Labour productivity estimates for detailed industries in the UK, 2009 to 2023

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Abstract

We construct labour productivity estimates for 184 industries spanning the entire UK economy – more than double the granularity available from official datasets. To do so, we use only publicly available data sources and transparent and reproducible methods in order to enable our estimates to be used, adapted and updated by other researchers. Our methods ensure a high degree of consistency with official productivity statistics and conformity with National Accounts concepts. While this level of granularity presents potential data quality concerns, the trade-off between granularity and quality in our estimates is more favourable than that inherent in official productivity statistics. We also include detailed discussion of measurement issues pertinent to UK productivity statistics. Two applications of our estimates are included: one providing new insights on the distribution of productivity across the UK economy, and one demonstrating the use for policy analysis.

1. Introduction

Productivity statistics broken down by industry (sector) are an important source of information to understand the structure of an economy, the international competitiveness of a country, and potential sources of growth, amongst many other applications. As such, these measures are widely used by economists, researchers and policy analysts. Demand for timely and detailed industry-level productivity statistics is high, including in the UK.

However, official statistics rarely provide a level of industry detail sufficient to meet the requirements of many analysts. Despite a considerable suite of productivity statistics published for the UK by the Office for National Statistics (ONS), there remains substantial demand for additional industry detail.[1] The lack of detail is particularly acute for services industries. As such, some estimates have been constructed using firm-level data, though these are typically not consistent with National Accounts concepts or other official statistics, making it difficult to draw comparisons.

This paper meets the demand for more detailed industry productivity estimates for the UK by constructing a new dataset of labour productivity measures for 184 industries. This represents a more than doubling of detail compared to the official labour productivity datasets published by ONS. The estimates are GVA per filled job, on an annual basis from 2009 to 2023, and are in nominal terms (current prices). These estimates are based entirely on publicly available data sources, and use a transparent and re-producible method, enabling the estimates to be customised according to user need. Alongside this paper we have published a dataset of productivity estimates, and a code package and instructions to reproduce or customise the estimates.[2]

The paper also provides a detailed discussion of measurement issues pertinent to UK productivity statistics, including National Accounts concepts, data source properties, and methodological considerations. This discussion is likely to be of interest to statistical practitioners and users of official statistics.

One concern with constructing productivity estimates for more detailed industries is that they will be of low quality due to data quality limitations at the necessary level of disaggregation. We apply a novel test to our estimates (following Dunn et al., 2024) to compare the granularity-quality trade-off at different levels of industry detail. This suggests that our measures are no less stable or robust than official estimates, given the increase in granularity – in fact, our estimates show relatively smaller revisions and more year-to-year stability, on average, than official estimates given the level of industry granularity.

Finally, the paper contains two applications of the data. First, we show that our estimates enable a more nuanced perspective on the relative productivity levels of different industries, and a richer understanding of the distribution of productivity across the economy. Second, we show that our estimates can be useful for policy analysis, by constructing productivity estimates for some of the sectors defined by the UK Government's 2025 Industrial Strategy.

Despite the advantages of the estimates constructed in this paper, there are several limitations. First, the estimates are only in current prices (nominal terms, i.e. not adjusted for inflation) and as such cannot be used to analyse productivity growth over time. The estimates are therefore useful primarily for a study of relative levels of productivity across

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[1] Both authors have in the past been involved in the production of ONS productivity statistics, and are familiar with such user demand. The authors have used their expertise gained through their experience in the statistical system to produce the estimates presented in this paper. However, this paper does not represent an ONS statistical product, and is not endorsed by the ONS.

[2] The dataset is hosted at The Productivity Institute's Productivity Data Lab: doi.org/10.48420/30104551

industries at a point in time. Second, we have been unable to advance industry detail beyond official statistics in some areas, notably the financial services industry and the government-dominated industries of public administration, education, and health and social care. Third, there are some methodological limitations and some areas of weaker adherence to National Accounts concepts, due either to data limitations, or the desire to use only publicly available data sources. These are described in detail, and reserved for future work.

Given these limitations, we recommend that the productivity estimates for individual industries constructed in this paper be used with caution, especially where the industries in question are small. Small differences in estimates of productivity levels between industries, especially small industries, should not be overinterpreted – industries with a difference in productivity or jobs of a few percent should be treated as being broadly similar rather than one industry being more or less productive than the other.

The paper proceeds as follows. Section 2 provides an overview of existing productivity estimates for UK industries, including from official datasets published by the ONS, and in academic studies. Section 3 describes the methods and data sources used to construct the productivity estimates introduced in this paper. Section 4 discusses the strengths and limitations of the methods, and assesses the quality of the results. Section 5 presents two applications of the data: on the distribution of productivity across the economy, and for policy analysis. Section 6 briefly concludes.

2. Existing UK industry productivity data

2.1 Official datasets

The Office for National Statistics (ONS) publishes a wide range of productivity statistics for the UK, including labour productivity, multi-factor productivity (MFP), public service productivity (PSP), and firm-level productivity statistics. Each of these has some industry-level breakdown (or equivalent).

The labour productivity statistics include estimates of output per hour worked (OpH), output per (filled) job (OpJ), and output per worker (OpW).[3] Of these, OpH and OpJ are available for the whole economy, market sector, and by industry, while OpW is available only for the whole economy and market sector.[4]

At the time of writing, OpH and OpJ estimates are available for 19 industry “sections” (letter-level) of the Standard Industrial Classification (SIC) 2007, with sections S (other service activities) and T (activities of households as employers) aggregated. These measures are also available for 78 industry “divisions” (two-digit level) of SIC 2007, with the following aggregations: 02 and 03, 11 and 12, 14 and 15, 37 to 39, 97 and 98, and with 07 and 08 omitted. ONS also publishes some "bespoke” industry aggregations, though these are no more detailed than the division-level breakdown.

The MFP estimates are produced only for industries (and parts of industries) in the market sector, with a 16-industry breakdown of mostly industry sections, and a few aggregations. In the broader growth accounting data suite, estimates for capital services are available for 19 industry sections and 64 industry divisions (with several aggregations thereof).

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[3] In all cases, “output” refers to Gross Value Added (GVA). We refer here to the names of the ONS datasets, but this paper will refer to equivalent metrics as “GVA per job” for clarity.
[4] ONS did previously produce estimates of workers by a 10 industry split, which were supplied to Eurostat (and can still be accessed on the Eurostat website up to 2023 Q3). However, this data supply ceased following the UK’s exit from the European Statistical System on 31 December 2020.

The public service productivity estimates are not broken down by industry but are published by “service area”, following the Classification of the Functions of Government (COFOG), which is akin to an industry breakdown but specifically for government activity. The annual PSP statistics have a 10-service area breakdown at time of writing.

The firm-level productivity statistics published by ONS using the Annual Business Survey (ABS) include estimates for 17 industry sections, 68 industry divisions (and aggregations thereof), and 134 more detailed industry groups (see ONS, 2024, for the latest of these statistics). None of these breakdowns cover the whole economy, given the coverage of the ABS is not comprehensive (see section 4.2) – notably, most of the finance industry and much of the public sector are not included. The most detailed breakdown covers industry “groups” (three-digit level) of SIC 2007, and aggregations thereof; however, only some industries are covered at this more detailed level, based on sample sizes and data quality. Finally, some of the estimates are supressed due to disclosure control rules, meaning these data are not available for all 134 industries (100 industries per year on average for mean productivity).

Relative to these official datasets, the labour productivity estimates presented in this paper are more detailed (at 184 industries – see Appendix D for more details on these) and have comprehensive coverage of the economy (unlike MFP, PSP and the firm-level estimates).

2.2 Academic and other estimates

Productivity estimates for detailed industries are available in academic work and can be derived from other data sources. It is beyond the scope of this paper to give a comprehensive account, but we note a few examples and common themes of these estimates.

Many studies use company financial accounts data – such as that collated by Bureau van Dijk (BvD) in their Financial Accounts Made Easy (FAME) dataset – to calculate productivity estimates for firms, and by aggregation for industries. Given the use of publicly available company-level data, these can in theory be used to generate “industry-level” estimates for detailed and bespoke industries.

There are a number of limitations of such productivity measures. First, financial accounts data are often disproportionately available for large companies, such that the coverage of firms in an industry will often not be complete. Second, even where data do exist for small firms, the data may be patchy or of lower quality, such that the resultant productivity estimates may be unreliable. Third, the necessary data often do not exist to produce estimates of output or gross value added (GVA) consistent with national accounts concepts. In particular, data on intermediate consumption is often unavailable or of low quality (in contrast to data on turnover which is often readily available). Of more minor concern, data on changes in inventories and output for own final use (see section 4.2) are usually unavailable. Fourth, data covering the self-employed tends to be entirely absent. As such, while these data allow for the calculation of a productivity measure for detailed industries, it will not be consistent with national accounts concepts or coverage.

Similarly, some studies construct labour productivity estimates for firms (and potentially industries) from the Business Structure Database (BSD), which is an annual snapshot of the Inter-Departmental Business Register (IDBR). The clear limitation here is the unavailability of data on intermediate consumption, and by extension GVA, such that productivity is measured as turnover per worker. The comparability of this across industries will be severely limited, given the variations in the share of intermediate consumption in turnover across industries.

Finally, some studies focussing on manufacturing are able to produce more detailed productivity estimates using datasets that provide more detail in manufacturing. This was particularly prevalent in the past, such as the detailed work by Oulton and O'Mahony (1994), which constructed productivity estimates for 130 manufacturing industries. By comparison, our breakdown in manufacturing is 59 industries, and there are 46 in the ONS firm-level productivity estimates, and 22 in the ONS division-level OpH estimates.

3. Methods

We measure productivity of all industries by gross value added (GVA) per filled job. As such, our target variables for each industry are GVA (in current prices) and the number of filled jobs, on an annual basis. Before describing the methods for each of GVA and jobs in detail, it is worth setting out some basic principles.

First, both GVA and jobs should relate conceptually to annual values, rather than an estimate from a point in time in the year. For GVA, that is straightforwardly the sum of GVA across the year, or equivalently the sum of total output over the year minus the sum of intermediate consumption over the year. For jobs, the appropriate measure is the average number of filled jobs over the course of the year. Ideally that would be an average of the value on each day, but more practically it is the average value in each month or each quarter. As such, we make some adjustments to the data on jobs to align it to annual averages.

Second, our estimates must be national accounts consistent, conceptually and empirically, as far as possible. This means that we aim to use measures which are constructed following national accounts concepts wherever possible. In the case of GVA, it also means that we constrain all the estimates to sum back to published totals at higher levels of industry aggregation, and ultimately back to total economy GVA. More precisely, we apportion national accounts industry GVA data to more detailed industries, preserving additivity.

Finally, we use only data sources that are publicly available and methods that are entirely replicable and transparent. The instructions and code accompanying this paper allow interested readers to re-construct our industry productivity estimates without the need to use microdata or have any specialist access. Some conceptual improvements would be possible with access to unpublished data (section 6), but that is not in scope of the present paper.

3.1 GVA

To construct annual GVA estimates for detailed industries we start from the Supply and Use tables (SUTs) published by ONS. At the time of writing, the latest SUTs are consistent with the Annual National Accounts 2024 (also known as Blue Book 2024), and cover years from 1997 to 2022. The SUTs provide data on total output (at basic prices: that is, before distributors trading margins and before net taxes on products) and intermediate consumption (at purchasers' prices: that is, the price actually paid by the purchasers), from which GVA (at basic prices) can be easily constructed. The SUTs contain data for 114 industries – this comprises considerable detail in manufacturing, and mostly division-level breakdowns outside of manufacturing. We use most of this industry detail, with a few exceptions, and break down some industries (notably services industries) further. At the level of detail published in the SUTs, our GVA estimates are already fully National Accounts consistent.

To break down the SUT data to more detailed industries, we use published data from the Annual Business Survey (ABS). The ABS is a large annual survey of UK businesses conducted by ONS. It has run in much the same form every year since 2008, when the ABS replaced the similar Annual Business Inquiry (ABI). The ABS collects data by industry on a SIC 2007 basis, while the ABI collected data following the SIC 2003 industry breakdown.

While it is certainly possible to covert SIC 2003 to SIC 2007, this is more accurately done at the microdata level. The limitations of the published ABS/ABI data before 2008 is one reason why we construct productivity estimates for years only since 2009 in the present paper.

