Academy for the Mathematical Sciences

Economic contribution of the UK mathematical sciences: an updated & refined quantification

AcadMathSci's methodology

September 2025

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The Academy for the Mathematical Sciences (AcadMathSci) was established in 2022 to be the single, authoritative voice for the UK mathematical sciences community, spanning education, academia, and business, industry, and government. It was registered as a charity in 2023 and the first cohort of Fellows will be appointed in late 2025.

The Academy engages actively with national policy and strategic priorities—responding to government consultations and reviews and contributing to debates on issues from curriculum reform to AI. We work across all four nations to influence policy and champion the role of the mathematical sciences. Through the Learned Societies Forum (LSF), we bring together the five learned societies in the mathematical sciences to collaborate on shared priorities and amplify our collective voice.

Following ground-up, sector-by-sector and nation-by-nation analysis of the contribution of the mathematical sciences to the UK economy in 2024, we are delighted to publish:

- A detailed report presenting the methodology and results for the whole UK **(this document)**;
- A detailed report presenting the methodology and results for the nation-by-nation analyses;
- A summary infographic, presenting key findings for the whole UK; and
- Four summary infographics, presenting key findings for each of the four nations.

AcadMathSci President, Professor Dame Alison Etheridge DBE FRS writes:

"This ground-up analysis confirms what many of us have long known: the mathematical sciences are critical to the UK economy. In 2024, over five million people were working in mathematical science occupations, contributing £489 billion in direct economic value—nearly 20% of the UK's entire Gross Value Added. These are well-paid, high-productivity roles, embedded in every part of our modern economy—from data science and financial services to education and engineering.

"Behind these numbers lies a powerful story: when we invest in mathematical sciences—in education, research, and people—we build a more innovative, resilient, and prosperous future. The Academy is committed to ensuring that the mathematical sciences continue to thrive, not only as an engine of economic growth, but as a force for opportunity, understanding, and progress across society."

An updated and refined quantification of the mathematical sciences' contributions to the UK economy

The Academy for the Mathematical Sciences has undertaken a significant piece of work to derive new best estimates for the UK's mathematical science (MS) workforce and its associated economic contributions in 2024. Our new estimates benefit from several methodological refinements to previous work, as well as the availability of newer, more comprehensive data sets. We calculate that 5.11 million people were working in mathematical science occupations in 2024, representing 15% of all UK employment; that those workers directly contributed £489 billion to the UK economy in 2024, representing 19% of total UK gross value added (GVA); and that those workers were, on average, paid salaries nearly 50% higher than workers in other occupations. We estimate that even a 1% increase in MS workers could be worth £5 billion to the UK economy. Our new analysis also identifies the occupations and industries where the mathematical sciences play particularly significant roles in the UK. This report provides context and rationale for the new analysis; details the methodology and data sources; and discusses some of the findings. A shorter companion report highlights key results.

1 Introduction

Mathematics—the universal language of science—has become increasingly critical to nearly every aspect of modern life, from healthcare and finance to smartphone technology and artificial intelligence. But just how much do the mathematical sciences (which we take to include pure and applied mathematics and closely-related disciplines such as statistics, operations research, and discrete mathematics) contribute to the UK's economy?

In 2013, Deloitte published an independent report seeking to answer exactly this question. The seminal "Deloitte report" catalogued the UK's mathematical science (MS) workforce in 2010, thereby quantifying for the first time the MS contribution to the UK economy. The Deloitte report remained widely-quoted as recently as 2024, when we (the Academy for the Mathematical Sciences, hereafter "the Academy" or "AcadMathSci") extended Deloitte's analysis to produce revised estimates for 2023.

When producing those revised estimates, we mirrored Deloitte's original methodology as closely as possible to facilitate an "apples-with-apples" comparison of the MS contributions to the UK economy in 2023 vs 2010. In other words, we analysed how the MS footprint had changed relative to the UK economy as a whole, taking Deloitte's assumptions as a given.

Our analysis for 2023 represented a long-overdue albeit stop-gap update to Deloitte's work, providing a valuable first approximation of the contributions of the mathematical sciences to the modern UK economy. It was clear, however, that our methodology would ultimately need to be superseded by a new, "ground-up" analysis unconstrained by Deloitte's assumptions circa 2010; not requiring a series of complex transformations and approximations to extend the lifespan of Deloitte's foundational work; and taking into account changes in the nature of many occupations over the past decade or more.

We have thus undertaken a significant piece of work to estimate, from the ground up (without relying on Deloitte's work), the UK's MS workforce and its associated economic contributions in 2024. Our new analysis benefits from several methodological refinements; the availability of newer, more comprehensive data sets; and qualitative research into contemporary occupations that rely on the mathematical sciences.

This report presents our new analysis in full, with a focus on the underlying methodology.

Section 2 summarises relevant previous analyses, while Section 3 identifies some limitations of—and thus scope for improving—previous analyses. Section 4 details the methodology underlying our new analysis, and discuss several key results, while Section 5 concludes.

2 Review of previous work

To contextualise our recent work, we outline below Deloitte's analysis for 2010 and our analysis for 2023.

2.1 Deloitte's analysis for 2010

Deloitte combined qualitative research and in-depth quantitative analysis to quantify the MS contribution to the UK economy in 2010.

The first major part of Deloitte's analysis was identification of occupations they classified fully or partially as mathematical science (MS) occupations. Deloitte identified 56 such occupations, each associated with a single "unit group" and corresponding 4-digit code from the UK's 2000 Standard Occupational Classification (SOC2000) framework, a framework covering ~350 such unit groups.

They then estimated the MS employment levels in each of these 56 occupations. This involved combining ONS data with graduate employment destination data; an analysis of employment

profiles of mathematics learned societies' members; literature review; sector-specific insights; and input from expert stakeholders. Of the 56 occupations, they deemed 39 to comprise 100% MS workers, and 17 to comprise between 4% and 10% MS workers.[1]

The second major component of Deloitte's analysis was distributing their MS workforce across some 600 different sectors of the UK economy, with each sector classified by a 4-digit code in the 2007 Standard Industry Classification (SIC2007) framework. This was enabled by a bespoke, 600×315-element SIC-SOC conversion matrix[2] provided to Deloitte by the Office for National Statistics (ONS). Deloitte then mapped MS occupation numbers in each SIC category to the ~100 broader economic sectors used in the UK's Domestic Use Matrix (DUM), and thence constructed an Input-Output model to calculate the gross value added (GVA) attributable to mathematical science research (MSR).

The most widely-quoted figures from Deloitte's report tell us that, in 2010, the economic contributions of the mathematical sciences were (i) £208 billion GVA, 16% of UK GVA, and (ii) 2.8 million jobs, 10% of UK employment.

2.2 A stop-gap update from 2010 to 2023

Even in 2024, Deloitte's report and estimates—by then, well over a decade old—were still widely quoted to substantiate the importance of MS and MSR to the UK economy. Given the likely obsolescence of these estimates, the Academy combined Deloitte's analytical framework with publicly-available datasets from the ONS to produce, via a principled methodology, revised estimates of the MS contribution to the UK economy in 2023.

The basis for that analysis was Deloitte's "ground-up" catalogue of the 2010 MS workforce, i.e. the entirety of around 39 occupations and relatively small fractions of about 17 further occupations.

