perhaps because this is the most widely utilised skill across the entire labour market (Dickerson *et al.*, 2023).

[3] We restrict the subpopulation to 'Workers' because some of the controls in our regression models are only applicable to this subpopulation.
[4] Socio-economic status index is not included as a control in our models because of the high degree of missing values of this variable.

Figure 7 The partial effects of occupation group (SOC major group) on Skills Supply among 'Workers', before and after netting out the effects of other individual differences[5]

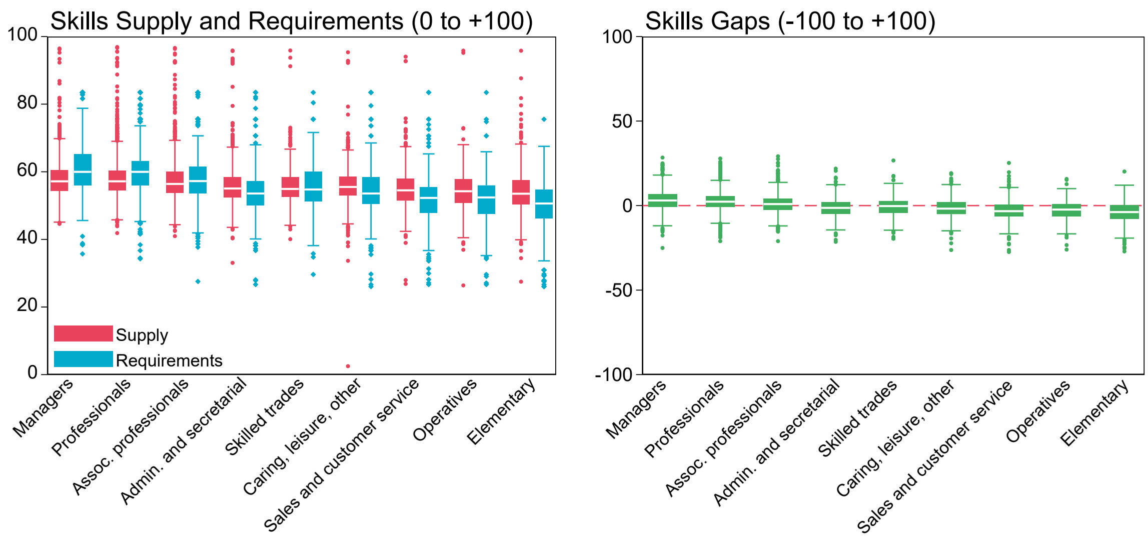


As shown in the boxplot below (Figure 8), the differences between occupations in average Skills Requirements are greater than the differences in Skills Supply between occupations. This may reflect the fact that job requirements vary substantially between occupations, whereas opportunities to develop EES are not confined to work-related contexts. Alternatively, the greater variability in Skills Requirements between occupations may be somewhat attributable to the use of scale anchors in the survey items about the 'Level' of each skill people require in their jobs (these anchors are taken from the O*NET questionnaires used in the US); these anchors may have increased the variance in respondents' assessments of their Skills Requirements, whereas our Skills Supply scales did not use anchors.

Figure 8 also suggests that Skills Gaps vary by occupation, with 'Managers, directors and senior officials', 'Professionals' and 'Associate professionals' typically experiencing skills deficiencies, whereas workers in mid and low skill level occupations have under-utilised skills. This is shown by the fact that the median Skills Gap is above the zero line for 'Managers, directors and senior officials', 'Professionals' and 'Associate professionals' in the chart on the righthand side below, whereas it is below the zero line for other occupational groups. Between-occupation differences in Skills Gaps are larger than between-occupation differences in Skills Supply – this is shown by the larger interquartile range (i.e. height) of the blue boxes below relative to the red boxes. This is largely because Skills Requirements increase at a faster rate than Skills Supply as we ascend the occupational hierarchy. It is difficult to determine the extent to which this may be attributable to differences in the benchmarks / reference points that people in different occupations commonly use when self-assessing their behaviours.

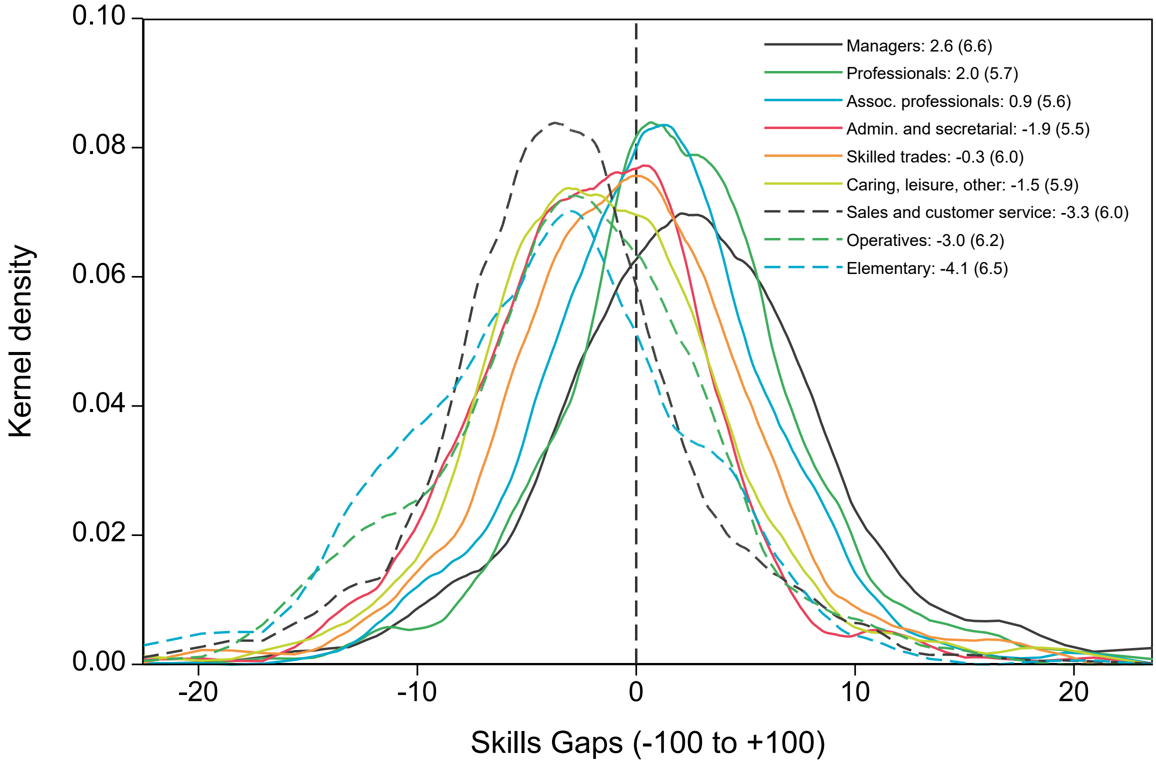
[5] 'Model 1' controls for gender, age, ethnicity, country of birth, and health status. 'Model 2' extends this list of controls to also include employment status, whether they are in a managerial position or not, region, local area deprivation (IDACI), highest qualification level, participation in off-the-job and on-the-job training, and industry.

Figure 8 Boxplot showing variation in Skills Supply and Skills Requirements among the overall population by occupation (SOC major group), and Skills Gaps among 'Workers' by occupation (SOC major group)



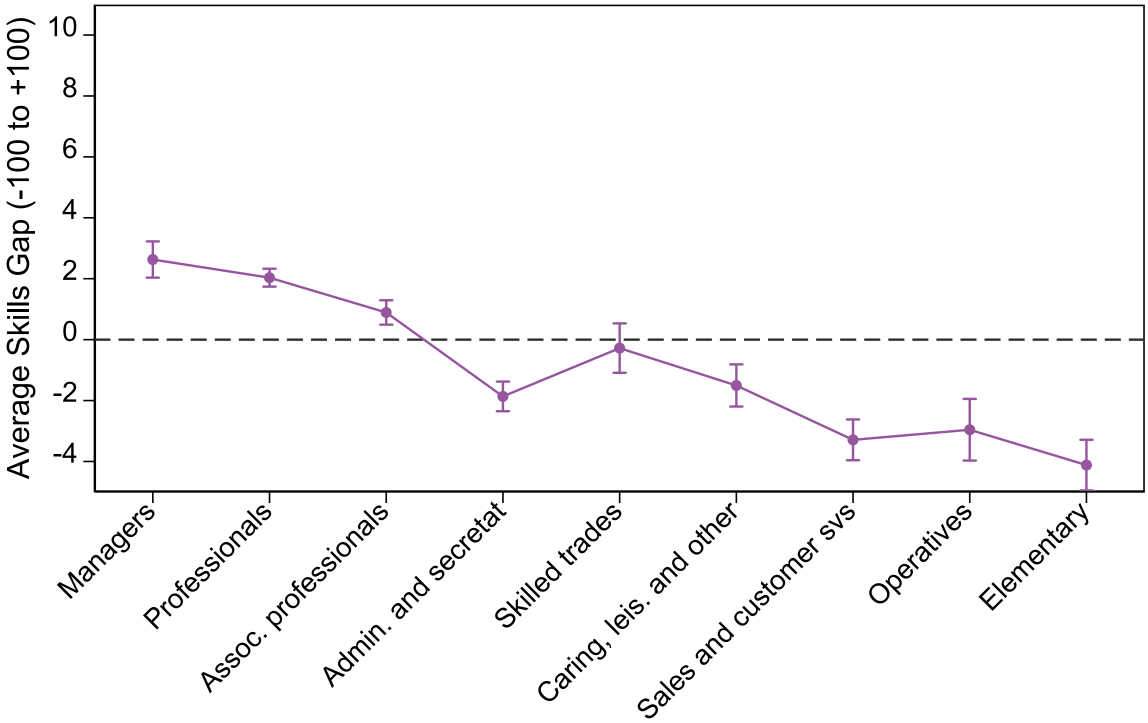
Our data also suggests that average Skills Gaps change as we move up the occupational hierarchy, switching from skills deficiencies in high skill level occupations to growing levels of skills under-utilisation among mid and low skill level occupations. This is shown by the fact that the distribution of Skills Gaps shown in Figure 9 shift to the left as we descend the occupational hierarchy. Figure 10 shows that average Skills Gaps are positive for high skill level occupations (indicating Skills deficiencies) but negative for all mid to low skill level occupations. For all occupational groups except 'Skilled trades' the error bars do not cross the zero line, indicating that we can be 95% confident we would not have observed Skills Gaps by chance.

Figure 9 The distribution of Skills Gaps among 'Workers', by occupation (SOC major group)



Note: The legend shows the mean and the standard deviation (in parentheses) of the Skills gap within each broad occupational group. Skills Gaps are calculated by subtracting Skills Supply from Skills Requirements and are on a scale of -100 to +100. The legend shows the mean and the standard deviation (in parentheses) of the Skills Gap for each domain. The y-axis shows the density of the population with each Skills Gap score.

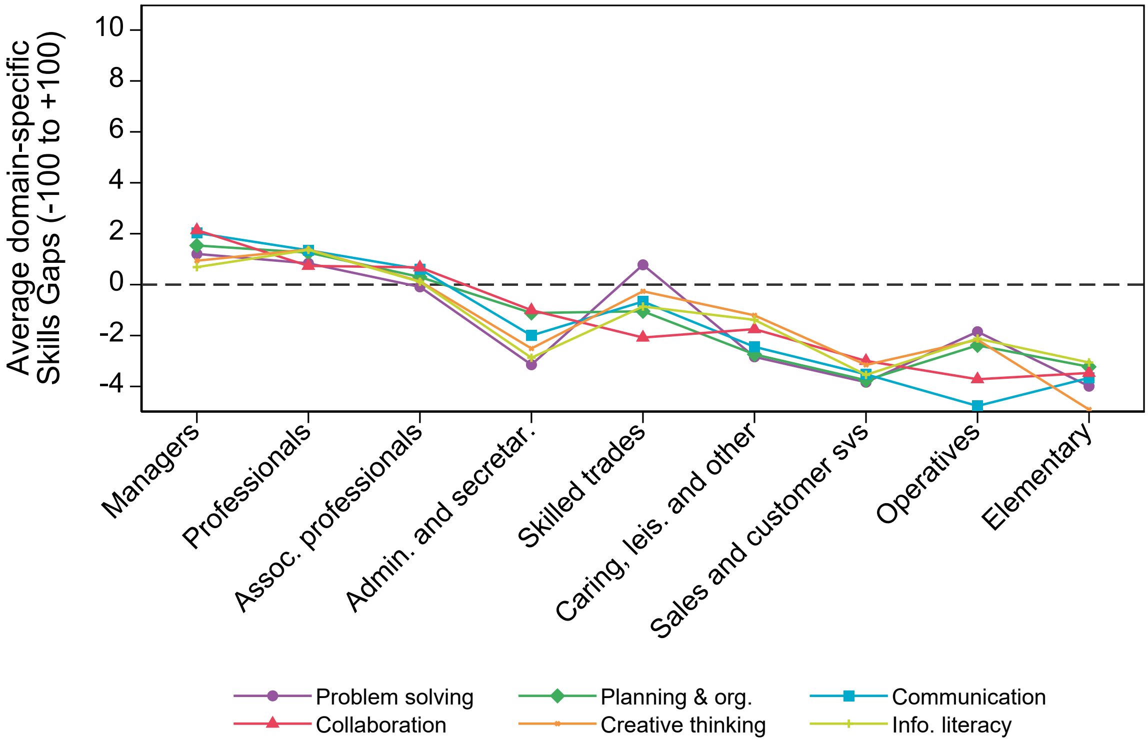
Figure 10 Average Skills Gaps among 'Workers' by occupation (SOC major group)



Note: Individuals' Skills Gaps are calculated by subtracting their Skills Supply from their Skills Requirements. Skills Gaps are on a scale from -100 to +100, where positive gaps indicate Skills deficiencies and negative gaps indicate skills under-utilisation.

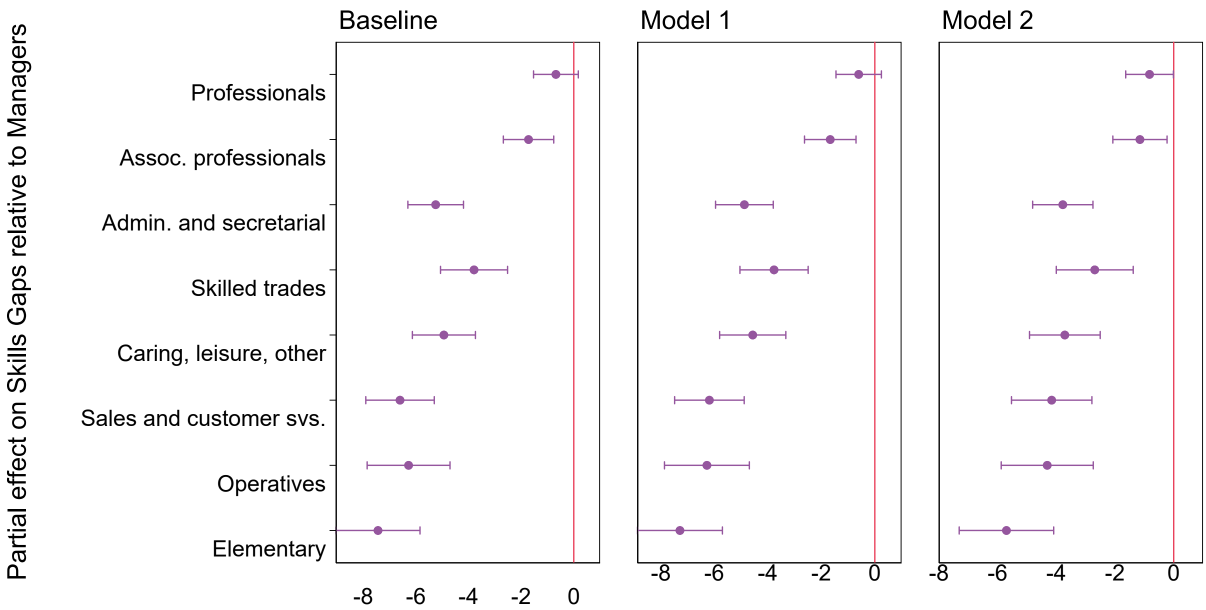
Occupation-related differences in average Skills gaps are similar across the six EES domains, although there is greater variation between occupations in some skill domains (e.g. Problem solving and decision making) compared to others (e.g. Communication). This is shown in Figure 11 below.

Figure 11 Average Skills Gaps among 'Workers' by occupation (SOC major group) by EES domain



Between-occupation differences in Skills Gaps remain significant after controlling for differences in demographic characteristics and health status ('Model 1'), and once differences in employment (employment status and managerial status), geography (region and local area deprivation), education and training (highest qualification level and participation in off-the-job and on-the-job training) and industry are accounted for ('Model 2'). Skills Gaps remain statistically significantly different relative to 'Managers, directors and senior officials' (SOC1) for almost every occupational group. 'Model 2' indicates that workers in 'Elementary occupations' (SOC9) have average Skills Gaps that are around six percentage points lower than otherwise comparable 'Managers, directors and senior officials' (SOC1).

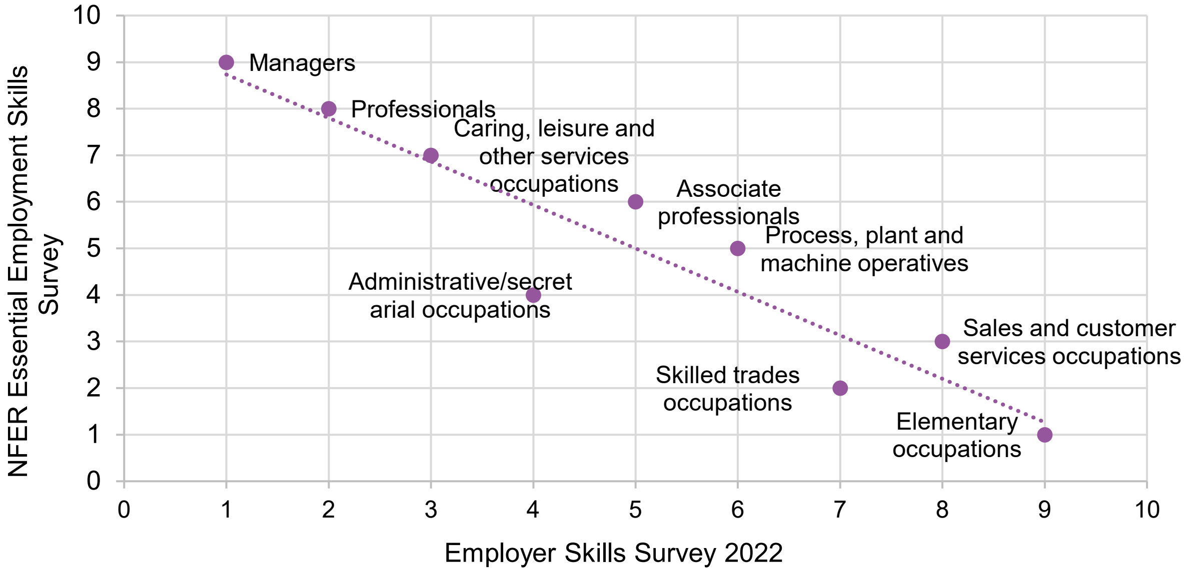
Figure 12 Partial effect of occupation (SOC major group) on Skills Gaps among 'Workers', before and after netting out the effects of other individual differences[6]



This contrasts with patterns reported in the existing literature which are based on employers' perspectives. Employers tend to report increasing skills *gaps* as we move down the occupational hierarchy and attribute a large share of these gaps to deficiencies in people and personal skills that overlap with our EES (Employer Skills Surveys, 2011-22). To compare the occupation-related differences in Skills Gaps identified by workers and employers, we rank order occupations (SOC major groups) based on the size of skills gaps identified by workers in our Essential Employment Skills survey (1 = highest skills under-utilisation, 10 = highest skills deficiency) and then based on the density of (overall) skills gaps reported by employers in the 2022 Employer Skills Survey (1= lowest density of skills gaps, 10 = highest density). We plot these against one another in Figure 13 below. Figure 13 indicates strong negative correlation between the rank order of skills gaps by occupation identified by workers and employers.

[6] 'Model 1' controls for gender, age, ethnicity, country of birth and health status. 'Model 2' also controls for employment status, whether they are in a managerial position or not, region, local area deprivation (IDACI), highest qualification level, participation in off-the-job and on-the-job training and industry.

Figure 13 Rank order of occupations based on Skills Gaps identified by 'Workers' in our Essential Employment Skills survey and the density of (overall) skills gaps reported by Employers in the 2022 Employer Skills Survey



Note: In Figure 13 skills gaps identified by 'Workers' in our Essential Employment Skills survey are ranked 1 = highest skills under-utilisation, 10 = highest skills deficiency. The density of (overall) skills gaps reported by employers in the 2022 Employer Skills Survey are ranked 1= lowest density of skills gaps, 10 = highest density.

However, there are a number of plausible explanations for this apparent contradiction. First, the skill types assessed in these surveys only partially overlap. Furthermore, skills deficiencies and skills under-utilisation may co-exist at the group-level, with low skill level occupations experiencing the highest levels of both Skills Gaps and skills under-use amongst different individuals. This could be the case of low skill level occupations have a higher share of people that are over-skilled and over-qualified for their jobs. However, were this the case, we would expect workers in mid and low skill level occupations (SOC4-9) with higher level qualifications (Levels 4+) to have under-utilised skills and workers in the same occupations with lower-level qualifications to have skills deficiencies. Regression analysis suggests this is not the case, as shown in Figure 14. Workers in mid and low skill level occupations with lower-level qualifications are more likely to report skills under-utilisation than more qualified workers, after netting out the effects of individual differences in other factors. Therefore, a more plausible explanation for the discrepancy might be that employers and workers experience a perception gap, with misalignment being greatest between employers and workers in low skill level occupations.

