Department for Education

Skills and UK productivity

Estimating the contribution of educational attainment to productivity growth

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Glossary of terms and abbreviations

APS	Annual Population Survey
Capital Deepening	Change in capital stock per hour worked
Consumption of fixed capital	Depreciation of capital assets
CPI	Consumer Price Index
GDP	Gross Domestic Product
Gross fixed capital formation (GFCF)	Acquisition of capital assets
GVA	Gross Value Added
ICT	Information and Communication Technologies
Intangible capital	Knowledge or intellectual capital, assets that do not have a physical or financial embodiment
ITL	International Territorial Level (previously NUTS)
Labour Productivity	GVA per hour worked
Labour Composition (LC) changes	Difference between change in QALI and change in hours worked
LFS	(Quarterly) Labour Force Survey
ONS	Office for National Statistics
QALI	Quality Adjusted Labour Index
SIC	Standard Industrial Classification of Economic Activities
Tangible capital	Physical capital, assets that do have a physical or financial embodiment
TFP	Total Factor Productivity

Executive summary

Background

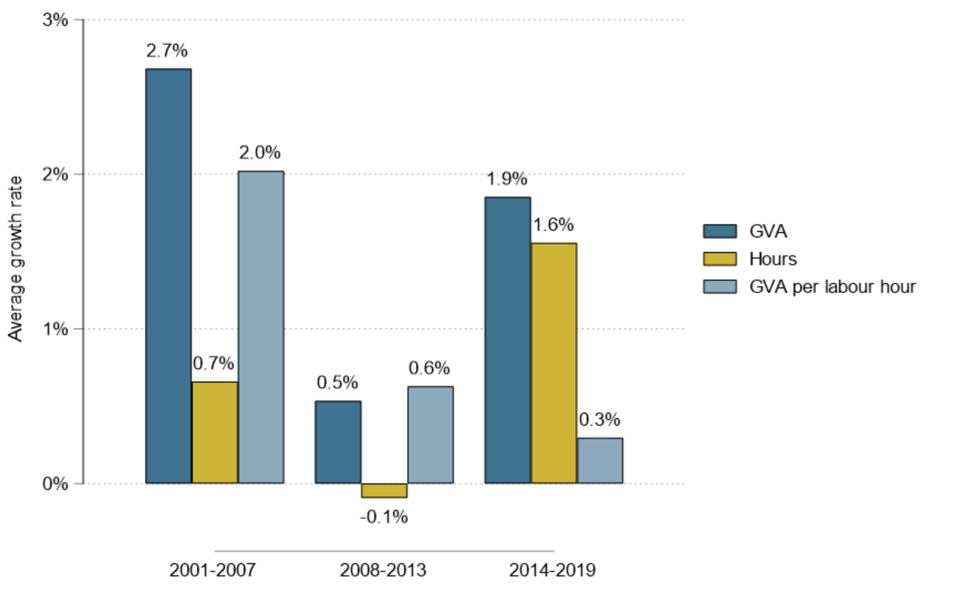
A country's ability to grow and increase productivity is one of the key targets of economic policy. Productivity refers to how efficiently production inputs like labour or capital are transformed into output. Historical trends show that the growth in UK labour productivity has been lower in recent years compared with the growth rates observed at the beginning of the early 2000s. This is referred to as the *productivity puzzle*, and it is not unique to the UK. It is therefore critical to understand the reasons for this decline.

According to standard economic theory based on the Solow growth model (Solow, 1957), productivity depends on labour, capital, and technological progress. Hence, it has often been of interest to study these underlying determinants of labour productivity growth (or lack thereof). This study aims to look at the contribution of the **labour input to productivity** (defined as Gross Value Added per hour worked) in more detail, and understand the impact of changes in the composition of the labour force (i.e. the quality of labour) on labour productivity growth in the UK.

What has happened to labour productivity growth over the last two decades?

The growth in UK labour productivity has slowed over the last twenty years. GVA per hour worked (presented by the light blue bar in Figure 1 below) grew by 2% per annum between 2001 and 2007, but only 0.6% per annum between 2008 and 2013, and further declined to 0.3% per annum between 2014 and 2019[1].

Figure 1: Growth in GVA, hours worked and labour productivity



Sources: LFS and London Economics' calculations

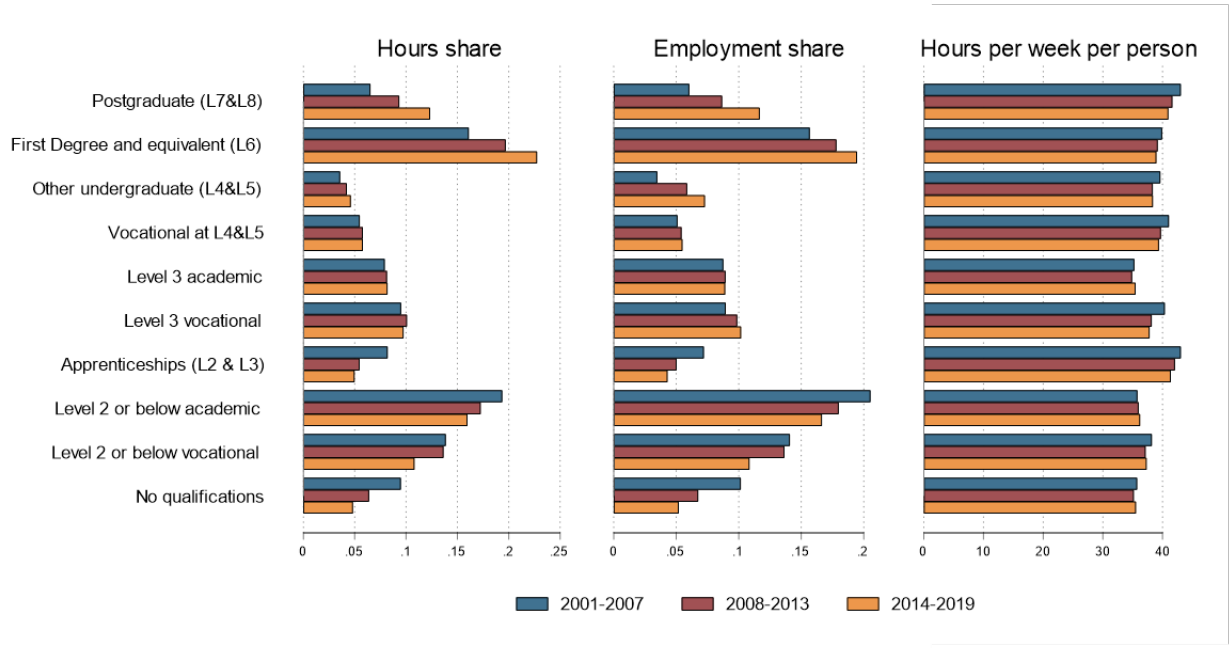
[1] The analysis uses data from the Quarterly LFS between 2000 and 2019. Variables are expressed as growth rates between two consecutive years, so the analysis relates to the years 2001 to 2019.

In particular, the recovery in **overall GVA growth** observed after 2014 (increasing from 0.5% to 1.9% and presented by the dark blue bar in Figure 1) was primarily driven by an increase in **hours worked** (presented by the yellow bar in Figure 1), rather than by an increase in labour productivity. In fact, total usual weekly hours worked increased at a rate of 0.7% per annum in the first sub-period, before stalling in the period after the 2008 Financial Crisis and rebounding after 2014 (average growth of 1.6% per annum)

What has happened to workforce composition over time?

Since 2001 there has been a considerable **change in the proportion of total hours worked across qualification levels**. For example, the proportion of usual hours worked by those with a first degree qualification or above rose from an average of 23% (of total hours worked in the UK economy) between 2001 and 2007 to 35% between 2014 and 2019 (left panel of Figure 2)[2]. This trend has been driven by a greater proportion of those in employment holding higher level qualifications (middle panel of Figure 2) rather than by those with higher level qualifications working longer hours on average (which remained stable or declined over time, see the right panel in Figure 2).[3]

Figure 2: Workforce composition change, by qualification level



Sources: LFS and London Economics' calculations

Given the slowdown in labour productivity that occurred over the period (identified in Figure 1) **despite** the considerable improvements in educational attainment and changes

[2] London Economics' analysis based on the Labour Force Survey
[3] A summary explanation of the derivation and interpretation of labour composition can be found in Box 3 in Annex A3.

in workforce composition, it is important to understand how these changes may have affected labour productivity in the UK.

Methodological approach

Two different methodologies have been employed to analyse the impact of changes in educational attainment on **output (defined as GVA)** and **labour productivity (defined as GVA per hour worked)**: the **growth accounting approach** and an **econometric approach**. These approaches use productivity and skills data at the national, industry, and regional level and identify **the contributions to labour productivity growth from changes in different input factors, such as capital and labour**. In general terms, the growth accounting approach decomposes productivity using a top-down approach, whereas the econometric approach provides a more bottom-up approach and identifies the impact of changes in input factors on labour productivity growth.

In particular, for the **labour input**, which is the main focus of this analysis, it is possible to refine the standard measure of hours worked and construct a measure accounting for changes in the **composition (or "quality") of the employed workforce** *as well as* changes in **hours** worked by different types of workers (the **Quality-adjusted labour input (QALI)**).

Figure 3: The Quality-adjusted labour input (QALI)

Use average income shares as weights

Change in hours

Change in QALI

$$\Delta QALI = \sum_i \frac{IS_{i,t} + IS_{i,t-1}}{2} * \ln \frac{hours_{i,t}}{hours_{i,t-1}}$$

i=qualification types

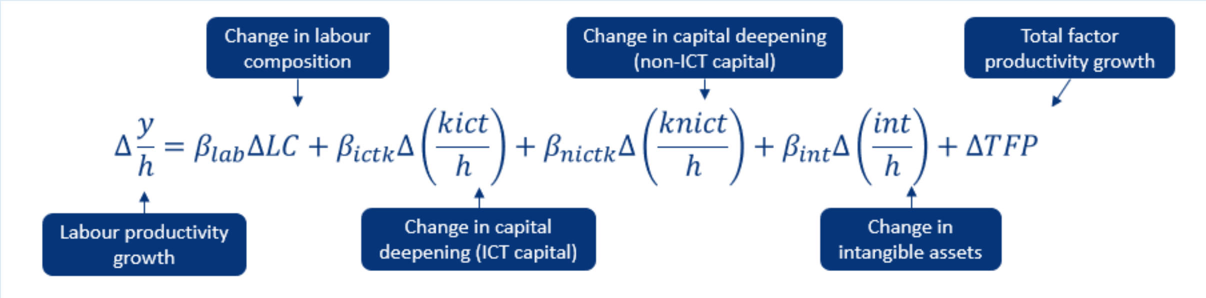
The difference between the change in QALI ($\Delta QALI$) and the change in the unadjusted index of hours ($\Delta hours$) identifies changes in labour composition or labour quality (ΔLC) between two time periods.

Box 1 overleaf summarises the two approaches and key differences between them.

Box 1: Summary of methodological approach

Growth accounting

In **growth accounting**, the growth in output per hour worked (i.e. labour productivity growth) can be decomposed as follows:



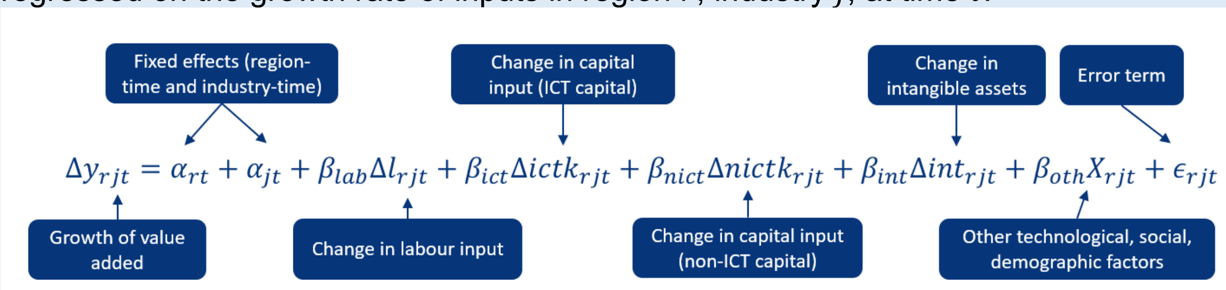
$$\Delta\frac{y}{h} = \beta_{lab}\Delta LC + \beta_{ictk}\Delta\left(\frac{kict}{h}\right) + \beta_{nictk}\Delta\left(\frac{knict}{h}\right) + \beta_{int}\Delta\left(\frac{int}{h}\right) + \Delta TFP$$

In this relationship, *LC* denotes labour composition (proxy for labour quality), $\frac{k}{h}$ denotes capital deepening (capital per hour worked) associated with ICT, non-ICT and intangible capital, and TFP denotes total factor productivity (the gain in productivity that is not explained by changes in factor inputs). A fuller explanation of the decomposition of labour input can be found in Box 9 in Annex A3.