Using annual ONS datasets detailing directly-employed worker numbers vs occupation unit groups, we estimated the growth or shrinkage of workforces in individual occupations over time, and thus transformed 2010 MS employment numbers to 2023 terms. These transformations were complicated, however, by the adoption of a revised occupational classification framework (SOC2010) in the majority of ONS datasets from 2011 onwards, followed by another revision (SOC2020) in datasets from 2021 onwards.

The SOC2000, SOC2010, and SOC2020 frameworks contain, respectively, 359, 369 and 412 occupations at the level of fine-grained unit groups, each associated with a 4-digit code. Each framework contains different codes, descriptions, and scope for occupations inherited from the preceding framework; additional granularity, e.g. sub-division of 4-digit codes into 6-digit codes in SOC2020; as well as some wholly novel occupations not present in any preceding frameworks, e.g. data analysts. As such, there is a many-to-many relationship between unit groups in SOC2000, SOC2010, and SOC2020, making translation between these frameworks complex in general (see, e.g., this ONS note and this EngineeringUK report), which indeed proved to be the case in our analysis.

Once we had estimated the distribution of MS employees across occupations in 2023, we used other ONS datasets to transform this into a distribution across industry sectors, mirroring the second stage of Deloitte's analysis. Another complex and many-to-many relationship arose, now between occupations and industries: e.g., workers with the *occupation* of physicist may be found in *industries* including defence, education, manufacturing, mining, programming, research and development, etc. Conversely, the air transport *industry* relies on workers whose *occupations* include pilots, air traffic controllers, aircraft maintenance workers, clerical and administrative occupations, managerial occupations, etc.

Finally, we used ONS data detailing GVA vs industry sector to estimate the total GVA contribution from the MS workforce.

By running 48 variant analyses, each with a different combination of methodological assumptions—e.g., different schemes for estimating matrices for re-basing between SOC frameworks—we obtained (mean ± std dev. across the 48 analyses) 4.1 ± 0.2 mn MS jobs and an MS GVA contribution of £475 ± 28 bn. Our best estimates, corresponding to the methodological assumptions we deemed most realistic, were of an MS workforce of 4.2 mn people and associated direct GVA contribution of £495 bn.

The above distributions could not, however, encapsulate uncertainty due to our reliance on Annual Survey of Hours and Earnings (ASHE) datasets—which covered directly-employed but not self-employed workers—or, even more fundamentally, on Deloitte's catalogue of the MS workforce in 2010. Accordingly, we noted that "a different catalogue of MS occupations would clearly have a significant impact on our estimates" but suggested that our work supported a "conclusion that $\gtrsim$ 4 million people worked in MS occupations in 2023, with an associated GVA contribution approaching £500 billion."

3 Scope for improving previous analyses

3.1 Definition of MS occupations

Perhaps the biggest drawback in extending Deloitte's work was that we necessarily inherited the ambiguity in their definition of an MS occupation.

> **Previous definition:** (per Deloitte)
>
> "Mathematical science occupations are [...] occupations which either entail mathematical science research, or which use mathematical science research-derived tools and techniques. This includes the generation of new mathematical science research. The direct usage of mathematical science research-derived tools and techniques may, in some circumstances, require a high degree of understanding of the underpinning mathematical concepts, but this is not always essential."

The "mathematical science research" referred to here is relatively straightforward but "the usage of mathematical science research-derived tools and techniques...[without] requiring a high degree of understanding of the underpinning mathematical concepts" is

more problematic. This definition does not distinguish, for example, between tools and techniques that were enabled by recent MSR (and if so, then *how* recent?) as opposed to mathematics over the past centuries or even millennia.

Perhaps counter-intuitively, then, Deloitte classified 100% of computer installation and maintenance workers, web designers, and IT consultants as MS workers (presumably on the basis that computers and the internet could not exist without MSR)—even though many of these workers would not have needed any mathematical training or make direct use of mathematical tools in their jobs. There *were* some IT occupations (e.g., IT support technicians) Deloitte deemed to comprise zero MS workers; still, by their appraisal, the computer science sector accounted for the largest absolute number (nearly 350 000) of MS workers in 2010.

As other examples of potentially counter-intuitive classifications, Deloitte deemed only small fractions of accountants, taxation experts, and credit controllers—and *no* chartered or quantity surveyors, architects, or maths teachers—to be MS workers, at odds with other appraisals of the mathematical knowledge and skills required in these occupations, e.g. this Royal Society report (2023). Conversely, Deloitte regarded 100% of social science researchers to be MS workers (perhaps reasoning that mathematics is ingrained in research methods generally) and even 100% of public service administrative professionals to be MS workers.

3.2 Changes to occupational classifications

When re-basing the MS workforce between SOC frameworks, we previously assumed that the statistical mapping of MS workers across frameworks was identical to the mapping for the UK workforce as a whole (or rather, the UK's *directly employed* workforce, as we lacked SOC re-basing data for self-employed workers), with the total number of MS workers remaining unchanged during re-basing. While superficially sensible, and in alignment with our decision to mirror Deloitte's work as closely as and straightforwardly as possible, this approach has flaws.

First, novel occupations tend to be missed or at least under-represented. E.g., in the current SOC2020, unit groups such as *3544: data analysts*, *2135: cyber security professionals*, *2126: aerospace engineers*, and *3120: CAD, drawing and architectural technicians* have no direct counterparts in SOC2000 and/or SOC2010, so these unit groups' MS workers should ideally be identified directly rather than assuming that they would emerge correctly, during statistical re-basing, from MS occupations encoded in an earlier SOC framework.

Other subtle problems—but sometimes with significant implications—arise from changes to the scope of unit groups across SOC frameworks. For example, around 98% of workers in the SOC2000 unit group *5242: telecommunications engineers* map statistically, in SOC2020, to *5242: Telecoms and related network installers and repairers* (workers who "install, maintain and repair public and private telephone systems and maintain, test and repair telecoms cables," per ONS guidance) while just 2% to *2124: electronics engineers* (workers who "research and design, direct construction and manage the operation and maintenance of electronic motors, communications systems, microwave systems, and other electronic equipment"). Deloitte regarded 100% of the SOC2000 unit group 5242 to be MS workers; hindsight, and the benefit of the more nuanced SOC2020, reveals this classification to have been inappropriate.

As another example, 75% of workers in the SOC2000 unit group *3511: air traffic controllers* map statistically, in SOC2020, to *3511: air traffic controllers*, and 25% to *8233: air transport operatives*, the latter being workers who "refuel, load and unload aircraft, direct the movement of aircraft at airports, and positions gangways or staircases to allow passengers to board and disembark aircraft." This statistical mapping reflects the lack of an appropriate SOC2000 unit group for air transport operatives, rather than air traffic controllers changing careers en masse. Disregarding the qualitative differences between these SOC2000 and SOC2020 unit groups would lead to specious estimates of MS worker totals.