The ABS collects data retrospectively for annual totals. For instance, the 2024 ABS collects data for the 2023 reference year. Respondent firms are asked to report data for the calendar year (i.e. 1 Jan to 31 Dec of the reference year) where possible. Where that is not possible, respondents can report for a different reference year, for instance a financial year. However, the reporting period must end between 6 April of the reference year and 5 April of the following year (e.g. between 6 April 2023 and 5 April 2024 for the 2023 reference year). This means that the reported data correspond largely to the correct calendar year. However, respondents reporting for a period other than the calendar year are not excluded from the published data and no adjustment is made for this (ONS, 2025; OSR, 2012).

The available published variables include “total turnover”, “total purchases of goods, materials and services” and “approximate gross value added (aGVA)”. As described in detail in Ayoubakhani (2014), the ABS variables of total turnover and total purchases are not fully consistent with National Accounts concepts of total output and intermediate consumption. ONS makes various concept adjustments using other ABS variables to produce derived variables of “approximate total output” and “approximate intermediate consumption” and from these derives “approximate gross value added” (aGVA). However, approximate total output and approximate intermediate consumption are not available in published datasets.

The published ABS data include estimates for detailed industries, including by industry class (four-digit level of SIC 2007), industry group (three-digit level) and industry division (two-digit level). By construction, these are consistent in aggregation.

However, at the lower levels of industry detail there are often suppressions due to statistical disclosure control. Supressed values are not usually equal to zero, but rather a value which is potentially disclosive of a contributing business (or businesses). In order to avoid difficulties caused by these suppressions, we impute the values of supressed cells while maintaining additivity up the industry hierarchy.

To do this, we calculate each industry’s share of a variable in its parent industry’s total – for instance, an industry group’s share of total turnover within its parent industry division’s total turnover. For supressed cells, we estimate the industry’s share of that variable in its parent industry’s total. Since the same industries are not supressed every year, we often have data from nearby years. Where possible, we estimate the suppressed share by linearly interpolating between the industry shares in nearby years. For years before the first data is available, and after the latest data is available, we hold the shares of the parent industry’s total constant (i.e. we do not extrapolate the share) – we do this using an average of two years where that is possible (to reduce the effect of year-to-year volatility), or one year where that is necessary. Finally, we rescale the imputed values to ensure additivity up the industry hierarchy. For instance, if two industry groups are supressed within a given industry division, but three others are published, then the imputed values for the two industry groups must sum with the published three industry groups to equal the industry division – we rescale the imputed values of the two industry groups to ensure that is the case. Appendix B gives an example based on stylised data. Interested readers can review the code to see how this is done in practice.

The use of SUTs and ABS allow us to construct GVA estimates for detailed industries for years covered by the SUTs, which is up to 2022 at time of writing. We are interested in producing productivity estimates that are as up-to-date as possible, and so have constructed a preliminary estimate for 2023 – one year after the current SUTs finish. This uses a slightly different method, but the same broad principles, and remains additive.

For 2023, we use industry-level GVA estimates from the GDP(o) low-level aggregates dataset published by ONS. This has essentially the same level of industry detail as in the SUTs, but contains data only for GVA (not output and intermediate consumption). As such, we use aGVA from the ABS to apportion GVA to detailed industries. To avoid discontinuities between the estimates based on the SUTs (up to 2022) and afterwards (2023), we construct the aGVA-based estimates for 2022 as well, and use that measure as an indicator to extrapolate the SUT-based estimate.

3.2 Jobs

Our estimates of jobs for detailed industries follows a similar process as for GVA, starting with a fairly detailed comprehensive data source, and breaking it down further using auxiliary sources.

We start with data on employee jobs in Great Britain (GB), as published by the ONS as part of the Workforce jobs (WFJ) statistics. Employee jobs account for about 87% of all jobs on average between 2009 and 2023 (the remainder being self-employment jobs and other smaller categories, see below), while employee jobs in GB account for about 97% of all employee jobs in the UK (Northern Ireland accounting for the remaining 3% or so), such that employee jobs in GB account for about 85% of total jobs in the UK. As such, this is a very comprehensive data source to start from. We describe the estimates for Northern Ireland employee jobs and UK self-employment jobs below.

It is useful to start with the data on GB employee jobs since this dataset has considerably more industry detail than either UK employee jobs or UK total jobs. The published data on GB employee jobs is available for 116 industries – mostly industry divisions, but with additional detail in many industries, including many outside of manufacturing. By contrast, the published data on UK employee jobs is available only for 82 industries, with no detail below the industry division level.

Jobs estimates from WFJ are available for March, June, September and December of each year. An annual estimate is not published. While the monthly estimates are often treated as representing the average value of the calendar quarters (March for Quarter 1, June for Quarter 2, etc.), this is not accurate or optimal. The data for these months come from three primary data sources: the Short-Term Employment Surveys collect data on private sector employees, the Quarterly Public Sector Employment Surveys collect data on public sector employees, and the Labour Force Survey is used for Self-Employment.

The Short-Term Employment Surveys (STES) collect data on the numbers of jobs on the second or third Friday of every third month (i.e. March, June, September, or December). As such, the jobs data do not relate to the average value over the quarter. Similarly, the Quarterly Public Sector Employment Surveys collect data on jobs for a specific reference date; for the local authorities survey is the first Friday after the second Thursday of the last month of the calendar quarter, for the Civil Service and Public Bodies surveys it is the last day of the calendar quarter (ONS, 2018). Several other data sources are also used for the public sector employee numbers, including (for example) NHS workforce statistics, Ministry of Defence statistics for HM Forces, and Home Office data for police. Finally, for self-employed jobs, data from the Labour Force Survey (LFS) are used for the three-month period centred on the reference month; so, for example, estimates for March are based on the average number of self-employed jobs between February and April. While the reference dates used are not consistent, it is more appropriate to treat them as being representative of the third month of a calendar quarter than as an average of the quarter as a whole.

In order to produce an estimate of annual jobs by industry, we take an appropriately weighted average of the monthly data. If the data represented quarterly averages, then each calendar quarter in the year would have a weight of a quarter, such that one would take a simple arithmetic average. Instead, we must use weights of 3/12 for each of March, June and September, 2/12 for December of the reference year, and 1/12 for December of the previous reference year. To see this, consider constructing a quarterly average for Quarter 1 as the weighted midpoint between the observation in December of the previous year and March of the current years, which require weights of 2/3 on March and 1/3 on December. Repeating this for each calendar quarter yields the result for the year described above. See Appendix C for a worked example.

To breakdown GB employee jobs to detailed industries, we use data from the Business Register and Employment Survey (BRES) available via nomis[5]. BRES is a very large annual business survey conducted by ONS, which collects data on filled jobs of respondent businesses. The number of jobs is collected for a specific reference date (a Friday in mid-September) of each year, rather than an annual average. It also collects data on the number of jobs and type of activity of each business site (local units), as well as breakdowns of jobs by sex and whether they are full-time or part-time.

The published BRES data and WFJ data use an industry allocation based on local units (i.e. sites) rather than reporting units (i.e. parts of a business grouped together for statistical reporting purposes). The limitations of this are discussion in section 4.2.

Estimates of employee jobs in Great Britain from BRES are available for all levels of the SIC 2007 industry classification, with only a handful of exceptions. There are no supressed cells in the BRES data available from nomis, although all the estimates are rounded to some degree. Therefore, unlike with the ABS, there is no need to impute for supressed cells. It is therefore straightforward to use the pattern of jobs across detailed industries within a parent industry to apportion the number of employee jobs of the parent industry (from WFJ) to detailed industries. Like for WFJ, we apply an adjustment to the BRES data to make an estimate of the number of jobs for the calendar year, since the data represent the point in time number of jobs for September. By the same logic as described above, we construct an estimate for the annual midpoint (June) as a weighted average of the current and previous year's September values, with weights of 9/12 and 3/12 respectively.[6] See Appendix C for a worked example. This has the added benefit of smoothing the data slightly.

We calculate employee jobs in Northern Ireland as the difference between employee jobs for Great Britain and employee jobs for the UK in the published WFJ data. This is limited by the industry breakdown in the data for the UK, which is for 88 industries (industry divisions and a few aggregations thereof). We breakdown Northern Ireland employee jobs to detailed industries using the pattern of GB employee jobs, calculated first as described above. This still preserves the distribution of Northern Ireland jobs across 88 industry divisions – as such, it still reflects the relatively higher employment share of manufacturing in Northern Ireland

[5] Nomis is a service provided by the ONS to access official census and labour market statistics: https://www.nomisweb.co.uk/

[6] Strictly, this is not an estimate of the annual average, but rather the annual midpoint (i.e. middle month of June). To construct a true annual average would require a half-month's weight on the subsequent year's September value as well (6/24, 17/24 and 1/24 respectively). The gain in precision is small relative to the loss of timeliness of an entire year. In any case, the estimates for higher-level industries from WFJ (described above) are correctly adjusted to annual averages, and the BRES data are used only to split this into lower-level industries. We judge that the benefit of timeliness far outweighs the small loss of accuracy here, and so use an annual midpoint.

relative to GB in recent decades, for example. It is only below the level of industry divisions that we use the GB pattern. An alternative would be to use the Northern Ireland BRES, but this is only available publicly at the necessary level of industry detail for 2022 onwards. A comparison of the results when using the NI BRES is available in Appendix A, which shows it would have a small impact on the overall estimates in 2022 in most cases.

For UK self-employment jobs, published WFJ data are for 88 industry divisions (the same breakdown as for Northern Ireland). We apportion these data to detailed industries using the pattern of UK employee jobs (i.e. after accounting for Northern Ireland employee jobs, as described above). The use of employee jobs as a pattern for allocating self-employment jobs is a clear limitation of the current methodology, and is discussed in more detail in section 4.2. However, this only applies to the breakdown *within industry divisions* – as such, this still preserves the concentration of self-employment jobs in selected industries such as agriculture, construction, and professional services. However, within industry divisions, the allocation of self-employment jobs to detailed industries follows the pattern of employee jobs (see section 4.2 for further discussion).

We repeat all of the above for full-time jobs and part-time jobs (which in practice means repeating it for Male Full-time, Male Part-time, Female Full-time and Female Part-time, and then collapsing the sex dimension, due to the way the data are published). This allows the construction of some approximate full-time equivalent (FTE) measures of jobs. Given that part-time workers usually work fewer hours than full-time workers, a measure of total jobs that sums full-time and part-time jobs together will overstate labour input in industries with a lot of part-time jobs. The preferred measure of labour input for productivity estimates is hours worked, and while it is beyond the scope of this paper to construct a measure of hours worked, an FTE measure is an approximation. Based on the average hours worked of part-time workers relative to full-time workers from the LFS and ASHE[7], we construct our FTE measure by giving a weight of one-half to part-time jobs relative to full-time jobs.

3.3 Productivity

With annual estimates of GVA and jobs constructed, the calculation of productivity is then straightforward as GVA divided by jobs.

These productivity estimates are in current prices – that is, not adjusted for inflation. This means that the estimates are appropriate for the comparison of productivity levels across industries at a point in time (e.g. in a given year). However, they are not appropriate for the analysis of productivity growth over time, since the growth of GVA will partly reflect price changes and partly reflect volume changes. It is beyond the scope of this paper to construct measures of productivity in constant prices (i.e. adjusted for inflation) – we discuss this further in section 4.2 and section 6.

[7] Based on the average actual weekly hours of work reported by people on the Labour Force Survey (LFS), and as published by ONS in their “HOUR01” dataset, people whose main job is part-time work on average about 40-45% of the hours of people with a full-time main job (about 40% for men and 47% for women, on average over 2009-2023). Data from the Annual Survey of Hours and Earnings (ASHE) on paid basic hours or paid total hours (including overtime) give a similar result – hours worked in part-time jobs are on average about 45-47% of those in full-time jobs (about 43% for men and 49% for women, on average over 2009-2023). We use one-half (i.e. 50%) which is broadly consistent with these figures, and to avoid spurious accuracy. Interested readers can amend this assumption in the accompanying code package if they wish.

4. Discussion of methods

While section 3 described the methods as implemented, this section briefly discusses the strengths and limitations of those methods. This should help the interested reader better understand how the resultant estimates should be used, and sets an agenda for the improvement of these estimates in future work (see also section 6).