All variables are expressed in log-terms to represent growth rates and weighted by their imposed factor shares (β). Growth accounting assumes constant returns to scale (i.e. that an increase in inputs results in a proportional increase in output), meaning that all factor inputs sum up to 1 ($\beta_{lab} + \beta_k = 1$).

Econometric approach

In the **econometric approach**, the growth rate of output per hour worked can be regressed on the growth rate of inputs in region r, industry j, at time t:



$$\Delta y_{rjt} = \alpha_{rt} + \alpha_{jt} + \beta_{lab}\Delta l_{rjt} + \beta_{ict}\Delta ictk_{rjt} + \beta_{nict}\Delta nictk_{rjt} + \beta_{int}\Delta int_{rjt} + \beta_{oth}X_{rjt} + \epsilon_{rjt}$$

Where α_{rt} and α_{jt} denote region-time and industry-time fixed effects, LC denotes labour composition, $\frac{k}{h}$ denotes capital deepening (split by ICT, non-ICT and intangible capital), X_{rjt} denotes additional technological, social, or demographic factors, and ϵ_{rjt} denotes the unexplained variation. The estimated parameters (β) can be interpreted as output elasticities to factors of production. They do not need to sum up to 1.

Given the methodological differences between the two approaches, the results are not directly comparable.

A full explanation of the comparability of the results as well as the limitations of each approach are presented in section 4.1.1 and section 4.2.1.

The results of both methodologies should be interpreted alongside several important caveats, summarised in Box 2 below.

Box 2: Main caveats

Data quality

The quality of the Labour Force Survey data used in the analysis has deteriorated in recent years due to high non-response rates. There are limited alternatives to using the Labour Force Survey in terms of coverage over time, but in those cases where alternative data could be made use of (i.e. the Annual Population Survey in the most recent time period), the results were highly consistent.

Key limitations of growth accounting

- The productivity decomposition is constructed using a top-down approach and the share of growth not accounted for by changes in capital and labour is ascribed to Total Factor Productivity (a residual component, which is typically pro-cyclical and accounted for more than half of total GVA growth in the first sub-period, while became negative or negligible after 2008).
- There are a series of strict assumptions on constant returns to scale, factor input shares, perfectly competitive factor input markets, no interactions between factor inputs.

Additional discussion of the caveats associated with the growth accounting approach are presented in section 4.1.1.

Key limitations of the econometric approach

- The econometric estimates presented in this report should not be interpreted as providing causal estimates of the effect of labour and capital inputs on productivity growth due to possible endogeneity (e.g. omitted variable bias, reverse causality);
- the number of observations available for the econometric analysis may become quite limited when disaggregating by time period

Additional discussion of the caveats associated with the growth accounting approach are presented in section 4.2.1.

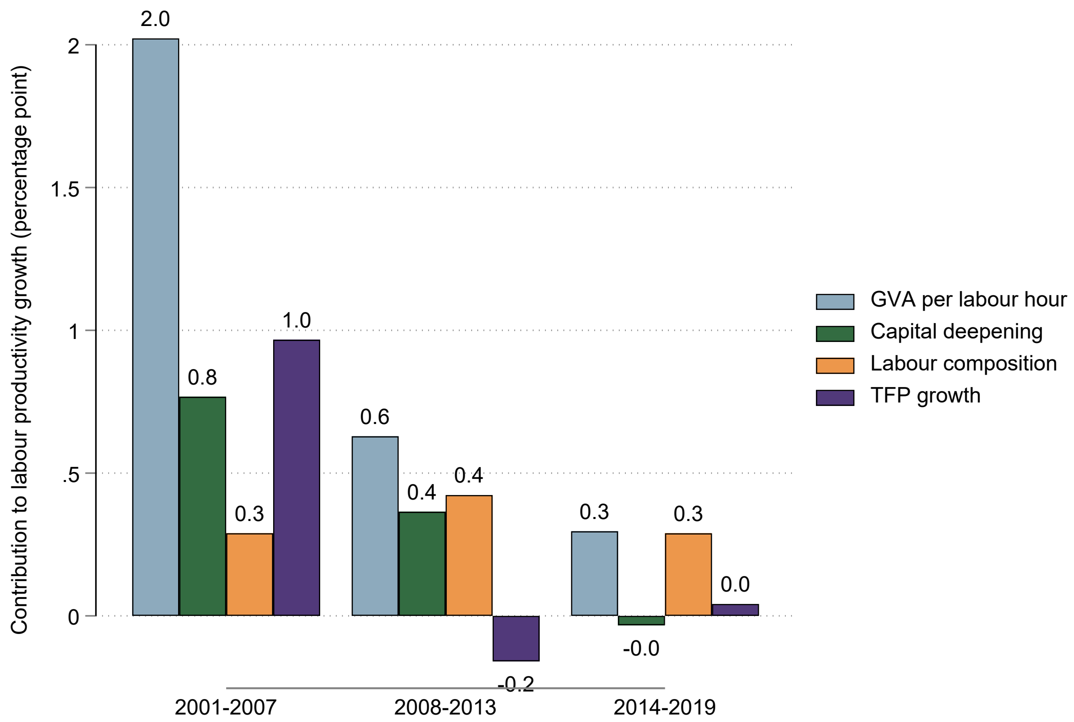
Main results – growth accounting[4]

- Over the period, growth in **labour productivity** (GVA per hour worked) declined significantly (identified by blue bars in Figure 4), from 2.0% in the first sub-period to 0.6% in the middle sub-period and 0.3% in the third.

- Changes in **labour composition** (or labour quality) contributed around 0.3 percentage points of annual productivity growth in the first and final sub-period and 0.4 percentage points in the middle sub-period (identified by the gold bars in Figure 4).

- Thus, the relative **contribution of labour composition** (or labour quality) to UK labour productivity growth is greater when productivity growth is lower (i.e. in the period post 2008).

Figure 4: Decomposition of contributions to average annual labour productivity growth



Sources: LFS, ONS, and London Economics' calculations

- In contrast, the contribution of **capital deepening** (defined as the change in capital per hour worked identified by the green bars in Figure 4) declined over time from

[4] The findings of this report may not be fully consistent with previous results (e.g. [BIS Research Report No. 262](#) (2015)) or published ONS figures, due to methodological differences and revisions in the data used (further information is provided in section 5.2.3).

around 0.8 percentage points in the first sub-period (2001-2007) to a zero contribution in the last sub-period (2014-2019).

- The contribution of the residual **Total Factor Productivity** component (represented by the purple bars) was relatively strong in the early 2000s (around 1 percentage point), but turned negative in the aftermath of the Financial Crisis and remained negligible in the final period.

- The contribution of labour composition is predominantly driven by the increase in employment share accounted for by graduate and postgraduate qualifications (presented in section 5.2.2).

- Despite variation in productivity growth and contributions of other factors, the contribution of labour composition to productivity growth is also generally consistent across regions, while variation by sector is driven by a combination of changes in labour composition and the importance of the labour input within particular sectors (with the results presented in sections 5.2.4 and 5.2.5).

- In particular, the contribution of labour composition to GVA growth was particularly strong in the Manufacturing sector, Financial and Insurance services and in the Public Administration sector (ranging between 0.4 and 0.5 percentage points), but also in Health and Social Services and the Arts, Entertainment, and Recreation sectors. At the regional level annual contributions of labour composition ranged between 0.1 and 0.5 percentage points and were relatively high in the North East (first and last period), London (first two periods) and also Northern Ireland (final period).

- In terms of the robustness of the results, the contribution of labour composition to productivity growth was consistent across a) different definitions of hours and wages in the data and b) when using the Annual Population Survey (available only for the latest sub-period) instead of the Labour Force Survey (presented in section 5.2.3). As such, despite the underlying caveats associated with the analysis (presented in section 4.1.1), it is possible to have some confidence in the results.

Main results – econometric analysis

The econometric approach estimates **the impact of a given change in the composition of the labour input on overall GVA growth and productivity growth**. The overall change in the Quality Adjusted Labour Index (QALI) can be broken down into its two constituent components: changes in hours worked and changes in labour composition.

- The econometric analysis suggests that **changes in QALI are positively associated with GVA growth** over the entire period of analysis (2001-2019), with a 1% increase in QALI associated with a 0.1% growth in overall GVA growth.
- However, these positive changes in GVA growth seem to be mainly driven by changes in labour composition (labour quality) between 2001 and 2007 but by changes in hours in the post-2008 period (although results are not statistically significant).
- The decline in the contribution of labour composition is almost entirely due to a decrease in the impact of higher-level qualifications in the post-2008 period. This is presented in Table 16.

Key remarks

Acknowledging that there are externalities to education that have wider benefits over and above what can be directly observed through labour market outcomes, this report explores the impact of education attainment on the narrower economic outcome of UK labour productivity growth. Two main methodologies are used: growth accounting and an econometric approach. Both try to assess the impact of changes in the labour input on growth broken down into contributions from total hours worked in the economy and labour composition. The latter is a proxy for the quality of the labour input and allows for the estimation of the contribution of changes in the composition of labour across qualifications, such as changes in the share of hours worked by those with different educational qualifications.

The growth accounting results suggest that the contribution of changes in labour composition towards productivity growth is positive and generally stable across time.

While the growth accounting analysis suggests that changes in labour composition (such as increases in the proportion of the labour force who hold higher level qualifications) have affected GVA growth at a consistent rate across time, the **econometric approach** seems to suggest that the **impact of the labour input on GVA growth was mostly driven by labour composition before 2008 but only by hours worked in the post-2008 period**. Further research could investigate the long-term impact of the Financial Crisis on skills under-utilisation, or other factors that may explain this structural break.

Overall, the evidence presented in this report, together with the findings from recent literature showing the positive effect of educational attainment on labour market outcomes[5], shows that the acquisition of education and skills is productivity enhancing[6]

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[5] See for example DFE-RR808 (2018), DFE-RR974 (2020) and CVER-DP007 (2017)

[6] Although the growth accounting findings suggest that higher level qualifications are the main drivers of economic growth, it is not possible to conclude that investment should be directed at specific skills levels.

and it is not simply a device used by individuals to signal their ability to potential employers.

As mentioned previously, both the results from the growth accounting and econometric approaches should be interpreted with appropriate caveats. Both approaches rely on relatively strong methodological assumptions, the quality and comprehensiveness of the data, as well as being based on a relatively small number of observations.

Further research could investigate heterogeneity in the impact of changes in post-18 educational attainment, such as the differences in the impact of education, training and skills acquisition by age or gender. In addition, changes in the composition of particular qualifications across time may also be important. For example, the skills obtained from a university degree in a given subject in 2002 may be different to those from a university degree in the same subject in 2022 (such as proficiency in ICT). These trends may also be important in explaining the impact of attainment on UK productivity growth.

In fact, the question on which skill levels or types to invest in cannot simply be answered by looking at the macro-level analysis presented here, but needs to be combined with micro-level analysis on returns to individuals from qualification acquisition (considering benefits and related costs), costs and benefits for the Exchequer, and the analysis of the impact of training on productivity at the firm level.