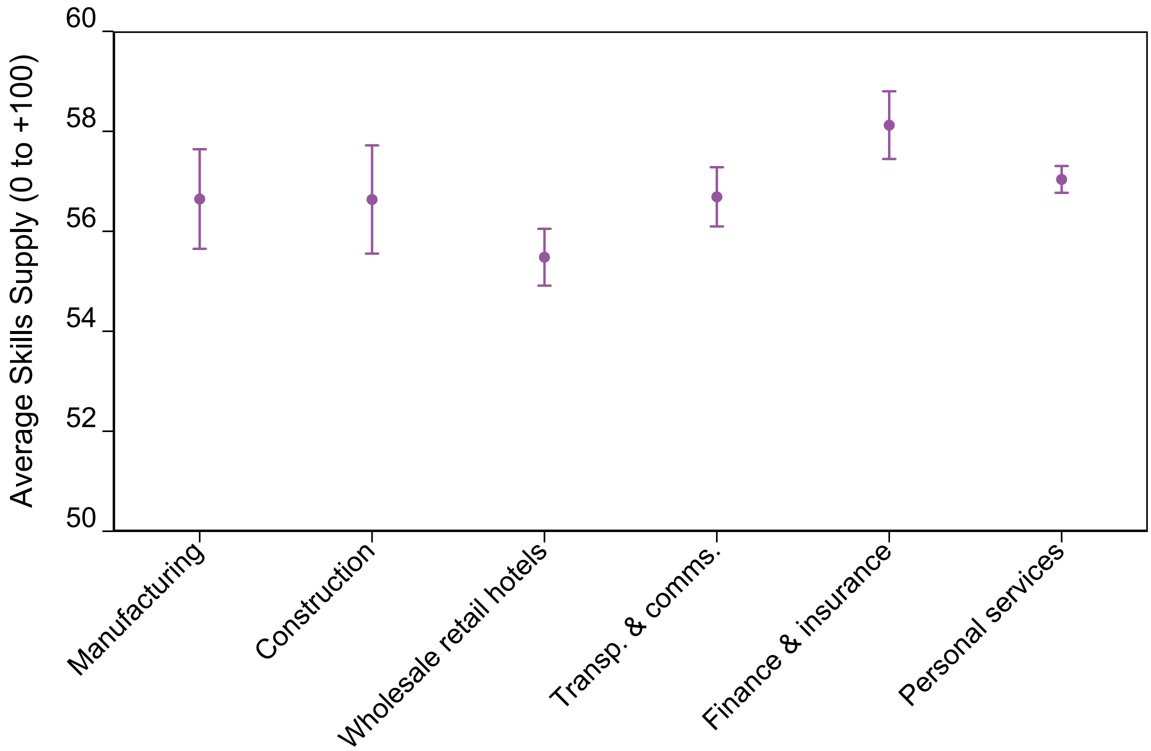
Figure 14 Partial effect of qualification level on Skills gaps among 'Workers' in SOC4-9, showing those with lower-level qualifications relative to those with higher level qualifications, before and after netting out the effects of other individual differences[7]

3.3 Differences in Essential employment skills by industry

To compare average Skills Supply by industry we collapse the 21 industry sectors in the Standard Industrial Occupation (SIC) 2007 into 8 groups, based on industry similarities.[8] Figure 15 below shows that average Skills Supply does not vary greatly by industry, with the exceptions being finance and insurance professionals (who have higher Skills Supply on average, particularly in 'problem solving and decision making' and 'planning, organising and prioritising') and workers in wholesale and retail (who self-report behaviours consistent with lower than average Skills Supply).

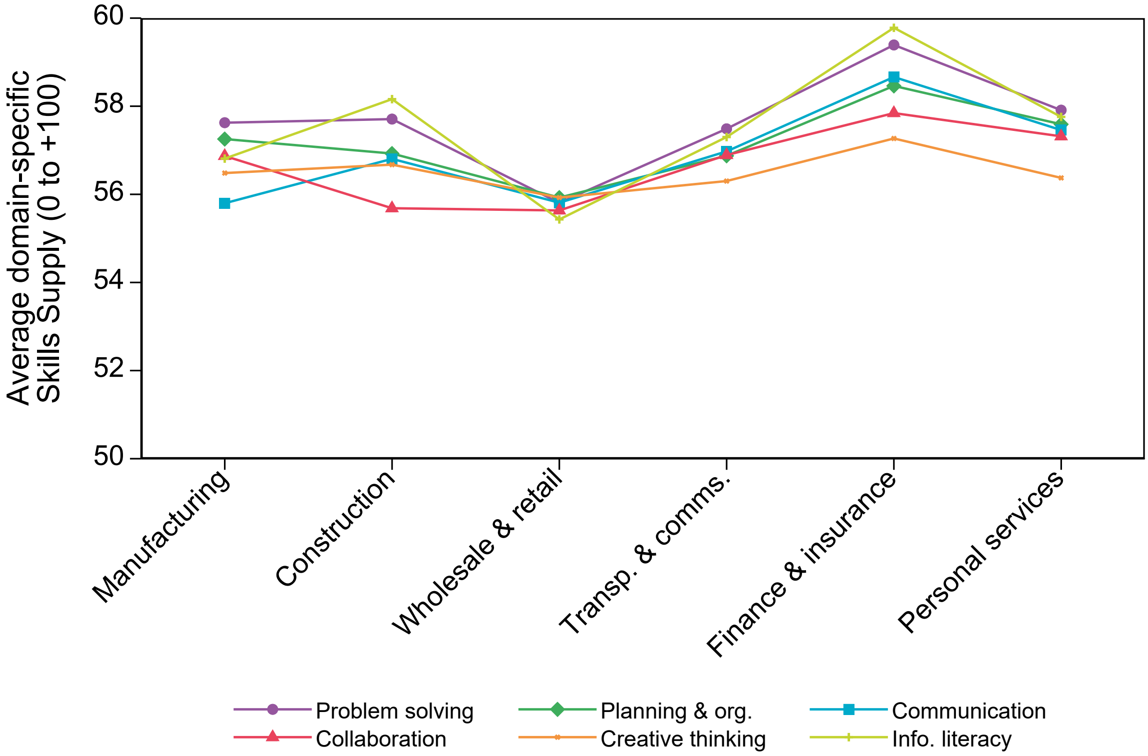
[7] 'Model 1' controls for gender, age, ethnicity, country of birth and health status. 'Model 2' also controls for employment status, whether they are in a managerial position or not, region, local area deprivation (IDACI), participation in off-the-job and on-the-job training, occupation and industry.
[8] Specifically, the first group is comprised by Section A (Agriculture, forestry and fishing industry). The second group by Sections B, D and E (mining, electricity, gas and water production industry). The third and fourth groups included only Section C (manufacturing) and F (Construction), respectively. The fifth group is comprised of Section G (wholesale and retail) and I (accommodation) while the sixth includes Sections H and J (transportation and information). The seventh group includes Sections K (Financial and insurance) and L (Real estate). The last group encompasses Sections M to S (personal and public services). The charts that follow exclude individuals employed in the first and second group of industries, which have fewer than 100 observations in each.

Figure 15 Average Skills Supply in the overall population, by industry



Between-industry differences in Skills Supply are slightly larger for some EES domains than others, with workers varying more in their 'Planning, organising and prioritising' skills than in their 'Creative thinking' skills for example. This is shown in Figure 16 below. Differences in Skills Supply by EES domain are also larger within some industries compared to others. For example, there is greater variation in Skills Supply by domain within the 'Construction' and 'Finance and insurance' sectors compared to the 'Wholesale and retail' sector. This is likely to reflect differences in the occupational distribution of employment between industries.

Figure 16 Average Skills Supply in the overall population by industry, broken down by EES domain



4 The distribution of Skills Supply and Skills Gaps across the population

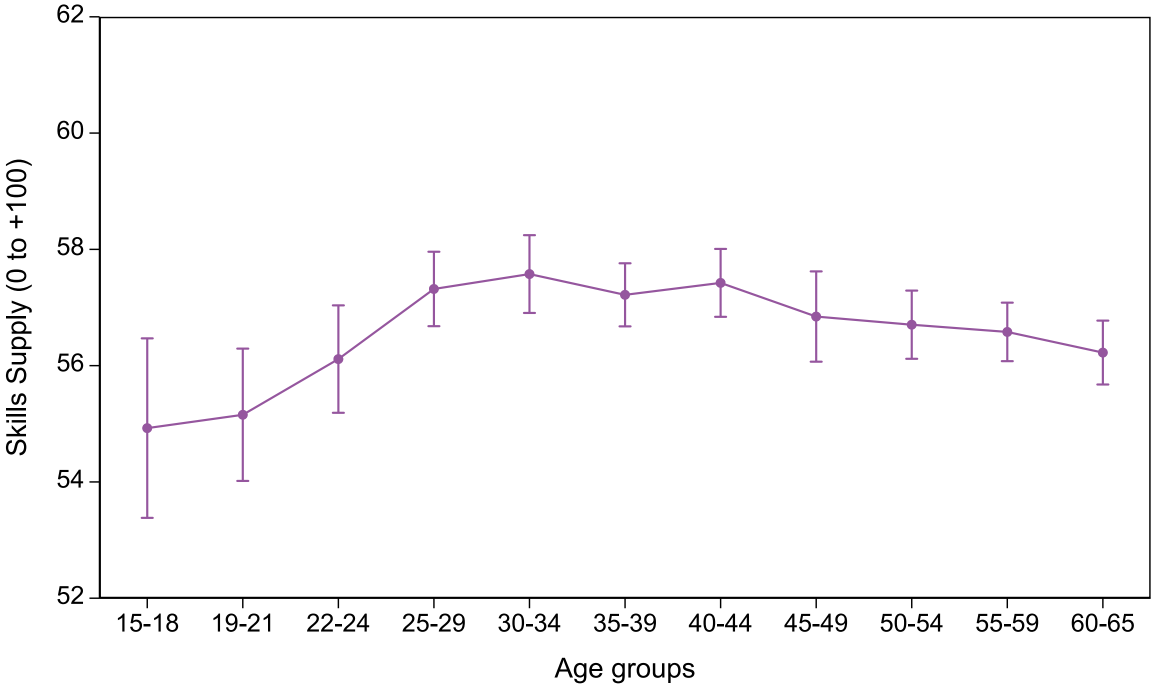
- Skills Supply is unevenly distributed across the population, with average Skills Supply varying by demographic characteristics, geography, employment status, managerial status, qualifications, training participation, health status, childhood socio-economic status and personality traits.
- Regression analyses indicate the relationships remain statistically significant between people's Skills Supply and their employment and managerial status, highest qualification achieved, training participation and personality traits, even after controlling for a broad range of other individual differences.
- We are unable to explain most of the variation in Skills Supply amongst 'Workers', highlighting a need for further research into the determinants of EES.
- Isolating the marginal effect of each factor suggests that most of this variation is attributable to differences in 'education and training' (highest qualification obtained and participation in training), 'occupation' and 'employment' (employment status and managerial status).

4.1 Differences in Essential Employment Skills by demographic characteristics

Skills Supply varies by age. Comparisons of the literacy and numeracy performance of adults in the OECD Survey of Adult Skills (part of the Programme for the International Assessment of Adult Competencies, PIAAC) have shown that average skills increase with age up to adults in their thirties and then decline amongst adults approaching retirement (OECD, 2016). A substantial share of these age-related differences in skills may be attributable to differences in other individual characteristics, for example increases over time in average qualification levels and years spent in education.

Our findings indicate that age-related differences in EES Skills Supply follow a similar pattern to age-related differences in numeracy and literacy skills measured by PIAAC.

Figure 17 Average Skills Supply among ‘Workers’ by age band



The relationship between age and Skills Supply varies across the population. Skills Supply is more strongly associated with age amongst men (relative to women), amongst White and African ethnicities (relative to Asians) and among those who speak English as a first language (relative to those for whom English is an additional language).

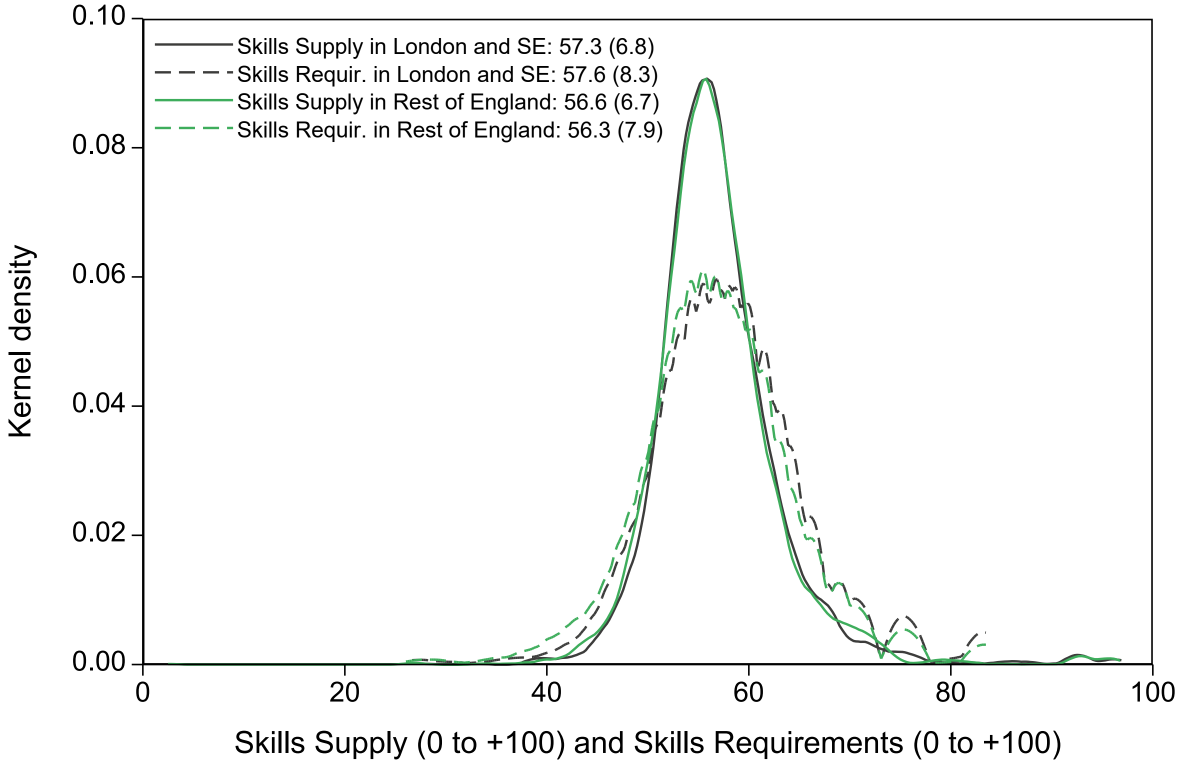
Regional differences in average Skills Supply are small. However, as shown by Figure 18, our analysis finds that workers in London and the South-east do have significantly higher average Skills Supply and Skills Requirements than their counterparts in the North-east. This is perhaps unsurprising given London and the South-east have the highest density of workers in 'professional' occupations that normally require a degree or equivalent work experience and utilise EES most intensively. Average Skills Supply amongst ‘Young people’ in London is also higher, potentially reflecting the inter-generational influence of parental education levels on their children’s skill development.

Our analysis shows that, amongst workers in the North-east, the Skills Requirements of people’s jobs do not greatly differ from the average, but average Skills Supply is lower. Consequently, Skills Gaps in the North-east are larger than in any other regions, both overall and in each EES domain (except communication). Skills Gaps are not significantly larger in London and the South-east than other regions – Skills Requirements are higher in these regions as well as Supply.

Our analysis also suggests average levels of Skills supply do not vary significantly by level of local area deprivation (measured using IDACI, which is based on the proportion of all children aged 0 to 15 living in income deprived families in the area), despite the fact people with higher levels of education and higher skill level occupations tend to live in areas of lower deprivation.

4.2 Differences in Essential Employment Skills by geography

Figure 18 Distribution of skills supply and requirements among 'Workers' in London and the South-east compared with other regions combined

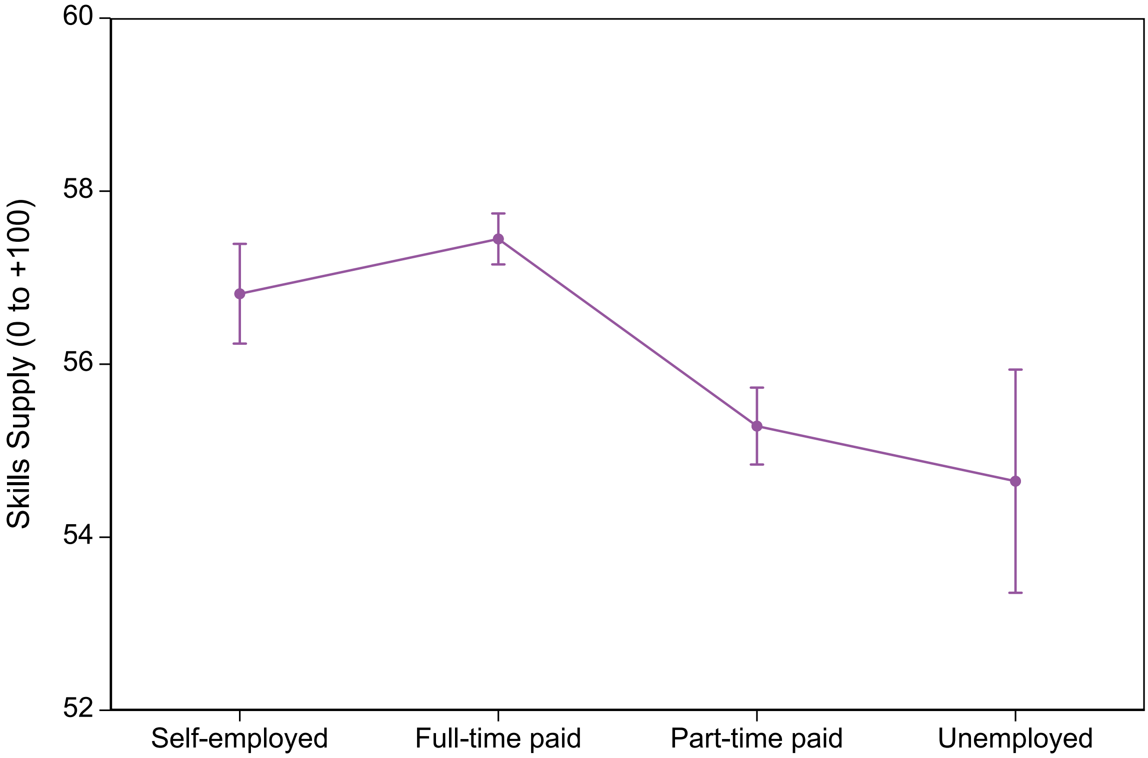


Note: The legend shows the mean and the standard deviation (in parentheses) of Skills Supply for each domain. The y-axis shows the density of the population in London and the South-east / the rest of England with each Skills Supply score.

4.3 Differences in Essential Employment Skills by employment status

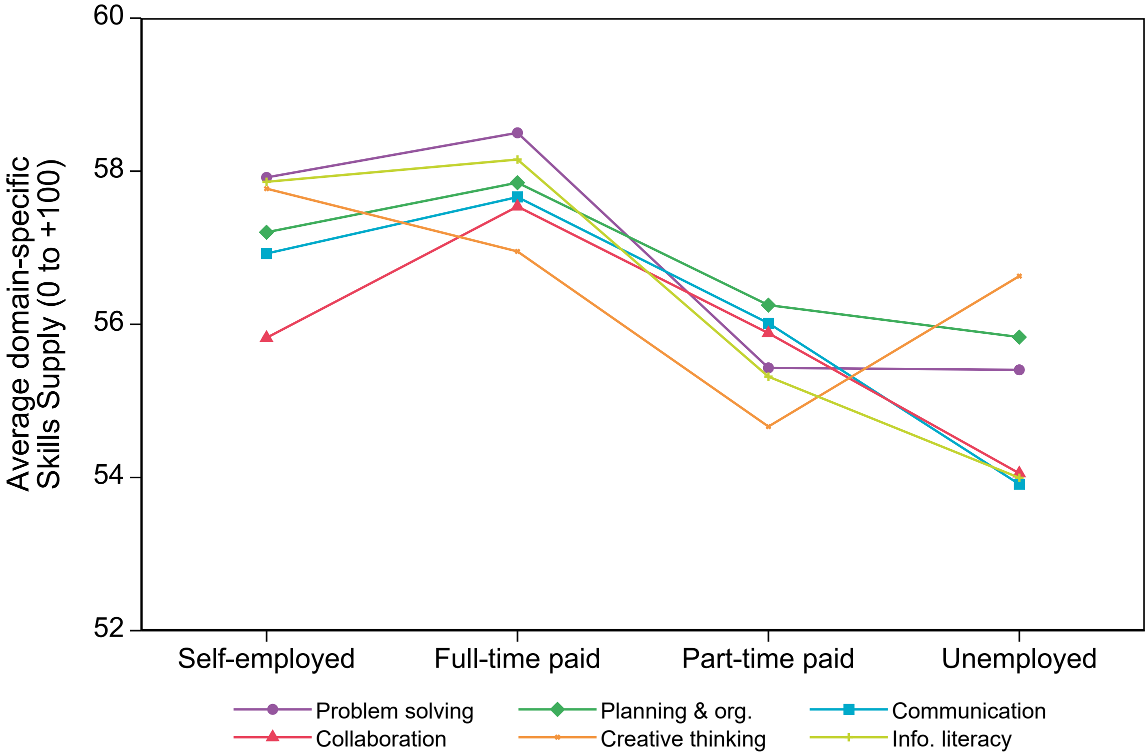
Figure 19 suggests average Skills Supply is significantly (though not substantially) higher amongst the full-time employed and self-employed, compared to part-time workers and the unemployed. This is perhaps unsurprising given higher levels of education are associated with a lower probability of being unemployed or working part-time (OECD, 2014), and more years in education and the workplace are likely to afford more opportunities to utilise and develop EES.

Figure 19 Average Skills Supply in the overall population, by employment status



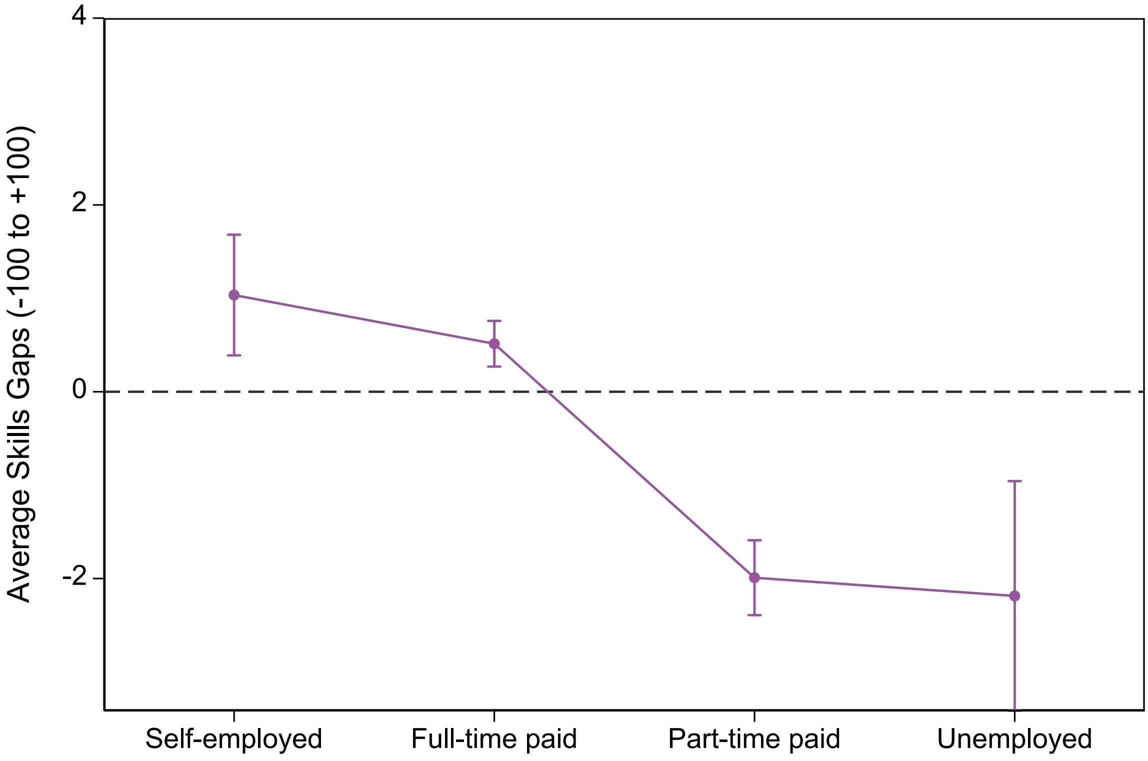
Differences in Skills Supply by employment status are similar across the six EES domains, with the exception of creative thinking, where unemployed people report behaviours reflective of creative thinking levels comparable to those of full-time workers. This is shown in Figure 20 below.