3.3 Approximations: self-employed workers

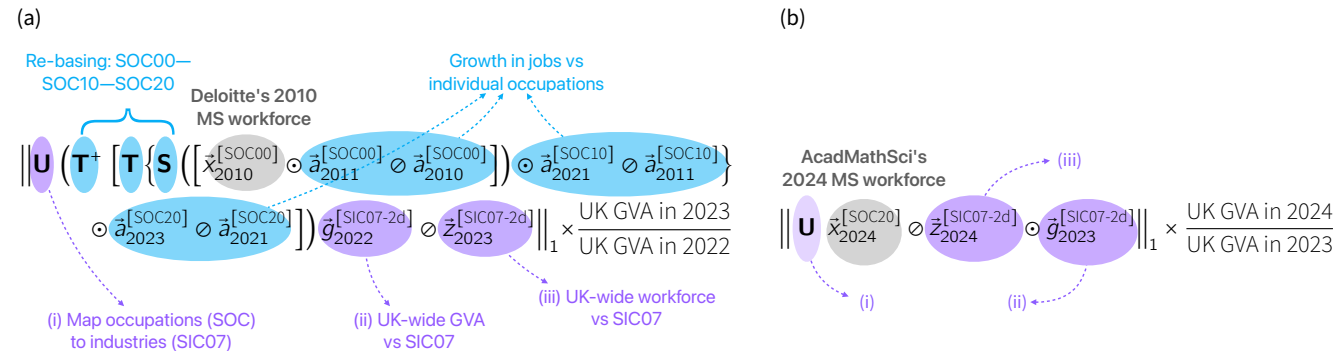
In our previous analysis, we relied extensively on large, publicly-available datasets estimating the total number of *directly-employed* workers vs occupations; the relevant datasets were available for *all* years between 2010 and 2023. We could not, however, find any equivalent (similarly granular and UK-wide) datasets for *self-employed* workers. Deloitte's 2010 catalogue also did not disaggregate their MS worker-vs-occupation estimates into directly-employed and self-employed workers. Thus we used publicly-available directly-employed datasets as a proxy for the whole workforce, both when estimating year-on-year changes in workforce sizes in different occupations, and when statistically re-basing MS workers from occupations to industries. This was a reasonable approximation—at least to first order—given that directly-employed workers outnumber self-employed workers about 7 to 1 in the UK.

However, detailed examination of our previously-estimated MS workforce revealed some inconsistencies with other publicly-available datasets that had not formed part of the original analysis. In particular, we found that there were some fine-grained industrial divisions where our estimated number of MS workers seemed to exceed the UK-wide number of workers in the respective industrial divisions (notably, mining support services and pharmaceutical product manufacturing), which we estimated by combining ASHE with Labour Force Survey (LFS) datasets. This indicated that our statistical transformations had led to MS workers being over-represented in at least some industry divisions and under-represented in others.

It would have been possible, in principle, to incorporate additional mathematical constraints into our previous analysis to ensure that MS workforce estimates were, at all stages of the process, consistent with any number of external datasets. We did not do so in our previous analysis because this would have represented a significant departure from Deloitte's methodology, and would in any case have been complicated by data quality issues in and inconsistencies between various external datasets. We noted that, in a subsequent analysis, it would be conceptually simpler and require far fewer approximations instead to make

Figure 1 — (a) A concise mathematical representation of the main linear algebraic transformations used, in our previous analysis, to update Deloitte's MS workforce and GVA estimate from 2010 to 2023 terms. The superscripts denote the SOC or SIC framework on which a vector is based; the subscripts denote the year to which it refers. For more details, refer to the Academy's detailed methodology paper.

(b) Equivalent representation for our new methodology. Estimating MS workforce stratified by occupation, $\vec{x}^{[SOC20]}_{2024}$, is labour intensive though conceptually straightforward. Mapping the resultant workers to industries and GVA contributions is also straightforward and mirrors the final stage of our previous analysis.



a "one-shot" estimate of the MS workforce in 2024 (say), directly taking correct account of self-employed and directly-employed workers, obviating most approximations and transformations of Deloitte's catalogue from 2010 to present.

3.4 Uncertainty quantification

Deloitte's 2010 MS worker catalogue was based on point estimates (with zero attendant uncertainty) of MS proportions across different occupations. E.g., their analysis—and consequently our own—assumed that *exactly* 10% of psychologists and *exactly* 4% of taxation experts in the UK to be MS workers.

A more nuanced and realistic approach would allow the MS proportions to vary within plausible ranges. E.g., detailed consideration of the pharmacist occupation might lead us to conclude that something between 80% and 90% of pharmacists would meet our own definition of an MS worker (Deloitte, by contrast, assumed exactly 100% of pharmacists to be MS workers in this example); incidentally, these ranges should also not be expected to be the same today as several years ago, or several years hence. Such quantitative, occupation-by-occupation uncertainty would translate meaningfully and directly into uncertainty in the final MS workforce and associated GVA contribution. By contrast, the uncertainty estimates in our previous analysis were indirect, reflecting assumptions necessitated to mirror as closely as possible Deloitte's analysis, but not any data uncertainty.

The publicly-available data used in our analyses—e.g., ASHE datasets from the ONS—are all themselves subject to uncertainty. This uncertainty (whenever published) should ideally be factored into all relevant stages of analysis. Doing so would be relatively straightforward starting from a new catalogue of MS occupations, though this was not the case in our previous analysis that relied on a complicated patchwork of datasets to update Deloitte's catalogue from 2010 to 2023 via two changes of SOC framework and an uncertain mapping from occupation to industry.

3.5 Methodological complexity

Given our method's foundational dependence on (and complex transformations of) Deloitte's 2010 MS worker catalogue, it cannot be straightforwardly adapted, say, to allow for different interpretations of an MS occupation, nor indeed for workforces in different fields altogether, e.g., health sciences.

While we published the software and methodology used to implement our previous analysis (both having been independently peer reviewed), it was potentially opaque: the software ran to well over 1 000 lines of Python code and entailed extensive linear algebra, patching together heterogenous datasets spanning 14 years, etc.

4 Methodology for our new analysis

Taking into account the opportunities for improvement detailed in the previous section, we devised the following new, "ground-up" methodology to estimate the MS workforce and associated GVA contribution for 2024 onwards. See Figure 1.

1. Produce clear criteria for a worker to be an MS worker, avoiding any issues identified in Deloitte's older definition.
2. Carefully estimate the fraction (or plausible range of fractions) of workers in each SOC2020 unit group who are MS workers, and thus compute MS workers per unit group.
3. Statistically map the resultant catalogue of MS workers vs occupations, $\vec{x}^{[2024]}_{2020}$, to MS workers vs industry divisions, with the linear mapping $\mathbf{U}$ constrained by UK-wide worker totals (directly-employed + self-employed workers) vs industry divisions.
4. Apportion GVA by assuming MS worker productivity equals average productivity (GVA per worker) within given industry divisions.

5. Monte Carlo simulation: repeat steps 2–4 many times, but varying all estimates within their plausible statistical ranges, to quantify the uncertainty in final estimates.

We provide more detail, below, on each of these five steps.

4.1 Defining an MS worker

To avoid issues related to ambiguity and counter-intuitive classification, we formulated the following "common-sense" definition of an MS worker, which makes no reference to MSR.

> **New definition:** (per AcadMathSci)
>
> "A mathematical science worker is (i) one whose day-to-day duties involve the use of non-trivial mathematical science tools or knowledge (e.g., mathematical optimisation, statistical analysis, trigonometry, calculus, data analytics) and/or (ii) one specifying a formal mathematical qualification (e.g., A-Level maths) as an entry requirement."

Occupations explicitly specifying mathematical prerequisites will almost invariably be those in which workers will need to draw on mathematical tools and knowledge, so criteria (i) and (ii) will usually both be met. We nevertheless found it useful to include both criteria in the definition as in practice, information relevant to criterion (i) or (ii), but not both simultaneously, may be more readily available for some occupations.