4.1 Strengths

Use of published sources and transparent methodology

The primary strength of our methodology is the use of entirely publicly available data sources and a transparent and replicable methodology. This allows the interested reader to replicate our findings through the use of the accompanying code and instructions, without need for access to restricted data. We believe this will help interested readers to understand better the properties of the resultant productivity estimates for detailed industries, and so conduct further analysis on the causes and drivers of industry productivity levels.

Our methodology also allows for alternative industry breakdowns and aggregations to be constructed, such that National Accounts consistent labour productivity estimates can be constructed for user-defined industries. The industry breakdown used in this paper and accompanying dataset is based on our judgement of what is most appropriate, given the trade-off between data quality and granularity (see more in section 4.3). However, this work gives a basis for other industry productivity estimates, constructed in a consistent way, which should aid comparability across studies and applications.

National Accounts consistency

We have, as far as possible given the use of publicly available sources, ensured consistency with National Accounts concepts and data. This is an advantage relative to other studies which use data sources and methods which are not National Accounts consistent, such as the use of the ABS or ARDx without constraint to industry GVA data, or the use of company financial accounts data. While the use of those sources allows for rich analysis of firm-level productivity, they are not directly comparable with official productivity estimates.

Notably, the GVA estimates for detailed industries are additive up the industry classification, and are therefore consistent with National Accounts GVA estimates by industry, and total economy GVA. Therefore, the productivity level of a detailed industry can be compared with the productivity level of a higher-level industry on a like-for-like basis – for instance, in section 5.2 we compare the productivity of a bespoke industry aggregation to traditional high-level industries such as manufacturing.

We also use methods to adjust the data sources to better match National Accounts concepts. For instance, we adjust the data on jobs (WFJ and BRES) to align to calendar years, and so better align with the timing of the GVA data, following National Accounts concepts. Studies using company accounts data are often based on headcount estimates at a point-in-time during the year (rather than an annual average) which may distort results (e.g. due to seasonality).

4.2 Limitations

Output

Starting with our GVA estimates, the most significant limitation is the treatment of non-market output. Total output in the National Accounts is composed of three main types: 1) market output – goods and services sold at economically significant prices; 2) output for own-final use – goods and services produced and retained by the same economic unit (e.g. business) for a 'final' use, most often capital investment; and 3) other non-market output – goods and services given away for free or sold at prices that are not economically significant. The latter two types together are non-market output.

Total output from the SUTs includes all of these types of output, but output from the ABS is principally market output. As such, at lower levels of industry detail than available from the SUTs, total output is apportioned by a measure for market output. Put another way, the detailed industry breakdown for non-market output follows the breakdown for market output. It is worth reiterating that this limitation only applies to the split between detailed industries within the level of industry breakdown available from the SUTs. For instance, the SUTs give a total output estimate for industry division 75, which we do not break down further and so does not suffer this limitation; however, for industry division 74, which we split into three industry groups, the pattern of non-market output implicitly follows the pattern for market output, based on the ABS data.

This is likely most significant in industries with significant non-market output, and especially where that is concentrated in some detailed industries within an industry division, and not others. For instance, we split industry division 91 (Libraries, archives, museums and other cultural activities) into three parts: 91.01-02 (Library and archive activities; and Museum activities), 91.03 (Operation of historical sites and buildings and similar attractions) and 91.04 (Botanical and zoological gardens and nature reserve activities) – of these, the first (91.01-02) is likely to contain more non-market output (i.e. government-run and/or non-profits) than the latter two (likely more for-profit businesses). As such, the allocation based on market output may overstate output (and thus GVA) for industries 91.03 and 91.04 and understate it for industry 91.01-02. Indeed, our productivity estimates for industries 91.03 and 91.04 are notably higher than for 91.01-02, though it is difficult to be sure how much of this is genuine and how much is due to this methodological limitation.

A smaller limitation of our output measures is that the ABS data on output is not fully National Accounts consistent in other ways. Ayoubakhani (2014) provides a thorough discussion on the differences between ABS output and National Accounts output. Other the non-market output, the most significant differences are changes in inventories of finished goods and works in progress, and net taxes on production. There are also similar conceptual differences between National Accounts intermediate consumption and the ABS measure of spending on goods and services, notably in changes in inventories of raw materials. In most industries, these will be small effects. In the case of changes in inventories, the sign of the effect will vary from year to year (positive when adding to stocks, and negative when drawing down stocks) meaning this is unlikely to cause a persistent bias. For taxes on production, the effect is likely to be fairly similar across detailed industries within a higher-level industry. As such, while clear limitations, we think this should have a small effect in most cases, and unlikely to have a persistent effect across time (unlike in the case of non-market output).

Self-employment

Turning to the estimate of jobs, a notable limitation is the allocation of self-employment jobs across detailed industries. As described in section 3.2, we allocate self-employment jobs to detailed industries within industry divisions (the level of detail available in WFJ) using the estimated pattern of employee jobs at that level. It is worth reiterating that this only applies to the split between detailed industries within industry divisions, since we have the breakdown of self-employment jobs by industry division already from WFJ, which we use. As such, our estimates capture the high level of self-employment in industries such as construction, agriculture, and professional services. However, within industry divisions, the allocation is based on employee jobs which may not be appropriate.

A clear example is in the case of construction. From the WFJ data we know the number of self-employed jobs in industry division 41 (Construction of buildings). We split this into two detailed industries: 41.1 (Development of buildings projects) and 41.2 (Construction of residual and non-residential buildings). It seems likely that there are relatively more self-employed jobs in industry 41.2, compared with the split of employee jobs between these two. As such, our method may under-estimate self-employment jobs (and thus total jobs) in industry 41.2, which would lead to its productivity level being overstated. Since self-employment jobs account for an estimated roughly 40% of total jobs in these industries, there is potential for this to have a significant effect. It is for this reason that we chose not to provide more detailed industry estimates within industry division 43 (Specialised construction activities) which includes some sub-industries likely to have significant self-employment activity (e.g. group 43.2: Electrical, plumbing and other construction installation activities) and others likely to have relatively more employee jobs (e.g. 43.1: Demolition and site preparation).

Local units and reporting units

The use of local unit (LU) based estimates from both BRES and STES (via WFJ) results in a slight inconsistency with the GVA data, which is aligned with Reporting Units (RU).[8] RUs group portions of a business together based on their kinds of activity. For small businesses, RUs will cover all of the activity in a business. But for large businesses, they may have several RUs covering separately, for example, their manufacturing activities and their retail activities. For businesses with multiple, complex activities, this may mean the industry classification of employment in that business will differ depending on whether the data are collected and calculated for LUs as opposed to RUs. For example, a small business could have two sites (LUs) – one which manufactures a product and employs 10 people, and a smaller separate site which sells those products as a retail activity and employs 5 people. As a small business, it may be classified to a single RU which would take its industry classification from its main activity – which in this case is manufacturing. Employment based on RU data would show 15 people employed in manufacturing, while LU data would show 10 people employed in manufacturing while 5 people are employed in retail. As BRES and STES data are only publicly available based on LUs, this means our productivity estimates divide RU GVA data by LU labour data. This conceptual discrepancy between the numerator and denominator should be kept in mind when considering the quality of our data, as well as when comparing it with published ONS series.

Industry breakdown

The objective of this paper and accompanying dataset is to provide detailed industry breakdowns of productivity, so an obvious limitation is where we have been unable to provide additional industry detail relative to published statistics. There are two main areas: the finance and insurance industry (section K), and public services industries (notably sections O, P and Q).

The finance and insurance industry is largely not covered by the ABS, so we were unable to use this source to produce more detailed GVA estimates than the division-level breakdown available from the SUTs. There is a more detailed jobs breakdown here, that we were unable to exploit. Given the way that output in the finance industry is calculated, including through

[8] ONS labour productivity statistics also use BRES and STES data, but use a version of the data aligned to RUs for National Accounts consistency; this version of the data is not publicly available.

financial intermediation services indirectly measured (FISIM), we suspect that any further breakdowns would be challenging, and require a specialist study.

Public services are also largely not covered by the ABS, although the private elements of the education (section P) and health and social care (section Q) industries are covered. The issues on the treatment of non-market output are also particularly notable here (see discussion earlier in this section). As such, we do not provide any detail below the division-level which is available from the SUTs. The ONS public service productivity statistics provide some additional detail of productivity for service areas of the public sector, though not on a basis that is easily comparable with the estimates presented here.

Current prices

This paper has constructed estimates of productivity only in current prices (nominal terms), i.e. not adjusted for inflation. As such, the estimates in the accompanying dataset should not be used to analyse productivity growth over time, as changes will reflect a mix of price changes and 'real' changes.

The data should only be used to compare the level of productivity across industries in a given year. For instance, as in section 5, it is appropriate to identify industries that are high or low productivity relative to the average level. One could also compare industry rankings over time – for instance, if an industry is the 20th most productive in 2019, and the 15th most productive in 2023, then it appears to have become more productive relative to other industries. But one should not calculate the growth of productivity between years.

Estimating productivity for detailed industries in constant prices (real terms) presents a range of challenges. First, one would need to identify relevant price indices for industry GVA to use as deflators. This is likely to be challenging, especially in services industries where price indices are often lacking. Second, it would be considerably more challenging to ensure consistency in aggregation for constant prices than for current prices. Current prices are additive, which makes it straightforward to test and ensure additivity; this is not the case for constant price measures or chained volume measures. Third, official estimates of GVA and productivity in real terms are constructed using "double deflation" – that is, the separate deflation of output and intermediate consumption. We would need to follow the same method to be consistent at lower levels of aggregation, which would require the identification or construction of intermediate consumption deflators as well as output deflators. While output price indices are partially available, intermediate consumption deflators would need to be constructed, and the necessary detail is likely to be lacking.

4.3 Evaluation of statistical quality

In this section we test whether our estimates are of a suitable level of statistical quality. This is difficult to do objectively, and there are many dimensions of statistical quality, some of which may be at odds with each other.

Following Dunn et al. (2024), we consider a statistical production possibility frontier as representing the trade-off between a measure of granularity and a measure of reliability. Intuitively, statistics for more detailed groups (e.g. industries) are likely to require the use of data and methods which are less reliable, perhaps due to smaller sample sizes in the data collection at that degree of granularity. At the other extreme, estimates for the whole economy or a large sector are likely to be most reliable[9], since they can make use of a range

[9] Some sectors or industries might have inherently better measurement than others, such that estimates of GVA for a particular industry might be more reliable than estimates for the economy as a whole. More broadly, however, and considering domains other than GVA, this trade-off is likely to hold.

of large comprehensive datasets, and any sampling variability is likely to be offsetting. As such, there is likely a negative relationship (i.e. a trade-off) between granularity and reliability.[10]

Granularity can be measured by the number of industries in our estimates, or by their average size. Table 1 summarises the level of granularity for productivity estimates at three levels of industry detail: sections (letter-level), divisions (two-digit level), and detailed (this paper). Naturally, the breakdowns with more detail (i.e. more separately defined industries) entail industries which are smaller on average (both in terms of GVA and number of jobs).

Table 1 – Summary of granularity of different industry breakdowns

	Section-level	Division-level	Detailed
Number of industries	19	78	184
Mean number of jobs per industry (thousands, 2023)	1,818	441	197
Median number of jobs per industry (thousands, 2023)	1,601	178	78
Mean GVA per industry (£m, 2023)	113,212	27,577	11,690
Median GVA per industry (£m, 2023)	121,444	15,424	4,773

Source: ONS, authors' calculations.

Notes: The SIC 2007 classification contains 21 sections and 88 divisions, but we refer here to the breakdowns included in ONS productivity statistics, which omit some sections and divisions, and combine some divisions. See Appendix D for the full 184 industry breakdown introduced in this paper. Average jobs and GVA based on ONS productivity statistics published May 2025 for sections and divisions, and based on this paper for detailed.

Reliability could also be measured in a range of ways, and we consider two. First, in Figure 1 we define quality by the stability of the estimates over time. If our estimates for detailed industries were very volatile, with large fluctuations from year to year, we may judge them to be of low quality. Instead, if they are relatively stable between years, we may judge them to be of higher quality. Of course, some year-to-year variation is expected (indeed, desirable) due to productivity change, price change (since our estimates are in current prices), and idiosyncratic shocks affecting industries. Thus, estimates with no year-to-year variation would be implausible. Nonetheless, we suggest that lower variation should, on average, suggest higher quality estimates. Thus, we measure stability by the natural log of the standard deviation of GVA per job between 2013 and 2019[11], which we then invert since lower variation reflects higher stability (higher quality).