Figure 20 Average levels of Skills Supply in the overall population, by employment status, broken down by domain.



Whilst full-time workers and the self-employed self-report higher average Skills Supply, our results suggest they typically experience skills deficiencies, whereas part-time workers and the unemployed have under-utilised skills. This is partly because differences in Skills Requirements by employment status are greater than differences in Skills Supply, with people in self-employed and full-time work more likely to work in higher skill level occupations that require higher levels of education and utilise EES more intensively.

Figure 21 Average Skills Gaps among 'Workers', by employment status



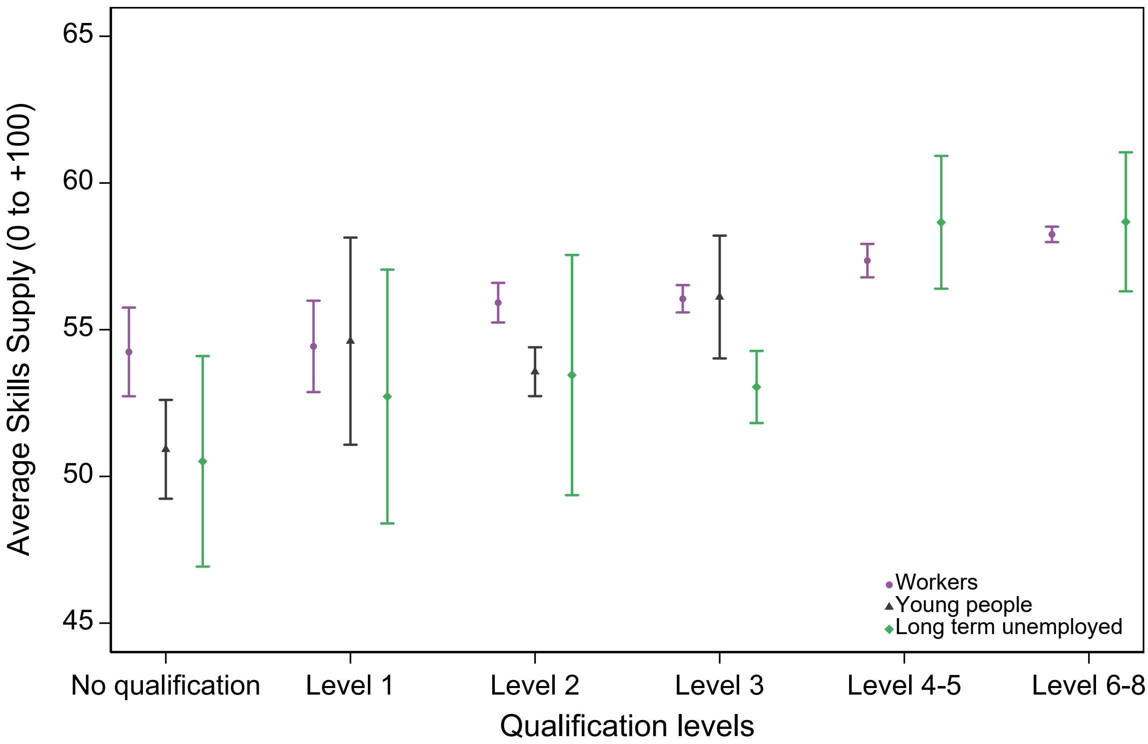
Note: Comparisons of average Skills Gaps by employment status are restricted to 'Workers', with the 'Unemployed' in Figure 25 below being people that are not currently employed but who have worked in the previous five years and who were asked about the Skills Requirements of their last job.

4.4 Differences in Essential Employment Skills by highest qualification achieved

Higher levels of qualifications are associated with a range of positive and statistically significant benefits, including in earnings and employment status (Social Mobility Commission, 2023 and Bibby *et al.*, 2014). In part, this is likely to be because qualifications create opportunities for people to develop new skills - including EES – and evidence them to employers. Qualifications and skills are not, however, synonymous. Based on analysis of job advertisement data, Brown and Souto-Otero suggest employers are placing greater emphasis on job readiness and transferrable skills, at the expense of qualifications, potentially implying a (perceived) weakening of the relationship between skills and qualifications, or a change in the skills that are most valued by employers (Brown and Souto-Otero, 2020).

Our results indicate people with higher qualification levels have higher Skills Supply, on average, as shown in Figure 22 below. This is the case in all three sub-populations - 'Workers', 'Young people' and the 'Long term unemployed'. One potential explanation is that qualifications directly develop people's EES. Alternatively, young people with higher Skills Supply may be more likely to pursue a higher qualification in the first place. Other factors, such as family influences, are also likely to affect both educational choices and skill development.

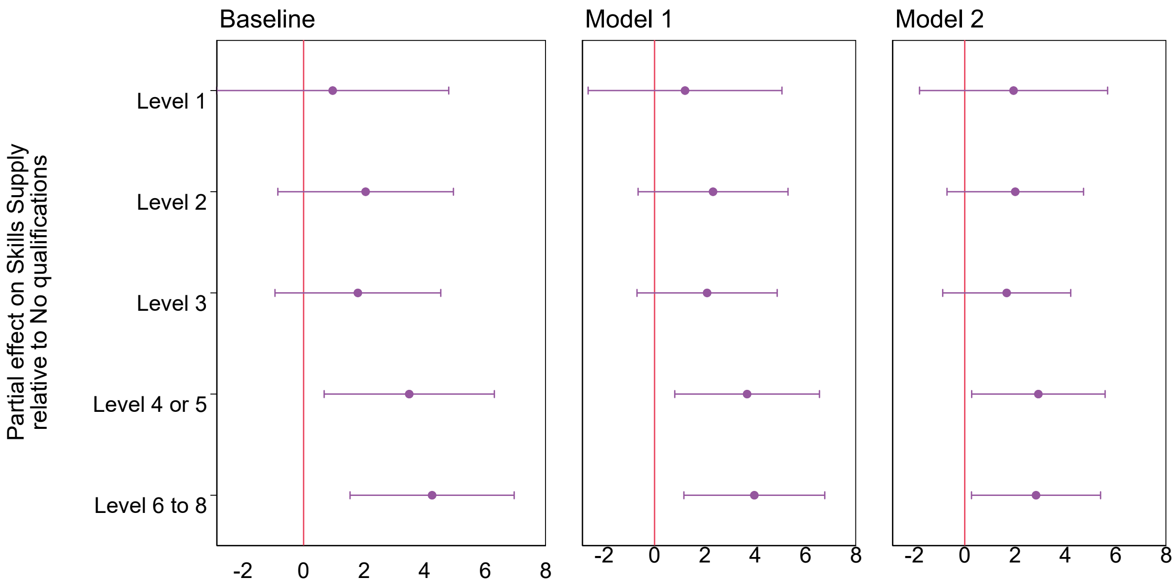
Figure 22 Average levels of Skills supply by highest qualification achieved, broken down by sub-population



Note: Qualifications are classified using the Regulated Qualifications Framework (RQF) - No qualification: Entry level qualifications below level 1; Level 1: Low grade GCSE (grade 3 and under) and equivalent; Level 2: High grade GCSE (grade 4 and above); Level 3: A level and equivalent; Level 4-6: Degree at undergraduate level and equivalent; Level 7-8: Postgraduate degree level and equivalent. Average Skills Supply for young people at Level 4 and above are not displayed because very few young people aged under 19 have yet achieved qualifications at these levels.

The strength of the relationship between qualification levels and average Skills Supply diminishes after controlling for other differences between individuals, although people with Level 4+ qualifications continue to have significantly higher skill levels relative to people with no qualifications. In 'Model 1' of Figure 23, we control for differences in demographic characteristics and health status. 'Model 2' also control for differences in employment variables, geography, training participation, occupation and industry.

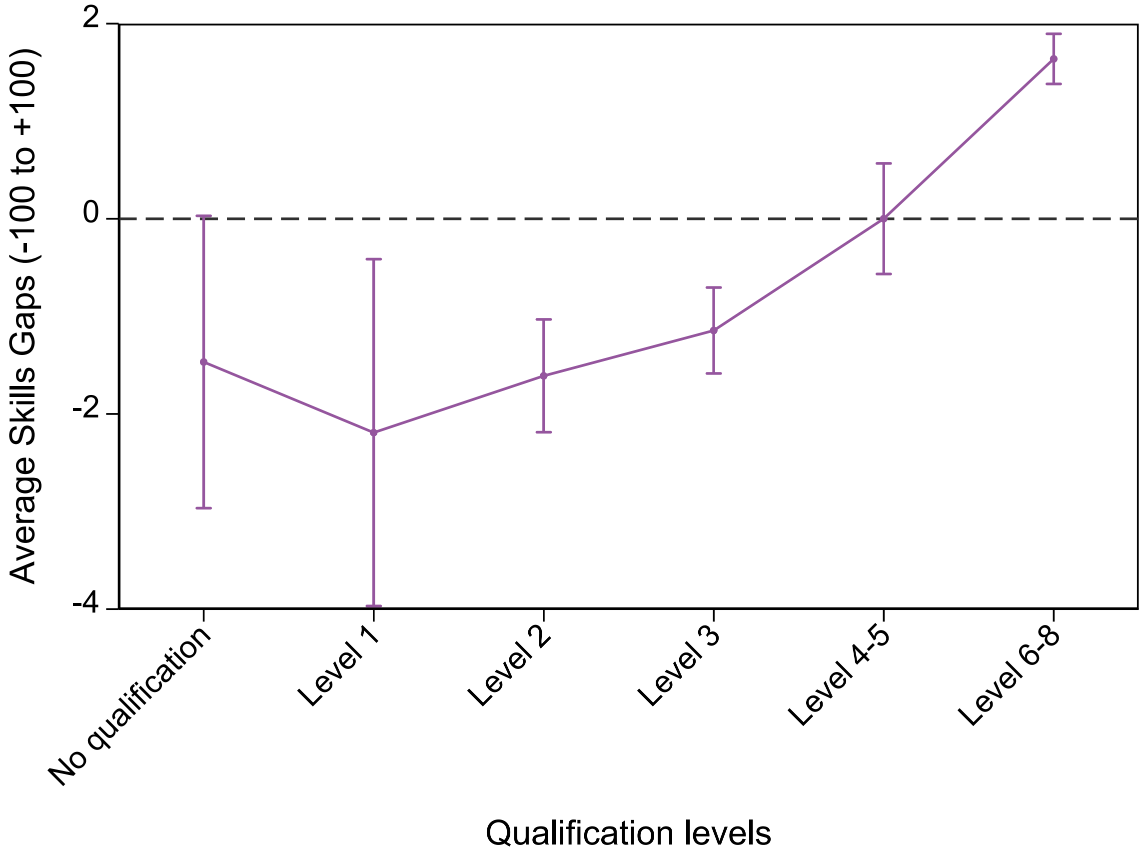
Figure 23 Partial effect of higher qualification levels on Skills supply among the overall population, before and after netting out the effects of other individual differences[9]



Results from Figure 24 suggest workers who leave the education system with at most A-levels or equivalent vocational qualifications (Level 3 or below) tend to have under-utilised EES whereas degree educated workers (Levels 6+) tend to experience skills deficiencies. These differences are partly attributable to the fact that higher skill level occupations are more likely to require higher qualifications, and the rate at which Skills Requirements increases as you move up the occupational hierarchy appears to be greater than the rate at which Skills Supply increases.

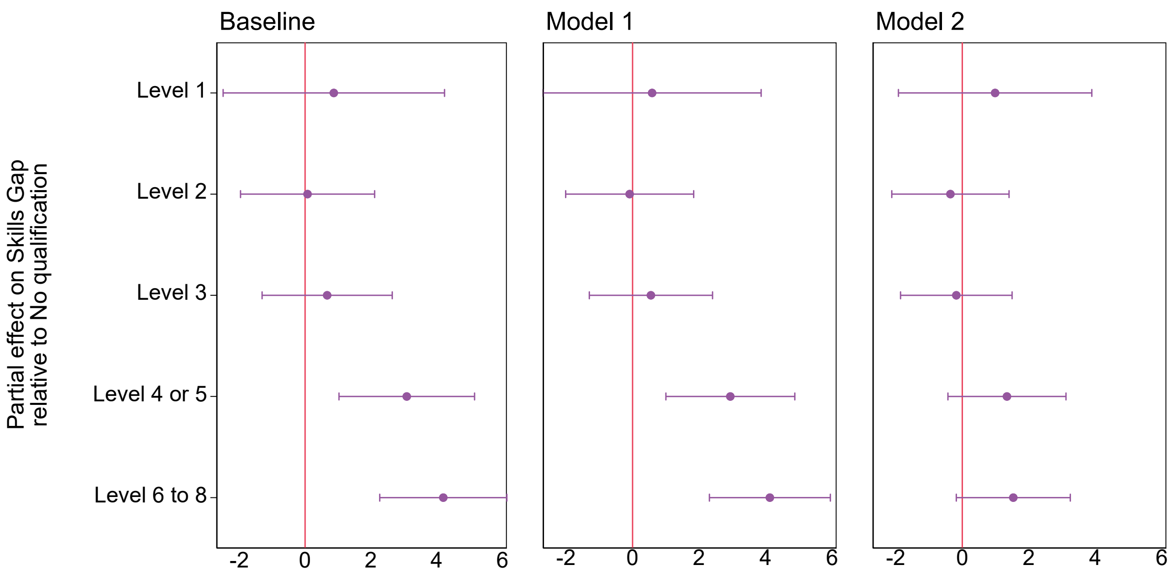
[9] 'Model 1' controls for gender, age, ethnicity, country of birth and health status. 'Model 2' also controls for employment status, whether they are in a managerial position or not, region, local area deprivation (IDACI), participation in off-the-job and on-the-job training, industry and occupation (SOC major group).

Figure 24 Average Skills Gaps, by highest qualification level, among 'Workers'



A large share of the difference in Skills Gaps between people with different qualification levels is attributable to other differences between the same individuals, including differences in the occupation that their qualifications help them to access. 'Model 2' of Figure 25 shows that the differences in Skills Gaps between people with high-level qualifications (relative to 'no qualifications') are no longer statistically significant after netting out the effects of other individual characteristics, including differences in their occupation and employment status.

Figure 25 Partial effect of highest qualification level on Skills Gaps among 'Workers', before and after netting out the effects of other individual differences[10]



4.5 Differences in Essential Employment Skills by participation in training

Employer-funded training plays a significant role in the development of workforce skills. The Employer Skills Surveys report that over 60% of the UK workforce access training, but only 17% (2.5 million) of the over 15 million adults who participated in employer-provided training in 2019 trained towards a qualification. The incidence and intensity of informal learning is far greater amongst adults than formal (i.e., qualifications-bearing) learning (Winterbotham *et al.*, 2020). Over the past decade, there has been a decline in the number of training days per employee, and a corresponding reduction in investment in training per employee (Employer Skills Surveys). Whilst the UK's training participation rate is fairly middle-of-the-road compared to other European countries, the UK has experienced a relatively pronounced decline in training (Tahir, 2023). Studies also suggest training in the UK tends to be shorter and cheaper than in other European countries (Li, Valero and Ventura, 2020 and Clayton and Evans, 2021).

Participation in non-formal and informal training is associated with sizeable wage and productivity returns. OECD research suggests participation in non-formal learning is associated with 11% higher wages, while participation in informal learning is associated with 3.5% higher wages, with tertiary-educated workers experiencing the largest wage premiums from participation in training and participating in the most training (Fialho, Quintini and Vandeweyer, 2019). By age, returns to training are significantly lower for young workers than for older workers in all forms of training. Gains in productivity for employers may be even larger than returns to wages (Fialho, Quintini and Vandeweyer, 2019).

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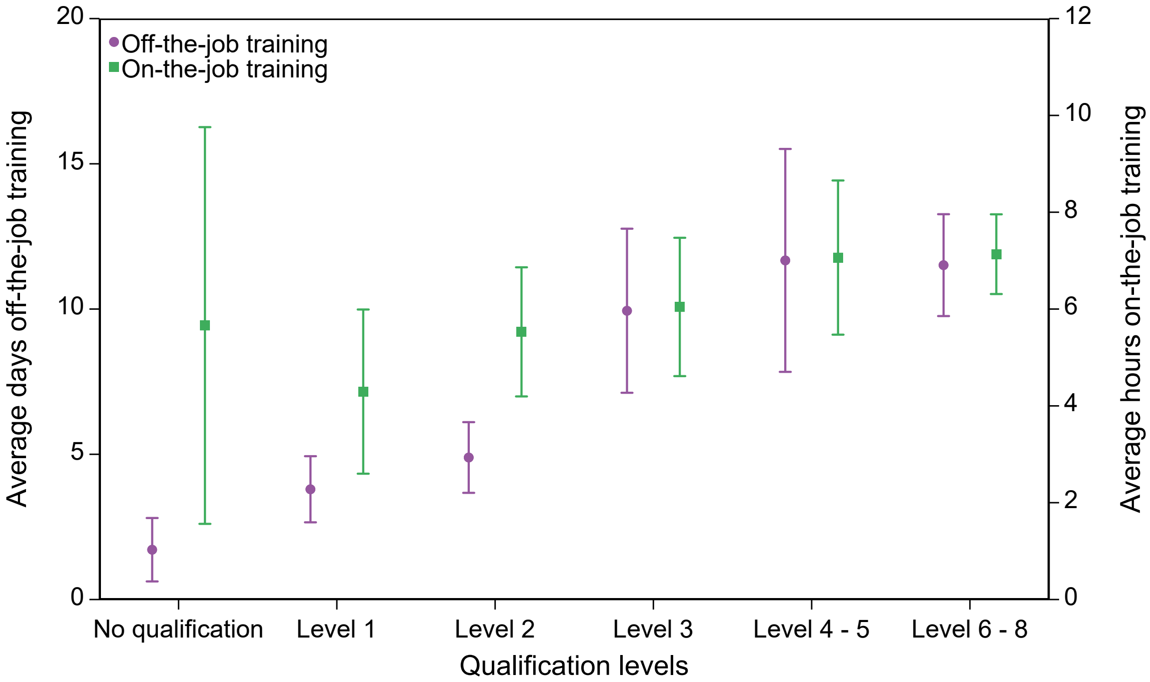
[10] 'Model 1' controls for age, gender, ethnicity, country of birth and health status, and 'Model 2' also controls for employment status, managerial status, region, local area deprivation, participation in training, occupation (SOC major group) and industry.

There is relatively little research on how non-formal and informal learning are distributed across the workforce. Data from our survey suggests that 'Workers' access 10 days of off-the-job[11] training per annum, on average, and 7 hours of on-the-job[12] training and development per month, on average. It suggests that participation in training varies by qualification-level and age, as shown in Figure 26 and Figure 27 below. More qualified workers access more training on average (Figure 26), as do younger workers (Figure 27). Differences in training participation between occupational groups are not statistically significant.

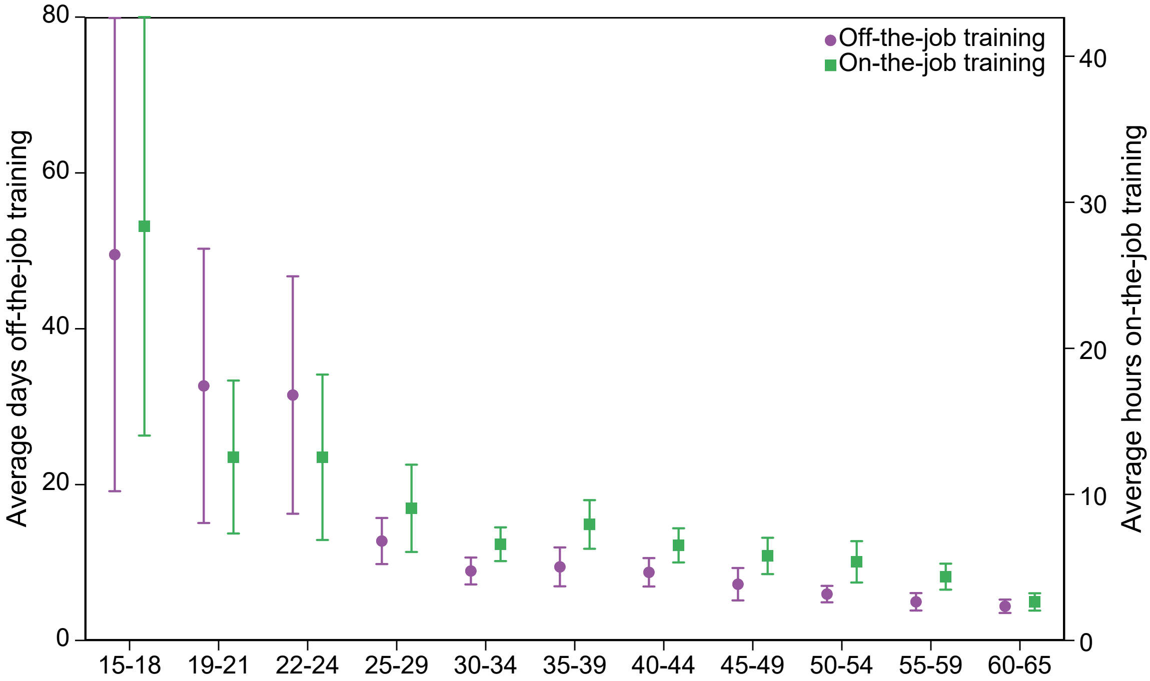
Figure 26 Average days of off-the-job training and average hours of on-the-job training by highest qualification achieved, amongst 'Workers'



11 Defined as an education or training course, seminar, or distance learning, provided by the employer, or an external trainer.

12 By 'on-the-job training' we mean training that takes place at your usual place of work (but not the sort of learning by experience that could take place all the time).

