Methodology

Occupation as the Unit of Analysis

A career refers to a job or series of jobs performed by an individual over time within a field of work. All jobs are classified by government statistical agencies into occupations based on the task requirements of that job. An occupation is therefore a group of closely related jobs and can be thought of as a career. For this reason, we report data for careers using occupations as the basic unit. For income and job growth, we used data from each country's national statistics office. For each country, there were changes in the occupational coding over the period of analysis. This required converting jobs in the old coding system to jobs in the latest coding system. This process relied on harmonisation matrices provided by the national statistical offices, so that career titles in the baseline year matched titles in the final years. This process inevitably introduces errors in estimated job growth for cases in which there were large changes to the job categorisations, but we have done our best to minimise these.

United Kingdom National Data

U.K. data on the number of workers, pay and educational requirements by occupation were obtained by the U.K. Office of National Statistics (ONS). The income and employment data were available for 2014 and 2022. We used median annual pay as our baseline measure. The underlying source for earning and jobs is the Annual Survey of Hours and Earnings. To get data on education by occupation, we used a 2019 summary table from ONS. The occupations are classified using the U.K.'s Standard Occupational Classification (SOC) system.

The employment and wage data are based on 1% samples of the workforce. ONS withholds disclosing the number of jobs at the four-digit level when the coefficient of variation reaches a certain threshold, as would be the case for careers with relatively small numbers of total workers in the U.K. For these cases, we do not report the number or jobs, but we calculate growth using three-digit employment levels, which are available.

ONS also publishes data on education by occupation, based on Census data. A career is considered professional — or requiring a college degree — If the percentage of workers with "level 4 qualifications or higher" is 50% or higher. This is similar to a U.S. bachelor's degree.

French National Data

French data on pay and the number of jobs were drawn from INSEE, the French statistical office. The original data were compiled from the Nominative Social Declaration (NSD) database, which requires all employers subject to social security taxation to report employment and compensation information to the French authorities. Data from workers in the public sector data are from the Information System on Public Services (Siasp), and data on self-employed workers come from other tax sources, compiled by INSEE. INSEE publishes microdata for one-twelfth of the French working population and includes detailed job categorisation using the nomenclature of occupations and socio-professional categories (PCS) system. These data are available for 2014 and 2021, but wages are reported only in categories, not precisely. To estimate precise measures of pay, we took the mean of the minimum and maximum pay for each category, multiplied by 12, and divided by the number of annual hours to estimate hourly compensation. This served as a preliminary estimate and was used to generate a more accurate estimate, as described below. We further eliminated employees who worked less than 1,000 hours in the previous year and less than 200 days to downward bias in compensation for occupations with many part-time or seasonal workers. The sum of workers fitting these criteria was calculated by occupation for 2014 and 2021, allowing us to calculate the rate of growth.

INSEE also publishes summary data on mean compensation data by PCS, adjusted for full-time equivalent employees. These data are more accurate measures of compensation than those available in the microdata, since they do not rely on categorical ranges. The published monthly compensation figures were adjusted to annual compensation by multiplying by 12. These data were available for 258 occupations. For 171 remaining occupations, annual pay was estimated by regressing mean annual pay — from the aggregated INSEE database — on estimated hourly pay at the 20th, 50th and 80th percentiles using the microdata. The adjusted R-squared in this model was 0.65, suggesting that the actual mean was well predicted by the estimated points on the distribution. For predicted values less than 10,000 Euros, the actual mean figure based on the categorical microdata was used (affecting only nine occupations). Finally, the reported 2021 Euros were converted into 2022 Euros by multiplying by 1.1, reflecting growth in the Eurozone consumer price index.

We could not identify any source of published data or microdata for the educational attainment of workers by occupation for France. As a result, we used the new PCS2020 structure to identify jobs as likely or unlikely to require a college degree. Using the first two digits of the PCS 2020, we identified jobs as likely to require a college degree if the first two digits were at or above 23 and at or below 46. Civil servants were also classified as professionals. This analysis was informed by class distinctions made by Amossé (2019).[6]

6 Amossé, Thomas, Olivier Chardon and Alexis Eidelman. La rénovation de la nomenclature socioprofessionnelle (2018-2019): rapport du groupe de travail du Cnis. Diss. Conseil national de l'information statistique (Cnis), 2019.

German National Data

Data on employment, skill requirements and compensation were obtained from Germany's Federal Employment Agency (Bundesagentur fur Arbeit), and their quarterly data on Employees by Occupation, using the German KldB 2010 classification system. These data were available for 2014 and 2022 and included educational attainment information for each occupation. The salary data were reported monthly and converted to annual pay by multiplying by 12. This reports uses the median level of compensation.