4.2 Estimating MS worker fractions

The SOC2020 framework contains 412 different occupations at the fine-grained level of unit groups, each associated with a 4-digit code. For each of these unit groups, we first studied detailed ONS guidance describing the unit group (usually several sentences per unit group); typical entry routes and associated qualifications (ditto); typical tasks performed by workers in that unit group (around 5-10 per unit group); and job titles typically associated with that unit group (ditto). From this first-pass analysis, we eliminated around three quarters of the unit groups on the basis that most of their workers would not meet either criterion (i) or (ii) in our definition.

Example: occupations with 0% MS workers.

We regarded around three quarters of all occupations, *prima facie*, to comprise 0% MS workers. Some occupations fit this category more straightforwardly than others, e.g.: sales and retail assistants; care workers; cleaning occupations; elementary administrative occupations; elementary agricultural occupations. Other occupations were more marginal cases, likely with non-zero percentages of MS workers, e.g.: specialist nursing professionals; logistics managers; process operatives; and some teaching occupations we excluded from further analysis. Lacking capacity to make detailed evaluations of all 412 unit groups, we took the pragmatic if cautious decision to classify almost all marginal occupations as comprising 0% MS workers.

On the other hand, many occupations straightforwardly met both our and Deloitte's criteria for qualifying as 100% MS occupations. Deloitte ended up with 39 (or 11% of 359 different SOC2000 unit groups) such occupations, while we ended up with 32 (or 8% of 412 different SOC2020 unit groups), with almost all of these having direct equivalents in Deloitte's set of 39 occupations.

Example: occupations with 100% MS workers.

In our analysis, as in Deloitte's, we deemed physicists; engineers of various categories; investment analysts; management consultants; actuaries, economists and statisticians; air traffic controllers; and credit controllers, among others, to be occupations comprising 100% MS workers. There were two new SOC2020 unit groups without any Deloitte or SOC2000 equivalents—namely, data analysts and cyber security professionals—which we deemed to comprise 100% MS workers. For some occupations the true MS fraction may be slightly lower than 100%, though we assumed that such errors would be more than compensated for by the far larger set of occupations for which we made the conservative assumption of strictly 0% MS workers.

We were then left with a set of around 60 occupations, for each of which we needed to estimate plausible MS fraction ranges. For each occupation, our estimated MS fractions drew on official ONS guidance; online job description databases; career guidance materials; further- and higher-education materials relevant to training for the occupation in question; and sector-specific reports, accreditation frameworks, etc.

We modelled our uncertainty in the MS fraction with a triangular probability density function (PDF), a piecewise linear PDF defined by a mode (our best estimate), a lower limit, and an upper limit.[3]

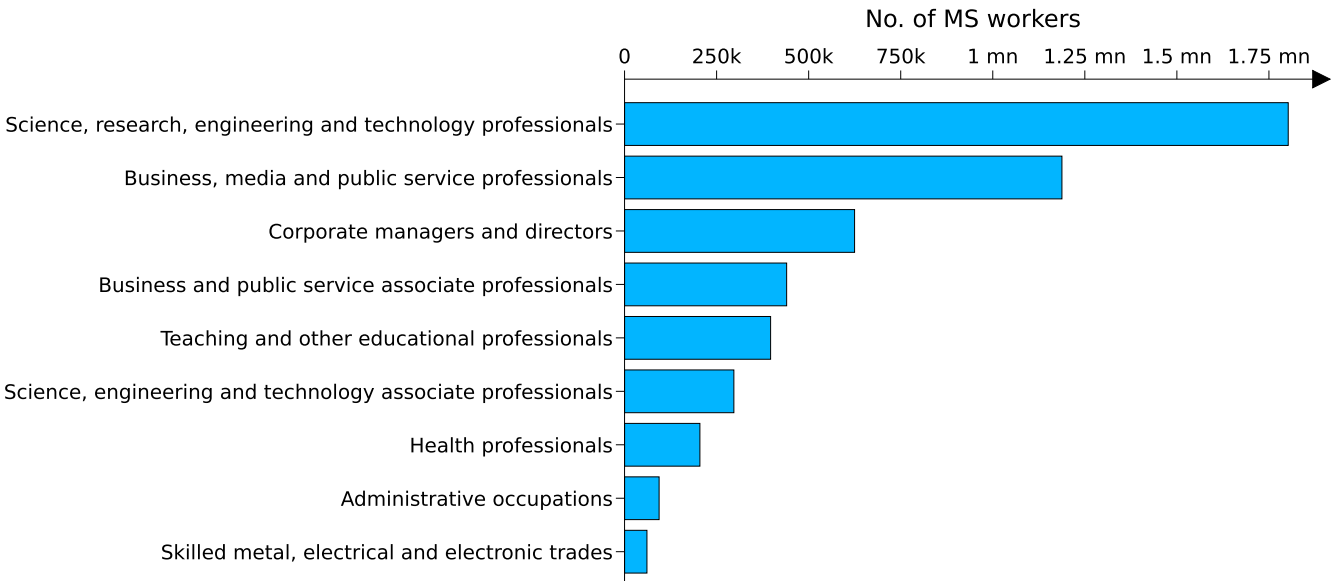
Example: secondary teachers (excluded by Deloitte).

We deemed secondary education professionals teaching subjects such as mathematics (incidentally, the most popular A-level subject for eleven consecutive years), further mathematics, physics, and economics to be MS workers. We also classified as MS workers specialist teachers and curriculum leads in subjects including chemistry, computing, business studies, and design and technology, and teachers of GCSE/A-Level students in those subjects. We thus estimated that 30–40% of secondary teaching professionals meet our definition of an MS worker. Deloitte, by contrast, did not consider any secondary teaching professionals to be MS workers.

Example: IT directors (↓ MS fraction vs Deloitte).

We regarded as MS workers most IT directors, chief information officers (CIOs), etc. with significant technical and analytical components to their roles, e.g., systems optimisation, performance analytics, AI/ML integration, cloud computing, algorithmic decision-making. However, we did not consider to be MS workers those with roles focused primarily on, e.g., governance or procurement, or those who oversee MS workers without having to engage deeply with technical or analytical tasks themselves. We thus estimated 40–60% of IT directors to be MS workers, down from Deloitte's 100%.

Figure 2 — The nine sub-major occupation groups (each associated with a 2-digit code in SOC2020) spanned by MS workers in our analysis; see Table A1.1 for more details. Not shown are 17 sub-major groups with zero (and one with close to zero) MS workers.



Example: taxation experts (↑ MS fraction vs Deloitte). While personal and small business tax consultants require high numeracy, we did not regard most of them as meeting our definition of MS workers, given their typical use of tax software, rule-based computation, structured calculations, etc. without necessarily needing "non-trivial mathematical tools or knowledge." On the other hand, taking into account typical entry requirements, professional training (including financial mathematics, cash flow analysis, data interpretation), and job duties especially of corporate and international tax specialists (e.g., scenario modelling, sensitivity testing, optimisation of tax exposure) and tax investigators and auditors (e.g., forensic analysis of large financial datasets, pattern detection, risk modelling), we estimated that around 30% of all UK taxation experts met our definition of MS workers, with low and high estimates of 25% and 40%, respectively. Deloitte, by contrast, deemed only 4% of taxation experts to be MS workers.