We measure granularity by the natural log of the number of jobs in an industry (on average between 2013 and 2019), inverted since smaller numbers reflect larger granularity. That is, a small industry will have a low number of jobs, and therefore have a high granularity. Our detailed industry estimates will typically have higher granularity than the less detailed breakdowns.

Figure 1 shows the relationship between stability and granularity of the estimates over time (as described above), for three levels of industry breakdown: i) sections (letter-level) in blue, of which there are 19; ii) divisions (two-digits) in orange, of which there are 78; and iii) our

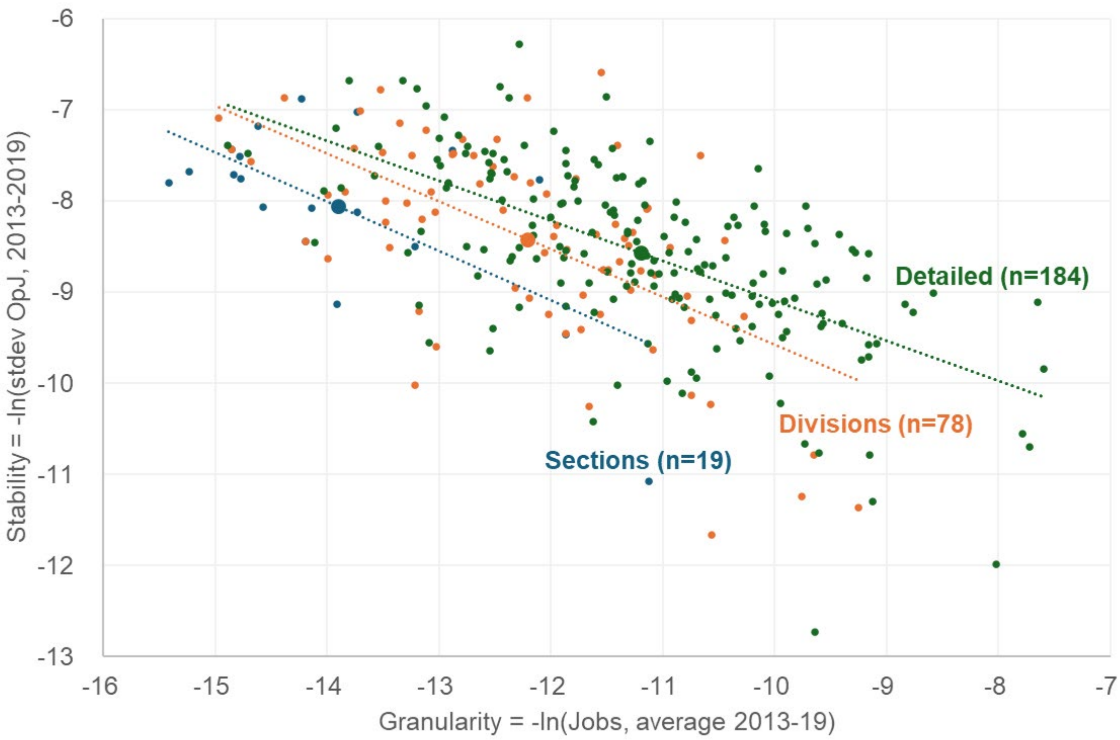
[10] A similar trade-off is likely to exist between timeliness and reliability, but the objective in this paper is not to improve timeliness.

[11] We use this period to avoid the very volatile period of the pandemic, which is likely not representative of the quality of the estimates; however, a similar finding holds when including years up to 2023. The period we use also has a relatively low rate of average price inflation (1.5% per year on average using the CPI), which limits the effect of price growth in invalidating the measure – price growth and productivity change will lead to some expected variation in productivity over the period, but lower price growth on average limits this somewhat.

detailed breakdown (green), of which there are 184. Each small dot is an industry in its respective breakdown – dots further to the right are smaller industries, and dots further to the left are larger industries; dots closer to the top have more stable estimated productivity, and dots closer to the bottom have less stable estimated productivity. The dashed lines show simple best fit lines for each of the industry breakdowns – these are all downward sloping, demonstrating the granularity-stability trade-off described above within each industry breakdown (that is, estimates for smaller industries tend to be less stable).

The large dots on the best fit lines are the mean average for granularity and stability across all industries in the respective breakdown. These points show that, on average, the industry estimates get more granular (shift to the right) and less stable (shift down) as the level of industry detail increases, consistent with expectations. However, the relationship between granularity and stability within each industry breakdown is similar, shown by the broadly parallel lines of best fit. In fact, our detailed industry breakdown represents an improvement in the trade-off between granularity and stability, since the best fit line is shifted up/out. Thus, we judge that the granularity-quality trade-off in our estimates for detailed industries is appropriate.

Figure 1 – Trade-off between granularity and stability of productivity estimates, by level of industry detail, 2013-2019



Source: ONS, authors' calculations.
Notes: The large points represent the unweighted average across industries for each breakdown, which lie on the dotted line of best fit for each breakdown. The small dots are individual industries. The x-axis shows a measure of granularity based on the number of jobs, with smaller (i.e. more granular) industries to the right. The y-axis shows a measure of stability based on the variation in the productivity estimates over time, with more stable (i.e. lower volatility) industries further up.

For a second measure of quality, we consider reliability, measured by revisions to the estimates for 2022 between data vintages. In the case of official data, revisions result from changes to the industry GVA estimates between Blue Book 2023 and Blue Book 2024, as well as revisions to the LFS and BRES causing revisions to the number of jobs estimated in each industry. For our detailed industry estimates, revisions result from those same sources, as well as revisions to the ABS between provisional and revised estimates for 2022, and any revisions to industry GVA, Workforce Jobs, and BRES at the more detailed level we use compared with the level used in official statistics.

If our estimates for detailed industries were revised significantly each year, we may judge them to be of low quality, at least in the first estimate. While revisions, particularly those resulting from Blue Book changes, will reflect a mixture of updates and improvements to source data, it will also include methodological and conceptual updates. Regardless of the cause, if data are more subject to revision, then the narratives and insights drawn from them will be less reliable. Thus, we suggest that lower revisions should suggest higher quality estimates on average.

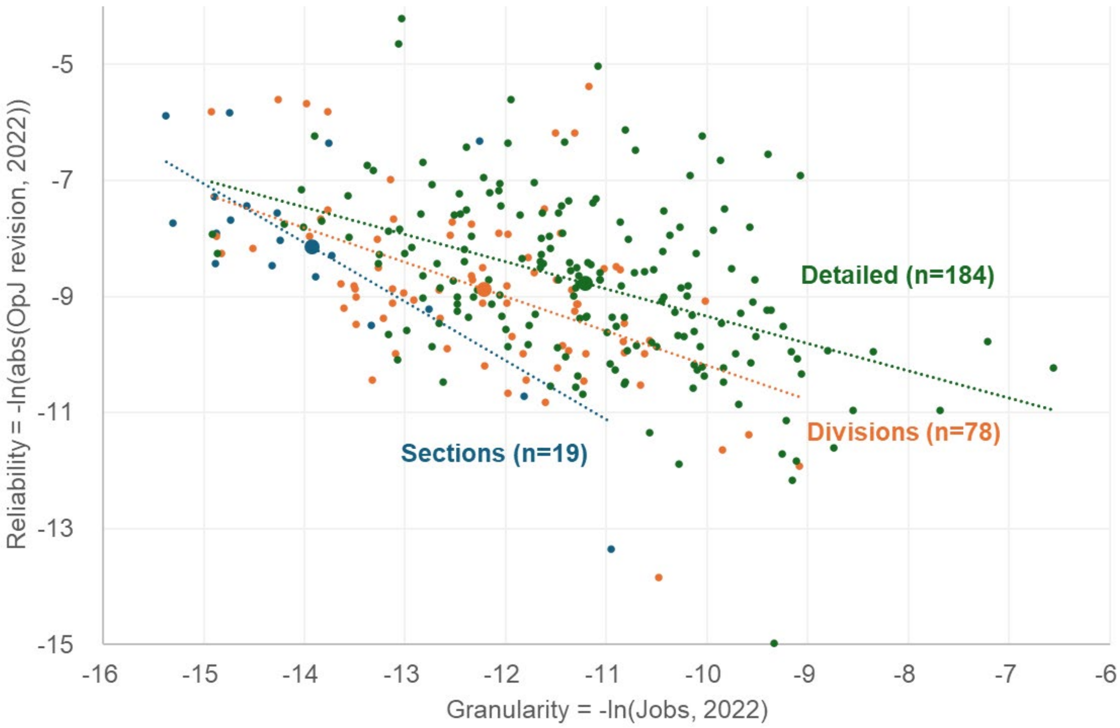
To calculate revisions to our productivity estimates for detailed industries, we re-run our methods using data available at the time of the publication of the provisional ABS data for 2022, in June 2024. This is the last of the data sources needed for our provisional estimates for 2022. We were unable to obtain the detailed BRES estimates available at the time, since nomis does not store earlier vintages of data, so use the latest vintage for this – however, we are using the Workforce Jobs estimates published in June 2024, which will be based on BRES from available at that time. Revisions for the published statistics are more readily available by comparing published data tables. In the case of the division-level breakdown, ONS temporarily suspended this due to issues with the LFS, so we use the division-level estimates published in October 2023, the latest available as at June 2024, and still on a Blue Book 2023 basis, which we consider a fair test.

Figure 2 shows the trade-off between granularity and reliability for the three levels of industry breakdown, in the same format as Figure 1. Granularity is measured by the (negative) natural log of the number of jobs in 2022, averaged across the two data vintages; dots further to the right are smaller industries, and dots further to the left are larger industries. Reliability is measured by the (negative) natural log of the absolute revision to GVA per job in 2022; dots closer to the top are industries that see smaller revisions (more reliable), and dots closer to the bottom are industries that see larger revisions (less reliable).

Similar to findings in Figure 1, we find that the best fit lines across industries within each industry breakdown (dotted lines) are downward sloping, reflecting the granularity-reliability trade-off – that is, smaller industries tend to see bigger revisions.[12] The large dots on the best fit lines show that revisions are on average smaller for the section-level industries, and similar for the division-level and detailed industry breakdowns. In fact, the average revision in our estimates is marginally smaller than the average estimate in the division-level breakdown, though the timing of that dataset is slightly different. The granularity-reliability trade-off (dotted line) is further out for our detailed industry breakdown than for the two less-detailed breakdown, which suggests that smaller revisions on average given the size of the industries. As such, we again judge that the granularity-quality trade-off in our estimates for detailed industries is appropriate.

[12] A major outlier is the revision to the oil and gas extraction industry (division 06), and similarly the mining and quarrying industry (section B), but excluding these points does not materially alter the findings.

Figure 2 – Trade-off between granularity and reliability of productivity estimates, by level of industry detail, 2022



Source: ONS, authors' calculations.
Notes: The large points represent the unweighted average across industries for each breakdown, which lie on the dotted line of best fit for each breakdown. The small dots are individual industries. The x-axis shows a measure of granularity based on the number of jobs, with smaller (i.e. more granular) industries to the right. The y-axis shows a measure of reliability based on revisions to the productivity estimates, with more reliable (i.e. smaller revisions) industries further up.