1. Background

A country's ability to grow and increase productivity is one of the key targets of economic policy. Productivity refers to how efficiently production inputs like labour or capital are transformed into output. Historical trends show that the growth in UK productivity has been lower in recent years compared with the growth rates observed at the beginning of the early 2000s[7]. This is referred to as the *productivity puzzle*, and it is not unique to the UK. It is therefore critical to understand the reasons for this decline. According to standard economic theory based on the Solow growth model (Solow, 1957), productivity depends on labour, capital, and technological progress. Hence, it has often been of interest to study these underlying determinants of productivity growth (or lack thereof). This study aims to look at the labour component of productivity, and in particular, understand the impact of changes in the composition of the labour force on productivity growth in the UK.

The share of employees with higher education (i.e., undergraduate degree or higher) is much larger today than it was twenty years ago. However, stagnating productivity growth appears to suggest that the increase in educational attainment has had limited impact on UK productivity. Therefore, it is key to investigate whether this increase in the number of graduates has led to increases in the share of labour contribution to productivity or not. This report also adds to the evidence base by considering the contribution of other forms of education, training and skills acquisition (such as apprenticeships or vocational training) on the growth in labour productivity, which has not been studied in detail previously.

Growth in productivity has not been uniform across different regions of the United Kingdom[8] and there are significant regional skill imbalances[9]**.** In London and the South East of England, productivity levels are generally much higher than elsewhere across the United Kingdom[10]. Understanding the distribution of skills across the UK, as well as the contribution to productivity at a regional level should provide an important insight to policymakers in line with the government's *Levelling Up* agenda[11].

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[7] Between 2001 and 2007, the average annual growth rate of GVA per hour (i.e. labour productivity) was estimated to be 2% per annum. This compares to an average annual growth rate of just 0.3% per annum between 2014 and 2019 (see Figure 13).
[8] See section 5.2.5.
[9] For example, in the period 2014-2019 graduates (those with a first degree (or equivalent) and above) represented more than 50% of the labour force in the London region and 34% in the South East, while the proportion was around 27-28% in the North East and East of England (figures based on pooled quarterly LFS).
[10] For example, in the final sub-period considered (2014-2019), the level of GVA per hour in the London and South East regions was approximately 70% and 35-40%% higher compared to the UK regions with the lowest ratios (Wales and the North East).
[11] See https://www.gov.uk/government/publications/levelling-up-the-united-kingdom

In addition to regional skills and productivity imbalances, the distribution of skills and the growth rates in productivity vary significantly across different sectors of industrial activity, which also requires further investigation.

This report aims to investigate a number of these issues and is set out as follows:

- In Section 2 we provide a detailed overview of the data that was used as part of the analysis.
- In Section 3 we provide a **brief summary of the recent empirical literature** providing estimates of the contribution of labour composition to labour productivity growth in the United Kingdom and internationally.
- In Section 4 we present the methodological approach, covering the two main elements of analysis. These are the **growth accounting approach**, which decomposes the growth of output in an economy into the growth of each weighted factor input; and an **econometric approach**, which estimates the impact of changes in different factors, including skills composition, on labour productivity growth.
- In Section 5 we provide the **findings of the growth accounting analysis**, as well as some additional information on previous analyses relating to the United Kingdom and international comparisons.
- Section 6 presents the main **findings of the econometric analysis** conducted at the industry level.
- Section 7 **concludes** with a brief summary of the main results, as well as implications and policy **recommendations** that can be drawn from the analysis.

2. Data and definitions

In this section we present the different data collections that were used in the analysis. As the analysis focuses on the United Kingdom only (apart from the analysis of international comparisons presented in Sections 3.2 and 5.3), we used UK specific data sources (mostly published from the Office for National Statistics); however, we refer to other data collections (both UK and international) that were also considered as part of the initial data exploration

Box 3: Data section - summary

Period of analysis

- Three sub-periods for the analysis: 2001-2007 (corresponding to the early 2000s economic boom, 2008-2013 (aftermath of the financial crisis), 2014-2019 (most recent period);

Key variables

- **Output:** Gross Value Added (from ONS publications) by sector and region;
- **Labour input:** Quarterly Labour Force Survey (ONS microdata) with information on wages, hours worked and highest qualification attainment by sector and region;
- **Capital input:** Capital stock data at the sector level from the ONS (divided into **ICT** capital, other **non-ICT tangible** (physical) capital, and **intangible** capital). Regional capital stock is not published and was constructed using an experimental approach;
- **Factor shares** for labour and capital from ONS publications

Level of aggregation

- **Industry at the SIC section level** (SIC letter covering 15 sectors);
- **Region at the ITL1 regional level** (9 English regions plus Wales, Scotland and Northern Ireland);
- **Highest qualification classification in 10 different groups**, from postgraduate qualifications to possession of no formal qualifications.

2.1 Definitions

Period covered by the analysis

The data used to undertake this analysis was from 2000 to 2019. However, since the analysis is conducted using growth rates, this implies that first time period starts in 2001 (i.e. using the change between 2000 and 2001). In addition, given the very different prevailing economic circumstances over the period, the analysis also considered three different time periods: 2001-2007, 2008-2013, and 2014-2019. This approach allows for the separate analysis of growth during the economic boom experienced in the early 2000s (period 1), the period immediately after the 2008 Financial Crisis (period 2), and the most recent period, which saw a general recovery in overall economic growth (GVA), but not in labour productivity (GVA per hour worked).

Regional classification

The analysis was undertaken at the national (UK), industry, and regional levels. As a consequence, the information needed for the analysis had to be collated or derived at the appropriate level for all relevant variables. To ensure a consistent definition across all data sources and sufficiently large sample sizes, regional analysis was undertaken at the International Territorial Level 1 (ITL 1) regional level[12], resulting in 9 regions for England, plus Scotland, Wales, and Northern Ireland.

Sector classification

When looking at sectors of industrial activity, the analysis was undertaken at the SIC[13] section (1-digit) level. However, some of the sample sizes were too small for a robust analysis (especially in respect of qualification data). Hence, we grouped together sectors ABDE (Agriculture and Energy) and RS (Other Services) to ensure robustness. This is presented in Table 1. Although some previous productivity estimates[14] only consider market sectors (i.e. all sectors excluding public administration, education and health), for this analysis we were able to consider the whole economy, with the exception of sector T (activities of households as employers) and U (extraterritorial organisations and bodies), due to extremely limited sample sizes and lack of data on capital stock for these sectors.

The main reason why non-market sectors are sometimes excluded is that measuring output in these sectors is less straightforward than in other sectors and different national statistical agencies have different means of estimating them (CEDEFOP, 2014). Also, data on capital stock and investment may not be consistently available for the non-market sector. However, as this study focuses on the UK economy only, comparability with other countries was less of an issue, and we were able to use information on capital stock also for the non-market sectors of the economy.

[12] This corresponds to NUTS 1 (Nomenclature of Territorial Units for Statistics) regions.
[13] Standard Industrial Classification of Economic Activities
[14] For example BIS research paper 262 (2015, prepared by NIESR) and CEDEFOP Research Paper 40 (2014, prepared by Mason et al.)

Table 1: Sector classification used for analysis based on SIC07 section codes

Sector(s)	Description
ABDE	Agriculture and energy
C	Manufacturing
F	Construction
G	Wholesale, retail, repair of motor vehicles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional and technical activities
N	Administrative and support services
O	Public administration and defence
P	Education (pre-primary, primary, secondary, higher, and other education and educational support activities)
Q	Health and social work
RS	Other services

2.2 Data on output

Gross Value Added

Measuring productivity growth requires data on the output produced by the economy. Since the analysis was undertaken at both regional and sectoral level, we used output data available at this required level of granularity. The two potential measures of output available for analysis are GDP (Gross Domestic Product) and Gross Value Added (GVA)[15]. GVA measures the value of an industry's output less the value of intermediate inputs used in the production process at basic prices. GDP is given by GVA plus taxes on

[15] The Gross Value Added series used is 'Regional gross value added (balanced) by industry: all International Territorial Level (ITL) regions'. The data series provide estimates of gross value added (GVA) derived by balancing the income and production approaches to measuring GVA See Regional economic activity by gross domestic product, UK - Office for National Statistics (ons.gov.uk).

products less subsidies on products, hence provided at market prices. Generally, GDP and GVA are relatively closely aligned, so GVA can often be used as a proxy for GDP[16].

GDP is available by region but *not* by sector, while GVA is available disaggregated both by region and sector. In particular, GVA data[17] are available disaggregated by geographical area and sector of industrial activity from the Office for National Statistics (ONS) between 2000 and 2019, both in current and chained volume measures[18]. Given this, we used the chained volume measure of GVA, available at both region and industry level for the analysis[19].

2.3 Data on labour inputs

2.3.1 The UK Labour Force Survey (LFS)

The analysis required detailed information on the qualifications held by the UK workforce, as well as their employment status, wage, hours worked, industry and region of employment. The **UK Quarterly Labour Force Survey** (LFS) was the source of information used for the labour input[20] as it contains consistent information on a variety of characteristics and labour market status for the UK workforce, including:

- Highest qualification obtained, allowing the construction of the disaggregated qualification categories required for the analysis;
- Labour market status (employee/self-employed etc.);
- Wages for employees (e.g. hourly pay and weekly pay) to generate income shares;
- Hours worked (both usual hours and actual hours worked in the reference week);
- Region of residence and workplace (International Territorial Level (ITL/NUTS 1); and
- Sector of industrial activity (SIC 1-digit).

[16] For the full definition of GVA and GDP see here
[17] The latest edition can be found here.
[18] Chain volume measures only vary with changes in the quantities of commodities produced or sold. Chain volume measures value quantities by using prices in a base period which is updated annually. These annually reweighted (rebased) volume change measures are then linked, or "chained" together to produce a time series of chain volume measures (see for example here for a detailed explanation).
[19] The chained volume measure used is based on single deflation.
[20] Although we also considered the feasibility of using alternative data sources to construct changes in the labour input (e.g. the Longitudinal Education Outcomes, the Annual Survey of Hours and Earnings), none of them were fully suitable for the analysis.

2.3.2 Approach and potential limitations using the LFS

Data gaps

The quarterly Labour Force Survey is available for the entire period of analysis (2000 onwards); however, there was a gap in the qualification data relating to the first quarter of 2004 and 2005, resulting in the absence of information on the highest qualification attained. Numbers were grossed up to reflect this lack of information for the quarters considered[21].

Sample used

The Labour Force Survey is collected on a rolling sample of respondents designed to be retained for five consecutive survey waves (although the presence of attrition means that some of them will drop out before Wave 5). Information on employment is collected in each wave and information on earnings collected in waves 1 and 5 only. As we were interested in the total number of hours worked during the year, we pooled together all quarters in the year (using all available waves) to construct annual estimates of hours and income shares.

Industry mapping

The industry classification as given by the SIC codes changes during the period of analysis. Until 2008, sectors are classified using SIC92 codes, while from 2009 onwards sectors are classified according to SIC07. To obtain a consistent sample over the entire period of analysis, the data from 2000-2008 have been mapped according to the SIC07 codes using STATA one-to-one mapping do-files provided by the ONS[22].

Inflation

Throughout the analysis, hourly and weekly pay is adjusted for inflation, using data on the Consumer Price Index (CPI) from the ONS and rebasing all values to June 2020.

Classification of highest qualification

Highest qualification achieved is not necessarily equivalent to skills obtained. Some individuals may gain skills through on-the-job training, while other individuals may work in an occupation that is not fully utilising their skills based on the qualification obtained. However, since there is no consistent way to measure skills, highest qualification is

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[21] For the actual number of hours worked we used ratios from ONS publications (reporting number of hours worked by quarter) to gross up the number of hours, while the usual number of hours worked are less influenced by seasonality and we adjusted assuming a constant ratio (based on information from the other quarters).