Table A1.1 in the Appendix gives the full list of 95 occupations for which we deemed the MS worker fraction to be greater than zero, along with MS fractions and corresponding workforces.

We multiplied our MS fractions with occupation-by-occupation workforce totals for 2024, which we extracted from the Annual Population Survey (APS), yielding a vector we denote $\vec{x}_{2024}^{[SOC20]}$: the subscript indicates that this is a MS workforce for the year 2024, while the superscript reflects (in shorthand) SOC2020 encoding. We note that APS datasets of sufficient granularity were not publicly available for most years between 2010 and 2024, precluding the possibility of this approach for our previous analysis.

Figure 2 shows the resultant distribution of MS workers across *sub-major* occupation groups, a categorisation two levels higher in the SOC hierarchy than unit-groups (sub-major groups being associated with 2-digit SOC codes vs 4-digit codes used for unit-groups). It shows, for example, that some 400 000 MS workers are categorised in our analysis as "teaching and other educational professionals" (as may be also be inferred from Table A1.1).

Aside: salary distributions

Before continuing with our primary analysis, we note briefly that we constructed salary distributions for the MS and non-MS workforces via Table 14 from the ASHE. Table 14 details remuneration distributions across SOC2020 occupations; for each occupation, a mean and up to eleven percentile scores (spanning the 10^{th} and 90^{th} percentiles) are given, though for many occupations only a subset of these summary statistics is publicly available.

To enable both full-time and part-time workers to be included in our analysis, we converted hourly pay to annual salaries, assuming a mean full-time equivalent (FTE) workload of 37.5 hours per week (ASHE hourly pay data cover a larger fraction of the workforce than is the case for annual salary data).

For a single occupation, we synthesised a sample salary distribution with mean and percentile scores equal to the values provided in the ASHE tables, and with size proportional to the corresponding number of workers in $\vec{x}_{2024}^{[SOC20]}$ (MS workers), $\vec{z}_{2024}^{[SOC20]}$ (all workers), or $\vec{z}_{2024}^{[SOC20]} - \vec{x}_{2024}^{[SOC20]}$ (non-MS workers). Final salary distributions were obtained by repeating this process for all occupations and aggregating the resultant distributions.

The high-level results of our salary analysis are shown in Figure 3. Table 1 lists the ten occupations with the highest salaries, among all those occupations comprising more than 50% MS workers and with at least 25 000 MS workers in total.

Figure 3 — Box-and-whisker plot summarising salary distributions for MS jobs (bottom row), non-MS jobs (middle row), and all jobs (top row) in the UK. The distribution includes part-time jobs converted to a full-time equivalent (FTE) of 37.5 hrs/wk. The bold and dashed vertical lines denote, respectively, mean and median (50th percentile) salaries; the boxes extend from the 25th to 75th percentile salaries; and the whiskers extend from the 5th to 95th percentile salaries. The data here show that MS jobs command significant salary premiums, with typical salaries around 50% higher than in non-MS jobs.

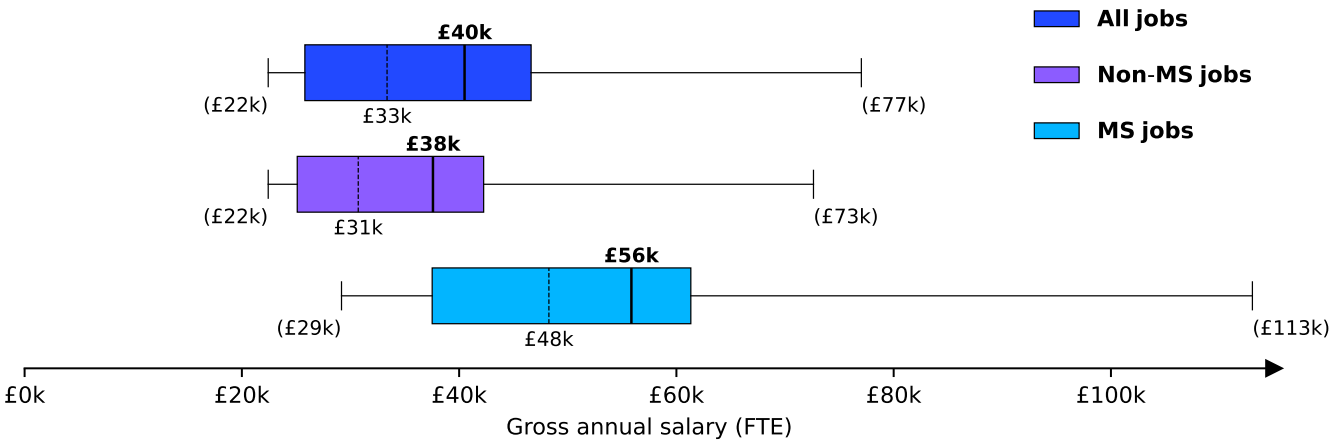


Table 1 — The ten occupations with the highest gross annual salaries in 2024 among common MS occupations (which we took to be those with MS fractions ≥50% *and* more than 25 000 MS workers in total, i.e., comprising ≥ 0.5% of the MS workforce). Examples of high-paying occupations with low but non-zero MS fractions and/or relatively few MS workers in total (therefore not tabulated below) are *1111: Chief executives and senior officials* (mean salary £116 000); *2321: Head teachers and principals* (mean salary £87 000); and *2212: Specialist medical practitioners* (mean salary: £86 000). Salaries estimated from ASHE data, which do not cover self-employed workers.

Occupation (unit group)	Mean salary	Median salary
3511: Aircraft pilots and air traffic controllers	£119 000	£107 000
1137: Information technology directors	£92 000	£83 000
2133: IT business analysts, architects and systems designers	£60 000	£55 000
2422: Finance and investment analysts and advisers	£60 000	£47 000
2161: Research and development (R&D) managers	£59 000	£56 000
2433: Actuaries, economists and statisticians	£59 000	£53 000
2134: Programmers and software development professionals	£58 000	£54 000
2123: Electrical engineers	£57 000	£57 000
2126: Aerospace engineers	£56 000	£52 000
2114: Physical scientists	£56 000	£49 000

4.3 From occupations to industries

Returning now to our primary analysis, we mapped MS workers $\vec{x}_{2024}^{[\text{SOC20}]}$ from occupations to industries via a linear mapping $\mathbf{U}$. We compute this mapping from a UK-wide distribution of worker occupation-industry pairs published by the ONS (covering directly-employed workers over the period July 2023 to June 2024) subject to the constraint that when $\mathbf{U}$ is applied to the entire UK workforce, each element in the resultant vector $\vec{z}_{2024}^{[\text{SIC07-2d}]}$ should not exceed the corresponding sum of directly-employed workers from ASHE Table 5 and self-employed workers from the JOBS04 dataset in the Labour Force Survey. The latter constraint prevented the inconsistencies related to self-employed workers discussed in Section 3.3.

Applying $\mathbf{U}$ to $\vec{x}_{2024}^{[\text{SOC20}]}$, we obtain a vector giving the MS worker totals for 88 different SIC2007 industry divisions, $\mathbf{U}\ \vec{x}_{2024}^{[\text{SOC20}]}$. The resultant distribution of MS workers is visualised in the left panel of Figure 4.