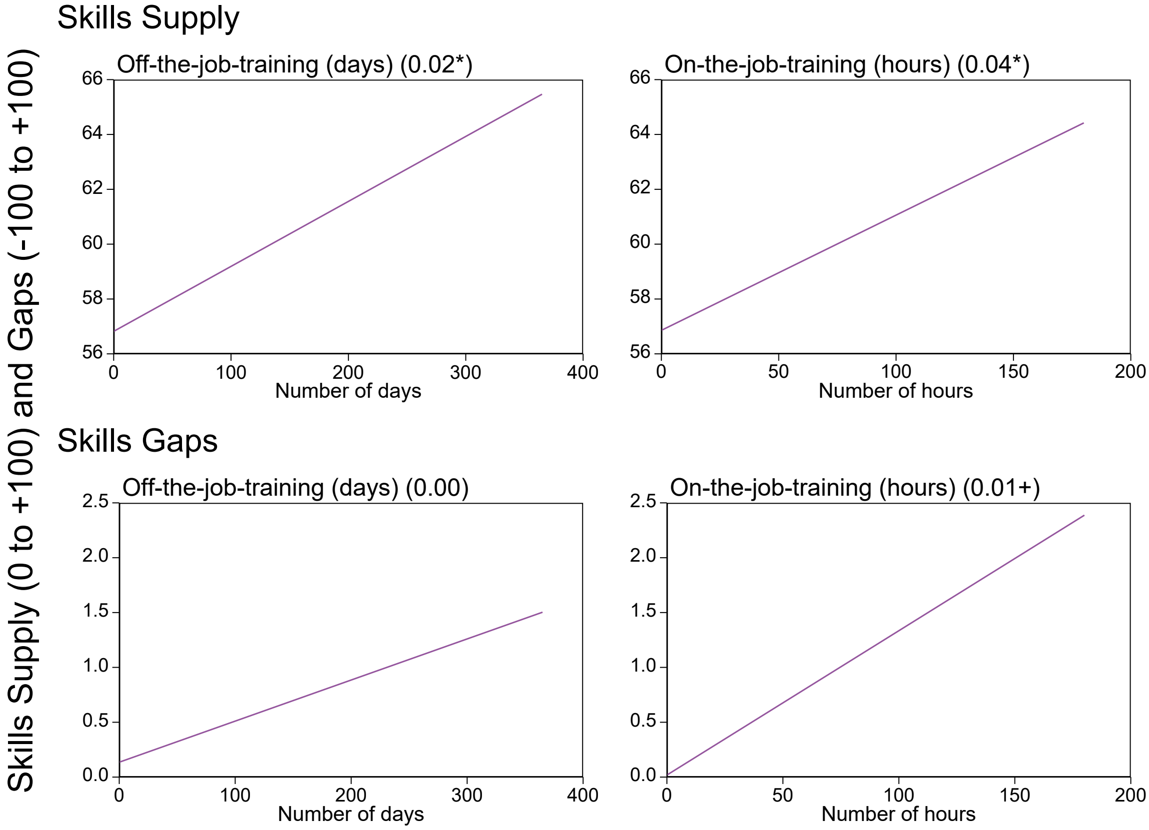
Figure 27 Average days of off-the-job training and average hours of on-the-job training, by age band, among ‘Workers’



Our research also provides evidence that Workers that participate in more on-the-job and/or off-the-job training have higher Skills Supply, on average, but differences are modest. A small increase in Skills Supply corresponds to a large increase in training participation. An increase of 1 point in Workers’ Skills Supply would require an increase of either 42 days of off-the-job training per year, or 23 hours of on-the-job training per week, which is clearly a very large, atypical amount of training.

Figure 28 below shows that Workers who participate in more on-the-job and/or off-the-job training appear to experience greater skills deficiencies, on average. This is largely because workers accessing relatively large amounts of training are more likely to work full-time in higher skill level occupations requiring high-level qualifications, and Skills requirements increase at a faster rate than Skills Supply as we ascend the occupational hierarchy.

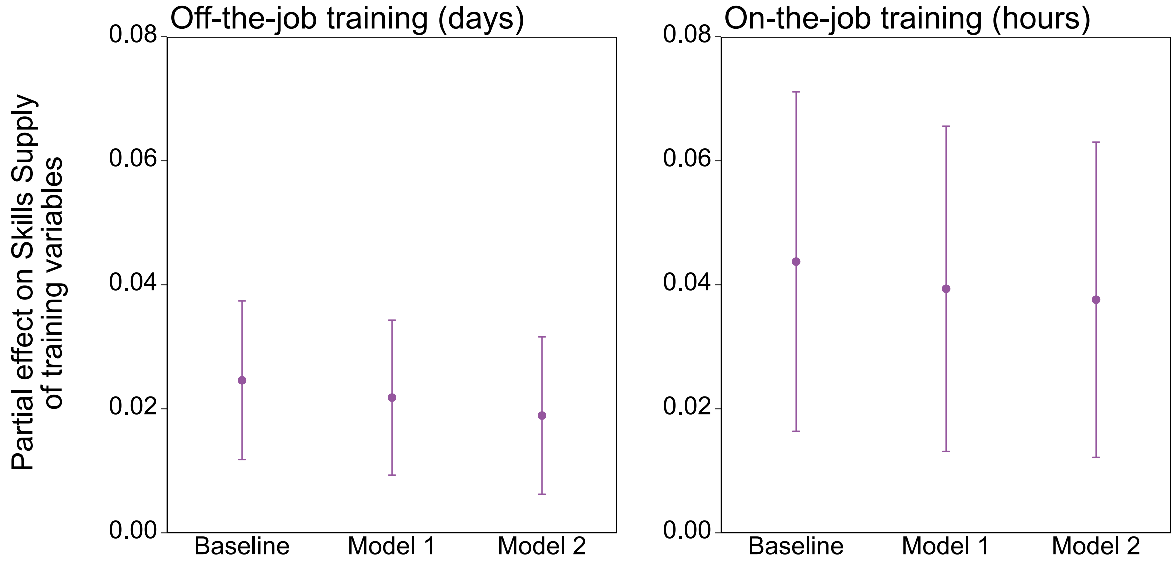
Figure 28 Average relationships between participating in on- and off-the-job training and Skills Supply and Skills Gaps, among 'Workers'



Note: Off-the-job training is measured in days per year and on-the-job training is measured in hours per month. The numbers in brackets represent the correlation coefficient for each relationship; a star indicates statistical significance at the 5% level and a + indicates significance at the 10% level.

Regression analysis suggests training participation is positively associated with Skills Supply even after netting out the effects of other individual differences, including differences in the occupation and industry people work in. This *could be because* higher levels of training develop people's Skill Supply, or alternatively it could be because people with higher EES are more proficient in identifying and accessing appropriate work-based training. Figure 29 below shows that the relationship between training and Skills Supply is not greatly affected by controlling for other differences in demographic characteristics, health status, employment variables, geography, highest qualification, industry and occupation ('Model 2').

Figure 29 Partial effect of training participation on Skills supply levels, before and after netting out the effects of other individual differences[13]



Note: Off-the-job training is measured in days per year and on-the-job training is measured in hours per month.

4.6 Differences in Essential Employment Skills by childhood socio-economic status

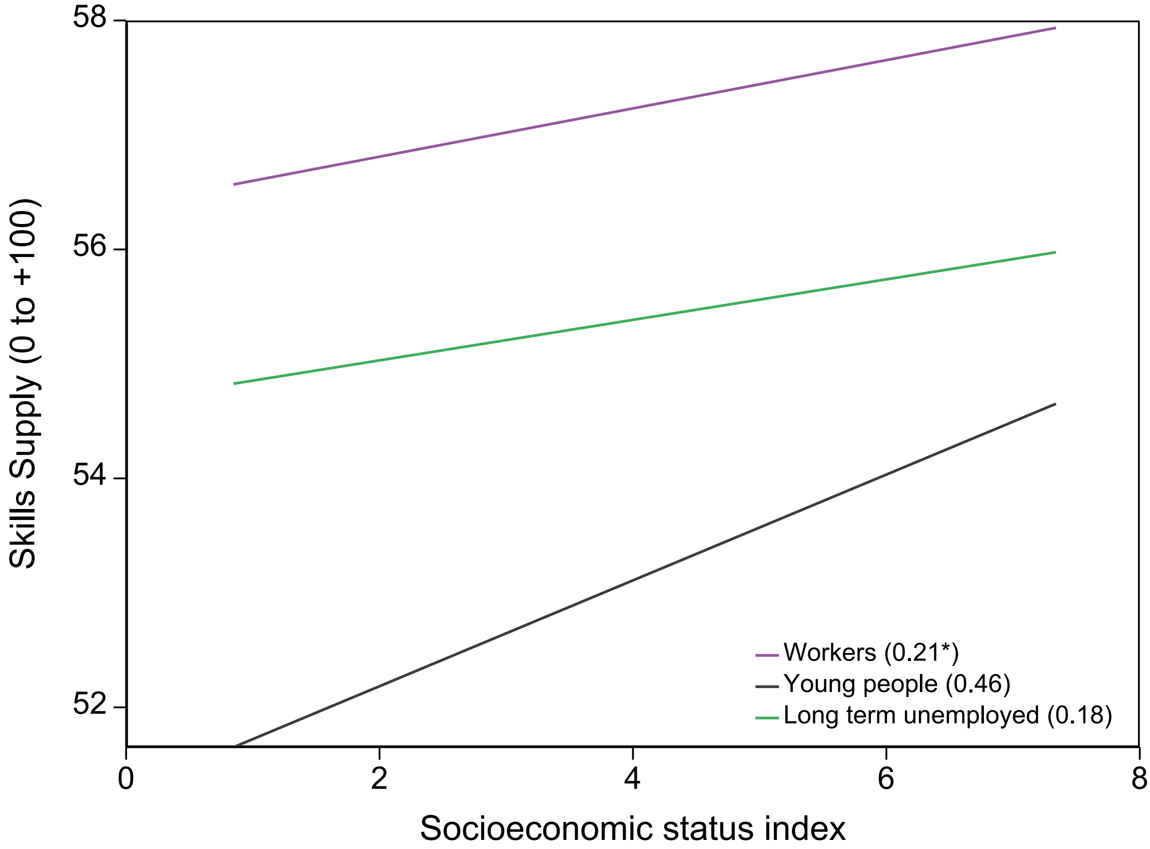
People's education level is strongly related to their parents' education level. Previous research has shown that young adults from a professional class background are 60% more likely to be in a professional job than their counterparts from working class backgrounds (State of the Nation 2022). Our research indicates that young people's family background[14] is also related to their Skills Supply, with more advantaged backgrounds associated with higher levels of EES (as shown in Figure 40 below). However, this relationship is modest and not statistically significant.

The direction of the relationship somewhat supports the importance of considering family influences on the development of EES outside of the workplace, as has been highlighted by previous studies (Heckman, Stixrud and Urzua, 2006, Cunha and Heckman, 2007). According to Boudon's,1974 influential 'positional' theory, this is likely to be because social stratification has both primary and secondary effects; young people from families with wealthier and more educated parents are likely to have more cultural assets which influence their behaviour, attitudes and cultural experiences, and these cultural assets are likely to affect their engagement and choices within the education system (Boudon, 1974). Comparing between sub-populations, the association between childhood socio-economic status index and Skills Supply is weaker among 'Workers' and the 'Long-term unemployed'

[13] 'Model 1' controls for gender, age, ethnicity, country of birth and health status. 'Model 2' also controls for employment status, whether they are in a managerial position or not, region, local area deprivation (IDACI), highest qualification, industry (SIC) and occupation (SOC major group).
[14] A childhood socio-economic status index score was calculated for each survey respondent from the first principal component of a linear combination of variables relating to their mother and father's education level and employment status when they were 14.

than 'Young people', potentially suggesting the impact of early family influences on skills diminishes over time.

Figure 30 Relationship between childhood socio-economic status and Skills Supply, by sub-population

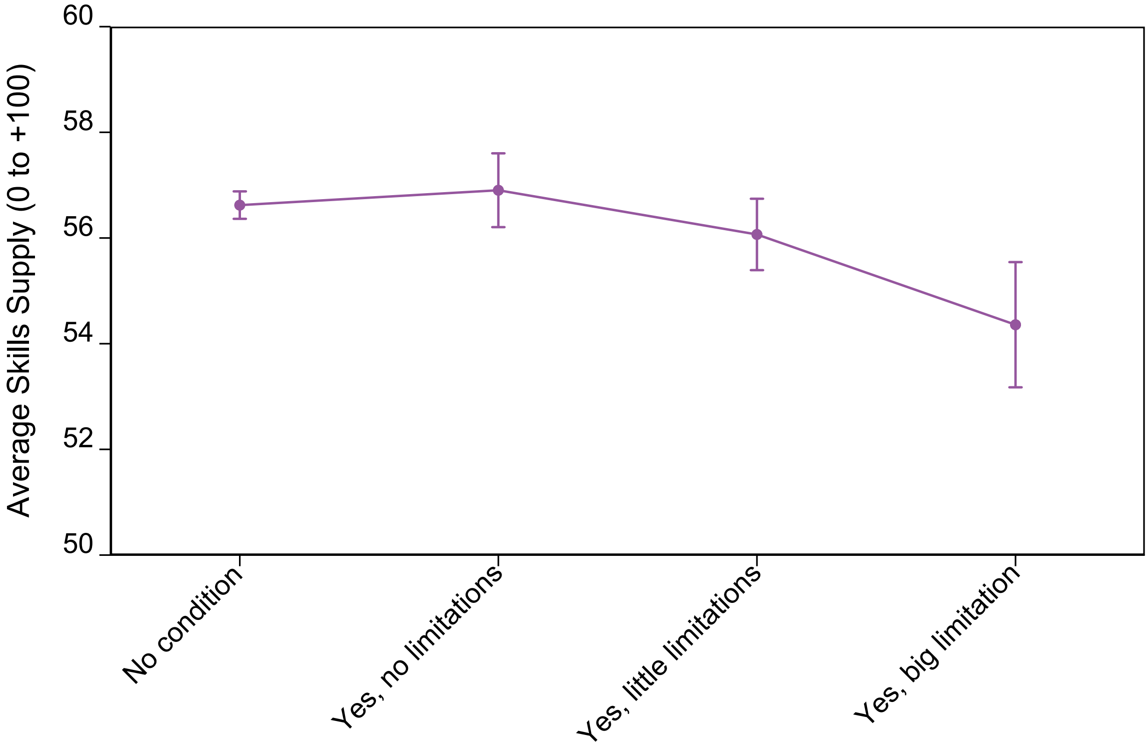


Note: The numbers in the legend above represent the correlation coefficient, which indicates the strength of relationship between Socioeconomic status index and Skills Supply for each subpopulation. A star indicates the relationship is statistically significant at the 95% level.

4.7 Differences in Essential Employment Skills by health status

People with disabilities are likely to have lower literacy, numeracy and digital skills (OECD, 2022). Our results indicate that workers who have a physical or mental health condition lasting 12 months or more are likely to have marginally lower levels of Skills Supply if their condition limits their ability to carry out day-to-day activities, as shown in Figure 31 below.

Figure 31 Average Skills Supply in the overall population, by health status[15]



However, the relationship between health status and Skills Supply is not statistically significant, either before or after netting out the effects of other individual differences. On the face of it, it is perhaps surprising that there is not a significant difference in Skills Supply between healthy people and those with a severely limiting long-term condition or illness, given people with long-term health conditions are more likely to drop out of work and also more likely to leave education with low-level qualifications. However, this may be due to the relatively small number of people in our sample with severely limiting health conditions.

[15] Health status is categorised as; 'No' = no long-term health condition or illness; 'No limit' = Long-term condition or illness that does not limit their ability to carry out day-to-day activities; 'Litt. limit' = Long-term condition or illness that limits their ability to carry out day-to-day activities *a little*; 'Big limit' = Long-term condition or illness that limits their ability to carry out day-to-day activities *a lot*.

Figure 32 Partial effect of health status on Skills Supply amongst the overall population, before and after netting out the effects of other individual differences[16]

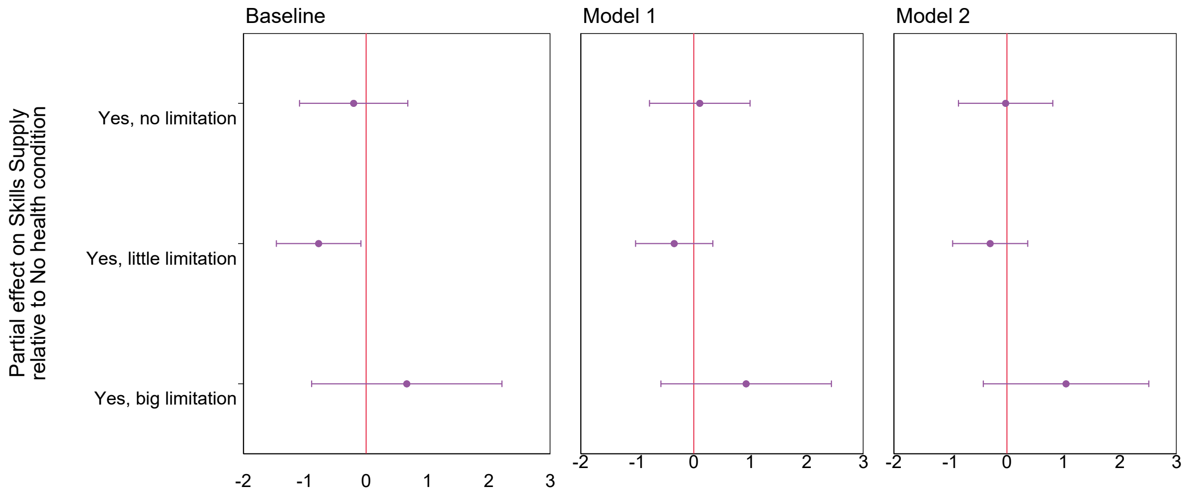
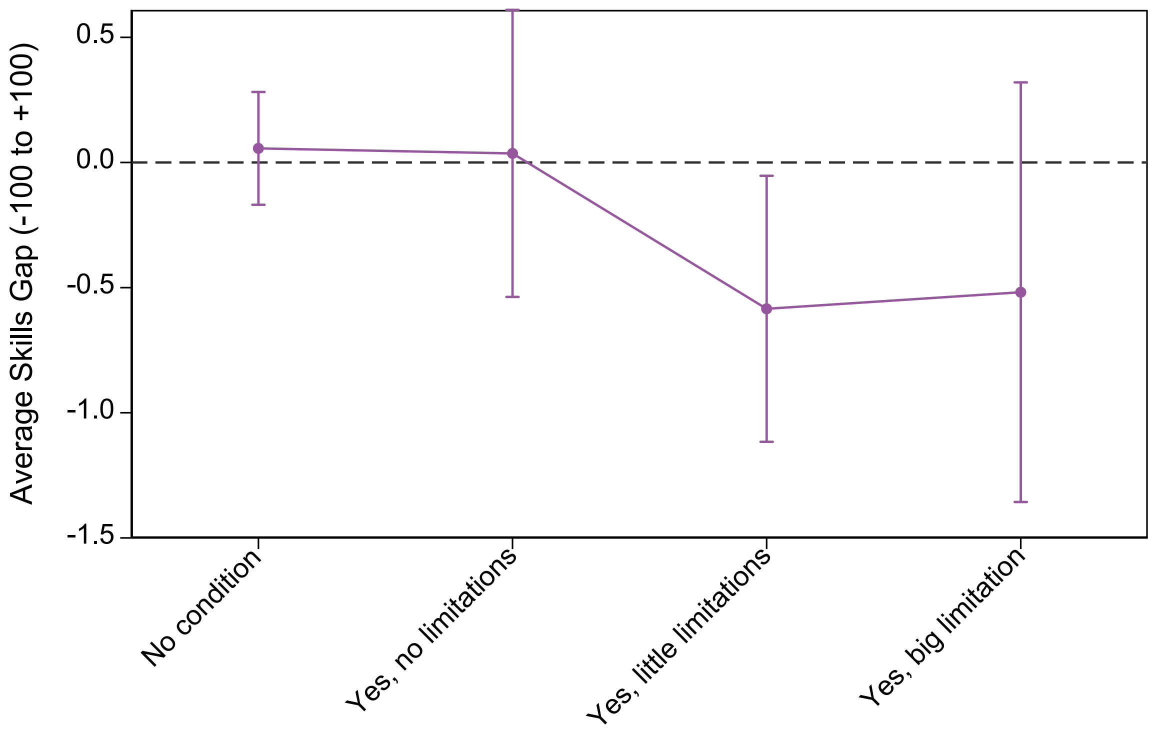


Figure 33 Average Skills Gaps by health status among 'Workers'

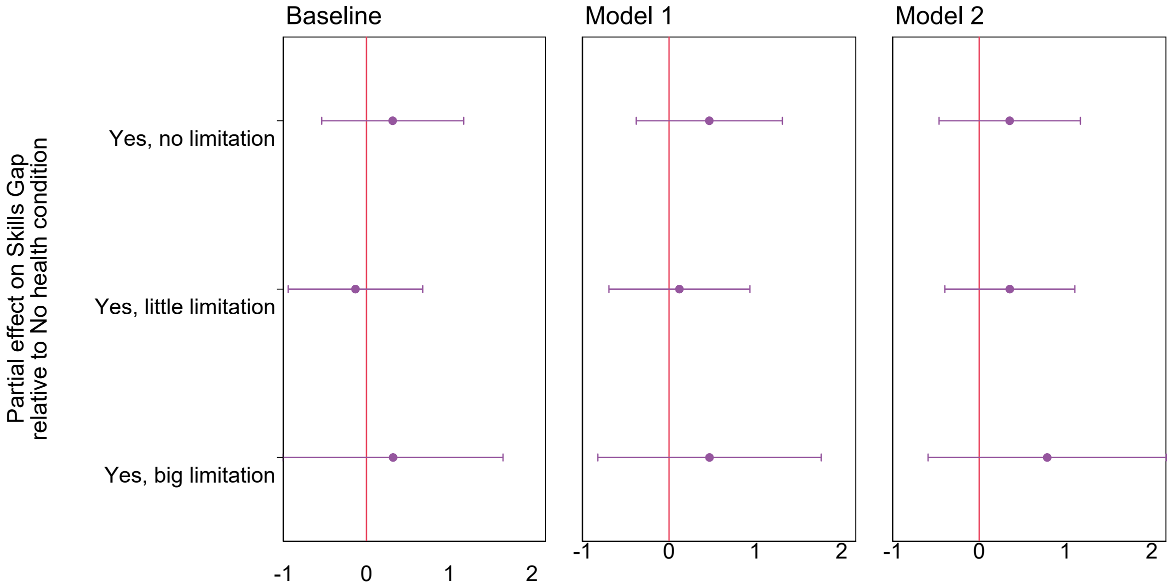


As shown in Figure 33 above, 'Workers' with health conditions are more likely to experience skills under-utilisation compared to 'Workers' without health conditions. However, as with Skills Supply, the relationship between health status and Skills Gaps is not statistically significant, either before or after controlling for other individual differences, as shown in

[16] 'Model 1' controls for gender, age, ethnicity, country of birth. 'Model 2' also controls for employment status, managerial status, region, local area deprivation (IDACI), highest qualification, training participation, industry and occupation (SOC major group).

Figure 34 below. Again, this may be partly attributable to the low incidence of people with severely limiting conditions in our sample.

Figure 34 Partial effect of health status on Skills Gaps amongst 'Workers', before and after netting out the effects of other individual differences[17]



4.8 Partitioning the total variance in Skills Supply and Skills Gaps into the effects of seven sets of related individual characteristics

Regression analysis enables us to identify how much of the overall variance in Skills Supply across the population is explained by specific characteristics. However, there is likely to be a complex web of relationships between the independent variables in our regression models. For example, consider the effect of education on someone's Skills Supply. Education might affect their skill development directly, but also indirectly by enabling them to access a higher skill level occupation that affords them more opportunities to develop their EES. Education might also affect their propensity to engage in training, as well as being affected by their personality traits, which themselves affect EES development directly. Consequently, the effects of specific individual characteristics on Skills Supply are vulnerable to being misattributed to other characteristics, and effect sizes attributed to each variable may vary depending on the order in which they were added to the model. Therefore, to partition the total variance in Skills Supply and Skills Gaps into the effects of related sets of variables (for example, variables related to 'education and training'), after eliminating the effects of other contributory factors, we perform a Shorrocks-Shapley decomposition. This technique involves assigning to each set of related variables the average of its marginal contributions in all possible elimination sequences.