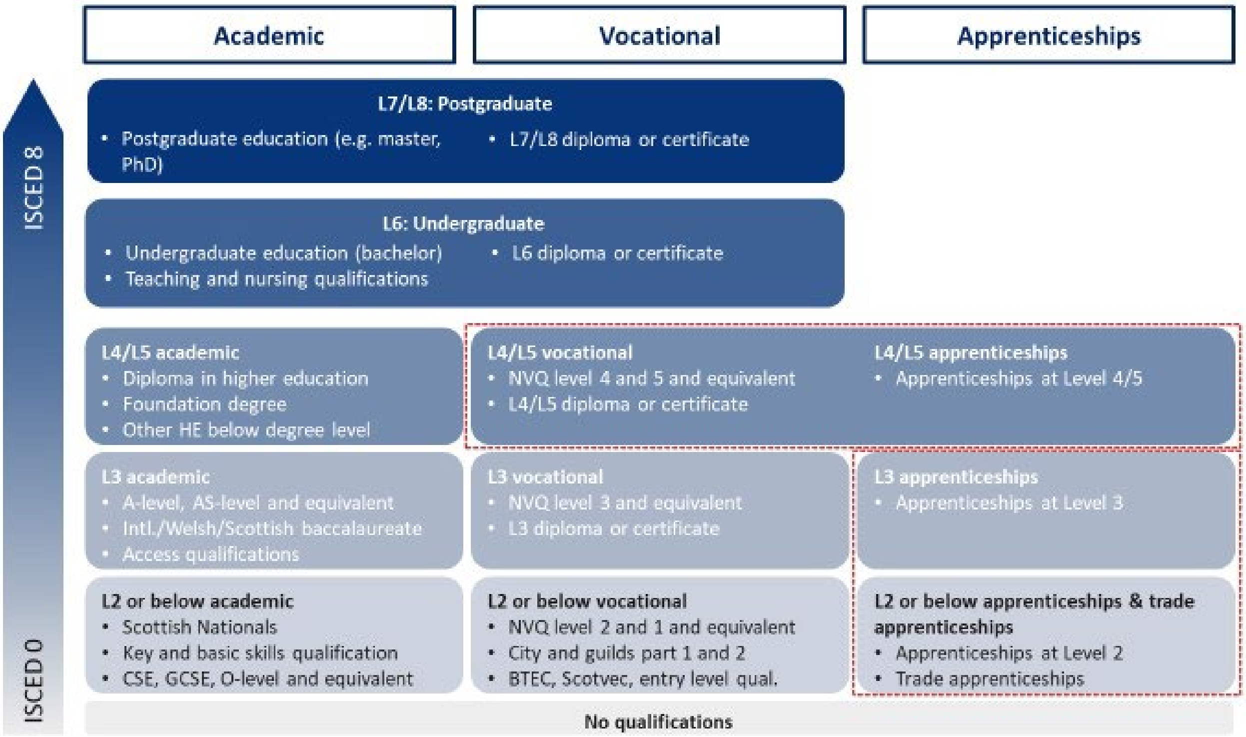
[22] https://warwick.ac.uk/fac/soc/economics/staff/jcsmith/sicmapping/resources/direct/

commonly used in the literature to assure comparability and consistency across studies and countries.

To determine the impact of various educational qualifications on labour productivity, the highest qualifications achieved by survey respondents were grouped together to provide as much detail as possible, while still retaining sufficiently large sample sizes for a robust analysis. The classification used allows for differentiation between academic and vocational education, undergraduate versus postgraduate qualifications, as well as the explicit inclusion of apprenticeships. Due to sample sizes, apprenticeships at Level 4 or Level 5 were grouped together with Level 4/5 vocational qualifications, and Advanced Apprenticeships (Level 3) were grouped together with Intermediate Apprenticeships (Level 2 or below) and ‘older’ trade apprenticeships. Individuals in possession of no formally recognised qualification were treated as a separate group[23].

[23] Those with highest qualification classified as “No answer” or “Don’t know” were removed from the analysis

Figure 5: Qualification groupings



Source: London Economics, based on LFS classification and ISCED 2011

2.3.3 The LFS and the Annual Population Survey

A general issue with the LFS data is that sample sizes (and in consequence, reliability) have declined over time[24]. As a result, this may lead to small sample sizes and less robust estimates especially when disaggregating by qualification type and for certain smaller regions (e.g. Northern Ireland). The **Annual Population Survey** (APS) uses data combined from 2 waves of the main Labour Force Survey (LFS), collected on a local sample boost. Hence, the APS contains larger samples than the LFS and is available on an annual basis. However, the APS is only available from 2004 onwards, and information on the highest qualification obtained is only available since 2013 (this information being clearly essential for the analysis). As a consequence, the Labour Force Survey was used as the main source of information, while the Annual Population Survey was used to provide a robustness check for the most recent time period considered (2014-2019).

[24] The overall number of observations was around 140,000 per quarter in the early 2000s declining to about 110,000 in 2010 and to less than 90,000 by 2019. Also, around one third of responses for individuals aged 16 and above are proxy responses (e.g. by spouse, partner, parent or other relative, co-habitee etc.). This has an effect on the quality of the information provided (this proportion of responses provided by individuals themselves has slightly declined over time from around 68% during the early 2000's to 66% in recent years).

2.4 Capital input data

Capital input data is available at the national and industry level by **type** of capital, whereas capital input data at the regional level is estimated using experimental estimates of gross fixed capital formation.

2.4.1 National-level and industry-level capital input data

Net capital stock data from the ONS[25] is used for the national and industry-level analyses (with further discussion of the available capital stock data provided in Annex A2). The ONS dataset provides net capital stocks by industry and by asset type. These asset types may be categorised into three types of capital: **ICT** capital, other **non-ICT tangible** (physical) capital, and **intangible** capital. Table 2 presents the categorisation of asset types used in the analysis.

Table 2: Capital type and included asset types

Capital type	Included asset types
ICT capital	ICT equipment: Hardware ICT equipment: Telecoms
Non-ICT tangible capital	Cultivated assets Dwellings Machinery and equipment: Transport Machinery and equipment: Other machinery and equipment Other buildings and structures, and costs associated with the transfer of non-produced assets
Intangible capital	Intellectual property products: Artistic originals Intellectual property products: Mineral exploration Intellectual property products: Research and development Intellectual property products: Software

Source: ONS

Net capital stock is provided in current prices and in the previous year's prices. To calculate net capital stock in constant prices, the percentage difference between net capital stock in current prices and net capital stock in the previous year is calculated for

[25] Net capital stock is defined as 'the gross capital stock (defined as the value of all fixed assets still in use at a point in time), less the consumption of fixed capital accrued up to that point. It takes into account the depreciation of the assets over time as a result of physical deterioration, foreseeable obsolescence or normal accidental damage' (see Capital stocks and fixed capital consumption, UK - Office for National Statistics).ONS Gross and net capital stocks for total UK economy, by industry and asset (November 2021 release) are available at Gross and net capital stocks for total UK economy, by industry and asset - Office for National Statistics (ons.gov.uk)

each year (for each industry and asset type). These percentage differences are used to construct a price index for net capital stock in each industry and asset type, which is in turn used to deflate the net capital stock series.

2.4.2 Regional-level capital input data

While only experimental gross fixed capital formation data is available at the (ITL1) regional level[26] (provided by the ONS[27]), it is possible to use this data in the Perpetual Inventory Method (PIM) to estimate regional net capital stocks at an industry level. PIM has previously been used to estimate European regional capital stock estimates by Cambridge Econometrics[28]. However, **as the gross fixed capital formation data is not disaggregated by asset type, it is not possible to estimate capital at the regional level *by type* of capital.**

The PIM estimates an initial net capital stock for each region (for a given industry) by assigning a share of the initial (in this case in 2000) net capital stock for the industry. Regional shares are calculated using each region's share of total gross fixed capital formation within the industry. Net capital stocks in subsequent years are calculated using gross fixed capital formation and depreciation rates (provided by EU-KLEMS data): the net capital stock in one year is gross fixed capital formation in addition to the net capital stock from the previous year (less consumption of fixed capital). A more detailed discussion of the estimation of regional capital stocks can be found in Annex A2. Due to data limitations, regional-level capital estimates are not provided for 2019, so the third time period is between 2014 and 2018, inclusive.

[26] Information on capital stock at the regional level is currently not available, while regional gross fixed capital formation is only published following user requests, but not as National Statistics. As part of their 'Productivity development plan: 2021 to 2023' (Productivity development plan - Office for National Statistics (ons.gov.uk)), the ONS are currently developing revised estimates of regional capital investment, with the objective, in the medium term, to also publish regional capital stocks, capital services, and multifactor productivity estimates. In particular, in May 2022 the ONS published experimental estimates for regional gross fixed capital formation, disaggregated by sector and asset type (Experimental regional gross fixed capital formation (GFCF) estimates by asset type: 1997 to 2020 - Office for National Statistics (ons.gov.uk)).

[27] ONS Regional gross fixed capital formation, ITL1 and ITL2, 2000 to 2019 (November 2021 release), available at Regional gross fixed capital formation, ITL1 and ITL2, 2000 to 2019 - Office for National Statistics (ons.gov.uk)

[28] https://www.camecon.com/wp-content/uploads/2020/02/2020-02-19-Regional-capital-stock-methodology.pdf

3. Brief review of the relevant empirical literature

Box 4: Previous findings - summary

Findings for the UK

- The UK economy grew relatively quickly (in excess of 3% per annum) between 1994 and 2007), before sharply contracting after the 2008 financial crisis and partially recovering after 2011;
- The contribution of capital was positive and strong in the early periods but declined over time;
- Total Factor Productivity (TFP) grew quickly in the early 2000s before falling sharply between 2008 and 2010, and remaining negative after 2011;
- The contribution of hours worked was positive in the first period before becoming negative between 2008-2010 and recovering after 2011;
- Across the main studies considered, the contribution of labour composition to UK economic growth ranged between 0.3-0.6 percentage points and was far more stable over time compared to the other inputs.

International findings

- The contribution of labour composition (LC) across the European Union as a whole was quite stable in the period 2002-2015, ranging between 0.2 and 0.3 percentage points, while in Germany the LC contribution rose to 0.4 percentage points in the period 2008-2010 but declined to 0.1 percentage points between 2011-2015. In France, labour composition ranged between 0.4 and 0.5 percentage points between 2008 and 2015;
- Research for the US suggests that the contribution of labour composition also ranged between 0.2 and 0.3 percentage points between 1995 and 2017 (but decreasing slightly in the most recent period).

3.1 Growth Accounting evidence for the UK

In general, previous studies that have looked at productivity growth in the UK have found that productivity growth was strong during the 1990s and the early 2000s (until 2007), but declined sharply as a consequence of the 2008 Financial Crisis, with only partial recovery after 2011. Specifically, a study from the Department for Business, Innovation and Skills (2015)[29] found that GDP growth between 2002 and 2007 was just over 3%, with labour composition contributing 0.47 percentage points to overall growth (see top panel of

[29] BIS Research Report No. 262

Figure 6). This estimate was similar to what was observed between 1994 and 2005 (BEIS, 2013)[30]. At the time of the economic downturn following the Financial Crisis, GDP growth fell to -1.5% between 2008 and 2010. However, the contribution from labour composition did not fall, and in fact was slightly higher at 0.62 percentage points, while the contribution of hours and TFP fell sharply. From 2011 to 2013, GDP growth rose to 0.9%, although still below pre-crisis level due to slow recovery of TFP growth. However, the contribution of labour composition was at the same level observed before the Financial Crisis (0.47 percentage points)[31].

More recently, Van Ark and Jäger (2017) used EU Klems data[32] and found that overall GVA growth between 2002 and 2007 was 2.7% but fell to -1% during the period of the Financial Crisis between 2008 and 2010 (see bottom panel of Figure 6). Between 2011 and 2015 GVA growth recovered to 1.9% (although still below the pre-crisis level). Despite large changes in overall GVA growth, the share of growth that was due to changes in labour composition remained relatively constant, between 0.3 and 0.4 percentage points in all three periods, while hours and TFP were negatively impacted by the economic downturn.