5. Applications

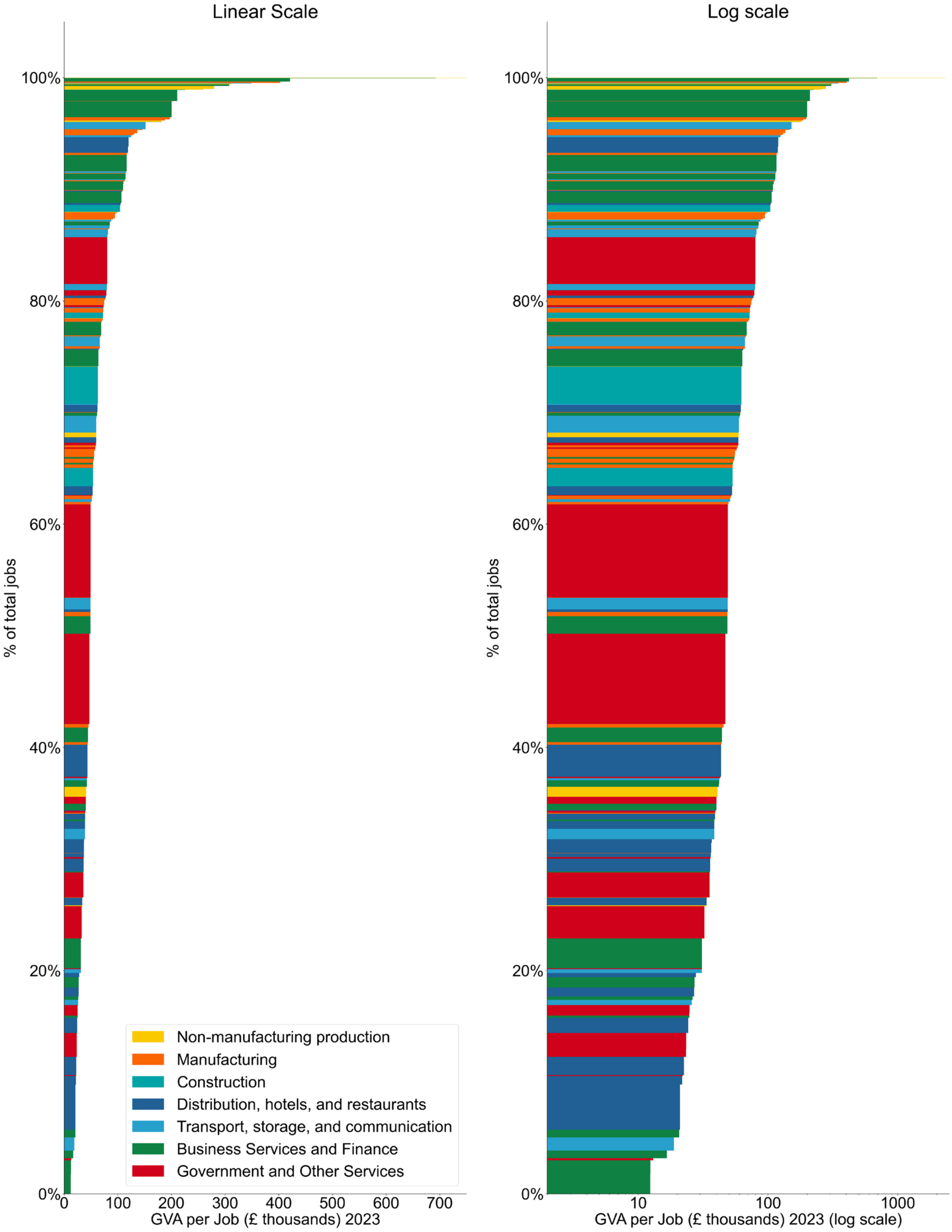
This section briefly presents two applications of the detailed industry productivity estimates constructed in this paper.

5.1 Distribution of productivity across industries

One key use of more detailed productivity statistics is to get a better idea of the distribution of productivity in the UK. Figure 3 summarises this distribution by showing the GVA per job of our detailed industries as a bar chart, where the horizontal width of each bar shows the level of GVA per job of an industry in 2023, while the height of each bar shows the percentage of total jobs in that industry. In this way it is possible to both look at the relative productivity of different industries while also getting a sense of the "size" of the industry.

Before turning to what these data can tell us about productivity in the UK, it is worth highlighting what Figure 3 tells us about the data itself. There is substantial variation in the heights of the bars – reflecting the fact that our detailed industries are very heterogenous in terms of their respective job shares. The cause of this is made clearer when focussing on the colours of the bars; each detailed industry has been categorised into a high-level industry grouping. This makes clear that, for example, there is very fine detail in our manufacturing data (in orange) as the height of many of the orange bars is very small. But our granularity in Government and Other Services (in red) is substantially more high level. Other industry groupings are more varied, containing some areas of fine detail but other areas of more aggregation.

Figure 3 – GVA per job (£k) and share of total jobs (%) by industry, 2023



Source: Authors' calculations based on ONS data.
Notes: Left panel shows productivity estimates on a linear scale, with the highest-productivity industry (B06 Oil & Gas extraction) extending beyond the x-axis limit. Right panel shows productivity estimates on a log scale.

A key feature of the distribution of GVA per job which Figure 3 highlights is its exponential shape. The panel on the left side shows GVA per job, using a linear scale on the x-axis. Using a linear scale highlights those highest productivity industries towards the top of the chart, where productivity levels increase rapidly as we approach the top of the distribution.

So, for example, the productivity of the industry at the 5th percentile of the distribution is about £18,900 compared with about £21,800 at the 10th percentile, an increase of about £2,900. In contrast the difference between the 90th and 95th percentiles are £109,400 and £130,700 respectively, a difference of £21,300. The extent of this curve is such that the x-axis has been truncated to end at £750,000 for practicality, meaning the width of the highest productivity industry is not visible – Extraction of crude petroleum and natural gas, which has a GVA per job of £2.32m.

The exponential nature of the distribution can make it difficult to compare productivity levels between industries towards the lower end of the distribution. For this reason, Figure 3 also includes a right-side panel where the x-axis, which measures GVA per job, uses a log scale. Doing this confirms the exponential shape of much of the distribution, as now there is a roughly linear increase in the width of the bars (representing their GVA level) as we move up the chart.

However, this in turn helps draw out a second general insight: while the width changes in a roughly linear way through the centre of the distribution, representing a fairly steady exponential distribution, this is not the case in the tails. At both the lower and higher end of the distribution, the gradient is sharper. This means that the log difference in productivity between, for example, the 1st and 5th percentiles is bigger than between the 21st and 25th percentiles, or that the log difference between the 95th and 99th percentiles is bigger than between the 75th and 79th. This is a similar narrative to that found in the firm-level literature, which has highlighted the prominence of "superstars" and "laggards" in the productivity distribution, and may have an important role in determining productivity dynamics in the UK.

Another key observation which Figure 3 draws out is the dispersion of productivity levels within high-level industry groupings, which adds nuance to some of the well discussed features of the industry dynamics of productivity in the UK. A prime example of this is manufacturing, often acknowledged as a high-productivity industry. While this is true on average as well as for many of the manufacturing sub-industries, our data highlight that not all detailed industries within manufacturing are high productivity. Several manufacturing industries lie below the 2023 (employment weighted) whole economy median of £46,900 per job. These are:

- 10.7 Manufacture of bakery and farinaceous products (£45,600 per job)
- 16.2 Manufacture of products of wood, cork, straw and plaiting materials (£43,800 per job)
- 32.9 Manufacturing not elsewhere classified (£39,100 per job)
- 30.2/4/9 Manufacture of railway locomotives and rolling stock, military fighting vehicles, and transport equipment not elsewhere classified (£36,500 per job)
- 10.2 Processing and preserving of fish, crustaceans and molluscs (£34,000)
- 10.4 Manufacture of vegetable and animal oils and fats (£2,800)[13]

Overall, according to our estimates, about 10% of manufacturing jobs are in manufacturing sub-industries with below-median productivity. This does not contradict manufacturing being high productivity in general, but it highlights the extent to which generalisations about productivity levels at one level of aggregation belie a more nuanced story at lower levels; this could be said of many industry groups. As such, it highlights the importance of lower-level

[13] It is worth noting that 10.4 is a particularly small industry, making up only 0.0003% of UK GVA in 2023, so this figure should be treated with caution. There is also a large discrepancy between the data in the Supply and Use Tables, and that in the Annual Business Survey, but since this industry is separately identified in the SUTs, we use this figure.

estimates of productivity in understanding more precisely which areas of the economy have what level of productivity.

At the top end, the most productive industries in 2023 included many industries that would be expected. Many are capital intensive, reflecting the fact that these are labour productivity measures, and so variations in capital input are not accounted for. While the lack of account of capital input is a limitation of all labour productivity measures, which are widely used, it is especially a problem when comparing productivity levels across industries (rather than growth rates, since capital input usually grows slowly), and for detailed industries where the variation in capital intensity can be greater than for more aggregate industries.

Interesting amongst the top 10 most productive industries in 2023 (listed below in order) are three that might go under the radar in the absence of the more detailed estimates constructed here: Leasing of intellectual property products; Renting and leasing of motor vehicles; and Construction of electricity and telecoms utility projects.

1. B06: Extraction of crude petroleum and natural gas
2. N77.4: Leasing of intellectual property and similar products, except copyrighted works
3. K65: Insurance, reinsurance and pension funding, except compulsory social security
4. C21: Manufacture of basic pharmaceutical products and pharmaceutical preparations
5. H50: Water transport
6. E37: Sewerage
7. N77.1: Renting and leasing of motor vehicles
8. D35.1: Electric power generation, transmission and distribution
9. D35.2-3: Manufacture of gas; distribution of gaseous fuels through mains (D35.2) and Steam and air conditioning supply (D35.3)
10. F42.22: Construction of utility projects for electricity and telecommunications

5.2 Bespoke industry aggregations

The derivation of GVA and jobs estimates for detailed industries allows the construction of bespoke industry aggregations, including aggregations across boundaries imposed by the SIC hierarchy. This section considers one such application of bespoke aggregations: the sectors defined for the UK Government's 2025 Industrial Strategy.

Table 2 summarises an approach to constructing productivity measures for the Industrial Strategy (IS) sectors, based on the SIC codes identified in the Industrial Strategy Sector Definitions List (DBT, 2025). In several cases our estimates are not sufficiently detailed to measure the IS sector precisely, and we use either a higher-level aggregate (including activity that should not be included) or omit the component entirely (excluding activity that should be included). However, we judge that the approximations made in Table 2 are reasonable to measure these sectors. In cases where we are unable to make a close approximation, we have not made an estimate.[14] Of the 16 sectors defined in Table 2, only 6 would have been possible from official productivity estimates.

[14] These include: Batteries; Agritech; Film and TV; Music, performing, and visual arts; Defence; Asset management and wholesale services; Capital markets and retail investment; Insurance and reinsurance markets; Electricity networks; Foundational: Ports.

Table 2 – Approach to estimating productivity of Industrial Strategy sectors using the industry estimates in this paper