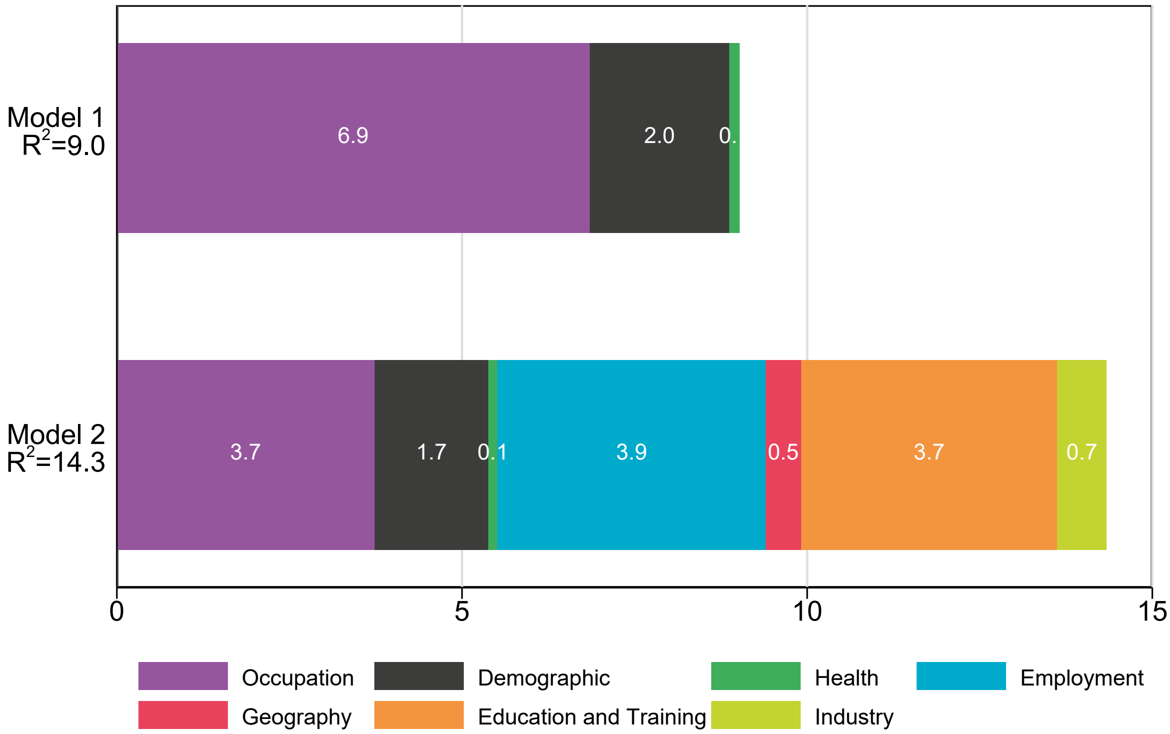
'Model 1' in Figure 35 below indicates that 9 per cent of the variance in workers' EES Skills Supply is explained by differences in people's demographic characteristics and occupation. However, 'Model 2' of Figure 35 shows that almost half of the variance in Skills Supply initially attributed to differences in occupation is explained by differences between occupations in people's employment and managerial status, education and access to

[17] 'Model 1' controls for gender, age, ethnicity, country of birth. 'Model 2' also controls for employment status, managerial status, region, local area deprivation (IDACI), highest qualification, training participation, industry and occupation (SOC major group).

training, geography and industry. Of these factors, differences in individual's 'occupation' (their broad occupational group), 'employment' (their employment status and managerial status) and 'education and training' (their highest qualification and participation in formal and informal training) each account for about 4 per cent of the variance in Skills Supply; more than any of the other factors measured by our survey.

This potentially indicates that increases in the average qualification and training levels of the population might increase the stock of EES and consequently also reduce employer-reported Skills deficiencies, whereas substantial declines in workplace training (IFF Research, 2023) and publicly-funded qualifications started by adults (Sibieta, Tahir and Waltmann, 2022) may have reduced the stock of EES across the population and exacerbated Skills deficiencies. That being said, we cannot rule out the possibility that higher Skills Supply influence people's propensity to pursue qualifications and training in the first place.

Figure 35 Shorrocks-Shapley decomposition of the share of variance in Skills Supply among 'Workers' that is attributable to seven different sets of related variables



Note: The R^2 in the figure above represents the proportion of the overall variance in Skills Supply that is attributable to the sets of independent variables in the model. 'Model 1' suggests that 9% of the variance in Skills Supply is attributable to 'occupation', 'demographic' characteristics and 'health' variables. 'Model 2' suggests that seven sets of variables, listed below, account for 14.3% of the variance in Skills Supply across 'Workers'. These 7 sets of variables are:

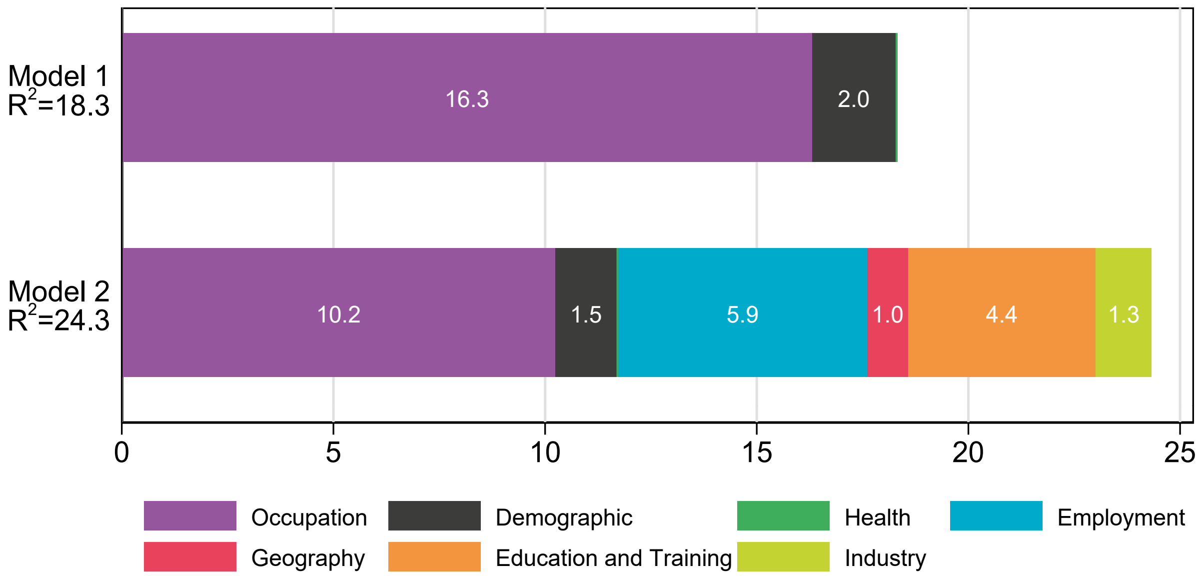
- *Occupation: Broad occupational sector (SOC major group)*
- *Demographic: Gender, ethnicity, country of birth*
- *Geography: Region, local area deprivation*
- *Education and Training: Highest qualification achieved, participation in on- and off-the job training*
- *Health: Health status*
- *Industry: Broad industrial sector*

- *Employment: Employment status and managerial status.*

Later in The Skills Imperative 2035 we will explore other factors that may explain more of the variance in Skills Supply. This will include people's choices of qualifications and subjects, their attainment levels at Key Stages 1-5, and the characteristics of the school they attended. Research by Skills Builder Partnership (2022) suggests people who attended non-independent or non-selective schools have lower essential skills levels, and it may well be that other school-related factors also affect people's Skills Supply.

'Model 2' in Figure 36 below indicates that 24.3% of the variance in Skills Gaps is attributable to differences in workers' occupation, geography, education and training, health, industry, employment and demographic characteristics. This means these individual characteristics explain a larger share of the variance in Skills Gaps than they do the variance in Skills Supply, largely because people's current job has a greater bearing on their Skills Requirements than their Skills Supply. A Shorrocks-Shapley decomposition indicates that most of the variance we are able to explain in Skills Gaps is attributable to differences in occupation (10.2%), employment and managerial status (5.9%) and education and training (4.4%).

Figure 36 Shorrocks-Shapley decomposition of the share of variance in Skills Gaps among 'Workers' that is attributable to seven different sets of related variables.



5 Projecting changes in Skills Supply and Skills Gaps between 2023 and 2035

- We explore how Skills Supply and Skills Requirements are likely to change between 2023 and 2035, accounting for changes in the population, changes in employment and changes in Skills Requirements by occupation.
- Our analysis shows that skills deficiencies among workers in high skill level occupations (SOC1-3) are projected to grow. Skills deficiencies are also anticipated to become typical in most mid- and low skill level occupations. This supports the case for placing greater emphasis on the development of these skills.
- This projected increase in skills deficiencies is largely driven by anticipated changes in Skills Requirements within occupations – specifically increases in the extent to which workers across most the labour market will be required to utilise EES.
- By contrast, changes in the composition of the population and the structure of employment are not anticipated to have a significant impact on average Skills Supply or Skills Gaps across the population. This is largely because the population and structure of the labour market are projected to continue changing steadily and inexorably, rather than dramatically, between 2023 and 2035, and because occupation, industry and population characteristics only account for a modest share of the variation in Skills Supply across the population.

To project how Skills Supply and Skills Gaps are likely to change between 2023 and 2035, we follow three steps. The first step involves re-weighting our survey data to account for projected changes in the demographic composition, health, education and working hours of the population, and comparing our 2035 projected data with our actual ESS survey data from 2023. We refer to these projections as 2035a. The second step involves exploring the impact that projected changes in the occupational and industrial distribution of employment are likely to have on EES supply and EES gaps. We refer to these projections as 2035b. The third step involves examining the effects of projected changes in Skills Requirements within occupations on anticipated Skills Gaps (without adjusting workers' Skills Supply, which may, in reality, be responsive to increased utilisation of these skills). These projections are labelled 2035c. Further detail on the methodology used can be found in the accompanying Technical Supplement. Overall, this approach enables us to explore the potential impact on Skills Supply and Skills Gaps of anticipated changes in the population, the jobs that will be available in the future, and the skills that will be needed to do these jobs. Our projections should be treated as exploratory, and comparisons between Skills Gaps today and potential Skills Gaps in 2035 should be interpreted cautiously. While no one can be certain about the future, quantitative projections provide a foundation for thinking about how Skills Gaps may change over time and the collective response that may be required to close them.

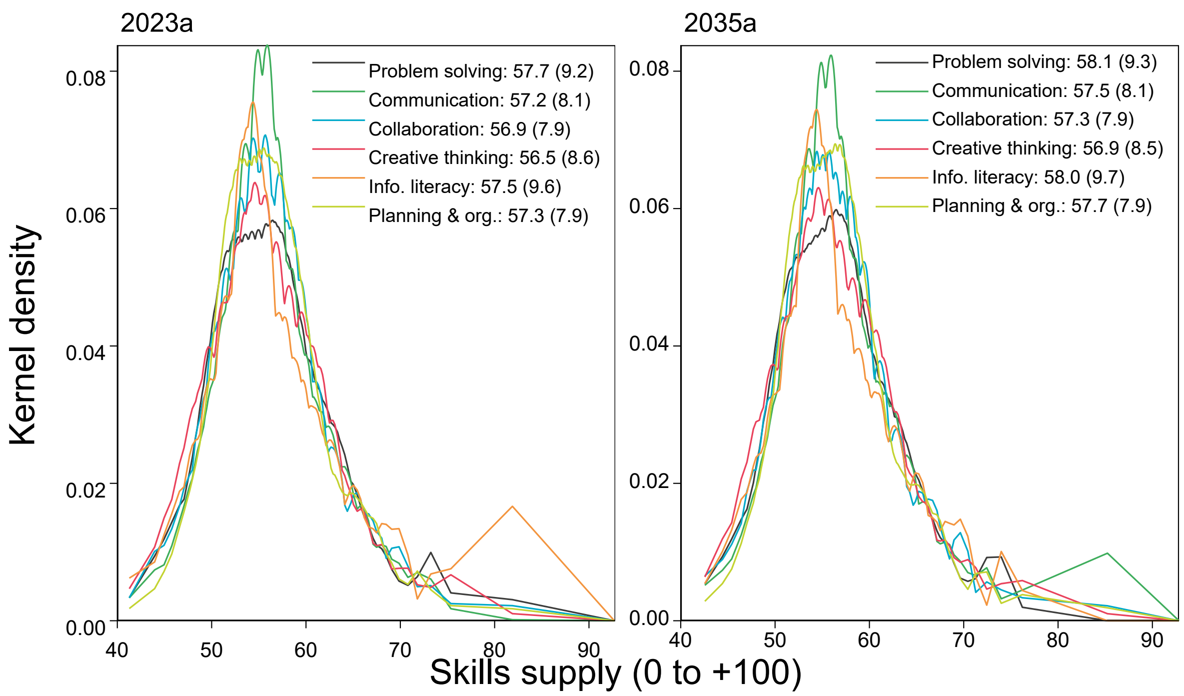
Overall, our projections indicate that skills deficiencies among high skill level occupations are likely to grow, and skills deficiencies are likely to become typical amongst most mid and low skill level occupations. These changes in Skills Gaps between 2023 and 2035 are being driven by projected increases across most of the labour market in the EES workers need to utilise. By contrast, changes in the composition of the population and labour market are not anticipated to have a substantial effect on average Skills Gaps.

5.1 Changes in Skills Supply and Skills Gaps due to projected changes in the population

We first project the demographic composition, health, education and working hours of the population in 2035. Re-weighting our survey data to account for these projected changes in the population (2035a) has no significant effect on average Skills Supply across the population, either overall or for specific EES domains. This is shown in Figure 37 below, which displays the distribution of Skills Supply by domain for workers in our 2035 projected data (labelled 2035a) relative to our 2023 data (labelled 2023a). The looks very similar when comparing between occupational groups (as shown in Figure 37 below). Similarly, Skills Gaps are also relatively unaffected by projected population changes, as shown in Figure 37 below.

This lack of change is because the factors in our models account for a modest share of the variance in Skills Supply and because the population and structure of the labour market are projected to continue changing steadily and inexorably, rather than dramatically, between 2023 and 2035.

Figure 37 Skills Supply among 'Workers' by domain in 2023 compared to projected Skills Supply in 2035



Note: The legend shows the mean and the standard deviation (in parentheses) of Skills Supply.

Figure 38 Average Skills Supply among 'Workers' by occupation (SOC major group) in 2023 compared to projected Skills Supply by occupation in 2035

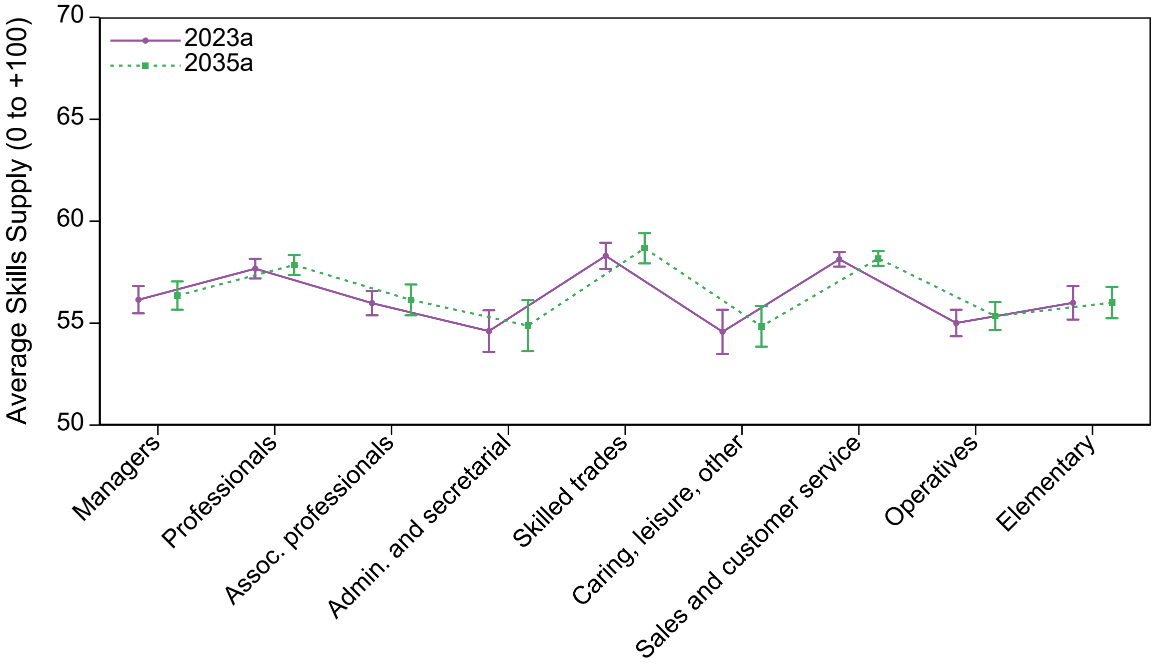
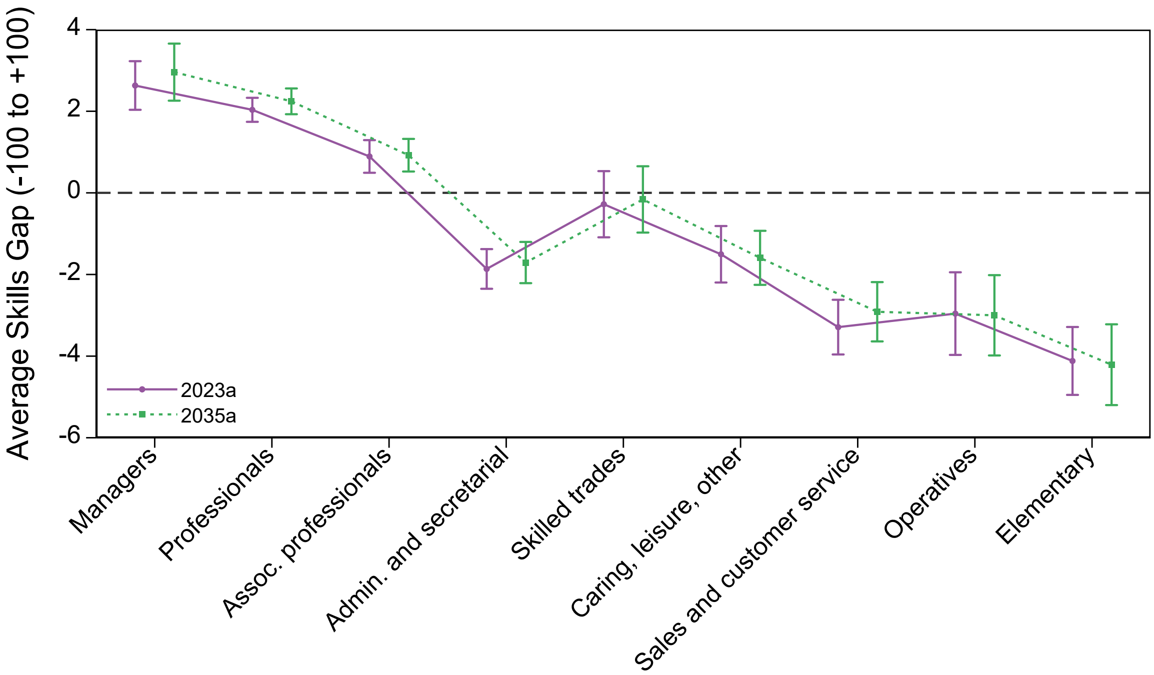


Figure 39 Average Skills Gaps among 'Workers' by occupation (SOC major group) in 2023 compared to projected Skills Supply by occupation in 2035



5.2 Changes in Skills Supply and Skills Gaps due to projected changes in employment

We utilise the 2035 employment projections produced for an earlier stage of The Skills Imperative 2035 (Wilson *et al.*, 2022a) and re-weight our survey data to account for projected changes in the industrial and occupational distribution of employment through to 2035. Again, this does not have a significant effect on average Skills Supply among workers. Figure 46 shows workers' average Skills Supply by occupation in 2023 (labelled 2023a) is very similar to the revised 2035 projections incorporating changes in employment (labelled 2035b). Similarly, Skills Gaps are also relatively unaffected by projected changes in the structure of employment, as shown in Figure 40 below. This is perhaps unsurprising given the structure of employment is projected to change steadily and inexorably, rather than dramatically, and the relationship between occupation / industry and Skills Supply is fairly modest.