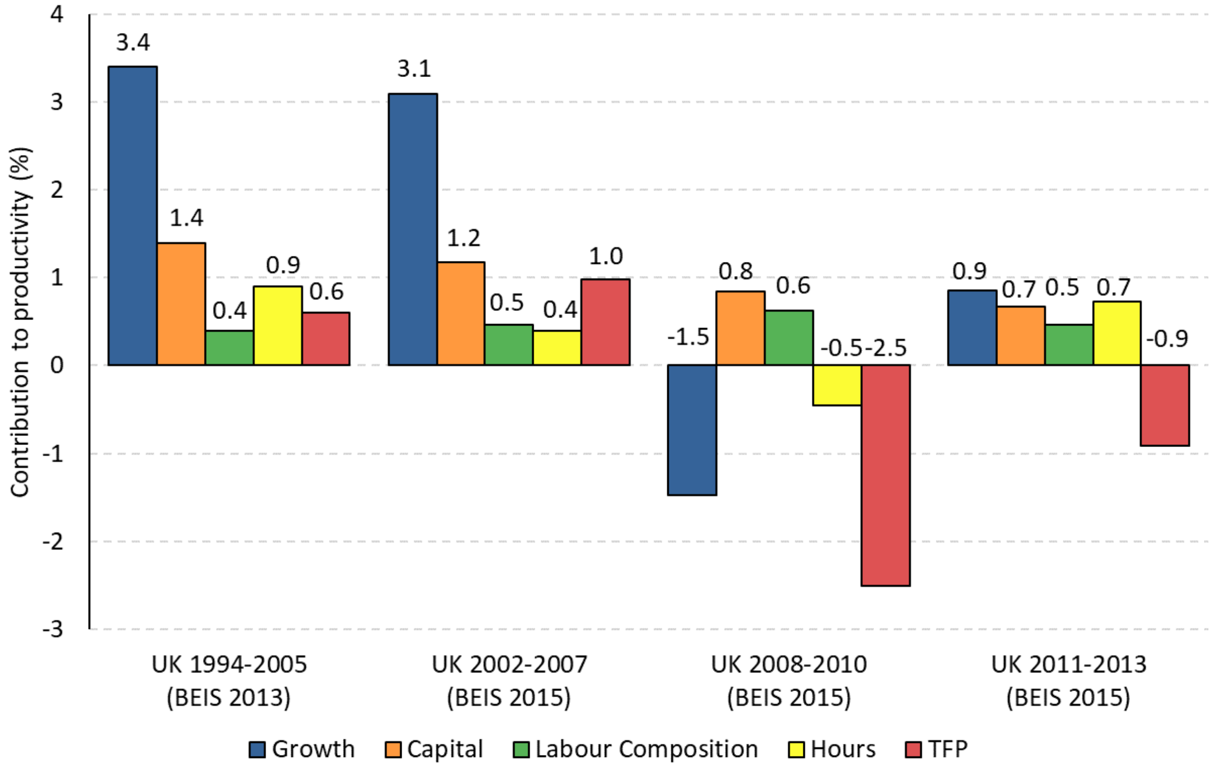
Overall, the findings indicate that while growth in hours and TFP appear to be highly dependent on economic conditions, **the contribution of labour composition has remained relatively stable over time** (and tends to increase in importance during economic downturns).

[30] BIS Research Report No. 110

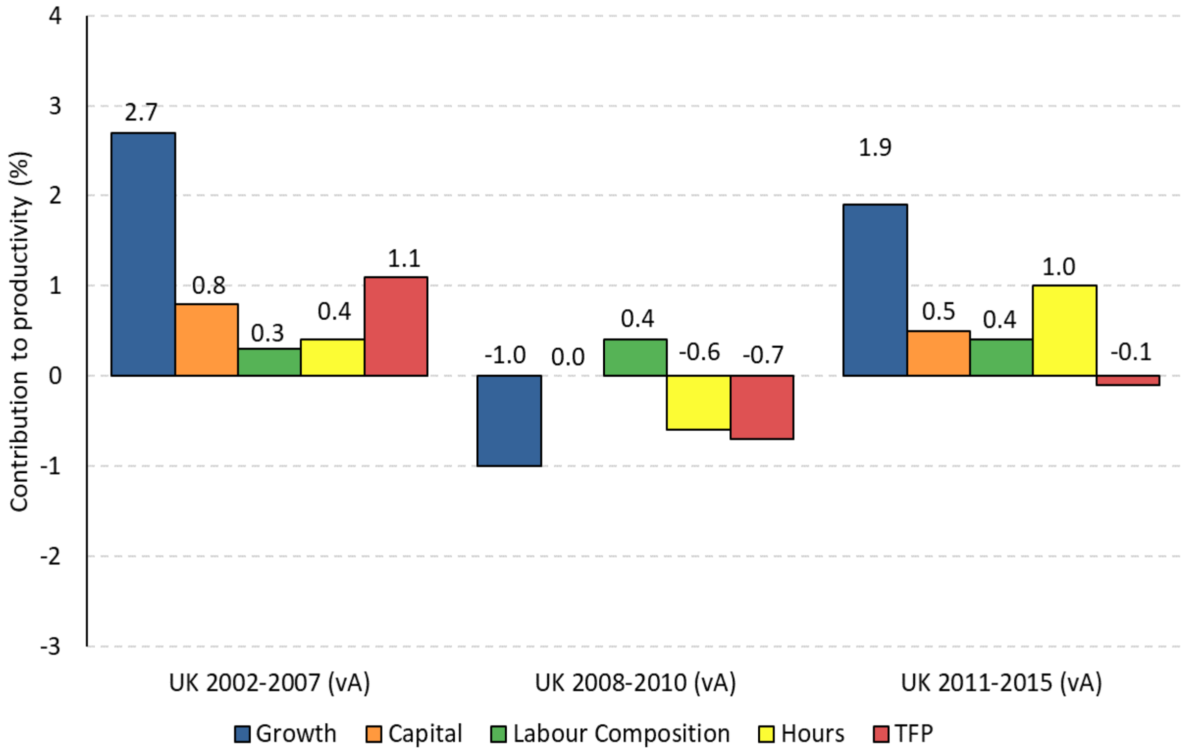
[31] Differences between these results and the findings of the current analysis are likely to be mainly driven by methodological differences (e.g. the current analysis looks at GVA rather than GDP; considers the whole economy rather than market sector; the definitions of hours used; and the granular approach used to construct QALI may be different etc.), potential revisions to GDP/GVA estimates, and the LFS release used (as, for example, weights have been updated over time).

[32] The findings presented by Van Ark and Jäger used data from the 2017 version of EU Klems (http://www.euklems.net/). However, more recent studies using the 2019 edition of EU Klems (https://euklems.eu/archive-history/) (in particular Goldin et al. (2021)) show a zero contribution of labour composition to growth in the UK between 2006 and 2017. The authors acknowledge that their results for the UK differ from other studies that rely on data from the ONS and also note that the labour composition index differs from previous versions of EU Klems in the case of the UK, due to discrepancies in labour survey data managed by the ONS and Eurostat.

Figure 6: Output growth contribution for the UK



Source: BEIS (2013; 2015)
Note: Growth in GDP



Source: Van Ark and Jäger (2017)
Note: Growth in GVA

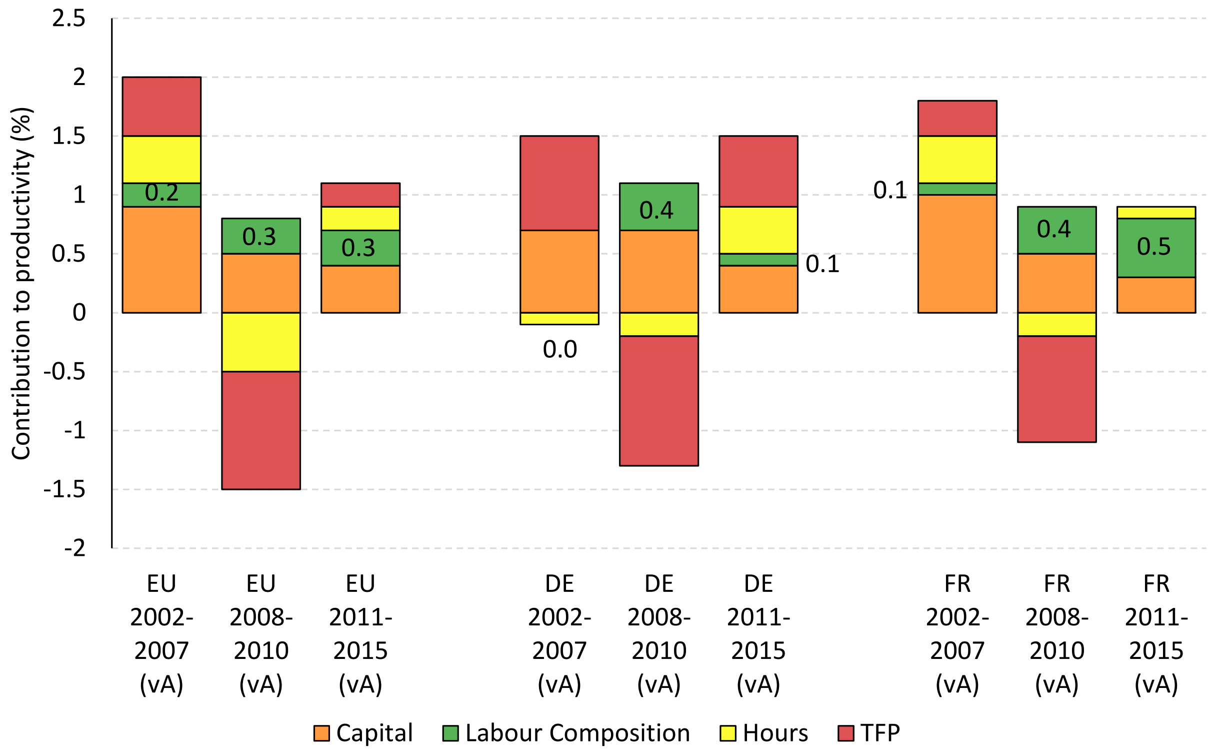
3.2 Recent Growth Accounting evidence internationally

A 2017 study from Van Ark and Jäger looked at productivity growth in various European countries (and the EU as a whole) between 2002 and 2015 using GVA (Figure 7). Similar to the findings specifically relating to the UK, the analysis identified that productivity growth declined as a result of the Financial Crisis and has only partially reverted to pre-crisis levels. In the EU as a whole, the contribution of labour composition to growth remained stable throughout all three time periods, and was of similar order of magnitude that was found in the analyses relating to the UK (between 0.2 and 0.3 percentage points).

Looking at Germany and France as being potentially the most comparable European countries to the UK in terms of size of the economy, these jurisdictions also display much lower growth in the period from 2008 onwards. However, the contribution of labour composition appears to be less consistent across the three time periods. While the share has increased from 0.1 to 0.5 percentage points in France since 2002, it has fallen in from 0.4 to 0.1 percentage points in Germany since 2010.