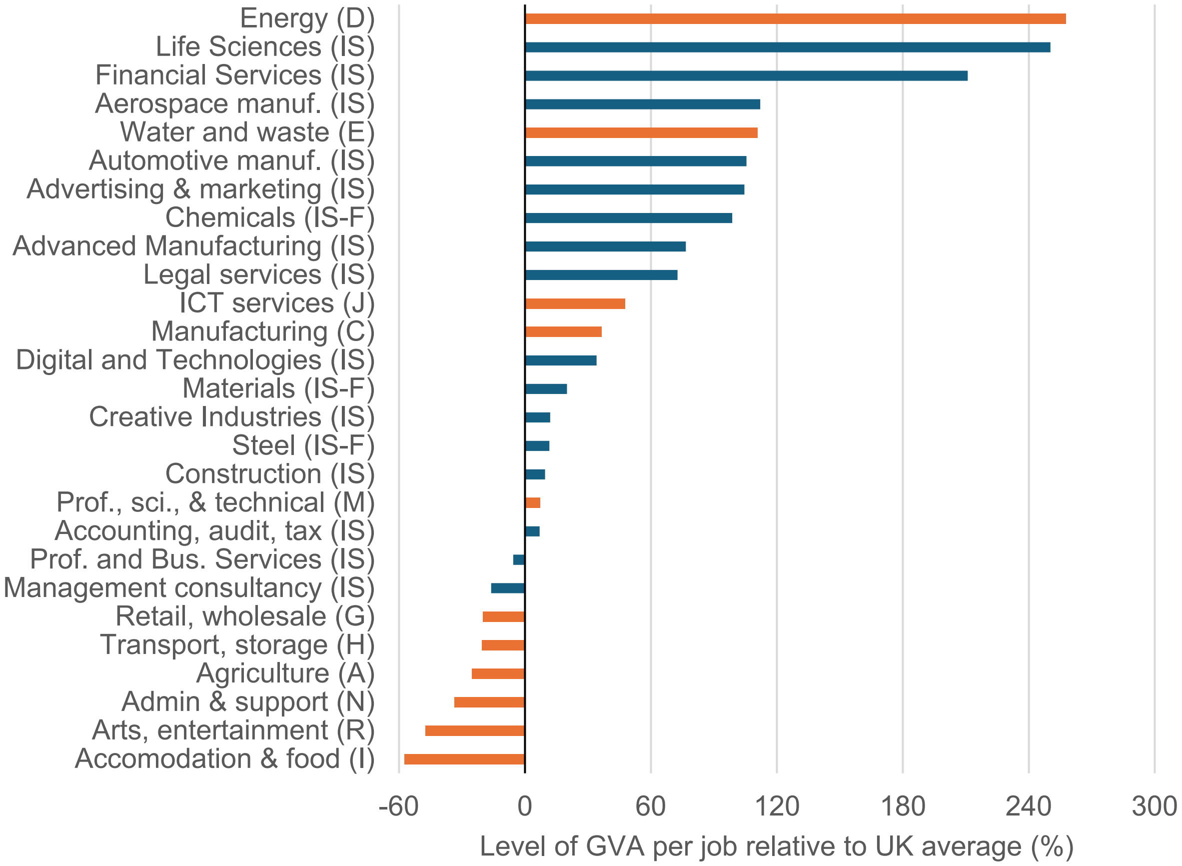
Industrial Strategy sector	SIC codes included in our measure	Omissions and approximations
Advanced manufacturing	20, 26, 27, 28, 29, 30	
Aerospace manufacturing	30.3, 33.16	
Automotive manufacturing	29	
Creative industries	58, 59, 60, 62.01, 62.02, 71.11, 73.1, 74.1, 74.2-3, 90, 91.01-02	32.12 missing (32.1-4 considered too imprecise); 70.2 missing (70.21 considered too imprecise); 85.52 missing (85 considers too imprecise)
Advertising and marketing	73.1	70.21 missing (70.2 considered too imprecise)
Digital and technologies	26.1, 26.2-4, 26.5/7-8*, 27.3-9, 46.5, 58, 59, 60, 61, 62, 63, 71.12, 71.2, 72*, 95.1	26.5/7-8 approx for 26.511, 26.512, 26.513, 26.701, 26.8; 27.3-9 approx for 27.31, 27.32, 27.9; 72 approx for 72.1
Financial services	64, 65, 66	
Life sciences	21, 26.6, 32.5	72.11 missing (72 considered too imprecise)
Professional and business services	69, 70, 71, 72, 73, 74, 77, 78, 82	
Accounting, audit and tax consultancy	69.2	
Legal services	69.1	
Management consultancy	70.2	
Foundational: Chemicals	20	
Foundational: Construction	41, 42, 43	
Foundational: Materials	23.1-4/7-9*, 23.5-6	23.1-4/7-9 approx for 23.1, 23.2, 23.3, 23.4
Foundational: Steel	24.1-3	

Notes: SIC codes with asterisks indicate approximations described in the third column. Aggregation of some lower-level industries as necessary (not shown).

Figure 4 shows how the estimated labour productivity of these industries relate to the productivity of more traditional industry groupings, and the economy as a whole. The bars show the industry's productivity (GVA per job) relative to the UK economy as a whole (excluding imputed rental), represented by the vertical line at zero. For instance, manufacturing (C) is at 36, i.e. 36% more productive on average that the economy as a whole. The Industrial Strategy sectors, for which we were able to construct estimates (Table 2) are shown in blue bars, and a selection of traditionally-measured industries (SIC 2007 sections) are in orange.

The majority of IS sectors for which we were able to construct productivity measures have productivity above the UK average. This conforms with analysis included in the Industrial Strategy White Paper, which estimated that the combined eight sectors of the Industrial Strategy (IS-8) were 27.1% more productive than the UK average (DBT, 2025; p.20). Note that the IS sectors can be overlapping, and that we have not made estimates for the combination of the IS sectors defined in Table 2. Notably, we did not make an estimate for the Clean Energy IS sector, but the energy industry of SIC 2007 (section D) is the most productive in Figure 4. The least productive industries in Figure 4 are several consumer-facing industries, and relatively more labour-intensive industries.

Figure 4 – Relative productivity of various industries including Industrial Strategy sectors, 2022-23 average



Source: ONS, Industrial Strategy Definitions List, authors' calculations.
Notes: Whole economy average excludes imputed rental. Industrial Strategy sectors (blue) based on estimates in this paper; SIC 2007 sections (orange) based on ONS "output per job" estimates from May 2025. Relative levels calculated in current prices, and then averaged over 2022 and 2023 to improve representativeness. Letters in brackets refer to SIC 2007 sections where appropriate, or signify Industrial Strategy (IS) sectors, including "Foundational" IS sectors (IS-F).

6. Conclusion

This paper has advanced the statistical landscape for UK productivity analysis by developing estimates of labour productivity for 184 industries spanning the entire economy. We believe that these estimates represent a good trade-off between granularity and quality on average, in line with or surpassing official estimates in this regard. There are many potential applications of the data, of which we have showcased just two. One insight gained from these applications is that there is considerable variation in the level of productivity within high-level industry groups, such as manufacturing.

We conclude with some considerations to extend these estimates in future work. First, estimates of productivity in constant prices (real terms, i.e. adjusted for inflation), which enable analysis of productivity growth over time, are likely to be of considerable interest. This would require the identification of relevant price indices to use as deflators for GVA. Official estimates of industry-level GVA constructed by ONS use "double deflation" – that is, the separate deflation of output and intermediate consumption. To produce consistent estimates for detailed industries would therefore require the identification of relevant deflators for both output and intermediate consumption for each detailed industry, which is likely to be challenging. Ensuring consistency in aggregation is also considerably harder for estimates in constant prices, than for estimates in current prices.

If estimates in constant prices were available, then a longer historic time series would likely be valuable in order to analyse the slowdown in productivity growth over time. The UK, like most advanced economies, experienced a slowdown in productivity growth from around the mid-2000s and the global financial crisis. Our estimates currently start in 2009, which would not enable an analysis of a slowdown in productivity growth relative to the pre-slowdown period. Extending the time series historically would be hampered by the change in the industry classification from SIC 2003 to SIC 2007, applied to data sources typically from 2008 or 2009. Two of our key data sources – BRES and ABS – were also introduced around this time, replacing earlier similar surveys. Bridging these discontinuities would be feasible, but likely challenging in places. This is only likely to be important if estimates in constant prices are feasible.

Second, some areas of the industry classification remain relatively coarse, including the financial services industry and the government-dominated industries of public administration, education, and health and social care. Increasing industry detail in these areas, as well as other industries that remain relatively large in our breakdown, would be worthwhile. However, data limitations are likely to make this challenging, as financial services and most of the public sector are not covered by the Annual Business Survey (ABS) – a key data source in our method. As such, additional data sources would likely be necessary to increase industry detail in these areas.

Third, some methodological changes to improve alignment with National Accounts concepts and increase quality would be possible with the use of additional (especially, non-public) data sources. One clear candidate is the treatment of non-market output, for which data on research and development (R&D) and own-account software investment could be used. This would add complexity to the estimates for relatively small gain in most cases, but would be a clear conceptual improvement. For other methodological limitations, it would likely not be feasible to improve them without the use of non-public data, while this paper has prioritised the use of publicly-available data sources and transparent methods. For instance, estimates of self-employment for more detailed industries would be feasible using the Labour Force Survey (LFS) microdata, but this level of detail is not published. The use of alternative data sources, such as from websites or social media data, could extend coverage but would likely not be representative or conceptually appropriate. The benefits of using non-public data on the estimates may be outweighed by the loss of reproducibility.

Finally, it would be valuable to have accompanying estimates of other variables at the same level of industry granularity, to enable richer analysis. For instance, estimates of capital input could enable production function estimation and shed more light on productivity levels relative to labour productivity estimates. Developing other estimates at a similar level of industry detail would require further research.

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Appendix A – Northern Ireland Employee Estimates

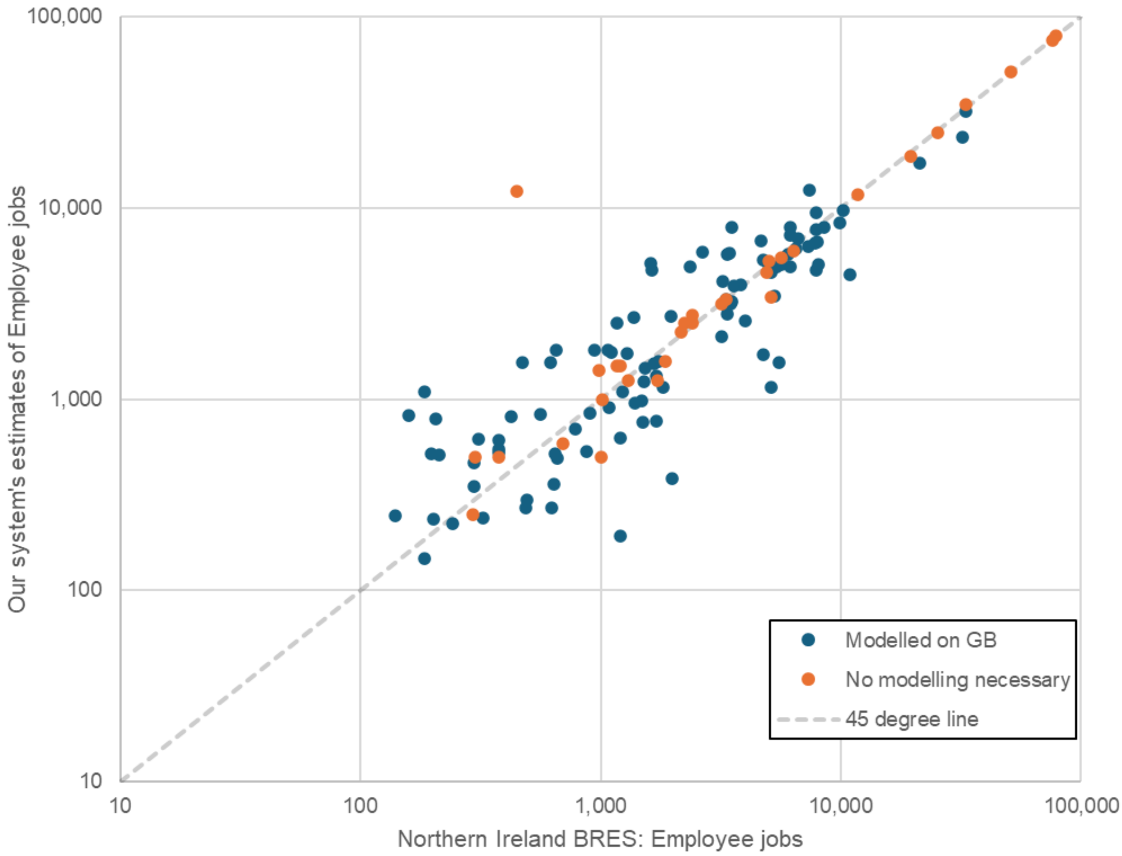
A separate approach to estimate employee jobs for Northern Ireland would be to use the Northern Ireland Business Register and Employment Survey (hereafter NI-BRES) estimates, published by the Northern Ireland Statistics and Research Agency (NISRA). However, the published estimates contain suppression to avoid disclosure, which prevents the use of this data source to comprehensively create employee job estimates at the same level of industry detail as the Great Britain (GB) estimates used in this article. For this reason, we did not use this data source and instead opted to apportion division level estimates of Northern Ireland (NI) employee jobs down to a more detailed level used the portions observed in the GB employee data. To be clear, this still preserved the “real” NI data at the division level, but at more granular levels of industry detail the estimates are modelled based on GB patterns.

However, despite the NI-BRES data being incomplete, it can be used to assess the quality of the apportionment model we have used. By comparing our “modelled” estimates to the “real” estimates from NI-BRES in industries which have not been supressed in the NI-BRES publication, this gives us a sense of the accuracy our modelling approach. This is done in Figure C1 which has a scatter of blue dots, each representing a detailed industry, where their x value is the “real” 2022 NI employee jobs number from NI-BRES, while their y value is the modelled estimate we create. An additional set of orange dots are also shown – these represent the industries where no apportionment/modelling is necessary in our processing. As such, these orange dots serve as a control-group of sorts, as the only different between x and y values for these dots will represent differences in rounding between data sources, as well as any additional processing we do to the data (such as interpolating an annual average from point-in-time estimates).