Figure 40 Average Skills Gaps among 'Workers' by occupation (SOC major group) in 2023 (2023a) compared to original 2035 projections (2035a) and revised 2035 projections that account for changes in employment (2035b below)

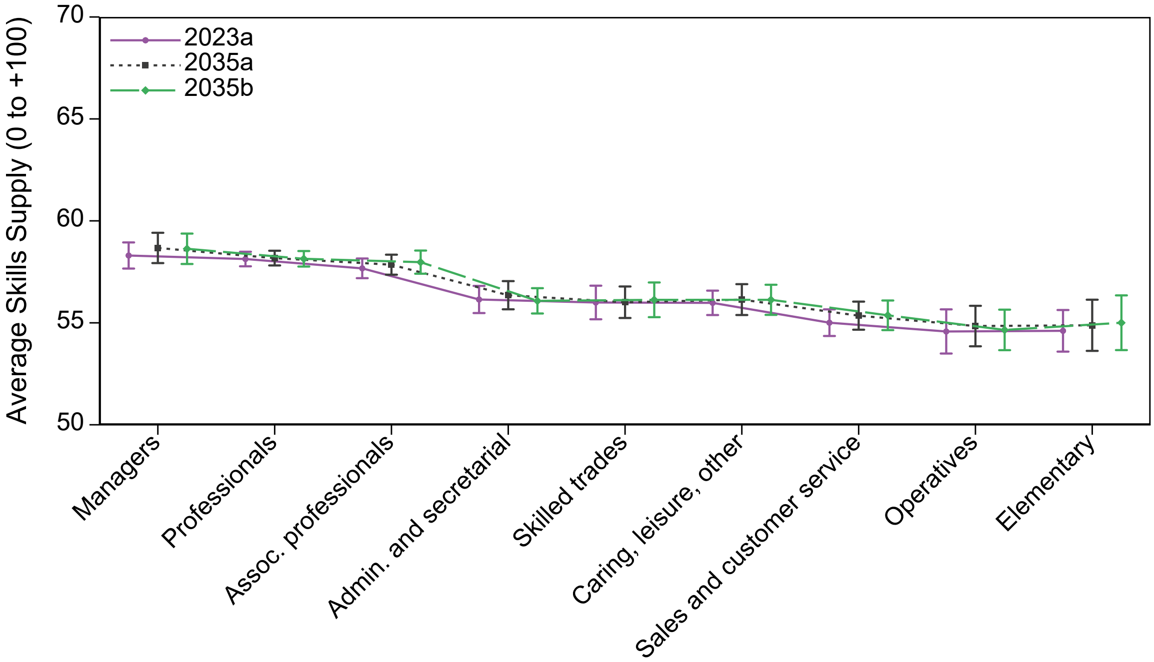
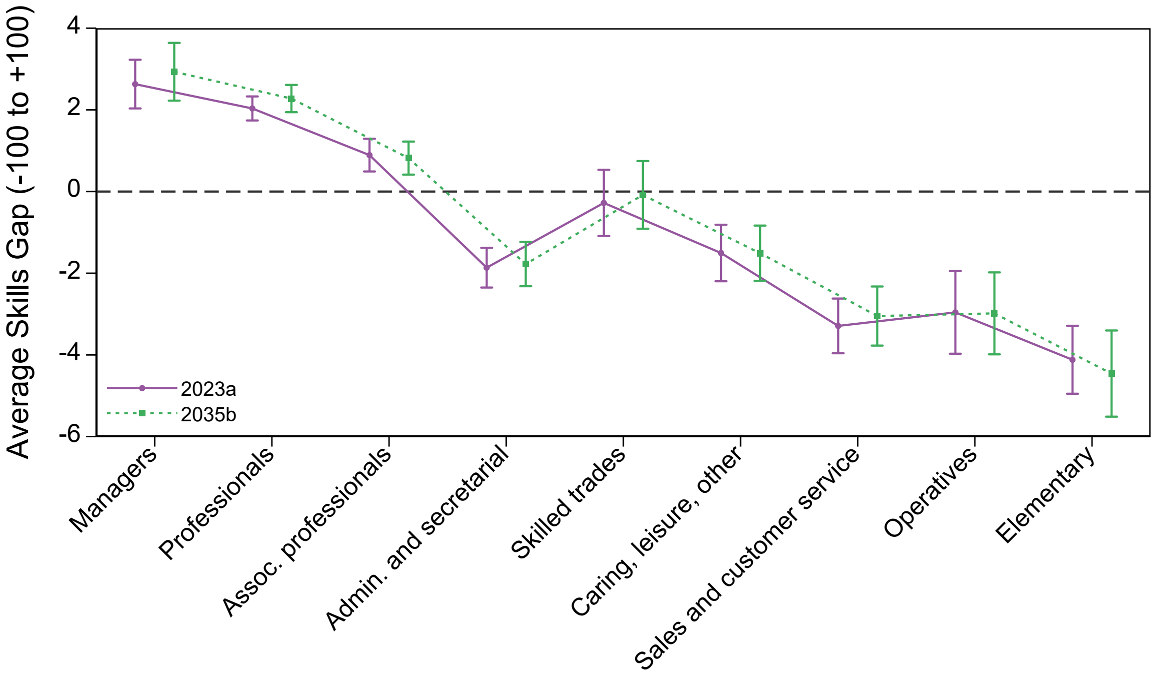


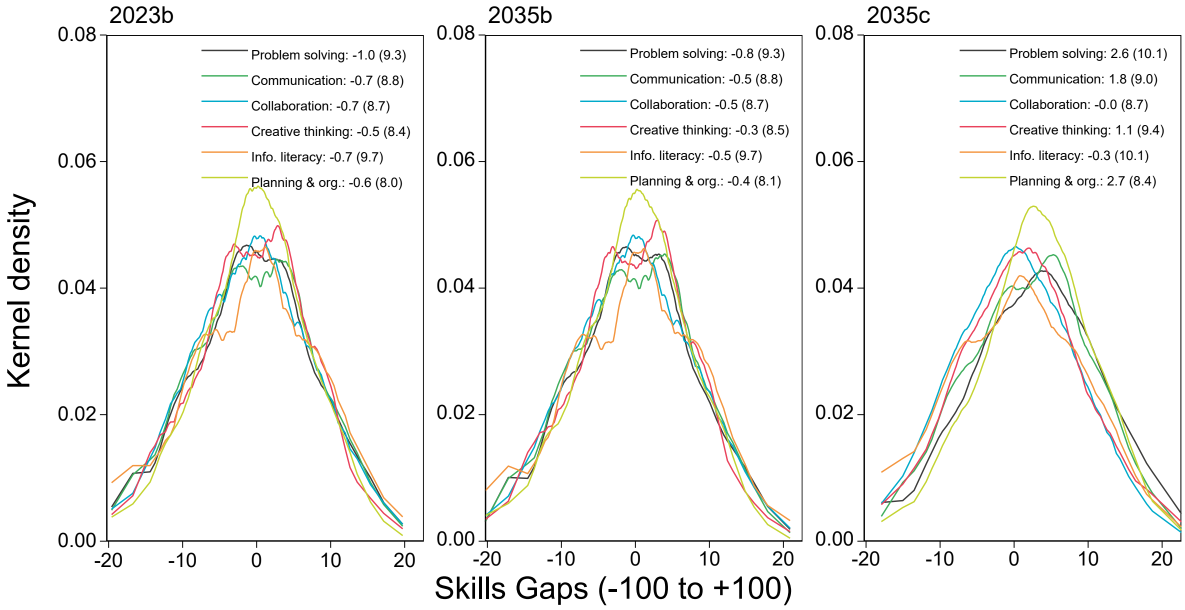
Figure 41 Average Skills Gaps among 'Workers' by occupation (SOC major group) in 2023 (2023a below) compared to 2035b projections (accounting for changes in the structure of employment)



5.3 Changes in Skills Gaps due to projected changes in skills requirements within occupations

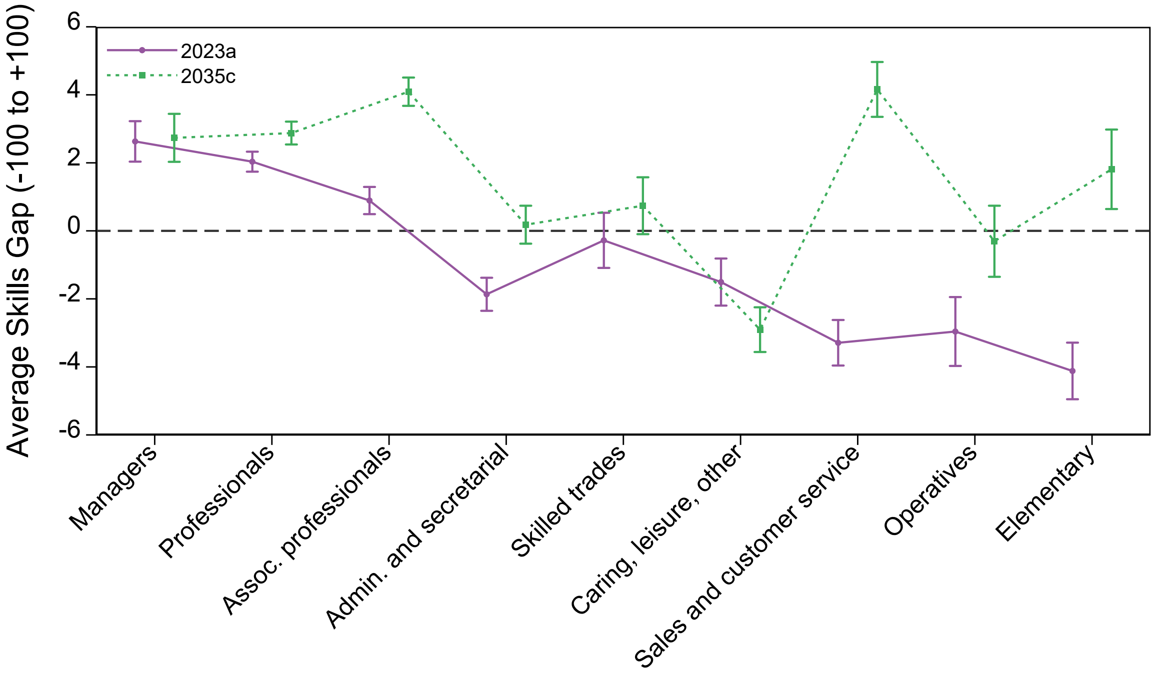
Finally, we utilise the 2035 skills projections produced for The Skills Imperative 2035 (Dickerson *et al.*, 2023) to anticipate changes in Skills Requirements for each occupational group (SOC major group) through to 2035, and to project the impact of these changes in Skills Requirements on likely Skills Gaps (without adjusting workers' Skills Supply, which may, in reality, be responsive to increased utilisation of these skills). Our analysis suggests changes in Skills Requirements within occupations are going to have a bigger effect on Skills Gaps than changes in the composition of the population and employment. This is shown in Figure 42 below by the fact that average Skills Gaps amongst workers in 2035b are similar to 2023b, but average Skills Gaps in 2035c are at least one percentage point larger for Problem solving and decision making, Communication, Creative Thinking, and Planning, organising and prioritising.

Figure 42 Skills Gaps among 'Workers' in 2023 (2023b below) compared to 2035b (accounting for changes in employment) and 2035c (also accounting for changes in Skills Requirements within occupations)



Our 2035 projections suggest skills deficiencies among high skill level occupations (SOC1-3) will get worse, and skills deficiencies will become the norm in most mid and low skill level occupations, as shown in Figure 43 below. Our projections indicate that, by 2035, skills deficiencies will be typical in seven of the nine broad occupational groups, which together comprise over 80% of workers whereas, by contrast, the three occupational groups in which workers typically experience skills deficiencies today only account for around half of workers. This reinforces the importance of fully-utilising workers' EES and supports the case for placing greater emphasis on the development of these skills, both in the workplace and as young people progress through the education system.

Figure 43 Average Skills Gaps among ‘Workers’ by occupation (SOC major group) in 2023 (2023a below) compared to 2035c projections (which account for changes in the population, employment and Skills Requirements)

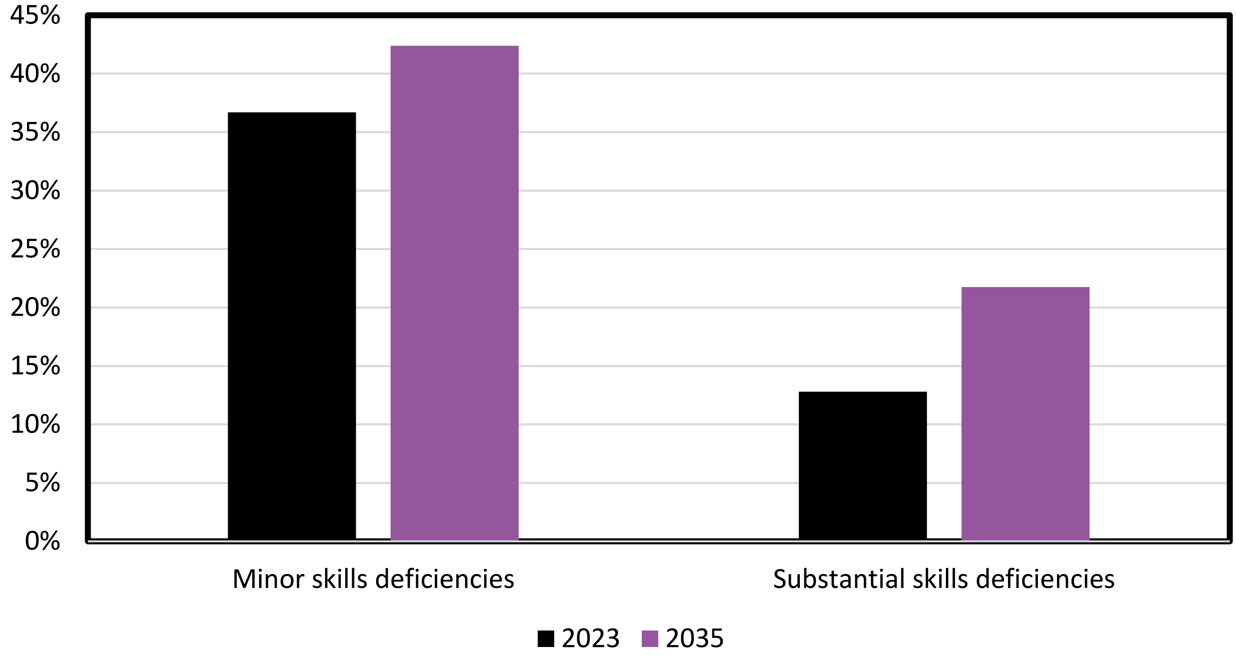


5.4 Exploring the proportion of the labour market that might have skills deficiencies in 2035, based on our projections

Our exploratory projections of how Skills Gaps might change between 2023 and 2035 indicate that up to around two-thirds of workers may experience EES-related skills deficiencies in 2035, compared to around a half today. We explore this further by categorising everyone with a projected skills deficiency in 2023 and 2035 as having either a 'minor' skills deficiency or a 'substantial' skills deficiency. We do this by standardising the distribution of Skills Gap scores in 2023 and identifying a threshold equivalent to 1 SD from the mean. We use this same threshold (from the distribution of 2023 Skills Gap scores) to categorise individuals as having either a 'minor' or 'substantial' skills deficiency in 2035 and explore the extent to which skills deficiencies change between 2023 and 2035.

We find that most workers with projected skills deficiencies will experience a ‘minor’ deficiency, but a significant minority may have a ‘substantial’ deficiency. Figure 44 below shows that 13 per cent of workers already have a substantial skills deficiency in 2023, in relation to their EES, meaning that their self-reported behaviours suggest they do not possess the skills required to fulfil their job requirements, and that we categorise their deficiencies as ‘substantial’. This is equivalent to almost 3.7 million workers in 2023. Our projections of how Skills Gaps may change between 2023 and 2035 indicate that the proportion of workers with substantial skills deficiencies has the potential to rise as high as 22 per cent by 2035. This would be equivalent to up to seven million workers lacking the EES they need to do their jobs in 2035, almost double the number of workers with skills deficiencies in 2023. This growth is primarily a consequence of increases in the intensity with which workers across the labour market, particularly professionals, will need to utilise EES in their jobs and partly also because of the overall job growth anticipated in the labour market (which would result in a higher number of workers with skills deficiencies even if the prevalence of Skills Gaps remained constant).

Figure 44 Proportion of workers with *Skills deficiencies in 2035 compared to 2023,* broken down by 'minor' and 'substantial' skills deficiencies



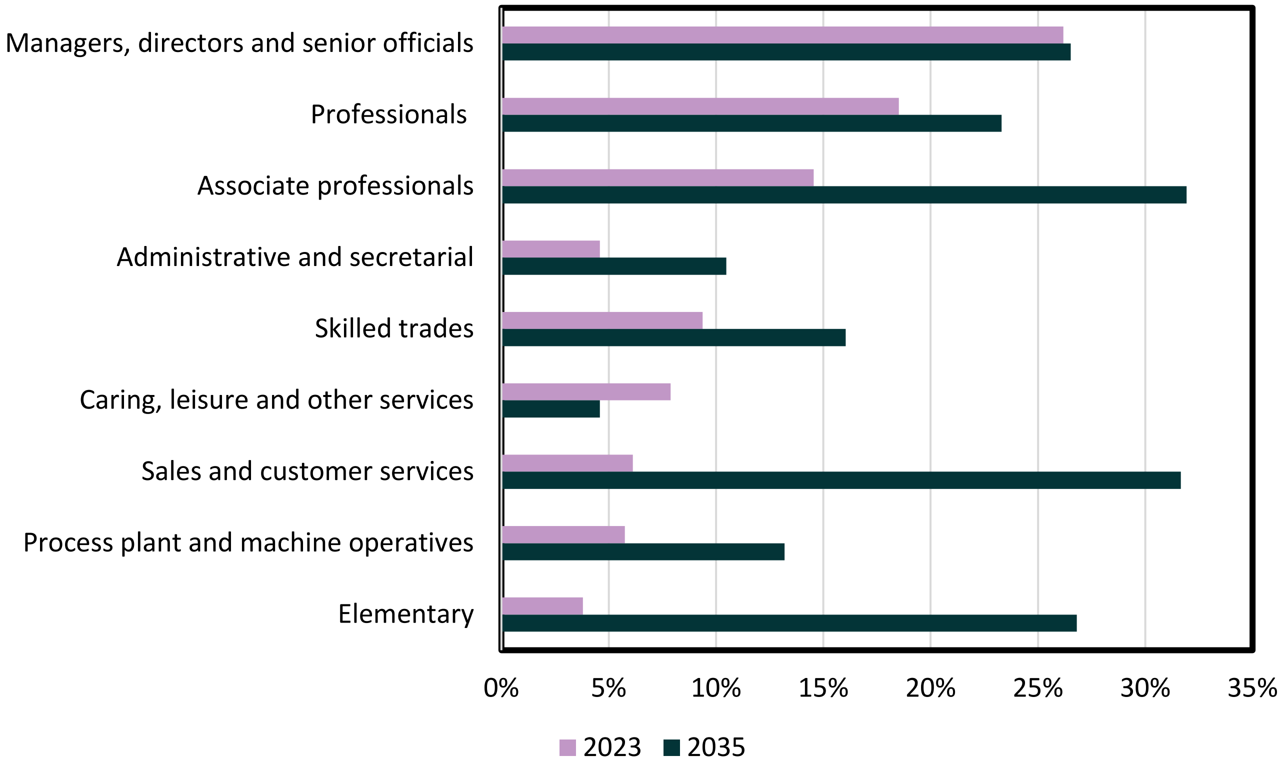
High skill level occupations are likely to have the largest skills deficiencies in 2035, but the prevalence of skills deficiencies in mid- and lower skill level occupations may also grow. Our analysis suggests that the proportion of workers in higher skill level occupations (SOC1-SOC3) with substantial skills deficiencies has the potential to increase from 19 per cent of workers in these groups in 2023 to 26 per cent in 2035, as shown by Figure 45 below.

Our projections also indicate that the proportion of workers with substantial skills deficiencies may increase more rapidly in most mid and low skill level occupations compared to high skill level occupations, albeit from a lower base[18]. This is largely because workers in mid and low skill level occupations are expected to experience a larger increase, relative to workers in higher skill level occupations, in the requirements for them to utilise EES in their jobs.

This underlines the importance of the education system in effectively developing young people's EES before they enter the workforce, and of employers and employees appreciating the importance of investing in developing these skills in their workforce. The consequence of inaction may be that substantial skills deficiencies become ever more prevalent across the labour market.

[18] The only exception to this is 'Caring, leisure and other services', in which substantial EES skills deficiencies are projected to decline slightly between 2023 and 2035. This is because EES Skills Requirements in this occupational group are projected to decline slightly.

Figure 45 Proportion of workers with substantial EES *deficiencies* by broad occupational group (SOC major group), in 2035 compared to 2023



6 Analysis of the benefits associated with higher levels of Essential Employment Skills

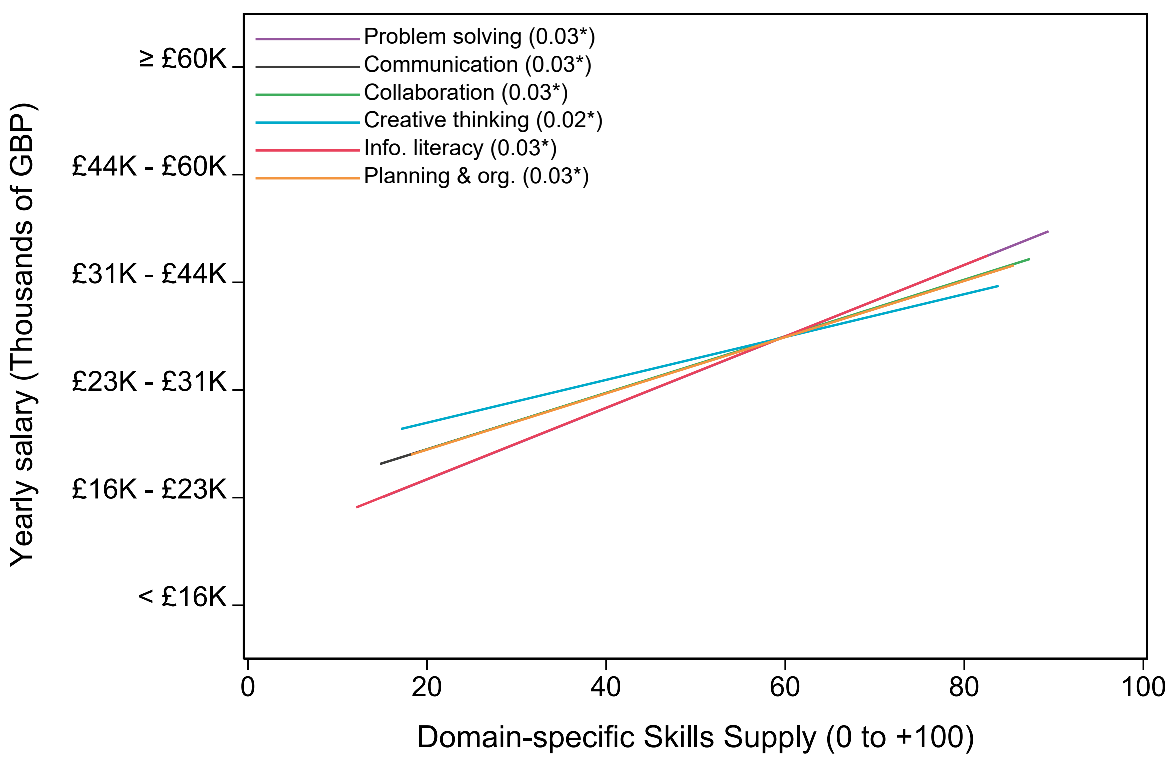
- Higher levels of EES are associated with a range of beneficial outcomes. Our analysis finds that people with higher Skills Supply tend to have higher salaries, are more likely to be in a management position, and have higher job and life satisfaction, on average.
- A substantial share of the relationship between Skills Supply and these outcomes is attributable to differences in other factors, including people's jobs. However, the benefits associated with higher levels of EES remain significant after netting out the effects of differences in a broad range of other individual characteristics.
- A 10-point increase in EES Supply (on a scale of 0-100) is also associated with an increased probability of being in management of over ten percentage points. However, for context, a 10-point increase in Skills Supply is large; roughly equivalent to the difference between the median and the 90th percentile of the Skills Supply distribution.
- This provides *suggestive* evidence that people's Skills Supply may affect their salaries and their likelihood of being promoted into a managerial position.
- People with higher levels of EES also experience higher job and life satisfaction. This could be in part because utilising EES is intrinsically satisfying, particularly interpersonal skills like collaboration.

6.1 How do people's Supply of Essential Employment Skills, and their Skills Gaps, relate to their wages?

Prior research has shown that people in higher wage jobs have higher levels of Skills Supply. In their 2023 Essential Skills Tracker, Skills Builder reported that moving from the lowest quartile skills score to the upper quartile of the essential skills distribution is associated with a wage premium of between 9.4% and 12.0%, which equates to an extra £3,600 to £4,600 per annum for the average full-time worker in the UK (Seymour and Craig, 2023).

Our results are comparable, suggesting that people with higher EES Skills Supply are likely to be in a higher income bracket, as shown in Figure 46 below. We do not find that the wage premium associated with higher Skills Supply varies hugely by skills domain.