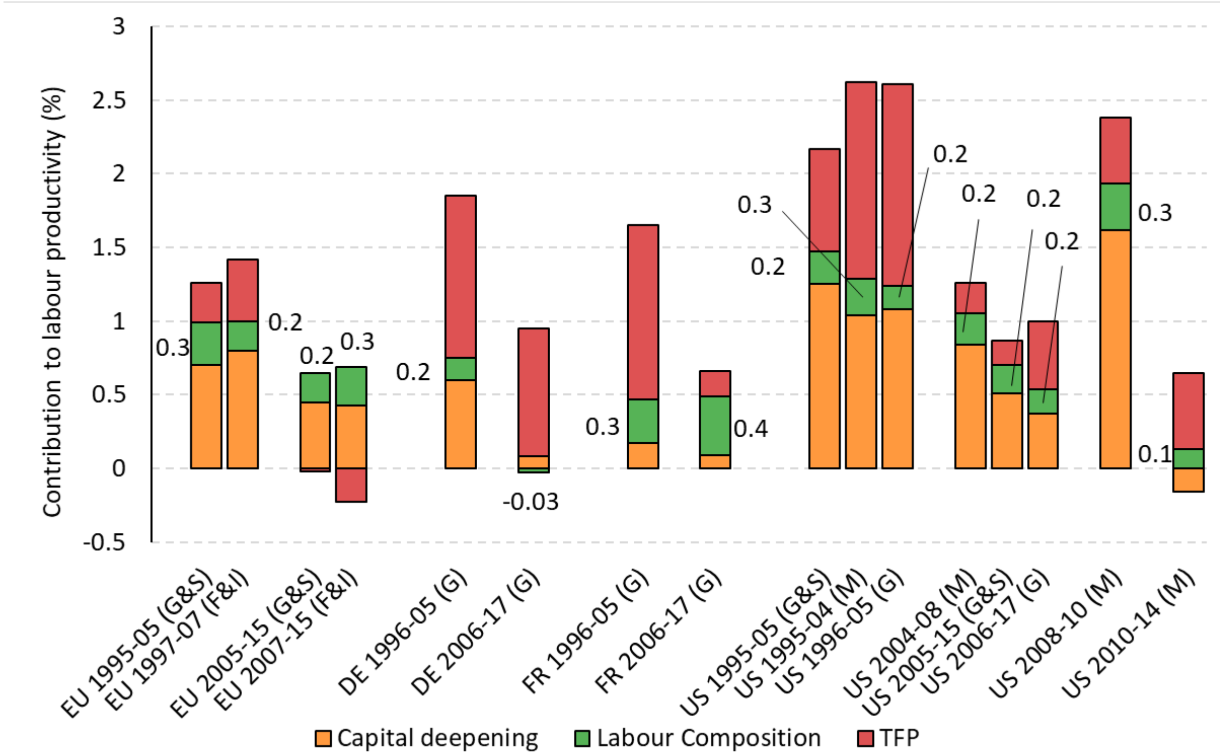
Other studies have used a growth accounting framework to analyse the contributions to labour productivity in various countries. As shown in Figure 8, all countries or regions display a significant decline in labour productivity growth after 2006, similar to the findings in previous studies looking at the UK. Capital deepening and TFP appear to be the main contributors to growth across the EU and the US. Similar to the findings for the UK, labour composition only had a relatively small impact on labour productivity in other countries, usually between 0.2 and 0.3 percentage points. In most countries and studies, the share of labour productivity growth attributable to labour composition has slightly increased since the Financial Crisis.

Figure 7: Results from international studies (GVA growth)



Source: Van Ark and Jäger (2017)

Figure 8: Results from international studies (GDP per hour growth)



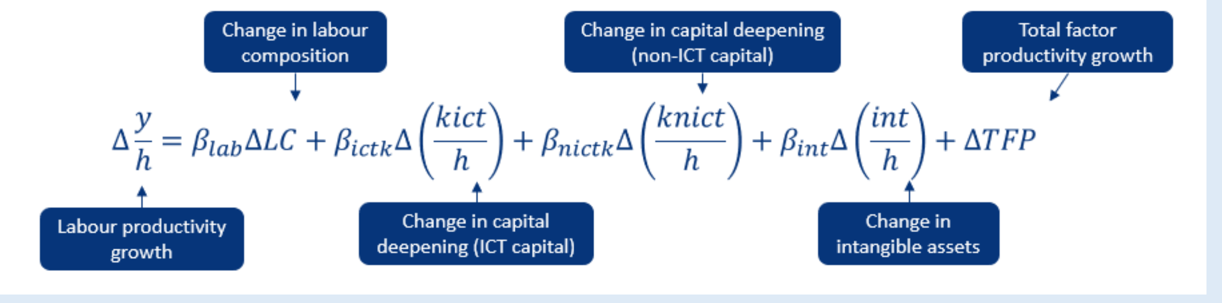
Source: Goldin et al. (2021) using EU KLEMS 2019 data; Gordon & Sayed (2019) using EU KLEMS 2012 and 2017 data; Fernald & Inklaar (2020) using EU KLEMS 2012 and 2017 data; Murray et al. (2018) using Bureau of Labour Statistics data

4. Methodology

Box 5: Growth accounting methodology – summary

Growth Accounting approach

In **growth accounting**, the growth in output per hour worked (i.e. labour productivity growth) can be decomposed as follows:



$$\Delta\frac{y}{h} = \beta_{lab}\Delta LC + \beta_{ictk}\Delta\left(\frac{kict}{h}\right) + \beta_{nictk}\Delta\left(\frac{knict}{h}\right) + \beta_{int}\Delta\left(\frac{int}{h}\right) + \Delta TFP$$

where *LC* denotes labour composition (proxy for labour quality), $\frac{k}{h}$ denotes capital deepening (capital per hour worked) associated with ICT, non-ICT and intangible capital, and TFP denotes total factor productivity (the gain in productivity that is not explained by changes in factor inputs). A fuller explanation of the decomposition of labour input can be found in Box 9 in Annex A3.

All variables are expressed in log-terms to represent growth rates and weighted by their imposed factor shares (β). Growth accounting assumes constant returns to scale (i.e. that an increase in inputs results in a proportional increase in output), meaning that all factor inputs sum up to 1 ($\beta_{lab} + \beta_k$ =1, where capital k is the sum of factor inputs across asset type: $\beta_{ictk}, \beta_{nictk}, \beta_{intk}$).

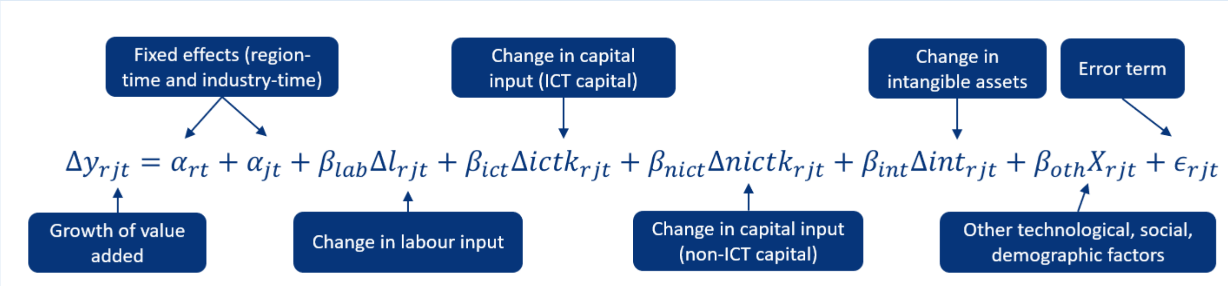
Key limitations of growth accounting

- The productivity decomposition is constructed using a top-down approach and the share of growth not accounted for by changes in capital and labour is ascribed to Total Factor Productivity (a residual component, which is typically pro-cyclical and accounted for more than half of total GVA growth in the first sub-period, while became negative or negligible after 2008).
- There are a series of strict assumptions on constant returns to scale, factor input shares, perfectly competitive factor input markets, no interactions between factor inputs.

Box 6: Econometric approach - summary

Econometric approach

In the **econometric approach**, the growth rate of output per hour worked can be regressed on the growth rate of inputs in region r, industry j, at time t:



$$\Delta y_{rjt} = \alpha_{rt} + \alpha_{jt} + \beta_{lab}\Delta l_{rjt} + \beta_{ict}\Delta ictk_{rjt} + \beta_{nict}\Delta nictk_{rjt} + \beta_{int}\Delta int_{rjt} + \beta_{oth}X_{rjt} + \epsilon_{rjt}$$

where α_{rt} and α_{jt} denote region-time and industry-time fixed effects, LC denotes labour composition, $\frac{k}{h}$ denotes capital deepening (split by ICT, non-ICT tangible, and intangible capital), X_{rjt} denotes additional technological, social, or demographic factors, and ϵ_{rjt} denotes the unexplained variation. The estimated parameters (β) can be interpreted as output elasticities to factors of production. They are not assumed to sum up to 1.

Given the methodological differences between the two approaches, the results are not directly comparable.

Key limitations of the econometric approach

- The econometric estimates presented in this report should not be interpreted as providing causal estimates of the effect of labour and capital inputs on productivity growth due to possible endogeneity (e.g., omitted variable bias, reverse causality);
- the number of observations available for the econometric analysis may become quite limited when disaggregating by time period

In this section we present the growth accounting and the econometric method used in the analysis. In discussing the methodology, we also consider some of the strengths and limitations associated with the approaches adopted. For a comprehensive review and critique of these methods (and also the microeconomic approaches used in the estimation of the economic benefits of education), see Cattan and Crawford (2013)[33].

On the one hand, the growth accounting method is rooted in economic theory and disaggregates the economic growth rate into the contribution of capital and labour inputs (weighted by their relative factor share) and residual total factor productivity. The approach has been adjusted over time to include more refined factors (e.g. measures

[33] Available here

accounting for the quality of human capital) and new forms of capital (e.g. broken down into physical capital and intangible capital). The approach may also be used to compare contributions across different countries and sectors.

Unlike growth accounting, the econometric approach aims at estimating, rather than imposing, the relationship between output growth and the inputs of the production function (changes in the stock of capital and labour across countries or sectors). The regression approach provides an indication of the total benefits (private and external) of skills accumulation, but does not directly provide an estimate of the contribution of each component.

Both approaches are subject to various caveats as discussed in this section and none of the approaches is likely to provide a definitive answer of the impact of education, training and skills acquisition on productivity. However, the findings from both approaches, taken together with the wider body of evidence on individual level returns to education, provide evidence on the economic benefits of skills acquisition, at both the aggregate and individual level.

4.1 Growth accounting

Growth accounting decomposes the growth of output in an economy into the growth of each factor input multiplied by its share in income. The residual component left unexplained by factor input growth is 'attributed' to total factor productivity (TFP)[34]. Starting from a standard production function, the growth rate of output can be expressed as the growth of inputs weighted by the share of output accruing to each factor plus TFP growth (Solow, 1957).[35]

$$Y_{j,t} = f_{j,t}(K_{j,t}, L_{j,t}, T_{j,t})$$

where $Y_{j,t}$ denotes output using GVA in real terms (chain-linked volumes) in industry (or region) j at time t. The variables $K_{j,t}$, $L_{j,t}$, and $T_{j,t}$ denote capital stock, labour (number of employed persons or hours worked), and the (unobserved) level of technology, respectively. The growth rate of output is thus given by:

$$\Delta lnY_{j,t} = \bar{v}_{K,j,t}\Delta lnK_{j,t} + \bar{v}_{L,j,t}\Delta lnL_{j,t} + \Delta lnTFP_{j,t}$$

[34] TFP growth is the difference between the growth of output and the growth of a combination of factor inputs (labour and capital). Improvements in TFP generally reflect the contribution to output of more efficient use of resources or the adoption of new production technologies.

[35] Following EU KLEMS methodology (https://euklems.eu/wp-content/uploads/2019/10/Methodology.pdf) and BEIS (2015)

where $\bar{v}_{K,j,t}$ and $\bar{v}_{L,j,t}$ are the factor shares, or Divisia cost shares of capital and labour costs in value added in industry j. The two-period average share of capital or labour compensation in gross output given by:

$$\bar{v}_{K,j,t} = \frac{1}{2}\left(v_{K,j,t} + v_{K,j,t-1}\right)$$

$$\bar{v}_{L,j,t} = \frac{1}{2}\left(v_{L,j,t} + v_{L,j,t-1}\right)$$

where $v_{f,j,t} = \frac{p_{f,j,t}F_{j,t}}{p_{Y,j,t}Y_{j,t}}$ for inputs $F_{j,t} = K_{j,t}, L_{j,t}$.

The residual component generates the growth rate of total factor productivity (TFP). Importantly, the growth accounting approach also relies on the assumption of constant returns to scale, which implies that $\bar{v}_{K,j,t} + \bar{v}_{L,j,t} = 1$.