A first point to note is the outlier amongst the orange dots towards the upper left of the scatter; this represents division 01: Crop and Animal Production, Hunting and Related Service Activities (i.e. a division of Agriculture). Within the Workforce Jobs statistics which are used in this paper’s methodology for calculating NI employee jobs, division 01 supplements data from the business-based jobs surveys with data from the Labour Force Survey, which accounts for intentional under-coverage of this division within the business surveys. In contrast, the NI-BRES data is from a single, business-based source, and so under-covers this division. The result is a large difference between our NI employee jobs estimate (12,333) and the NI-BRES based estimate (448), which while large is to be expected and so is treated as an outlier in the analysis that follows.

In general, while there is broad alignment between our estimates and the data from NI-BRES, there does remain substantial variation. The mean absolute log deviation of the blue dots (those industries which required modelling in our data) is 0.205, i.e. on average there is around a 20.5% difference between our estimates and NI-BRES. This compares with 0.06 for the orange dots, excluding the outlier of division 01. The root squared mean log deviation of the blue dots – which is a similar measure but places a greater weight on larger deviations – is 0.28. This compares with 0.10 for the orange dots. In both cases it is clear that the deviations are larger when modelling is necessary, but a sizable amount of deviation still exists even without modelling. In this context, while this shows the modelling does have inaccuracies, it approximates the broad nature of the data well.

Figure C1 – Employee jobs for Northern Ireland, 2022, by detailed industries, using different data sources / methods



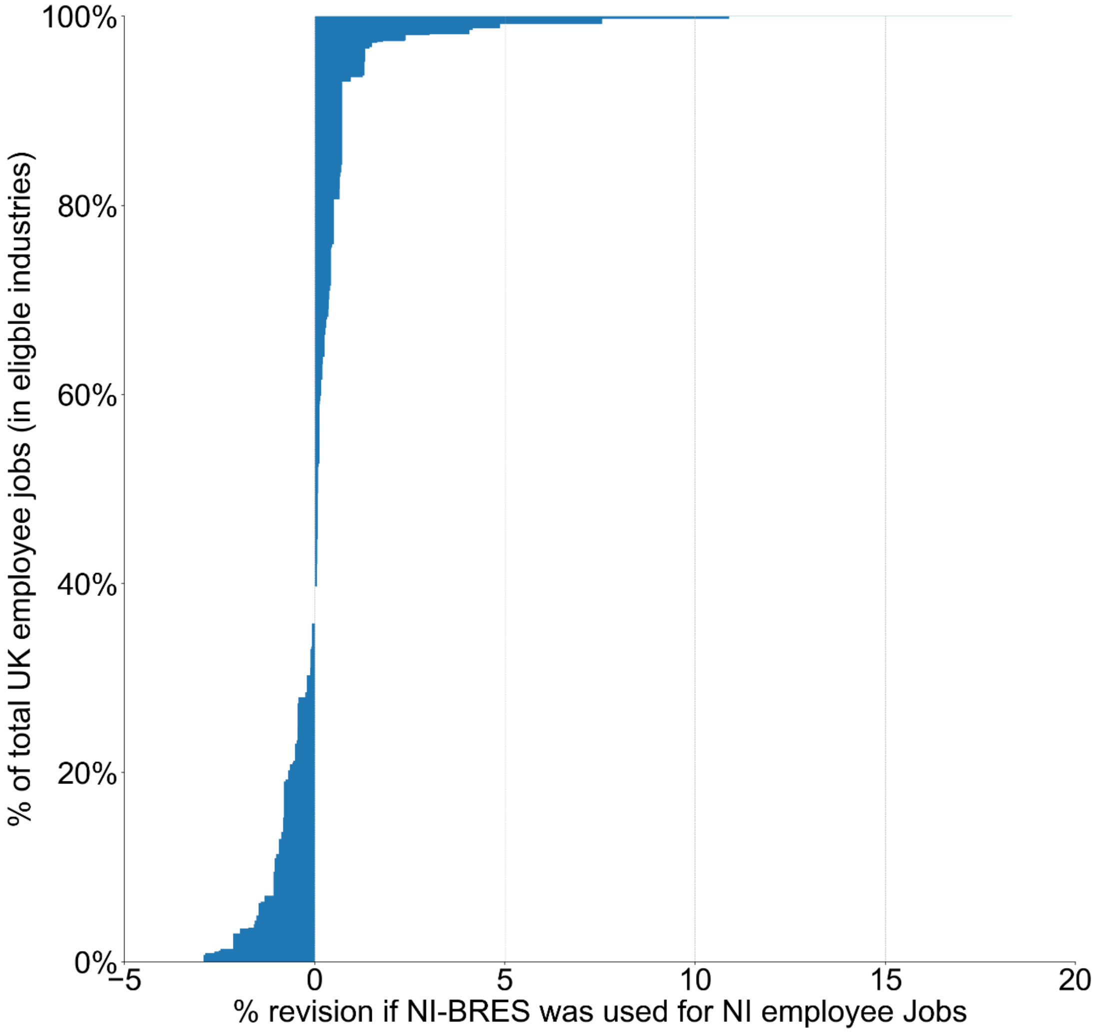
Source: Authors' calculations based on ONS and NISRA data.

The key test for the acceptability of the NI modelling is the impact it has on the UK figures, the construction of which is the intention of this article rather than an NI-specific breakdown. Figure C2 shows an indicative estimate of the revision size to our detailed industry estimates if the NI-BRES data were used. The horizontal width of the bars indicates the size of the revision as a percentage (on the x-axis), while the vertical height of the bars measures the size of the industry. This 'size' is measured using our estimates of employee jobs in each industry, as a percentage of the total amount of UK employees for which we can do this revisions analysis (i.e. accounting for the fact not all industries have published values in the NI-BRES dataset). Sizing the bars in this way helps not just understand the size of the potential revision on that industry, but also gives a sense of how impactful that revision may be. A 3% revision in a very large industry (reflecting a differences of thousands of people), for example, may be more impactful than a 3% revision in a very small industry (reflecting a difference of tens of people).

This sensitivity check provides an overall positive but mixed picture. Weighting by their size, 94.3% of industries would see a revision of less than 2%. Given the granularity of these data, and the differences in processing we introduce (e.g. calculating annual averages rather than point-in-time estimates), some amount of difference is to be expected, and less than 2% is a reasonable amount which should ensure trends and narratives in the data are robust.

However, there are cases where the revisions could potentially be much larger in percentage terms. Industry 42.22 (Construction of utility projects for electricity and telecommunications) sees the largest percentage revision, of 18.3%. In absolute terms, this represents an increase from our estimate of 8,676 to an estimate of 10,266, a difference of 1,590 jobs. Two other industries see indicative revisions over 5%; 47.3 (Retail sale of automotive fuel in specialised stores, with a revision of 10.9%) and 10.1 (Processing and preserving of meat and production of meat products, with a revision of 7.6%). These are all relatively small industries, each with less than 100,000 employee jobs according to other estimates.

Figure C2 – Indicative estimates of revisions if NI-BRES were used, by industry, 2022



Source: Authors' calculations based on ONS and NISRA data.

There are three key take aways from this sensitivity analysis. The first is that, overall, our estimation methodology for NI is fairly robust given that our aim is to estimate jobs at the UK level. The second is that care should be taken when focusing on individual industries where those industries are particularly small. We would encourage this as good statistical practice in general, but this gives a concrete example of why such caution is advisable. So, for example, small differences in estimates between small industries should not be overinterpreted – industries with a few % difference in productivity or jobs should be treated as being broadly similar rather than one industry being more/less productive than the other. Finally, this shows one of the ways these detailed productivity data could be improved in the future. A more complicated data process could see improvements by incorporating the NI-BRES data; but would need to accommodate both the missingness of the data (which may change from year-to-year) as well as the absence of these data in all but the most recent years.

Appendix B – Illustration of ABS imputation for supressed cells

Table B1 illustrates the ABS imputation for supressed cells used in our method as described in section 3.1 of the main text, using illustrative data based loosely on industry group 26.7. The second row details the derivation of each column. Cells coloured green (2012, 2016, 2017, 2020) use linear interpolation of the shares (equivalent to averaging of adjacent years in the case of only one missing year). Cells coloured blue (2008, 2009) hold the share constant for the years before the first observation, based on an average of the two subsequent years (in this case, 2010 and 2011) to dampen the effect of yearly volatility. Cells coloured orange (2022 and 2023) hold the share constant for the years after the last observation, based on only one preceding year (in tis case, 2021) given that is all that is available. These are then rescaled to ensure additivity up the industry hierarchy, as illustrated in the subsequent columns.

Table B1 – Workings for the imputation of supressed cells in the ABS for a stylised case

Year	Published turnover for group (£)	Published turnover for division (£)	Group share (%)	Group share interpolated and extrapolated (%)	Imputed group turnover (£)	Sum of published groups in division (£)	Supressed total to be allocated (£)	Sum of imputed group turnovers (£)	Rescaled group imputed (£)	Final series (£)
	a	b	c=a/b	d=c with extensions	e=d*b	f=sum(e) across all published groups in division	g=b-f	h=sum(e) across all imputed groups in division	i=e*(g/h)	j=a and i combined
2008		21,343		3.37	720	20,643	700	734	686	686
2009		17,802		3.37	600	17,247	555	616	541	541
2010	630	20,033	3.14	3.14		20,033				630
2011	705	19,592	3.60	3.60		19,592				705
2012		18,358		3.78	694	17,440	918	713	893	893
2013	778	19,642	3.96	3.96		19,642				778
2014	936	19,225	4.87	4.87		19,225				936
2015	814	18,773	4.34	4.34		18,773				814
2016		20,379		4.09	834	19,480	899	876	856	856
2017		22,451		3.85	865	21,642	809	877	798	798
2018	833	23,059	3.61	3.61		23,060				833
2019	965	23,389	4.13	4.13		23,389				965
2020		20,613		4.09	843	19,854	759	859	745	745
2021	896	22,084	4.06	4.06		22,085				896
2022		24,737		4.06	1004	23,606	1,131	1013	1,121	1,121
2023		26,340		4.06	1069	25,340	1,000	1080	990	990

Appendix C – Illustrative examples of constructing annual estimates of jobs

The text described the methods we use to construct annual estimates of jobs from Workforce Jobs and BRES. This appendix shows a worked example for each.

In order to produce an estimate of annual jobs from the end-quarter month data published in Workforce Jobs, we take a weighted average of the data using weights of 3/12 for each of March, June and September, 2/12 for December of the reference year, and 1/12 for December of the previous reference year, as shown in Table C1.

Table C1 – Illustration of estimating annual average from Workforce Jobs

Year	Month	Published	Interpolated monthly	Quarterly averages	Annual average
2022	Sep	108			
2022	Oct				
2022	Nov				
2022	Dec	90	**90**		
2023	Jan		100		
2023	Feb		110	110	
2023	Mar	120	**120**		
2023	Apr		130		
2023	May		140	140	
2023	Jun	150	**150**		
2023	Jul		145		126.25
2023	Aug		140	140	
2023	Sep	135	**135**		
2023	Oct		125		
2023	Nov		115	115	
2023	Dec	105	**105**		

In order to produce an estimate of annual jobs from the point-in-time data collected each September in BRES, we construct an estimate for the year midpoint (June) as a weighted average of the current and previous year's September values, with weights of 9/12 and 3/12 respectively, as show in Table C2. Strictly this is an annual midpoint rather than an annual average, but the loss of accuracy is small and the potential loss of timeliness would be large.