4.4 Apportioning GVA to MS workers

We made the simplifying assumption that the productivity of MS workers in a given industry division equals the average productivity of all workers in that division. (This may be an overly-cautious assumption, especially since MS workers in many industries may be expected to be more closely involved in production of high-value outputs—e.g., software or financial products—than non-MS workers, but interrogating in detail and possibly relaxing this assumption is beyond the scope of the present work.) By dividing the total MS workers in a given industry section by the total number of workers in that section, and multiplying by the industry section's total GVA contribution, we thus apportioned GVA to the MS workers. Repeating this across all industry sections and summing the results, we obtained our final GVA estimate for 2024:

$$\left\| \mathbf{U}\ \vec{x}_{2024}^{[\text{SOC20}]} \oslash \vec{z}_{2024}^{[\text{SIC07-2d}]} \odot \vec{g}_{2023}^{[\text{SIC07-2d}]} \right\|_1 \times \frac{\text{UK GVA in 2024}}{\text{UK GVA in 2023}},$$

where $\vec{g}_{2023}^{[\text{SIC07-2d}]}$ disaggregates GVA by industry division, per ONS data. The final scaling factor in the above equation is needed because GVA-disaggregated-by-industry data were only available (at the time of writing) for 2023, whereas an all-industry, UK-wide GVA total was available for 2024. This mirrors a simple re-scaling of estimates from 2022 to 2023 in our previous analysis; see Figure 1.

Our distribution of MS GVA across industries is visualised in the right panel of Figure 4, which shows, e.g., that the single biggest MS GVA contribution came from the financial and insurance industry in 2024.

4.5 Uncertainty quantification

We repeated the preceding analysis with different random realisations[4] of our MS workforce catalogue and of the total UK-wide workforce, and aggregated the results.

Final estimates (mean ± std across 1 000 samples):

- an **MS workforce of 5.11 ± 0.07 mn workers**, or **15% of all UK employment**;
- a direct economic contribution from MS workers of **£489 ± 7 bn GVA**, or **19% of total UK GVA**;
- an average **productivity of £95.5 ± 0.6 k per MS worker**, 28% higher than for non-MS workers; and
- an **average salary of £55 k/yr per MS worker**, 49% higher than for non-MS workers.

Based on the £489 ± 7 bn GVA contribution, **a 1% increase in the size of the MS workforce could be worth £5 bn to the UK economy** (in 2024 terms).

5 Discussion

Our new analysis—enabled by methodological refinements as well as the availability of newer and more comprehensive data sets—offers many advantages over our previous one. These advantages include increased transparency and simplicity; reliance on fewer assumptions and approximations;[5] more meaningful uncertainty quantification; and ready extensibility to contexts other than the mathematical sciences.

An additional and crucial advantage of our new analysis is that it enables fresh and detailed insight into the occupations (e.g., financial managers and directors; engineering professionals; programmers and software developers; higher and secondary education teaching professionals; financial analysts; data analysts) and economic sectors (e.g., finance and insurance; manufacturing; education) where MS workers are most active.

Yet reassuringly, our new analysis leads to high-level conclusions consistent with our previous findings: that there are several million people directly employed in MS jobs, that these MS workers earn significantly more and contribute significantly more GVA to the UK economy than workers in non-MS jobs, and that in total, these MS workers directly account for nearly 20% of total GVA in the UK. And these are only the workers *actively* using non-trivial mathematical science tools in their jobs: our analysis does not include any workers who benefit from mathematical skills and training (e.g., critical thinking, logical reasoning, data analysis) in nominally non-MS jobs.

In short, our new analysis reaffirms that the mathematical sciences are a critical—and flourishing—part of the UK economy. We estimate that even a 1% increase in the size of the MS workforce could be worth ~£5 bn to the UK economy (in 2024 terms).

One difference between the results of our new and previous analyses is the inference of a more modest economic productivity premium for MS workers in the new analysis. This is primarily because we revised downwards MS worker proportions in some nominally high-productivity sectors (e.g. real estate and mining, where we estimate productivity of ~£700k–£1m GVA per worker in 2024), while we revised upwards MS worker proportions in some

nominally low-productivity sectors (e.g. education and healthcare, ~£40k GVA per worker in 2024).

While GVA and its close proxy GDP[6] are easy to compute, they are ultimately reductive, aggregate measures of total *market value* created over a limited time frame (usually a fiscal quarter or year). GVA and GDP do not account for the value of education, human health and wellbeing, environmental health, unpaid work, leisure time, and other societal benefits that do not have market prices.

Returning to the preceding example of "low-productivity" industries: education and healthcare are of course utterly fundamental to the UK, including its economy, even if their value is not captured by GDP- or GVA-based metrics. Therefore, while MS workers' higher than average productivity already reflects their outsized role in creating market value in the UK economy, their additional contributions to the UK extend well beyond those captured by GDP- or GVA-based metrics.

Other differences between the results of our new and previous analyses emerge at more granular levels. For example, Deloitte's modelling for 2010 suggested that the computer science sector was the single largest employer of MS workers, followed by public administration and defence. By contrast, we find that more MS workers were employed in professional, scientific, and technical activities than any other industry section in 2024, with the next largest MS worker cohort in the education sector. On the other hand, we find that MS workers engaged in financial and insurance activities contributed more GVA than MS workers in any other industry section, which incidentally accords with Deloitte's findings for 2010.

In a forthcoming report, we will disaggregate the present analysis by UK nation. Longer term, we plan to stratify a similar analysis by education tier, e.g., to quantify the value of GCSE and A-Level maths to the UK economy: the former being critical for virtually all STEM-related, business, and management jobs (among others), and the latter for all STEM-related university courses, including in the medical profession. Subsequent work might include re-appraising the mathematical sciences' many *non-economic* benefits, e.g. its contributions to social and environmental well-being in the UK. ■

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Data sources and code availability

All datasets used in our analysis are publicly-available from the ONS. The Python code and input files required to reproduce this analysis are available via this GitHub repository.

Supplementary notes

[1] Deloitte listed 38 occupations as comprising 100% MS workers and 15 occupations as comprising 4–10% MS workers. Due to license restrictions they could not disclose estimated employment levels for three further occupations. Using publicly-available data, we retrospectively estimate the unpublished levels to be close to 100% for one of the occupations and in the 5–10% range for the remaining two occupations.

[2] This bespoke SIC-SOC matrix was (and is) not in the public domain.

[3] There is no unique closed-form maximum entropy distribution—i.e., a distribution whose choice can be justified as the least informative default—subject to the constraints only of a fixed support $[a, b]$ and specified mode $c \in (a, b)$. The triangular probability density function has the highest entropy among all piecewise linear distributions for which only the support and mode (most probable value) are known. Among distributions additionally constrained to be smooth, i.e. infinitely differentiable, a truncated Gaussian PDF centred on c is the maximum entropy distribution.

[4] As noted previously, we used triangular PDFs to model our uncertainty in MS fractions. We used Gaussian PDFs to describe our uncertainty in data from ONS surveys, with the std parameter σ computed in each case from the published 95% confidence intervals around the best estimate of the datum.

[5] The two main assumptions our new analysis inherits from the previous one are (i) that a generic statistical mapping between occupations and industries is a good first approximation to the occupation-industry mapping for MS workers (the mapping would in any case be trivially correct for those occupations we deemed to comprise 100% MS workers), and (ii) that the economic productivity of MS workers equals the average productivity within any industry division.