Further assumptions of the growth accounting methodology include the existence of perfectly competitive factor markets (i.e., factors are paid their marginal products), and full input utilisation. We provide further explanation of some of the caveats and implications of these assumptions in Section 4.1.1.

Changes in both the capital and labour inputs can be further decomposed. Changes in capital input can be decomposed into types of capital G (ICT, non-ICT tangible, and intangible), where $\bar{v}_{G,j,t}$ is the share of income for capital of type G.

Changes in the quality-adjusted labour input (QALI), can also be decomposed into two components, labour composition LC (proxying for quality) and hours worked H (measuring quantity):

$$\Delta lnY_{j,t} = \bar{v}_{K,j,t} \sum_{G} \bar{v}_{G,j,t}\, \Delta lnK_{G,j,t} + \bar{v}_{L,j,t}(\Delta lnLC_{j,t} + \Delta lnH_{j,t}) + \Delta lnTFP_{j,t}$$

The derivations of the decomposition of the labour and capital inputs can be found in Annex A3, while the labour share of income data is provided by the ONS[36]. The share of income for each capital type is estimated using rates of return from capital. The estimation method is outlined in Annex A3.

As previously discussed, growth accounting provides a framework to decompose productivity growth in its constituent parts – and can be used to analyse various sectors, regions, or time periods. Capital and labour can also be broken down into their

[36] ONS Labour costs and labour share, available here [Labour costs and labour income - Office for National Statistics (ons.gov.uk)]

constituent components (i.e., hours, and labour composition) as discussed in more detail in the next section.

4.1.1 Main limitations of the Growth Accounting approach

The growth accounting approach provides a useful tool to break down the contribution to productivity growth between the labour and capital inputs. However there are some limitations to the approach, involving:

- The assumption of **full input utilisation** may not always be realistic in practice. It assumes that input factors are used to their full capacity. However, some workers, especially new entrants to the labour market, may often be underutilised and work in occupations not fully utilising their education level. This may potentially lead to imperfect estimates.
- The analysis assumes **perfectly competitive input factor markets**, meaning that factor inputs are paid their marginal product (i.e. exactly their contribution to productivity), and that any observed differences in wages between workers with different qualification levels are solely driven by education. However, wages may be an **imperfect proxy** for productivity differentials with respect to the measurement of skills, as it assumes that wage differentials are not based on institutional factors or wage bargaining (or any other unmeasured factor) and reflect true productivity differences.
- The growth accounting approach assumes **constant returns to scale** (i.e. a constant ratio of inputs to output where factor shares sum up to 1). In practice however, there may be economies of scale, meaning that as production increases, the same given increase in inputs produces additional output as the marginal cost of production declines.
- The analysis depends on **estimates of factor input shares** used, since the factor shares are imposed and not estimated. Any inaccuracies in the factor input shares will distort the growth accounting results.
- With the growth accounting approach, it is not possible to consider and/or estimate **interactions** between inputs. However, the impact of skills on productivity could depend on capital inputs, e.g., if higher ICT capital reinforces the impact on skills on productivity.
- A **share of productivity growth is assigned to total factor productivity growth**, which is unexplained within the model. Total factor productivity captures the portion of output growth that cannot be attributed to capital or labour, and is usually said to capture technological change. However, it could also include other economic or cultural factors that are not captured as factors of production. Hence,

a (potentially) significant share or productivity growth may not be explained using the growth accounting approach.

4.2 Econometric approach

The econometric approach regresses the rate of growth in an economy on a variety of potential determinants. Fundamentally, econometric models are more flexible in terms of model specifications, and **require fewer restrictive assumptions**. When comparing the impact of skills on productivity across sectors, regions and time, applying panel data methods (such as fixed or random effect models) facilitate controlling for heterogeneity. In addition, econometric models are generally derived from 'new' growth theories (Romer, 1994), allowing for endogenous growth and non-constant returns to scale.

As with the growth accounting approach, the starting point is the production function. However, in contrast to the growth accounting approach, input factor shares are not imposed, but rather estimated econometrically. This means that the results are not dependant on previous estimates of the share of labour or capital. Further, the assumption of constant returns to scale is relaxed. This relaxation of the model's assumptions implies that the econometric approach allows for economies of scale (i.e. where the same given increases in inputs lead to increasing levels of output), which is considered a more accurate reflection of the functioning of an economy.

Unlike in the growth accounting approach, where the effect of technological progress and other 'efficiency' factors (as well as any effect on growth of the interaction between labour and other factors) are identified 'exogenously' (i.e. as an unexplained residual component, not directly identified within the model), the econometric approach allows (in theory) to explicitly control for other factors affecting growth and interactions between factors. For example, in a cross-country setting, growth may also be driven by country specific factors, such as the regulatory environment, quality of its institutions as well as the quality of is legal and tax system, and openness to trade etc. (with these 'efficiency' factors being explicitly included in the model if the data allow). Moreover, the econometric approach can model both the direct effect of the labour input, but also any interaction between the labour input and other variables, for example those proxying for technological change (such as R&D or ICT investment).

This econometric approach is often adopted in empirical analyses aiming to analyse productivity developments in respect of ICT capital and intangible assets (see Corrado et al, 2014; Timmer et al., 2010)[37].Regression-based models also allow for other sources of growth besides factor growth. These can be R&D, foreign direct investment (FDI) or

[37] Corrado, C., Haskel, J. and C. Jona-Lasinio (2014), "Knowledge Spillovers, ICT and productivity growth", Discussion Paper 2014/5, Imperial College London Business School.
Timmer, M.P., Inklaar, R., O'Mahony, M. and B. van Ark (2010), Economic Growth in Europe, Cambridge Books, Cambridge University Press, November.

measures of openness of the economy. Skills are not merely another factor of production, but also enhance a country's ability to develop innovations and contribute to overall productivity through various channels. Thus, an econometric approach is useful in estimating the impact of demographic, social, economic, or technological factors such as ageing, digitalisation, globalisation, migration or skill mismatch on productivity growth, as well as their interactions with production inputs and each other. However, due to data and sample size limitations, the present analysis does not include additional factors.

Based on the production function the baseline econometric model estimated is:

$$\Delta lnY_{j,t} = \beta_K \Delta lnK_{j,t} + \beta_L \Delta lnL_{j,t} + \epsilon_{j,t}$$

Where $\Delta lnY_{j,t}$ denotes the output growth in industry j at time t, the variable $\Delta lnK_{j,t}$ denotes the growth rate of capital input, $\Delta lnL_{j,t}$ denotes the growth rate of labour input, and $\epsilon_{j,t}$ denotes the unexplained variation (similar to the TFP component in the growth accounting framework). This equation is similar to the growth accounting analysis, but the factor shares are not imposed but estimated (β_K and β_L).

The **Quality-adjusted labour input (QALI**) is a measure accounting for changes in the **composition** (or quality) of the employed workforce (proxied by qualifications) and changes in **hours worked** by different types of workers with different levels of productivity (proxied by wages).

Following a similar logic as before, changes in labour input (QALI) can be decomposed into changes in hours worked and labour composition (see Box 9 for a detailed description), whereas changes in capital input can be disaggregated by type of asset (ICT, non-ICT, and intangible capital).

In addition, the econometric model allows the inclusion of other technological, social, or demographic factors in the model (if available) to test whether they have an impact on productivity growth. In the current analysis, we included age structure[38] as an explanatory variable (available from the LFS). Other variables that are often used in *cross-country* analyses include trade, inflation, proxies for the regulatory environment, or real interest rates. However, there is limited or no within-country variation for most of these measures, which meant that we were unable to include any of the standard cross-country controls in the econometric analysis.

To capture underlying industry/region-specific differences, we also include industry-time (region-time) fixed effects. The full model then looks as follows:

[38] The age structure variable captures the proportion of the workforce aged between 16 and 29, 30 and 44, 45 and 54, and 55+

$$\Delta lnY_{j,t} = \beta_{Kict}\Delta lnK_{j,t}^{ict} + \beta_{Knict}\Delta lnK_{j,t}^{nict} + \beta_{Kint}\Delta lnK_{j,t}^{int} + \beta_L \Delta lnLC_{j,t} + \beta_L \Delta lnH_{j,t} + \beta_x X_{j,t} + \gamma_{j,t} + \epsilon_{j,t}$$

Where the variables $\Delta lnK_{j,t}^{ict}$, $\Delta lnK_{j,t}^{nict}$, and $\Delta lnK_{j,t}^{int}$ denote the growth in ICT-capital, non-ICT capital, and intangible capital, respectively. The variables $\Delta lnLC_{j,t}$ and $\Delta lnH_{j,t}$ represent the change in labour composition and growth in hours worked. $X_{j,t}$ denotes the vector of other technological, social, and demographic variables, and $\gamma_{j,t}$ denotes industry-time fixed effects.

Similar to the growth accounting framework, the econometric specification can also be expressed in terms of labour productivity:

$$\Delta ln\left[\frac{Y_{j,t}}{h_{j,t}}\right] = \beta_{Kict}\Delta \ln\left[\frac{K_{j,t}^{ict}}{h_{j,t}}\right] + \beta_{Knict}\Delta ln\left[\frac{K_{j,t}^{nict}}{h_{j,t}}\right] + \beta_{Kint}\Delta ln\left[\frac{K_{j,t}^{int}}{h_{j,t}}\right] + \beta_L \Delta lnLC_{j,t} + \beta_x X_{j,t} + \gamma_{j,t} + \epsilon_{j,t}$$

4.2.1 Main limitations of the econometric approach

While there are some advantages of using an econometric approach, there are still several caveats that need to be considered:

- The results using the econometric approach do not provide **definitive proof of a causal relationship** between skills and labour productivity growth. Several factors could lead to biased or inconsistent estimates, meaning the results may not be fully accurate, including:
  - If the causal link does not only run from skills to productivity, but productivity in turn affects skills composition (so-called **reverse causality**), the econometric approach may overestimate the impact of skills on productivity.
  - If certain factors that affect productivity growth are not included in the model, which seems likely if there are large TFP estimates from the growth accounting approach, then the econometric estimates will probably be of **limited statistical significance**.
  - If these unobserved factors also affect the explanatory variables included in the model, the estimates may capture an indirect effect rather than a direct causal effect (**unobserved variable bias**).
- When using **time series data**, the values from one year to the next are unlikely to be independent of each other. This can lead to so-called spurious (invalid) regression results. A solution to this involves taking first differences of the variables, which is adopted for all time-series variables contained in the analysis.

- Due to **data limitations** it was not possible to undertake the analysis by sector and region at the same time (as the data became too granular), so we are unable to explicitly model any variability occurring by sector and region (although the model does include regional dummies as control variables)[39]. Results using regional disaggregations are presented in the Annex.

[39] In general, a larger the number of groups (i.e. number of regions (12 in this analysis) and/or the number of sectors (13 in this analysis)) is preferable for panel data analysis. If there was sufficient data to look at region and sector, we would have had 156 groups available, which would have yielded more robust results and allowed for additional variation by region and sector.

5. Results

Box 7: Growth Accounting results - summary

Growth in Gross Value Added and Hours worked (Figure 13**)**

- **Overall GVA growth** in the UK was very strong in the early 2000s (2.7% per annum), before declining to 0.5% per annum in the aftermath of the 2008 financial crisis (2008-2013) and recovering to almost 1.9% per annum between 2014 and 2019;
- **Total hours worked** grew by 0.7% per annum in the first period, before stalling after the financial crisis and rebounding to 1.6% per annum in the last period;
- As a result, the recovery in overall GVA growth observed in the third period was **mainly driven by hours worked, rather than an increase in GVA per labour hour** (**i.e. labour productivity**), which stood at just 0.3% per annum between 2014-2019;

Contribution of different factors to labour productivity growth (Figure 14)

- The contribution of **capital deepening** to labour productivity growth declined over time from 0.8 percentage points to zero between the first and last period;
- The contribution of **labour composition** to productivity growth was far more stable over time, ranging between 0.3pp and 0.4pp over the three periods;
- The contribution of **Total Factor Productivity** stood at 1.0pp in the first period (characterised by high growth in labour productivity) but negative or zero in the remaining two periods of low growth in labour productivity.