Table C2 – Illustration of estimating annual midpoint from BRES

Year	Month	Published	Interpolated monthly	Annual midpoint
2022	Sep	80	**75**	
2022	Oct		80	
2022	Nov		85	
2022	Dec		90	
2023	Jan		95	
2023	Feb		100	
2023	Mar		105	
2023	Apr		110	
2023	May		115	
2023	Jun		120	120
2023	Jul		125	
2023	Aug		130	
2023	Sep	135	**135**	
2023	Oct			
2023	Nov			
2023	Dec			

Appendix D – Descriptions of the 184 industry breakdown used in this paper

SIC 2007 Code	Industry Description
A01	Crop and animal production, hunting and related service activities
A02	Forestry and logging
A03	Fishing and aquaculture
B05	Mining of coal and lignite
B06	Extraction of crude petroleum and natural gas
B07	Mining of metal ores
B08	Other mining and quarrying
B09	Mining support service activities
C10.1	Processing and preserving of meat and production of meat products
C10.2	Processing and preserving of fish, crustaceans and molluscs
C10.3	Processing and preserving of fruit and vegetables
C10.4	Manufacture of vegetable and animal oils and fats
C10.5	Manufacture of dairy products
C10.6	Manufacture of grain mill products, starches and starch products
C10.7	Manufacture of bakery and farinaceous products
C10.8	Manufacture of other food products
C10.9	Manufacture of prepared animal feeds
C11.01-6 & 12	Manufacture of tobacco products (C12) and beverages excluding soft drinks, mineral waters, and other bottled waters (C11.01-06)
C11.07	Manufacture of soft drinks; production of mineral waters and other bottled waters
C13	Manufacture of textiles
C14	Manufacture of wearing apparel
C15	Manufacture of leather and related products
C16.1	Sawmilling and planing of wood
C16.2	Manufacture of products of wood, cork, straw and plaiting materials
C17.1	Manufacture of pulp, paper and paperboard
C17.2	Manufacture of articles of paper and paperboard
C18.1	Printing and service activities related to printing
C18.2	Reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20.11/13/15	Manufacture of industrial gases (C20.11), other inorganic basic chemicals (C20.13), and fertilisers and nitrogen compounds (C20.15)
C20.12/20	Manufacture of dyes and pigments (C20.12) and pesticides and other agrochemical products (C20.20)
C20.14/16/17/60	Manufacture of other organic basic chemicals (C20.14), plastics in primary forms (C20.16), synthetic rubber in primary forms (C20.17), and man-made fibres (C20.60)
C20.3	Manufacture of paints, varnishes and similar coatings, printing ink and mastics
C20.4	Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations
C20.5	Manufacture of other chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22.1	Manufacture of rubber products
C22.2	Manufacture of plastics products
C23.1-4/7-9	Manufacture of glass and glass products (C23.1), refractory products (C23.2), clay building materials (C23.3), other porcelain and ceramic products (C23.4), Cutting, shaping and finishing of stone (C23.7), and abrasive products and non-metallic mineral products n.e.c. (C23.9)
C23.5-6	Manufacture of cement, lime and plaster (C23.5) and articles of concrete, cement and plaster (C23.6)
C24.1-3	Manufacture of basic iron and steel and of ferro-alloys (C24.1), tubes, pipes, hollow profiles and related fittings, of steel (C24.2), and other products of first processing of steel (C24.3)
C24.4-5	Manufacture of basic precious and other non-ferrous metals (C24.4) and Casting of metals (C24.5)
C25.1	Manufacture of structural metal products
C25.2-3	Manufacture of tanks, reservoirs and containers of metal (C25.2) and steam generators, except central heating hot water boilers (C25.3)
C25.4	Manufacture of weapons and ammunition
C25.5/7/9	Forging, pressing, stamping and roll-forming of metal; powder metallurgy (C25.5), Manufacture of cutlery, tools and general hardware (C25.7), and Manufacture of other fabricated metal products (C25.9)
C25.6	Treatment and coating of metals; machining

C26.1	Manufacture of electronic components and boards
C26.2-4	Manufacture of computers and peripheral equipment (C26.2), communication equipment (C26.3), and consumer electronics (C26.4)
C26.5/7-8	Manufacture of instruments and appliances for measuring, testing and navigation; watches and clocks (C26.5), optical instruments and photographic equipment (C26.7), and magnetic and optical media (C26.8)
C26.6	Manufacture of irradiation, electromedical and electrotherapeutic equipment
C27.1-2	Manufacture of electric motors, generators, transformers and electricity distribution and control apparatus (C27.1) and batteries and accumulators (C27.2)
C27.3-9	Manufacture of wiring and wiring devices (C27.3), electric lighting equipment (C27.4), domestic appliances (C27.5), other electrical equipment (C27.9)
C28.1-2	Manufacture of general-purpose machinery (C28.1) and other general-purpose machinery (C28.2)
C28.3-9	Manufacture of agricultural and forestry machinery (C28.3), metal forming machinery and machine tools (C28.4), and other special-purpose machinery (C28.5)
C29.1	Manufacture of motor vehicles
C29.2-3	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers (C29.2) and parts and accessories for motor vehicles (C29.3)
C30.1	Building of ships and boats
C30.2/4/9	Manufacture of railway locomotives and rolling stock (C30.2), military fighting vehicles (C30.4), and transport equipment n.e.c. (C30.9)
C30.3	Manufacture of air and spacecraft and related machinery
C31	Manufacture of furniture
C32.1-4	Manufacture of jewellery, bijouterie and related articles (C32.1), musical instruments (C32.2), sports goods (C32.3), and games and toys (C32.4)
C32.5	Manufacture of medical and dental instruments and supplies
C32.9	Manufacturing n.e.c
C33.11-14/17/19/20	Repair of fabricated metal products (C33.11), machinery (C33.12), electronic and optical equipment (C33.13), electrical equipment (C33.14), Repair and maintenance of other transport equipment (C33.17), Repair of other equipment (C33.19), and Installation of industrial machinery and equipment (C33.20)
C33.15	Repair and maintenance of ships and boats
C33.16	Repair and maintenance of aircraft and spacecraft
D35.1	Electric power generation, transmission and distribution
D35.2-3	Manufacture of gas; distribution of gaseous fuels through mains (D35.2) and Steam and air conditioning supply (D35.3)
E36	Water collection, treatment and supply
E37	Sewerage
E38	Waste collection, treatment and disposal activities; materials recovery
E39	Remediation activities and other waste management services
F41.1	Development of building projects
F41.2	Construction of residential and non-residential buildings
F42.1+42.99	Construction of roads and railways (F42.1) and other civil engineering projects n.e.c. (F42.99)
F42.21+42.91	Construction of utility projects for fluids (F42.21) and Construction of water projects (F42.91)
F42.22	Construction of utility projects for electricity and telecommunications
F43	Specialised construction activities
G45.1	Sale of motor vehicles
G45.2	Maintenance and repair of motor vehicles
G45.3-4	Sale of motor vehicle parts and accessories (G45.3) and Sale, maintenance and repair of motorcycles and related parts and accessories (G45.4)
G46.1	Wholesale on a fee or contract basis
G46.2	Wholesale of agricultural raw materials and live animals
G46.3	Wholesale of food, beverages and tobacco
G46.4	Wholesale of household goods
G46.5	Wholesale of information and communication equipment
G46.6	Wholesale of other machinery, equipment and supplies
G46.7	Other specialised wholesale
G46.9	Non-specialised wholesale trade
G47.11	Retail sale in non-specialised stores with food, beverages or tobacco predominating
G47.19	Other retail sale in non-specialised stores
G47.2	Retail sale of food, beverages and tobacco in specialised stores
G47.3	Retail sale of automotive fuel in specialised stores
G47.4	Retail sale of information and communication equipment in specialised stores
G47.5	Retail sale of other household equipment in specialised stores

G47.6	Retail sale of cultural and recreation goods in specialised stores
G47.71-72	Retail sale of clothing in specialised stores (G47.71) and footwear and leather goods in specialised stores (G47.72)
G47.73-89	Dispensing chemist in specialised stores (G47.73), Retail sale of medical and orthopaedic goods in specialised stores (G47.74), Retail sales of cosmetic and toilet articles in specialised stores (G47.75), Retail sale of flowers, plants, seeds, fertilisers, pet animals and pet food in specialised stores (G47.76), Retail sale of watches and jewellery in specialised stores (G47.77), Other retail sale of new goods in specialised stores (G47.78), Retail sale of second-hand goods in stores (G47.79), and Retail sale via stalls and markets (G47.80)
G47.9	Retail trade not in stores, stalls or markets
H49.1	Passenger rail transport, interurban
H49.2	Freight rail transport
H49.31	Urban and suburban passenger land transport
H49.32/39	Taxi operation (H49.32) and Other passenger land transport n.e.c (H49.39)
H49.4-5	Freight transport by road and removal services (H49.4) and Transport via pipeline (H49.5)
H50	Water transport
H51	Air transport
H52.1	Warehousing and storage
H52.21	Service activities incidental to land transportation
H52.22	Service activities incidental to water transportation
H52.23	Service activities incidental to air transportation
H52.24	Cargo handling
H52.29	Other transportation support activities
H53	Postal and courier activities
I55.1	Hotels and similar accommodation
I55.2-9	Holiday and other short-stay accommodation (I55.2), Camping grounds, recreational vehicle parks and trailer parks (I55.3), and Other accommodation (I55.9)
I56.1	Restaurants and mobile food service activities
I56.2	Event catering and other food service activities
I56.3	Beverage serving activities
J58.11	Book publishing
J58.12-19	Publishing of directories and mailing lists (J58.12), newspapers (J58.13), and Other publishing activities (J58.19)
J58.21	Publishing of computer games
J58.29	Other software publishing
J59	Motion picture, video and television programme production, sound recording and music publishing activities
J60	Programming and broadcasting activities
J61	Telecommunications
J62.01	Computer programming activities
J62.02	Computer consultancy activities
J62.03/09	Computer facilities management activities (J62.03) and Other information technology and computer service activities (J62.09)
J63.1	Data processing, hosting and related activities; web portals
J63.9	Other information service activities
K64	Financial service activities, except insurance and pension funding
K65	Insurance, reinsurance and pension funding, except compulsory social security
K66	Activities auxiliary to financial services and insurance activities
L68.1-2	Buying and selling of own real estate (L68.1) and Renting and operating of own or leased real estate (L68.2)
L68.3	Real estate activities on a fee or contract basis
M69.1	Legal activities
M69.2	Accounting, bookkeeping and auditing activities; tax consultancy
M70.1	Activities of head offices
M70.2	Management consultancy activities
M71.11	Architectural activities
M71.12	Engineering activities and related technical consultancy
M71.2	Technical testing and analysis
M72	Scientific research and development
M73.1	Advertising
M73.2	Market research and public opinion polling
M74.1	Specialised design activities
M74.2-3	Photographic activities (M74.2) and Translation and interpretation activities (M74.3)
M74.9	Other professional, scientific and technical activities n.e.c

M75	Veterinary activities
N77.1	Renting and leasing of motor vehicles
N77.2-3	Renting and leasing of personal and household goods (N77.2) and Renting and leasing of other machinery, equipment and tangible goods (N77.3)
N77.4	Leasing of intellectual property and similar products, except copyrighted works
N78.1	Activities of employment placement agencies
N78.2-3	Temporary employment agency activities (N78.2) and Other human resources provision (N78.3)
N79	Travel agency, tour operator and other reservation service and related activities
N80	Security and investigation activities
N81.1	Combined facilities support activities
N81.2	Cleaning activities
N81.3	Landscape service activities
N82.1	Office administrative and support activities
N82.2	Activities of call centres
N82.3	Organisation of conventions and trade shows
N82.9	Business support service activities n.e.c
O84	Public administration and defence; compulsory social security
P85	Education
Q86	Human health activities
Q87	Residential care activities
Q88	Social work activities without accommodation
R90	Creative, arts and entertainment activities
R91.01-02	Library and archive activities (R91.01) and Museum activities (R91.02)
R91.03	Operation of historical sites and buildings and similar visitor attractions
R91.04	Botanical and zoological gardens and nature reserve activities
R92	Gambling and betting activities
R93.1	Sports activities
R93.2	Amusement and recreation activities
S94.1	Activities of business, employers and professional membership organisations
S94.2/9	Activities of trade unions (S94.2) and Activities of other membership organisations (S94.9)
S95.1	Repair of computers and communication equipment
S95.2	Repair of personal and household goods
S96.01	Washing and (dry-)cleaning of textile and fur products
S96.02	Hairdressing and other beauty treatment
S96.03	Funeral and related activities
S96.04-9	Physical well-being activities (S96.04) and Other personal service activities n.e.c (S96.09)
T97-98	Activities of Households as Employers; Undifferentiated Goods-and Services-Producing Activities of Households for Own Use