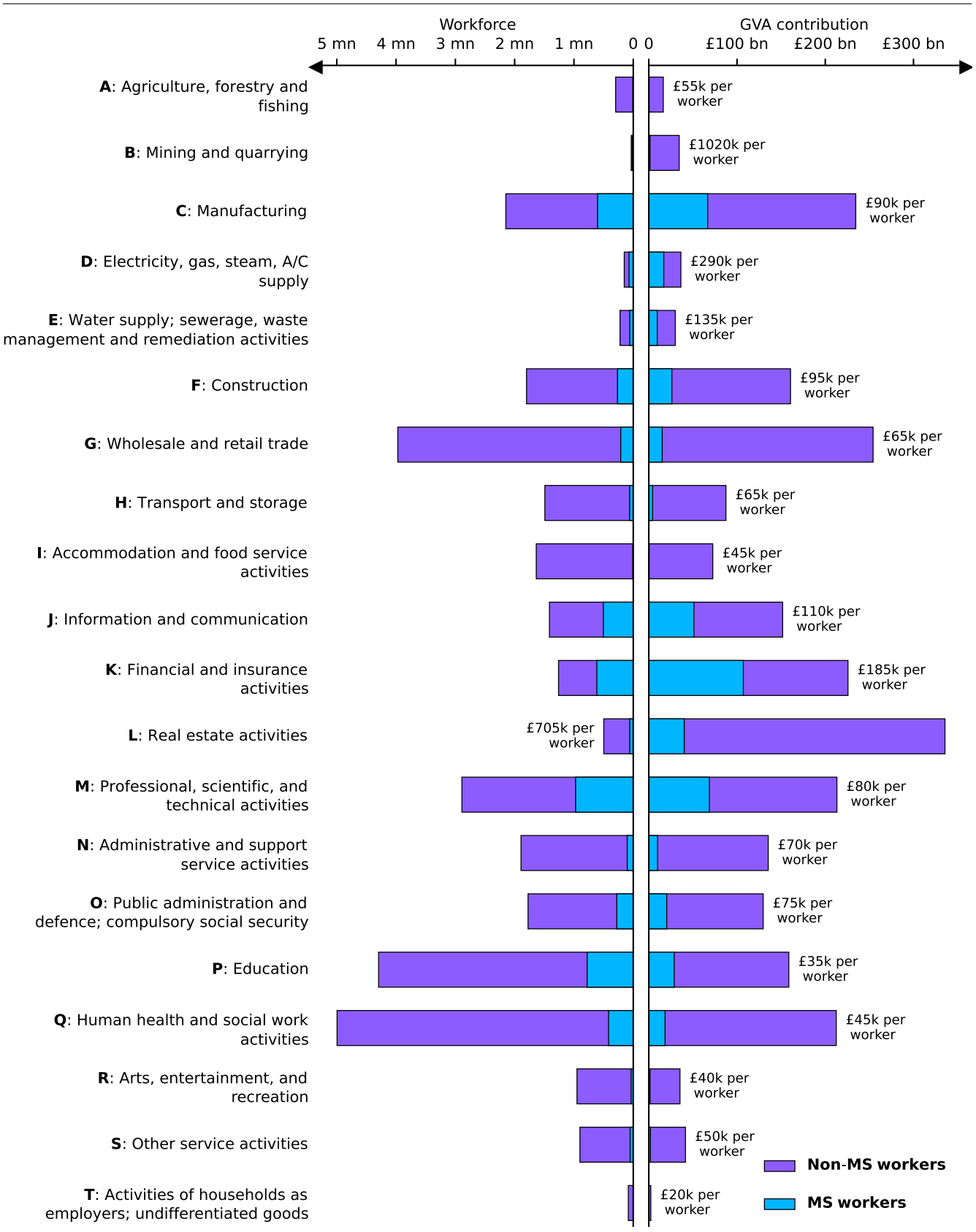
[6] GDP is related to GVA by the addition of taxes that consumers pay on products (such as VAT) and the subtraction of subsidies given to producers of specific products (such as for agriculture or fuel). E.g., in 2023, the ONS estimated total UK GVA to be £2.464 tn, and total GDP to be £2.720 tn. The UK uses GVA rather than GDP at sub-national levels (countries, regions, and local authorities) because taxes and subsidies on products are only fully measured at the whole-economy level. GVA allows for a clearer breakdown of the economic contribution of individual industries and geographical areas, providing more precise data for local economic policy-making, resource allocation, and understanding the unique economic characteristics of different parts of the UK.

Appendix

A1 Mathematical science workers vs occupation

Table A1.1, below, disaggregates our 2024 catalogue of 5.1 mn MS workers into 95 occupation unit groups spanning 10 sub-major groups. Our mean MS fraction was about 12.8% (averaged across 412 SOC2020 unit groups); for comparison, Deloitte's mean MS fraction was about 11.1% (averaged across 359 SOC2000 unit groups). The median MS fraction was 0% in both cases.

Figure 4 — The industry (SIC2007) sections in which MS workers were employed and contributed economically in 2024. For each industry, we also indicate the average productivity (e.g., "£55k per worker") that we computed by dividing a section's total GVA by the total number of workers in that section. Note that these industry sections are high-level categories (each associated in SIC2007 with a single letter, shown in bold on the vertical axis) that aggregate finer-grained industry divisions and sub-divisions (associated with 2-digit and with 4-digit codes, respectively). We apportioned GVA to MS workers at the level of industry divisions (88 in total); the relevant, granular data can be accessed via this GitHub repository.



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Table A1.1 — The 95 occupations (SOC2020 unit groups) we deemed to comprise non-zero fractions of MS workers. For each occupation, the table lists: the total number of UK workers in 2024 (per Annual Population Survey data); our estimated MS worker fraction, with upper and lower estimates where applicable; the number of MS workers we compute from our (best-estimate) MS fraction; and a comment indicating if our MS fraction is higher or lower than Deloitte's MS fraction for the identical or near-equivalent SOC2000 occupation included in their MS worker catalogue (occupations *not* included in Deloitte's MS worker catalogue, and/or occupations with no near-equivalent in SOC2000, are commented "n/a"). For readability, MS fractions and MS worker numbers are rounded in this table to the nearest 5 (e.g., 37% and 39% are rounded to 35% and 40%, respectively).