Figure 46 Average relationship between EES Skills Supply and salary among 'Workers', by domain

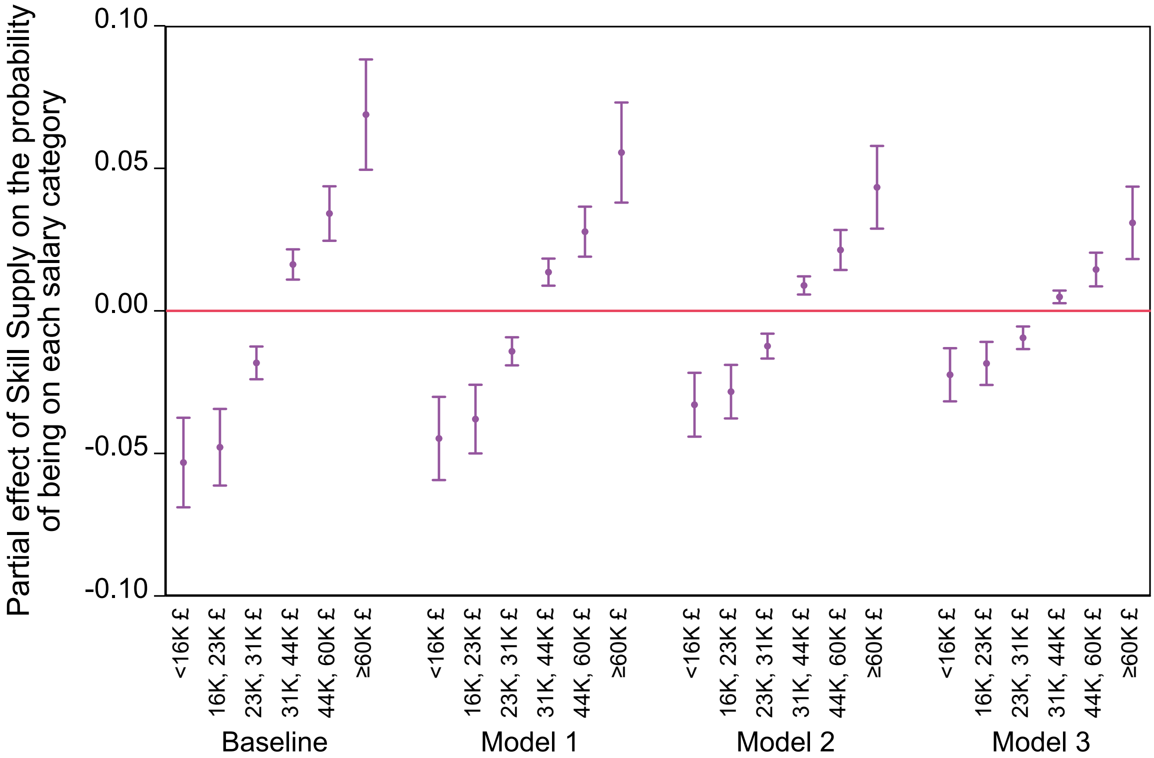


A large share of the wage premium associated with higher Skills Supply is attributable to other factors, including the occupation and industry that people work in, as shown in Figure 47 below. 'Model 1' controls for differences in demographic variables and health status, whilst 'Model 2' adds controls for employment and managerial status, geography and education and training, and 'Model 3' also nets out the effects of occupation and industry. Adding each successive set of controls diminishes the effect of Skills supply on salary. This is hardly surprising – it is likely that higher Skills Supply affects people's salary, in part, by increasing their ability to access higher skill level occupations that utilise EES more intensively and by increasing their probability of continuing in education, which has been shown to be associated with a range of positive and statistically significant benefits, including in earnings and employment status (Social Mobility Commission, 2023 and Bibby *et al.*, 2014).

However, Figure 47 shows that the relationship between Skills Supply and salary remains statistically significant after controlling for a broad range of other factors, potentially indicating that higher levels of EES may influence people's salary through other pathways, besides influencing their access to higher levels of education and higher skill level occupations. For example, higher levels of EES may affect people's salary by enabling them to execute more complex professional tasks which attract a wage premium (Galván *et al.*, 2014). Skills Builder suggest a range of pathways through which 'essential skills' may influence pay levels, including by influencing their commitment to Teamwork and their propensity to take false sick days (Seymour and Craig, 2023, p27). Research by Deming (2015) has also shown workers with high social skills trade tasks at a lower cost and earn a relatively higher wage in return.

However, the magnitude of the relationship between Skills Supply and salaries, after netting out the effects of occupation and other individual characteristics, is small. Taking £25,500 as the minimum salary that allows for a base standard of living (Davis *et al.*, 2022), our estimates suggest that moving from the 25th to the 75th percentile of the Skills Supply distribution corresponds with only a 3.2% increase in the probability of earning this minimum salary. If we assume that people are located in the middle of the income bracket and that the lowest wage is £16k and the largest wage £60k, then moving from the 25th to the 75th percentile of the Skills Supply distribution equates to a salary increase of only £1,290. This is substantially smaller than the £3,600 to £4,600 per annum reported by Skills Builder, but it must be remembered that our estimated coefficients reflect the effect of Skills Supply on salary after netting out the effects of a broader range of factors, including occupation, which are likely to partially mediate the effect of EES on salaries.

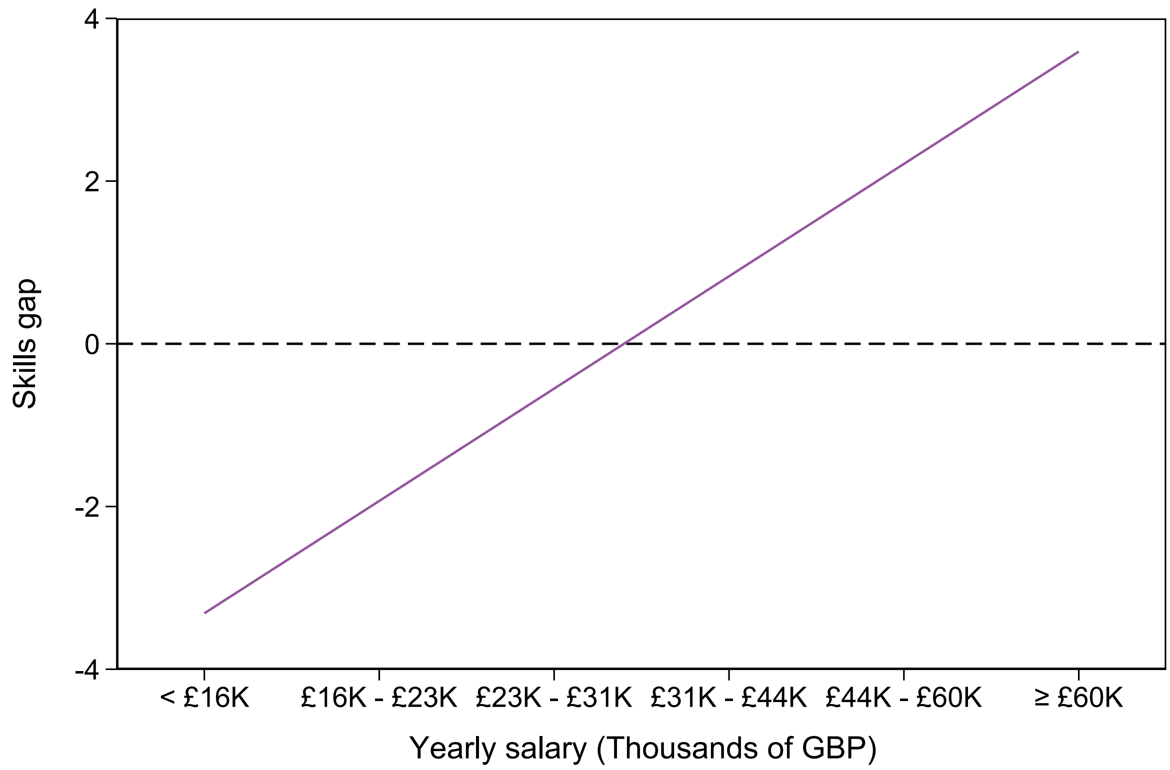
Figure 47 Partial effect of a 10-point increase in Skills supply on the probability of 'Workers' being in a higher salary category, before and after netting out the effects of other individual characteristics[19]



We also find that higher-earning workers (those with salaries above £31,000) typically experience Skills Gaps, whereas lower-earning workers experience skills under-utilisation. This is largely because workers in higher skill level occupations are paid more but also experience the highest Skills Requirements, and the difference in Skills Requirements between occupations at the top and bottom of the occupational hierarchy is larger than the difference in Skills Supply.

[19] 'Model 1' controls for gender, age, ethnicity, country of birth and health status. 'Model 2' adds employment status, managerial status, region, local area deprivation (IDACI), highest qualification level, participation in off-the-job and on-the-job training. 'Model 3' adds occupation and industry.

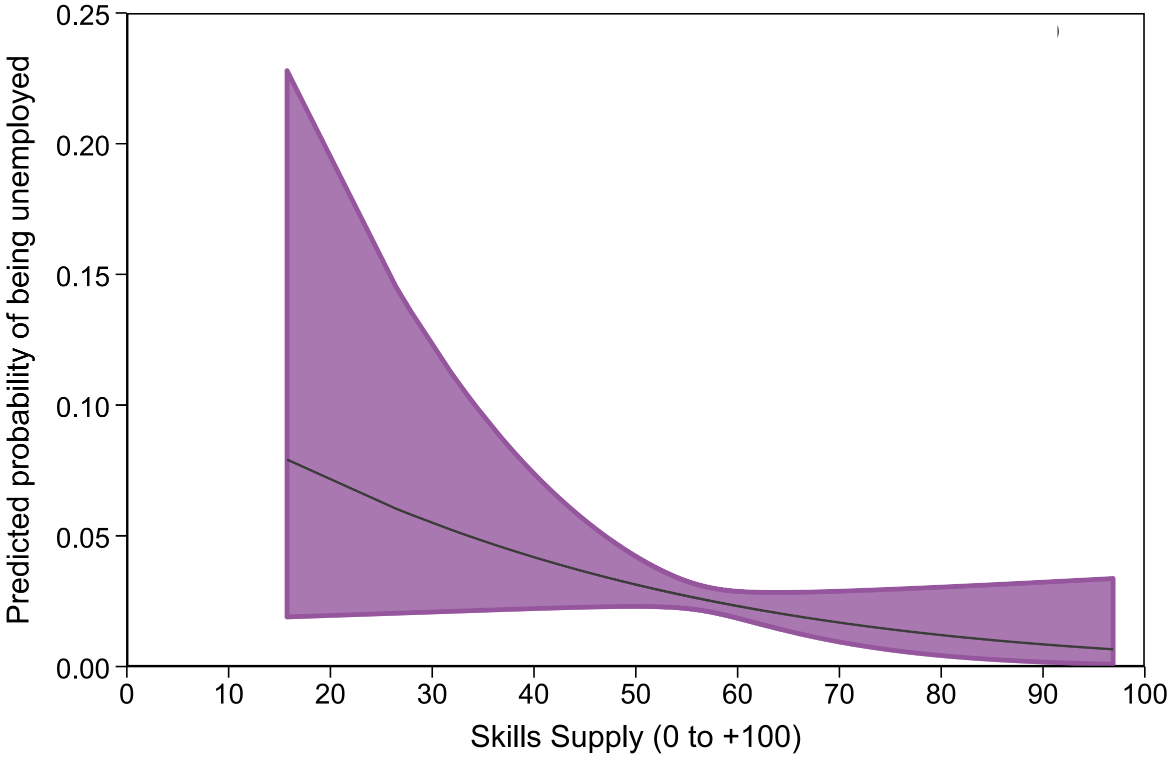
Figure 48 Relationship between salary and Skills Gaps among 'Workers'



6.2 How do people's Supply of Essential Employment Skills relate to their probability of being in employment?

Figure 49 shows that people with higher Skills Supply are less likely to be unemployed, but the relationship between these variables is a weak one. For example, moving from the bottom quartile to the top quartile of the Skills Supply distribution is associated with a fall of just half a percentage point in the probability of being unemployed.

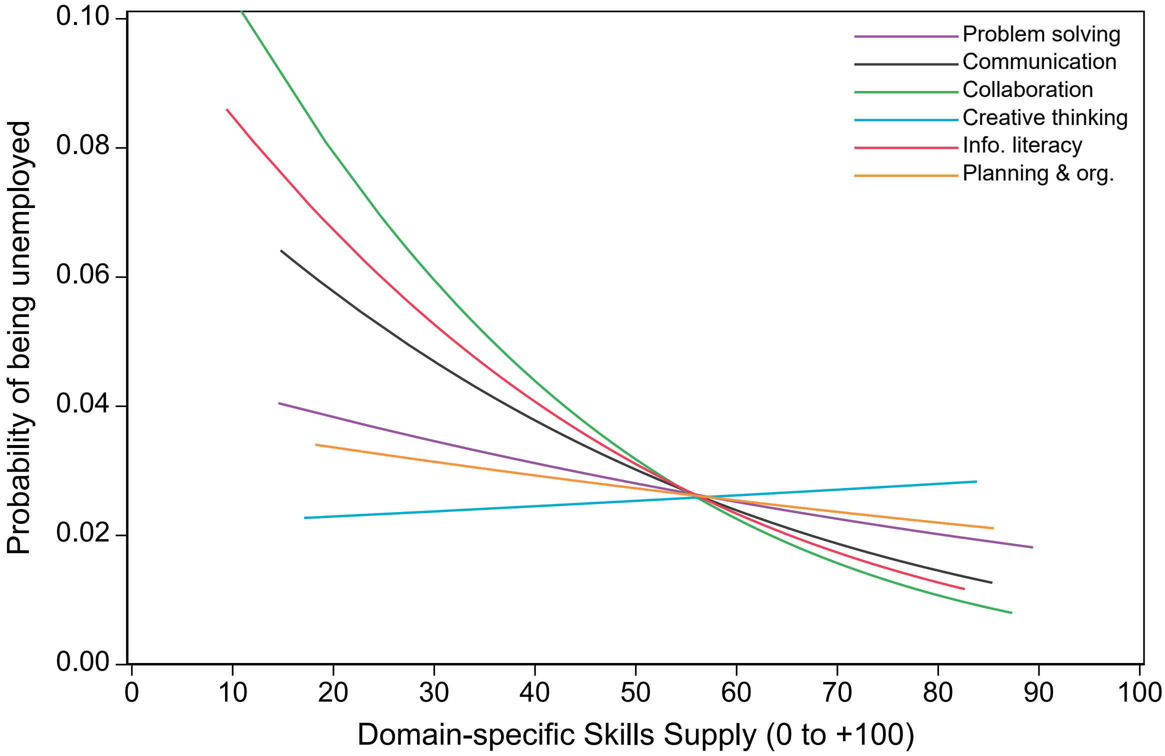
Figure 49 Relationship between Skills Supply and probability of being unemployed, amongst 'Workers' and the 'Long-term unemployed' (i.e. discounting 'Young People')



Note: The purple shading in the figure above indicates the confidence interval.

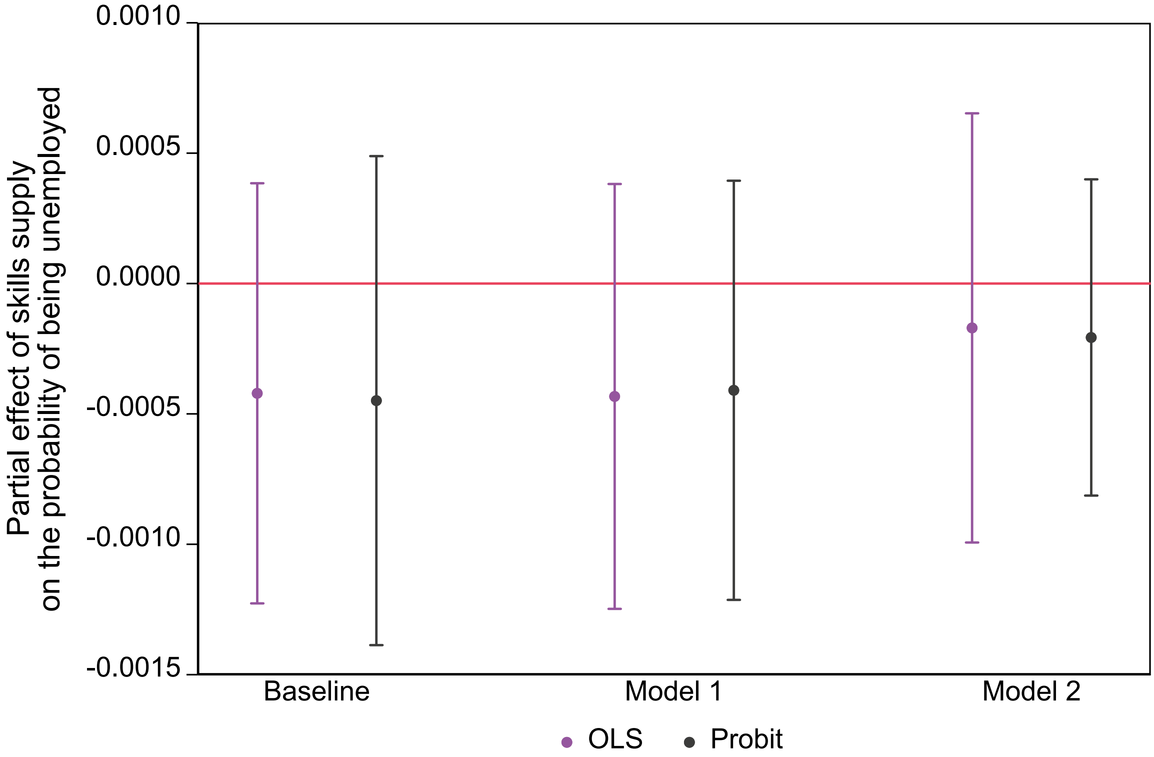
The relationship between Skills Supply and the probability of being unemployed is stronger for collaboration, information literacy and communication relative to the other three EES domains, as shown in Figure 50 below. This might indicate that these skills play a greater role in employers' hiring decisions, either because they are more highly valued or because they are more easily assessed.

Figure 50 Relationship between Skills Supply and probability of being unemployed, amongst 'Workers' and the 'Long-term unemployed' (i.e. discounting 'Young People')



However, the relationship between people's Skills Supply and their probability of being unemployed is not significant, and further diminishes after controlling for differences in other individual characteristics, as shown in Figure 51 below.

Figure 51 Partial effect of a 10-point increase in Skills supply level on the probability of being unemployed, amongst 'Workers' and the 'Long-term unemployed' (i.e. discounting 'Young People')[20]

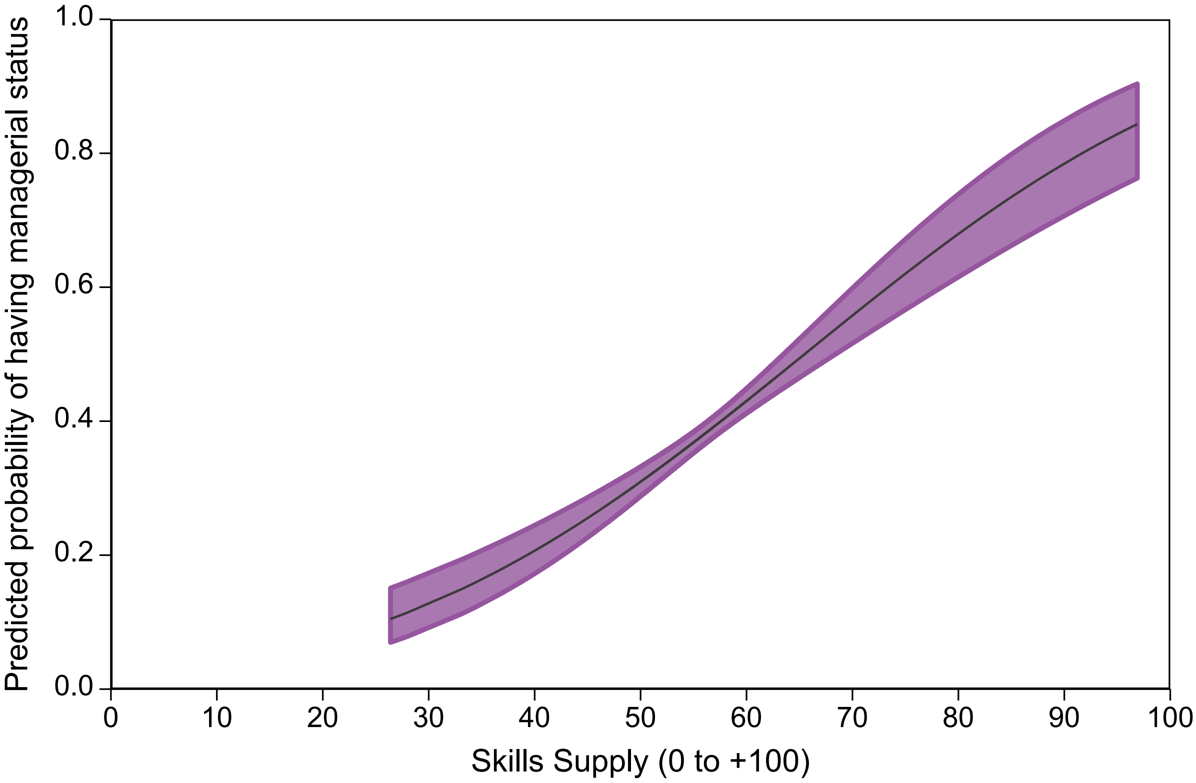


6.3 How do people's Supply of Essential Employment Skills relate to their probability of being in a managerial position?

Workers with a higher Skills Supply are more likely to be in a management position. Moving from the bottom to the top quartile of the distribution of skills scores is associated with an increased probability of being in management of eight percentage points, as shown in Figure 52 below. This relationship is very similar when comparing across EES domains.

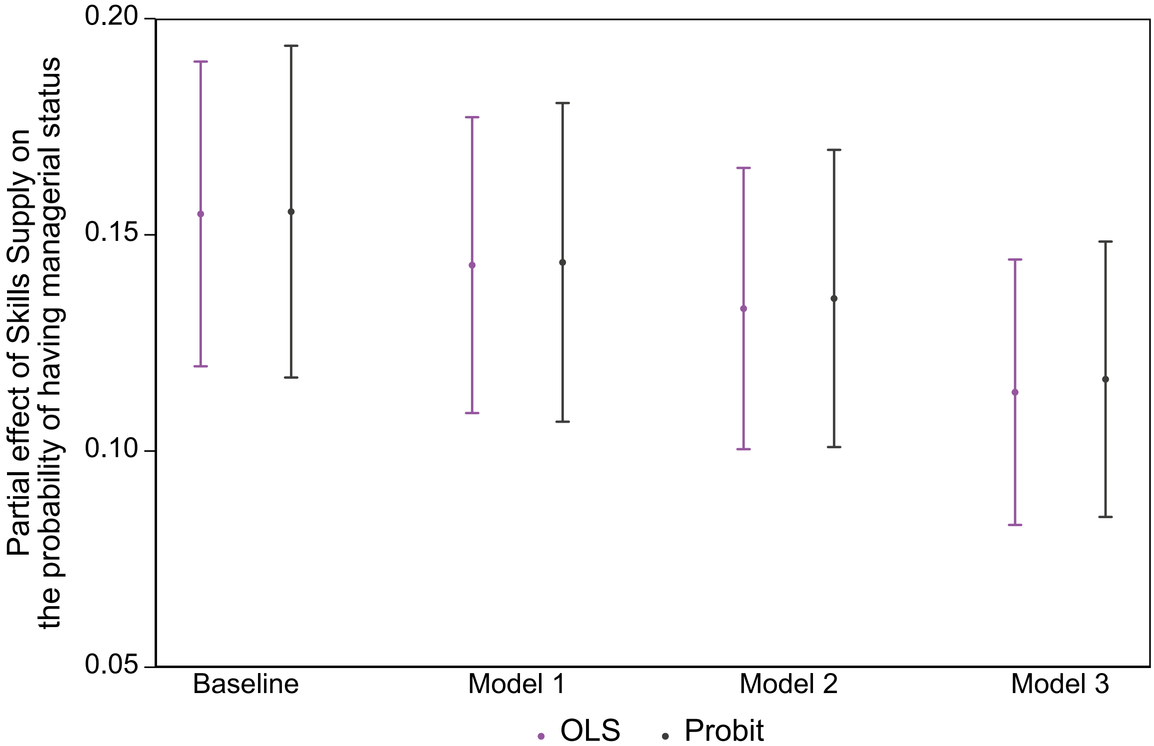
[20] 'Model 1' controls for age, gender, ethnicity, country of birth and health status. 'Model 2' adds region, local area deprivation (IDACI) and highest qualification level.