A career is considered professional — or requiring a college degree — if the percentage of workers with an "academic professional qualification" is 30% or higher. We apply this low threshold because many professional careers in Germany (e.g., pharmacist, computer scientist) can be entered with a non-academic "recognised professional qualification", which may involve post-secondary training and education. In this way, the German data do not clearly distinguish between tertiary education statuses. A threshold of 50% would overstate the ease of entering many careers that require advanced education.

The German Federal Employment Agency classifies many jobs by the level of expertise required to perform the job, in addition to the types of activities and tasks performed.7 The levels of expertise include 1) unskilled or semi-skilled, which are activities that do not require specialised knowledge beyond general schooling 2) specialist jobs, which require on-the-job-training or vocational training 3) complex specialist activities, which require expertise that goes beyond short-term training or vocational schooling and may include master craftworkers or managers 4) highly complex, which require a very high level of knowledge that often requires a graduate degree. Several of the top-scoring jobs are deemed highly complex.

7 Wiebke, Paulus and Britta Matthes 2013. "The German Classification of Occupations 2010 – Structure, Coding and Conversion Table" Research Data Centre of the German Federal Employment Agency, FDZ-Methodenreport 08/2013.

Job Vacancies for Each Country

Some high-paying jobs may, nonetheless, have few vacancies, and some fast-growing fields may have even faster growth in labour supply, through immigration or new entry from training programmes, leading to difficulty for new entrants. To estimate the ratio of demand to supply, we purchased data from Lightcast, which aim to scrape the universe of online job postings for each country and classify them by occupation (see below). The data are classified to occupations using the international ISCO system. To convert ISCO job vacancies to the national systems, Gallup downloaded correspondence tables created by ONS and INSEE for the U.K. and France. For Germany, Gallup created its own correspondence table to convert vacancies from ISCO to KldB 2010. Vacancies per occupation were divided by the number of workers to calculate vacancies per worker, which was used to estimate demand relative to supply. A limitation of these data is that Lightcast only collects and analyses English-language posts. This is not a problem for the U.K. data, but in Germany and France, this understates job postings. As described below, we estimate total job postings for Germany and France — including native-language postings — based on the number of English-language posts.

The CFI is not itself a forecast itself, but relies on trends in current and past data to measure future job potential. Past job growth and job vacancy rates predict current growth and vacancy rates, so current growth and vacancy rates will likely be predictive of future demand. However, there are some job roles, such as those in disruptive technologies like artificial intelligence, that are so new they are not reflected in the data.

Our method for calculating a career's capacity to withstand automation gives higher values to jobs that require complex, creative tasks and less value to jobs that require routine or repetitive tasks. This will be positively correlated with future job growth based on current economic theory and studies of automation.

Calculating the CFI score

The CFI is calculated using the following formula:

CFI = (0.502 x income) + (0.166 x vacancies/worker) + (0.166 x growth) + (0.166 x automation resistance index)

Since each measure uses a different scale, the underlying concept is first standardised to have a mean of zero and a standard deviation of one within each country. This is called a z-score and is a continuous variable with no upper or lower bound. It was clear that this process, however, resulted in a few outliers (extreme growth, for example) that would give too much weight to one of the concepts. To limit the influence of outliers and preserve something closer to the intended weighting, we replaced the z-score described above with one based on the centile rank of the underlying concept if the maximum z-score exceeded 6 standard deviations. For example, one career might have extreme job growth, giving it a z-score of 10. Even if the career were otherwise at the mean on the other three indicators, its CFI score would be 1.7 standard deviations above the mean, using the formula above. Ranking job growth on a centile scale before taking the z-score limits the maximum value to approximately 1.7 (and the minimum to -1.7). In this example, the final CFI score would fall from 1.7 to 0.29, which is much closer to the mean of zero and better reflective of the four components.

In practice, we used this centile-based z-score for the following concepts:

- U.K. — vacancies per worker
- France — job growth, income and vacancies per worker
- Germany — job growth and vacancies per worker

Otherwise, we used the z-score of the underlying value.

Identifying IT Skills Listed in Vacancies

Lightcast data are limited to English-language job postings that were advertised between 1 October 2022 and 10 October 2023. The database includes a list of the skills referenced in each job vacancy. To identify vacancies that require an IT skill, we tagged any job that mentioned one of these words as IT: machine, artificial, intelligence, software, data, information, technology, engineering, programming, code, coding, computer, hardware, graphic, design, interface, web, internet. For France and Germany, we estimate that approximately 10% of job vacancies are listed in English. This is calculated by comparing the number of vacancies per worker in the U.K. data to vacancies per worker in France and Germany. The ratio in the U.K. is roughly 10 times larger, which we interpret as evidence that Lightcast data include only a subset of total vacancies in Germany and France, since most jobs would be advertised in the native languages of each country.