Sub-major group	Unit group	UK workers	MS frac. (range)	MS workers	Frac. change
Corporate managers and directors	1111: Chief executives and senior officials	116 100	25% (10%–40%)	29 025	Increase
	1112: Elected officers and representatives	10 800	5% (0%–15%)	540	Decrease
	1121: Production managers and directors in manufacturing	270 400	30% (20%–45%)	81 120	n/a
	1122: Production managers and directors in construction	162 200	30% (25%–40%)	48 660	n/a
	1123: Production managers and directors in mining and energy	11 800	100%	11 800	No change
	1131: Financial managers and directors	411 400	50% (40%–65%)	205 700	Increase
	1132: Marketing, sales and advertising directors	238 700	40% (35%–50%)	95 480	n/a
	1134: Purchasing managers and directors	71 600	30% (15%–45%)	21 480	Increase
	1137: Information technology directors	138 700	55% (45%–65%)	76 285	Decrease
	1139: Functional managers and directors n.e.c.	154 300	10% (5%–15%)	15 430	n/a
	1171: Health services and public health managers and directors	77 300	35% (20%–60%)	27 055	Decrease
Other managers and proprietors	1231: Health care practice managers	19 100	10% (0%–20%)	1 910	Decrease
Science, research, engineering and technology professionals	2111: Chemical scientists	30 600	100%	30 600	No change
	2112: Biological scientists	44 100	100%	44 100	No change
	2113: Biochemists and biomedical scientists	85 400	100%	85 400	No change
	2114: Physical scientists	27 200	100%	27 200	No change
	2115: Social and humanities scientists	38 600	40% (30%–45%)	15 440	Decrease
	2119: Natural and social science professionals n.e.c.	42 500	65% (60%–75%)	27 625	Decrease
	2121: Civil engineers	96 800	100%	96 800	No change
	2122: Mechanical engineers	74 800	100%	74 800	No change
	2123: Electrical engineers	48 600	100%	48 600	No change
	2124: Electronics engineers	32 700	100%	32 700	No change
	2125: Production and process engineers	57 000	100%	57 000	No change
	2126: Aerospace engineers	30 300	100%	30 300	No change
	2127: Engineering project managers and project engineers	40 800	100%	40 800	No change
	2129: Engineering professionals n.e.c.	159 800	100%	159 800	No change
	2131: IT project managers	82 800	35% (25%–50%)	28 980	Decrease
	2132: IT managers	238 500	40% (25%–55%)	95 400	Decrease
	2133: IT business analysts, architects and systems designers	191 700	100%	191 700	No change
	2134: Programmers and software development professionals	560 900	70% (50%–85%)	392 630	Decrease
	2135: Cyber security professionals	65 000	100%	65 000	n/a
	2136: IT quality and testing professionals	30 900	100%	30 900	No change
	2137: IT network professionals	30 200	30% (25%–45%)	9 060	Decrease
	2139: Information technology professionals n.e.c.	154 500	35% (25%–40%)	54 075	Decrease
	2151: Conservation professionals	27 700	40% (25%–45%)	11 080	n/a
	2152: Environment professionals	67 900	60% (55%–65%)	40 740	n/a
	2161: Research and development (R&D) managers	82 600	100%	82 600	No change
	2162: Other researchers, unspecified discipline	71 400	60% (55%–65%)	42 840	Decrease
Health professionals	2211: Generalist medical practitioners	159 200	15% (10%–20%)	23 880	Increase
	2212: Specialist medical practitioners	159 100	35% (15%–50%)	55 685	Increase
	2225: Clinical psychologists	24 600	30% (20%–35%)	7 380	Increase
	2226: Other psychologists	30 900	55% (30%–70%)	16 995	Increase
	2251: Pharmacists	58 700	85% (80%–90%)	49 895	Decrease
	2259: Other health professionals n.e.c.	101 400	45% (20%–55%)	45 630	n/a
Teaching and other educational professionals	2311: Higher education teaching professionals	266 100	45% (40%–50%)	119 745	Increase
	2312: Further education teaching professionals	63 300	35% (30%–40%)	22 155	n/a
	2313: Secondary education teaching professionals	443 600	35% (30%–40%)	155 260	n/a
	2319: Teaching professionals n.e.c.	155 200	35% (30%–40%)	54 320	n/a
	2321: Head teachers and principals	43 500	20% (15%–25%)	8 700	n/a
	2322: Education managers	60 400	20% (15%–25%)	12 080	n/a
	2329: Other educational professionals n.e.c	81 300	30% (25%–35%)	24 390	n/a
Business, media and public service professionals	2421: Chartered and certified accountants	205 900	65% (50%–70%)	133 835	Increase
	2422: Finance and investment analysts and advisers	293 100	100%	293 100	No change
	2423: Taxation experts	49 300	30% (25%–40%)	14 790	Increase
	2431: Management consultants and business analysts	231 300	100%	231 300	No change
	2432: Marketing and commercial managers	127 300	25% (20%–35%)	31 825	Increase
	2433: Actuaries, economists and statisticians	67 300	100%	67 300	No change
	2434: Business and related research professionals	73 700	100%	73 700	No change
	2440: Business and financial project management professionals	317 800	35% (25%–40%)	111 230	n/a
	2451: Architects	48 400	15% (10%–20%)	7 260	Increase
	2452: Chartered architectural technologists, planning officers and consultants	43 700	25% (20%–35%)	10 925	n/a
	2453: Quantity surveyors	69 100	70% (60%–80%)	48 370	Increase
	2454: Chartered surveyors	67 500	70% (60%–80%)	47 250	Increase
	2455: Construction project managers and related professionals	87 000	30% (20%–40%)	26 100	n/a

Continued on next page

Sub-major group	Unit group	UK workers	MS frac. (range)	MS workers	Frac. change
	2481: Quality control and planning engineers	28 000	100%	28 000	No change
	2482: Quality assurance and regulatory professionals	157 000	40% (30%–50%)	62 800	Decrease
	2483: Environmental health professionals	11 900	30% (25%–35%)	3 570	Increase
Science, engineering and technology associate professionals	3111: Laboratory technicians	58 900	100%	58 900	No change
	3112: Electrical and electronics technicians	26 100	100%	26 100	No change
	3113: Engineering technicians	89 900	100%	89 900	No change
	3114: Building and civil engineering technicians	26 200	100%	26 200	No change
	3115: Quality assurance technicians	29 800	100%	29 800	No change
	3116: Planning, process and production technicians	19 100	100%	19 100	No change
	3119: Science, engineering and production technicians n.e.c.	24 900	100%	24 900	No change
	3120: CAD, drawing and architectural technicians	54 000	15% (10%–20%)	8 100	n/a
	3133: Database administrators and web content technicians	55 600	25% (20%–30%)	13 900	Decrease
Business and public service associate professionals	3511: Aircraft pilots and air traffic controllers	31 100	100%	31 100	No change
	3531: Brokers	64 700	40% (35%–45%)	25 880	Increase
	3532: Insurance underwriters	32 100	100%	32 100	No change
	3534: Financial accounts managers	154 400	20% (15%–25%)	30 880	n/a
	3541: Estimators, valuers and assessors	64 700	35% (30%–45%)	22 645	Increase
	3544: Data analysts	115 800	95% (90%–100%)	110 010	n/a
	3549: Business associate professionals n.e.c.	130 700	30% (25%–40%)	39 210	n/a
	3554: Marketing associate professionals	202 800	25% (20%–35%)	50 700	n/a
	3556: Sales accounts and business development managers	330 700	25% (20%–30%)	82 675	n/a
	3560: Public services associate professionals	150 200	10% (5%–15%)	15 020	n/a
Administrative occupations	4121: Credit controllers	36 300	100%	36 300	No change
	4122: Book-keepers, payroll managers and wages clerks	417 700	10% (5%–15%)	41 770	Increase
	4124: Finance officers	45 300	15% (10%–20%)	6 795	n/a
	4129: Financial administrative occupations n.e.c.	179 700	5% (0%–10%)	8 985	n/a
Skilled metal, electrical and electronic trades	5234: Aircraft maintenance and related trades	31 300	5% (0%–10%)	1 565	n/a
	5242: Telecoms and related network installers and repairers	66 500	5% (0%–10%)	3 325	Decrease
	5244: Computer system and equipment installers and servicers	39 400	10% (5%–15%)	3 940	Decrease
	5246: Electrical service and maintenance mechanics and repairers	31 900	5% (0%–10%)	1 595	Decrease
	5249: Electrical and electronic trades n.e.c.	50 400	100%	50 400	No change



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