Figure 52 Relationship between Skills Supply and the probability of 'Workers' being in a managerial position



Only a small share of the relationship between Skills Supply and managerial status is attributable to differences in other individual characteristics, as shown by the regression coefficient plots in Figure 53. 'Model 1' controls for differences in demographic characteristics and health status, 'Model 2' also controls for employment status, education and training variables and geography, and 'Model 3' also nets out the effects of occupation and industry. Even in 'Model 3', the relationship between levels Skills Supply and managerial status remains strong and significant, indicating workers in the same occupational group and with similar characteristics but different levels of EES have significantly different probabilities of being in a managerial position. This might be because EES are seen to contribute to greater leadership effectiveness in management (Riggio *et al.*, 2003). Alternatively, higher EES may be associated with personality traits that affect workers' propensity to apply for management positions.

Figure 53 Partial effect of a 10-point increase in Skills Supply level on the probability of being in a managerial position among 'Workers', before and after netting out the effects of other individual differences[21]



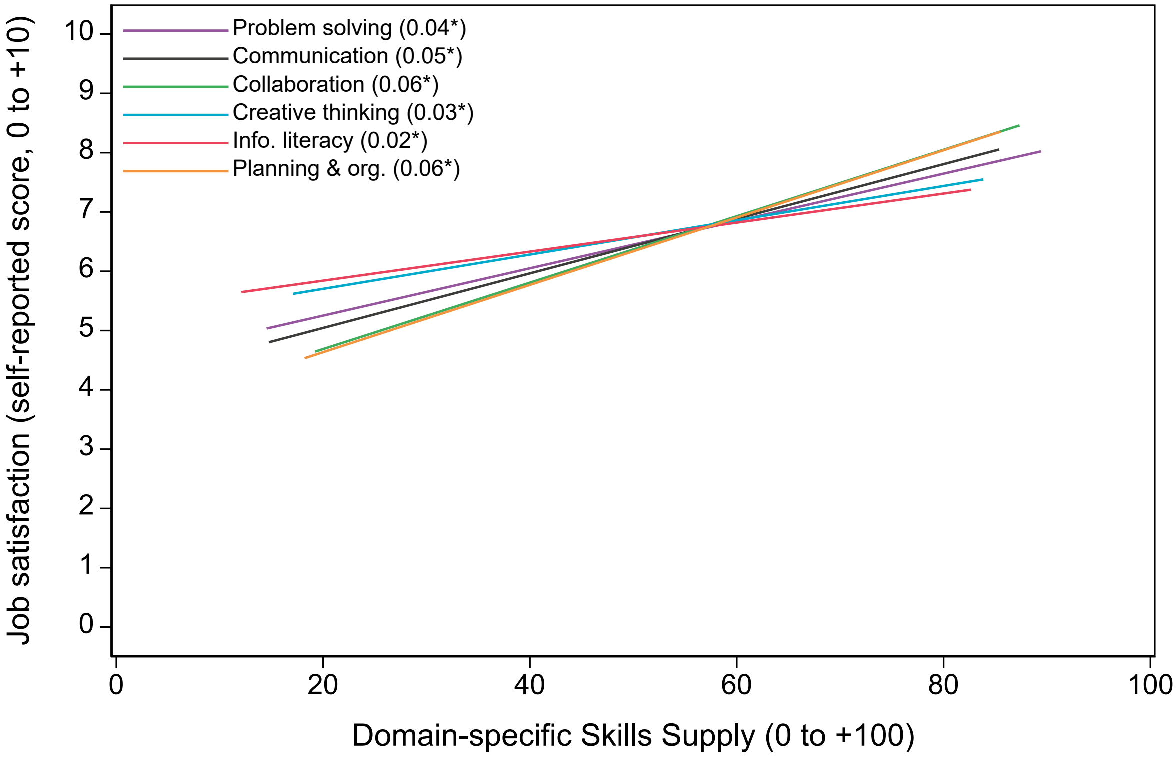
6.4 How do people's Supply of Essential Employment Skills relate to their job satisfaction?

We asked survey respondents to report how satisfied they were with their job on a scale of 1-10. 'Workers' with higher Skills Supply levels reported higher job satisfaction. Moving from the bottom to the top quartile of the skills score distribution is associated with an increase of almost 0.5 points on the job satisfaction scale, on average. This suggests employers that recruit or develop a workforce with higher average Skill supply levels are likely to have more satisfied workers, who may also therefore be more engaged and less likely to look for a new job.

This relationship between Skills Supply and job satisfaction is slightly stronger for some domains, particularly 'Collaboration' and 'Planning, organising and prioritising'. It might be that performing 'human' skills like collaboration is intrinsically satisfying, and that workers with higher Skills Supply experience greater levels of autonomy to plan, organise and prioritise their own work. Alternatively, higher levels of job satisfaction may be reflective of deeper engagement and work commitment which support the development of EES.

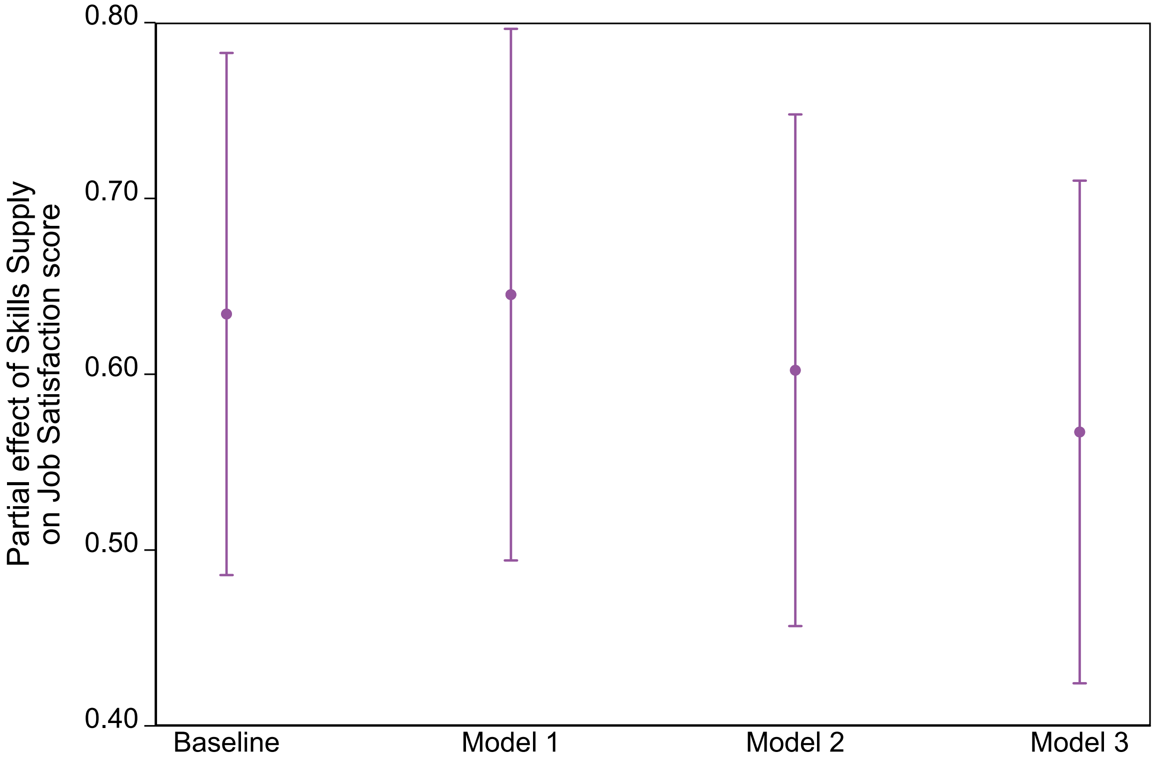
[21] 'Model 1' controls for age, gender, ethnicity, country of birth and health status. 'Model 2' adds region, local area deprivation (IDACI), employment status, highest qualification level and participation in training. 'Model 3' also controls for occupation and industry.

Figure 54 Relationship between Skills Supply and job satisfaction among 'Workers', by domain



The relationship between Skill Supply and job satisfaction remains statistically significant even after netting out the effects of other factors, as shown by Figure 55 below. This might be because Skills levels affect job satisfaction directly, as well as by influencing workers' access to high skill level occupations, higher-qualification levels and training. However, again the relationship is fairly weak - a ten-point increase in Skills Supply is associated with an increase in job satisfaction score (0-10) of just 0.6. For context, a 10-point increase in Skills Supply is large; roughly equivalent to the difference between the median and the 90th percentile of the Skills Supply distribution.

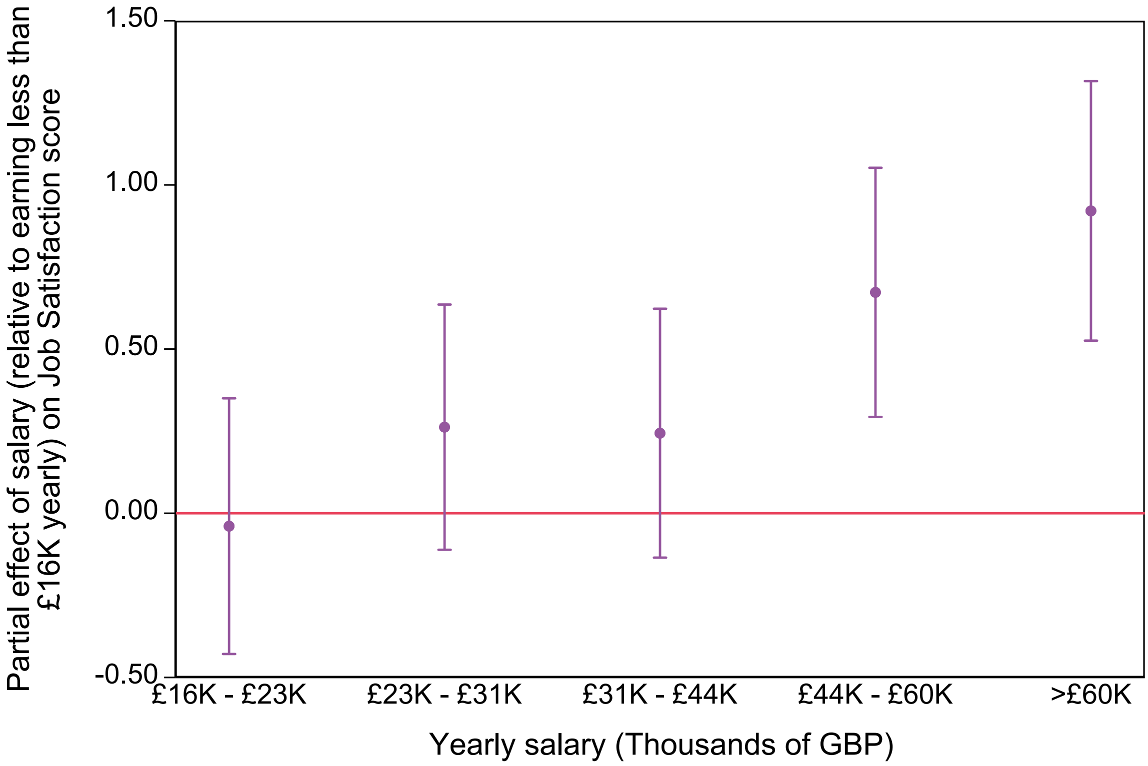
Figure 55 Partial effect of a 10-point increase in Skills Supply on job satisfaction among 'Workers', before and after netting out the effects of other individual characteristics[22]



Skills Builder report that people's levels of essential skills are a much better predictor of their job satisfaction than their income (Seymour and Craig, 2023, p31). Using our data to compare the effect of Skills Supply on job satisfaction with that of salary on job satisfaction, we find that a 10-point increase in Skills supply corresponds with the same increase in job satisfaction as moving from the <£16k per year salary band to the £31k-£44k salary band. This is shown in Figure 56 below.

[22] 'Model 1' controls for age, gender, ethnicity, country of birth and health status. 'Model 2' adds employment status, region, local area deprivation (IDACI), highest qualification level and participation in training. 'Model 3' also controls for occupation and industry.

Figure 56 Partial effect of salary on job satisfaction among 'Workers', before and after netting out the effects of other individual characteristics[23]



6.5 How do people's Supply of Essential Employment Skills relate to their life satisfaction?

We asked survey respondents how satisfied they are with their life on a scale of 1-10. Higher levels of Skills Supply are associated with higher life satisfaction, on average, although the relationship between these variables is weaker than the one shared between Skills and job satisfaction. Moving from the bottom to the top quartile of the Skills Supply distribution is associated with an increase in life satisfaction score of 0.3, on average. Again, this may be because performing EES is intrinsically satisfying or because people's general disposition affects their ability to develop and demonstrate these skills. Our analysis finds that the relationship between Skills levels and life satisfaction is strongest amongst the 'long term unemployed', as shown in Figure 57. This could be because higher levels of EES better enable the long-term unemployed to manage the multi-faceted challenges they encounter in their life.

[23] Controlling for age, gender, ethnicity, country of birth and health status, employment status, region, local area deprivation (IDACI), highest qualification level, participation in training, occupation and industry.

Figure 57 Relationship between Skills Supply and life satisfaction amongst the overall population, by domain

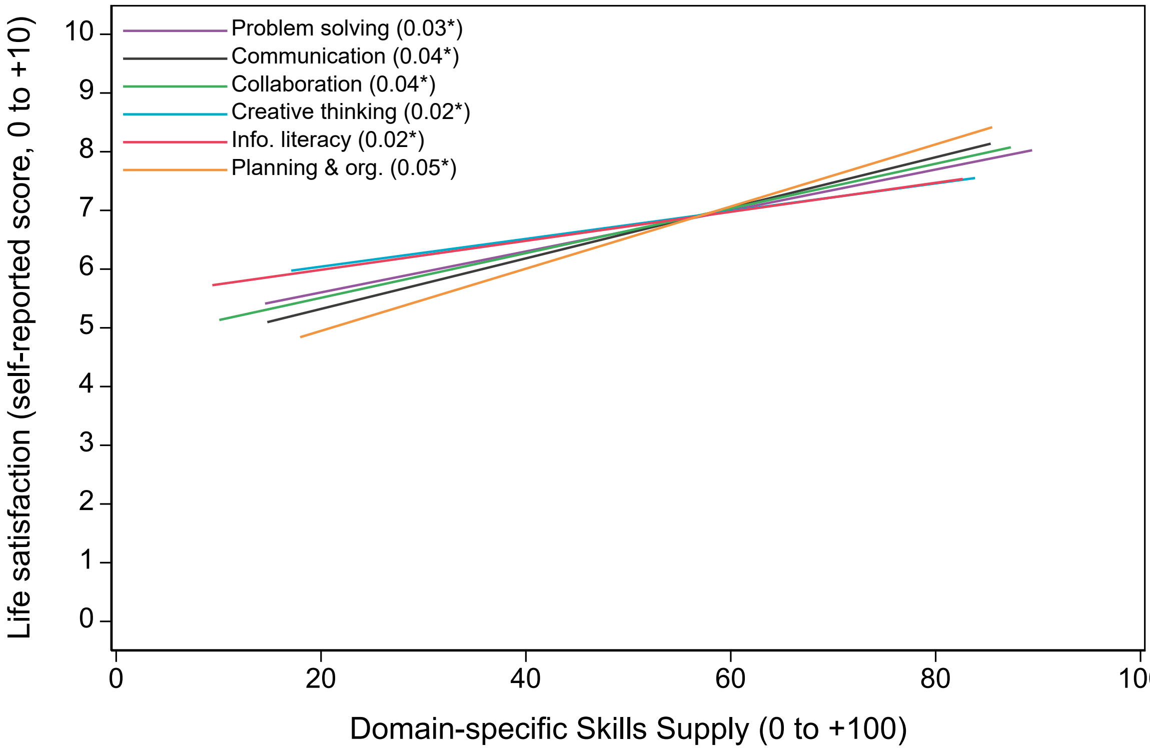
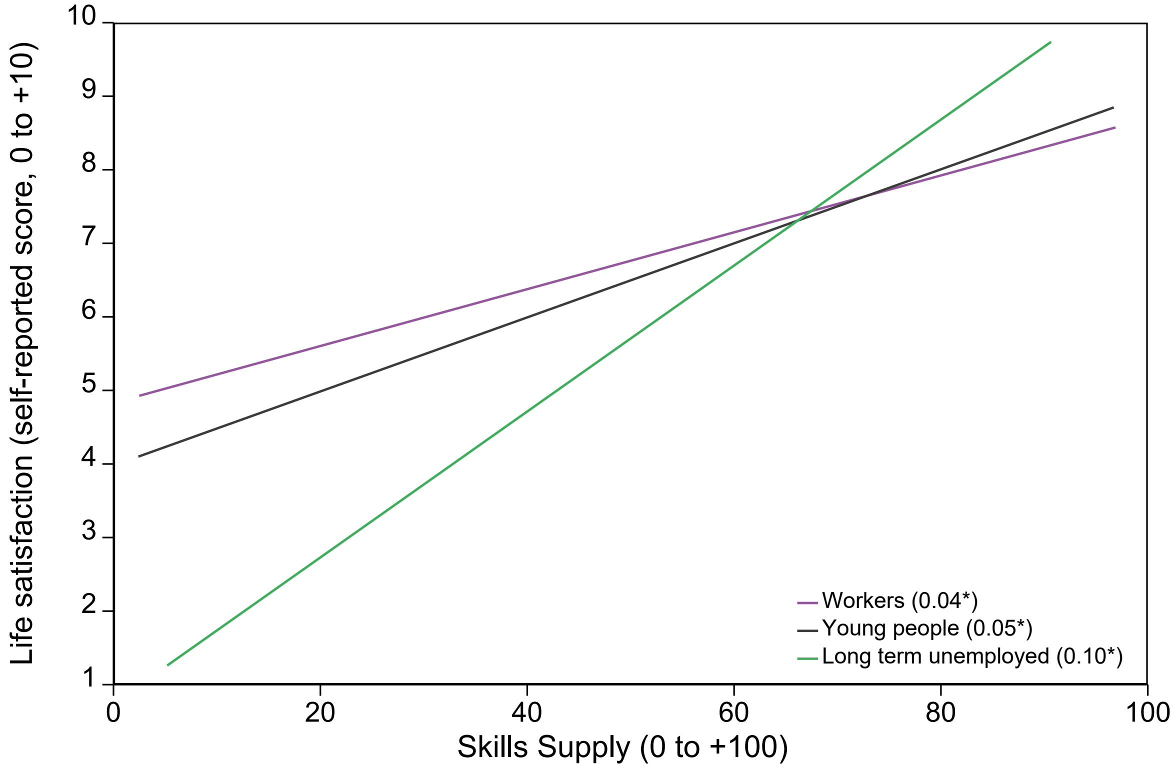
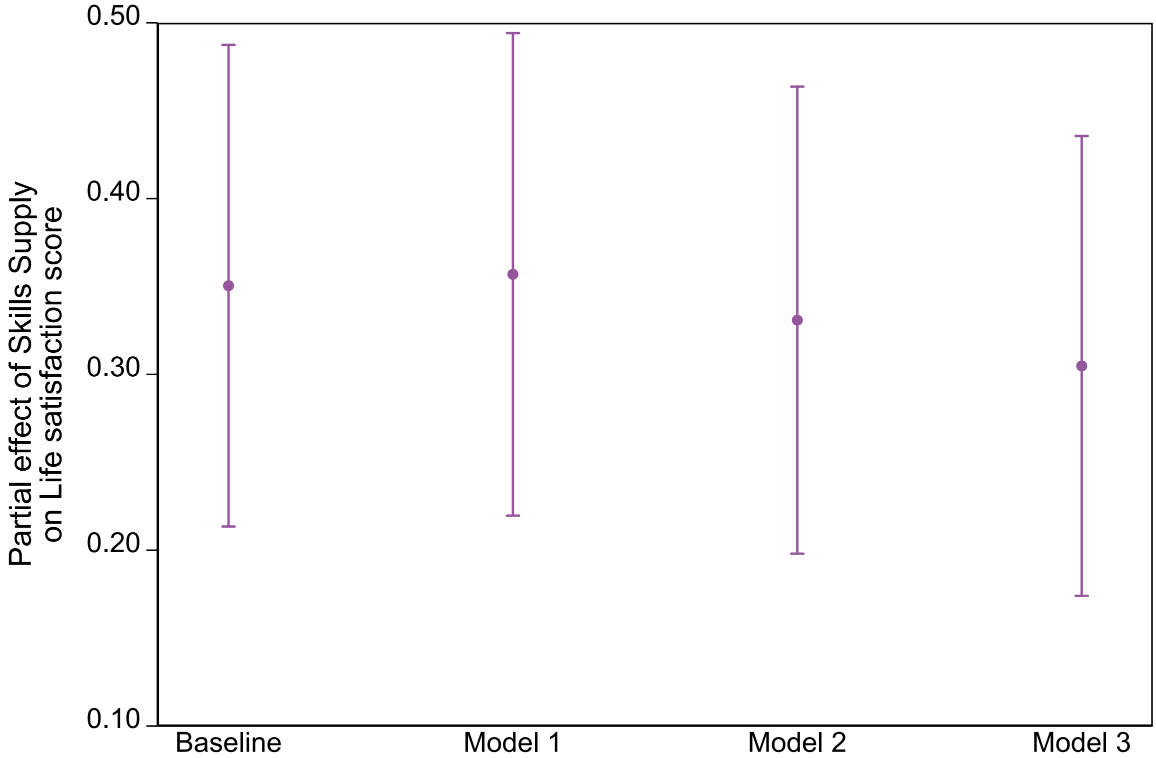


Figure 58 Relationship between Skills Supply and life satisfaction, by subpopulation



Differences in life satisfaction by Skills Supply remain significant after netting out the effects of other factors, including – in 'Model 3' of Figure 59 below – demographic characteristics, employment status, geography, education and training, occupation and industry. A 10-point increase in Skills Supply corresponds with a slightly larger increase in average life satisfaction score amongst 'Young people' (0.5) compared to 'Workers' (0.3).

Figure 59 Partial effect of a 10-point increase in Skills supply on life satisfaction amongst the overall population, before and after netting out the effects of other individual characteristics[24].



[24] 'Model 1' controls for age, gender, ethnicity, country of birth and health status. 'Model 2' also controls for employment status, region, local area deprivation (IDACI), highest qualification level and participation in training. 'Model 3' also controls for occupation (SOC major group) and industry.

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