Our focus in the analysis is on the share of total jobs that require IT skills, so the language limitation is unlikely to be a problem for our analysis, unless English-language jobs tend to be biased in their skill requirements toward or away from IT skills. We cannot know for sure, but in so far as the percentage of vacancies that mentioned IT skills in the U.K. (where English is the language for all vacancies) is similar to the percentage of vacancies in Germany and France, this bias is unlikely. The data indicate a small bias in favour of IT skills, since 25% of English-language jobs in the U.K. advertise IT skills, compared to 30% of jobs in France and 37% of jobs in Germany. Thus, English-language jobs in France and Germany may over-represent IT skills relative to native-language job vacancies, but it may also be the case that there is truly a higher share of job vacancies in Germany and France that require IT skills.

Capacity to Withstand Automation

We measure capacity to withstand automation as an index that summarises the level and importance of non-automatable tasks required for each career. The details are available in a previous Gallup report for Amazon, which uses the same method.[8] Economists have long been concerned about the potential for machines to displace humans and lower the demand for labour for specific tasks and careers. The automation of manufacturing plants is well known, but the effects extend much wider. To list some examples, bank ATMs, self-checkout kiosks at grocery stores, vending machines and automated customer service chatbots are among the tools that have specifically replaced tasks that were previously only performed by humans. With the recent release of open-source artificial intelligence tools like ChatGPT and DALL-E, the domain of jobs subject to competition from automation has been expanded still further. At the same time, economic theory holds that automation technologies expand demand for labour by enhancing the productivity of workers and production processes, thereby creating value that increases demand for complementary tasks, novel tasks or additional work. For example, if a law firm uses AI to streamline tedious research, law clerks and lawyers could become more productive, take on more cases and expand revenue, leading to higher salaries for and/or additional demand for work. Much of the extra value would go back to the economy in the form of increased consumption.

8 Gallup. "Data-Driven Career Advice: The Gallup-Amazon Careers of the Future Index" (2023), https://www.gallup.com/analytics/506930/amazon-future-engineer-interactive-careers.aspx

A career of the future should be able to withstand this trend and either perform tasks that cannot be automated or use these new technologies to make themselves more productive, as many workers did through the introduction of computers.

The approach to measuring the capacity to withstand automation is summarised here, but readers interested in details can see the appendix of the referenced report.[9] The first step was to identify a set of 24 constructs related to the tasks, skills, abilities and work context of occupations. These constructs are associated with capacity to withstand automation in the economics literature, and the United States Department of Labor's O*NET database collects and reports these data for every occupation in the U.S. economy. These constructs were weighted based on how well they predict worker agreement or disagreement with the statement: "A machine, robot, computer, could do my job", using data from a 2019 Gallup survey. The tasks performed by workers were highly predictive of their response to this statement. Using these data, we calculated a mean-weighted score of capacity to withstand automation per occupation, using the U.S. Standard Occupational Classification system. We then used a SOC-ISCO crosswalk to estimate automation risk using the ISCO system and applied this to each country using the ISCO-national occupational coding described above.

While the task data are based on U.S. research, the set of tasks performed in these occupations are broadly similar across countries. A doctor, for example, performs similar tasks whether in the U.K., France, Germany or the United States, and so does a software developer. Indeed, multinational corporations employ workers around the world, and while pay scales vary between country, the occupation-specific tasks are similar across locations.

PISA Data

The career interests of 15-year-old students are calculated using data from the Programme for International Student Assessment (PISA), part of the Organisation for Economic Co-operation and Development (OECD). As part of its background data collection for the PISA exam, the OECD asks, "What kind of job do you expect to have when you are about 30 years old?" Data on career preferences are analysed separately by boys and girls in each country. We also analysed data by whether the student spoke the native language of the country or a different language at home. We limited the analysis to groups with at least 100 responses to avoid large margins of error in the estimates. The sample size is 6,116 for Germany, 6,770 for France and 12,972 for the United Kingdom.

Additionally, we classified careers references in PISA into several aggregate classes using the ISCO-08 code that is provided by PISA: Information technology careers were identified as careers 25, management as careers 11, 12, 13 and 14. STEM careers are codes 25 and 21. The following titles were classified as engineering: 2141-2161 and 3111-3115, 3119. A similar method of coding ISCO-88 was used by Caprile et al (2015) in a study for the European Parliament.[10] Furthermore, jobs in healthcare were based on the two-digit code 22, which refers to "health professionals" and includes doctors, nurses, midwives, veterinarians, dentists, pharmacists and other specialists that diagnose and treat patients. Teaching professionals were identified with the two-digit code 23. Legal professionals, which includes judges and lawyers, were identified with the three-digit code 261. Sport occupations were identified using the three-digit code 342, which refers to sport and fitness workers, and includes athletes, coaches and fitness trainers.

9 Data-Driven Career Advice The Gallup-Amazon Careers of the Future Index, https://www.gallup.com/analytics/506930/amazon-future-engineer-interactive-careers.aspx

10 Maria Caprile, Rachel Palmén, Pablo Sanz, Giancarlo Dente. 2015. "Encouraging STEM studies: Labour Market Situation and Comparison of Practices Targeted at Young People in Different Member States" (European Parliament's Committee on Employment and Social Affairs).

Classifying aggregated job families using national data

To summarise the CFI score by larger career families (engineering, healthcare, IT, legal, management, sport and teaching) and compare the results of these careers to interest levels among youth (using PISA), we created aggregations of the national occupational coding systems for each country using the methods described below.

United Kingdom: The U.K. uses the Standard Occupational Classification (SOC 2020) system, which builds in hierarchical classifications with each additional digit. STEM jobs are defined as those in the major category "science, research and engineering professionals" (21) and associate professionals (31), plus additional IT and engineering roles outside of those categories. Management jobs are defined as corporate managers and directors (11) and other managers and proprietors (12). IT and engineering jobs are a subset of the STEM jobs. Engineering jobs are defined as the broad category 212. Information technology jobs are category 213 (IT professionals and IT managers), plus IT directors (1137), IT associate professionals/technicians (3120, 3131, 3132, 3133), data analysts (3544) and IT trainers (3573). Health professionals are grouped under the two-digit SOC code 22; teaching professionals fall under code 23; legal professionals are found within the three-digit group 241 and sport and fitness occupations fall under 343.

France: Management jobs are defined as two broad occupational categories "business leaders of 10 employees or more" (PCS 23) and "administrative and commercial executives of company" (PCS 37). IT jobs are listed above and classified as such if the job title mentioned "information technology", "computer(s)" or "telecommunications". Jobs were classified as engineering careers if the job listed "engineer" in the title. STEM jobs include engineering and IT jobs as well as the detailed titles, "directors and research managers in public research" (342F) and "public research fellows" (342H). Lawyers are classified as PCS 312A. Healthcare professional jobs include the following titles: hospital doctors without private practice (344A), non-hospital salaried doctors (344B), interns in medicine, dentistry and pharmacy (344C), salaried pharmacists (344D), dental surgeons (311C), psychologists, psychoanalysts, psychotherapists (non-doctors) (311D), veterinarians (311E) and all nursing occupations with code 431 in the first three digits. Careers in sport come from the title "sport instructors and educators, professional athletes" (424A). Teaching jobs are spread across school teachers (421A), school teachers (421B), general education teachers in colleges (422A), professional high school teachers (422B), auxiliary masters and contract teachers in secondary education (422C) and professors and lecturers (342B).

Germany: STEM jobs are defined at the two-digit KldB 2010 level, as 41, 42 and 43, which together are called "IT and scientific service professions". Management jobs are defined using two methods. One is to include all jobs that fall under "jobs in corporate management and organisation", which fall under the broad KldB code of 71, with the exception of clerical and secretarial jobs that fall under 714. The second method counted all jobs as managerial if the title included any of the words (in the English translation provided by the German statistical office): "manager", "director" or "managing". This took advantage of the fact that many industry-specific managerial jobs are classified outside of the 71 family. Jobs were classified as IT based on the broad IT family captured by KldB code 43. Additionally, one job in electronics was also classified as IT: "information, telecomm. Technology — complex" (KldB code 2631). Careers were classified as engineering if they used engineer in the title or "mechatronics", if also complex in skill level. "Medical health professions" is identified as KldB 81. Teaching careers were based on "teaching and training professions (Kldb 84). Legal careers are identified as "occupations in legal services" (KldB 731) and sport-related careers are identified as "actors, dancers, athletes and related occupations (KldB 942).

A Note About Novel Skills in Information Technology

The existing data sources used in this report, which cover the years 2014-2022, do not identify specific jobs in the fields of artificial intelligence (AI) or machine learning (ML). Jobs in those fields that do exist currently would largely fall under computer science or software engineering careers and related occupations. Statistical agencies have not developed specific classifications for occupations that rely on these skills/technologies, so the number of jobs requiring these specific skills cannot be estimated from national data sources. The report does break out the highest scoring current job titles in the field of information technology.

Further, we provide information on the share of job vacancies that mention IT skills, including those advertising the words "machine" and "artificial intelligence". Across the three countries, we find that 5% of jobs listing IT skills (defined above) mention the word "machine" and 2% mention the phrase "artificial intelligence". These skills are not yet nearly as common as skills involving data, software and programming.