Labour contribution across different qualification levels (Figure 16 and Figure 17)

- The positive contribution of labour to overall GVA growth was mainly driven by an increase in **hours worked from higher level qualification groups** (first degree and above), and a decline (negative contribution) from lower-level qualification groups (especially in the second period);
- Similarly, the overall positive contributions of labour composition to growth in labour productivity were mainly **driven by large and positive contributions from postgraduate and first degree qualifications** (and equivalent) across the three time periods.

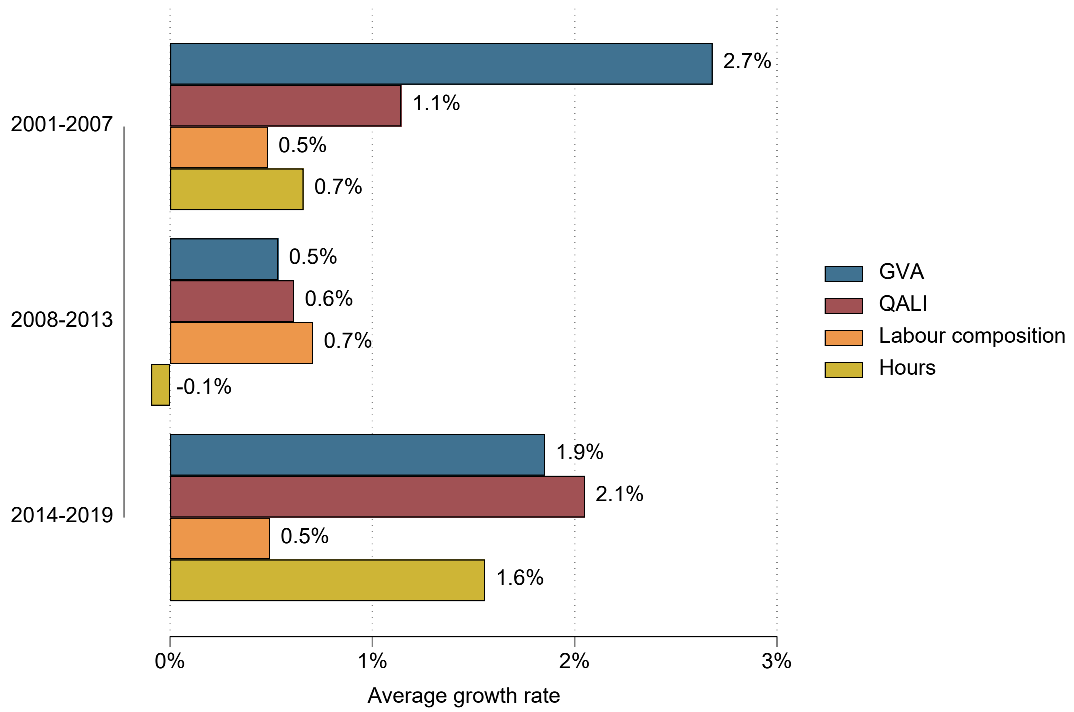
Labour composition contribution by sector and region (Table 7 and Table 9)

- The contribution of labour composition to productivity growth was particularly strong in the Manufacturing sector, Financial and Insurance services and in the Public Administration sector - all consistently ranging between 0.4pp and 0.5pp;
- All average annual contributions of labour composition to productivity growth at the regional level ranged between 0.1pp and 0.5pp, across all time periods and regions. In particular, labour contribution was relatively high in the North East (first and last period) and London (first two periods) areas.

5.1 Descriptive statistics

This section provides a summary of the descriptive statistics that illustrate changes in Gross Value Added, changes in labour composition[40] across different qualification levels (hours worked and employment shares), the share of pay bill paid to each group and the relative remuneration across qualification groups. The analysis consistently splits the full sample (covering the period 2001 to 2019) into three sub-periods: the first time period between 2001 and 2007 (covering the rapid increase in GVA experienced in the early 2000s), the second time period between 2008 and 2013 (covering the Financial Crisis and the immediate recovery), and the third time period between 2014 and 2019.

Figure 9: Growth rates of GVA and labour components (per annum), by time period



Sources: ONS, LFS, London Economics' calculations
Note: Annual growth rates for overall GVA and labour inputs are reported (not contributions). QALI growth rates may not be precisely identical to the sum of the growth rate in labour composition and growth rate in hours due to rounding.

Figure 9 presents the **raw average annual growth rate** of GVA, average annual growth in **Quality Adjusted Labour Index (QALI)**, which corresponds to the sum of average annual growth in hours and average annual growth in labour composition (across the three time periods: 2001-2007, 2008-2013, and 2014-2019). The average annual growth

[40] Labour composition changes are defined as the difference between changes in QALI (the Quality Adjusted Labour Index) and change in hours worked (see Box 3).

rates in labour inputs reported in Figure 9 are different from the contributions of labour inputs to GVA growth (as they do not account for the labour factor share).

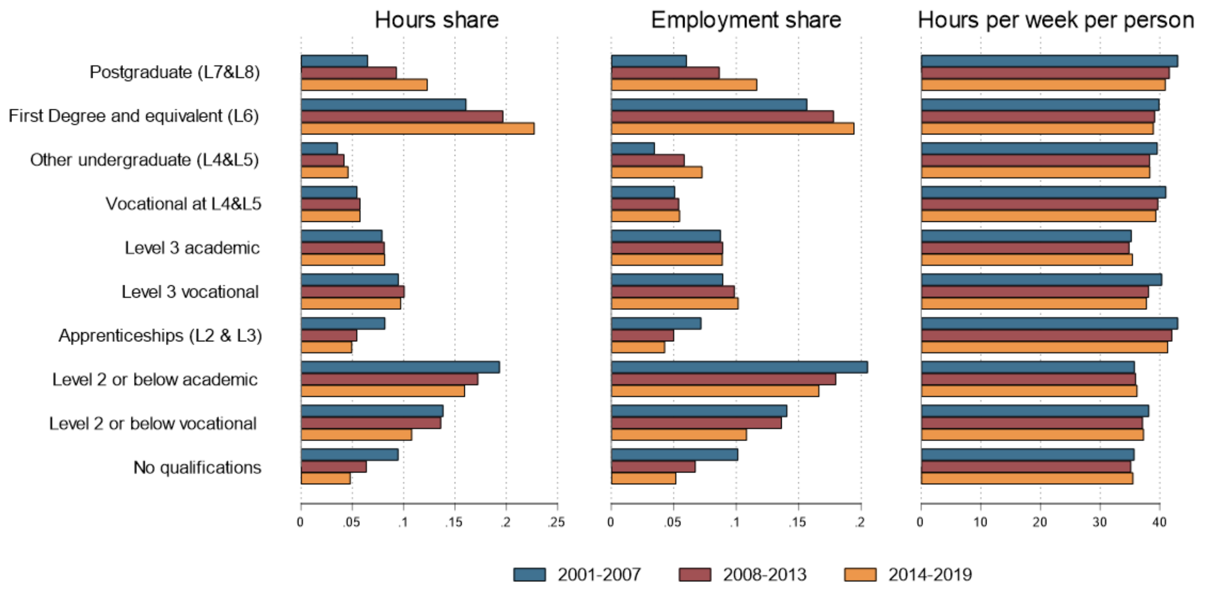
On average, overall GVA grew by 2.7% per annum between 2001 and 2007, but fell to a rate of just 0.5% per annum between 2008 and 2013 (largely due to a 0.2% and 4.1% fall in GVA in 2009 and 2010, respectively). Growth in usual hours worked stalled between 2008 and 2013 (due to a large fall in 2009 only partially compensated by the recovery after 2010). Average annual QALI growth declined in the second time period compared to the first time period (1.1% per annum), but was still positive at 0.6% per annum during the middle period, reflecting a 0.7% per annum positive change in labour composition.

Overall GVA growth recovered after 2014 (although it did not reach the growth rates experienced in the first time period), growing at an average annual rate of 1.9%. However this increase in GVA was mainly driven by hours worked, which grew by almost 1.6% per annum after 2014. In the same time period, QALI increased by almost 2.1% per annum, reflecting a change in labour composition of around 0.5% per annum. It should be noted that all these figures refer to the overall change in labour composition, and not to the contribution of labour to productivity growth (which is derived by weighting the change in labour composition by the relative factor share and presented in Figure 14).

Figure 10 looks in more detail into changes in the composition of hours and employment shares of labour across different qualifications levels. The first panel presents the proportion of total usual weekly hours worked across qualification levels, while the second and third panels disaggregate the hours share into employment shares and usual hours worked per week. As shown in the leftmost panel, the proportion of hours worked by those with higher level qualifications steadily increased across the time periods. For example, the proportion of hours worked by those holding at least a first degree increased from an average of 23% between 2001 and 2007 to 30% between 2008 and 2013, and then increased further to 35% in the final time period.

The proportion of hours worked by those with lower-level qualifications consistently decreased across the time periods. Specifically, the proportion of hours worked by those with a Level 2 qualification or lower fell from an average of 42% between 2001 and 2007 to 31% in the final time period considered (2014-2019).

Figure 10: Labour composition change, by qualification level



Sources: LFS and London Economics' calculations

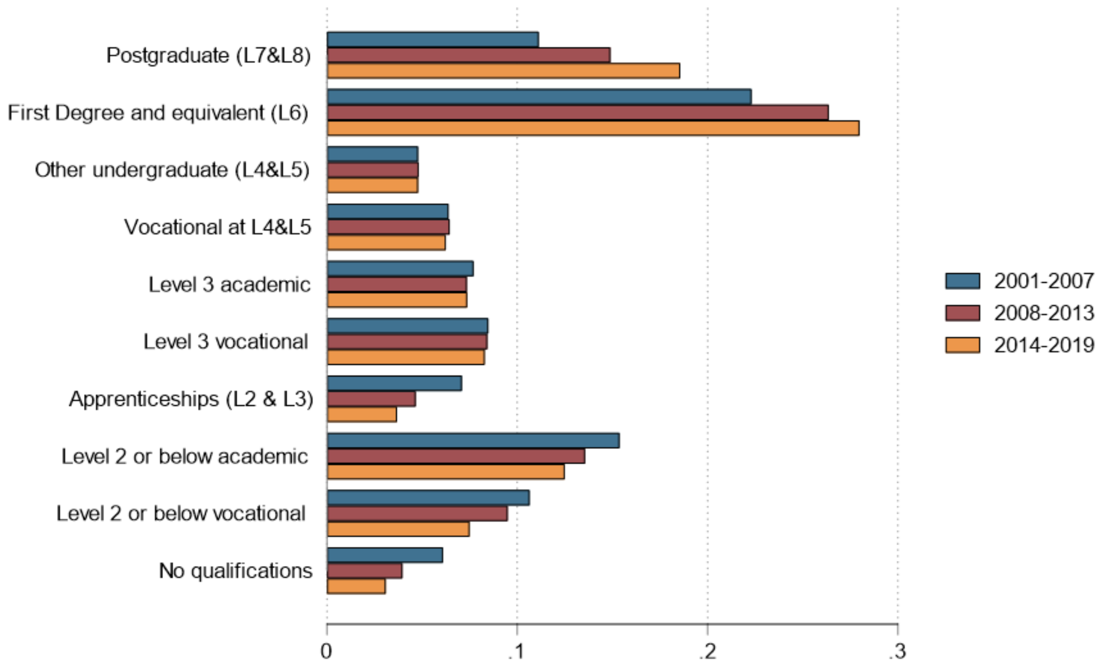
Breaking down the changes in hours share into employment shares and weekly hours worked (second and third panels of Figure 10), it is possible to see that **this shift in hours towards higher level qualifications is driven by a shift in employment shares** rather than a change in hours worked per person: in other words in the most recent period there was a much higher proportion of individuals in employment with graduate and postgraduate qualifications compared to the first time period, while usual hours worked per week did not change significantly over time (and actually slightly decreased for many of the groups considered). This is likely to be a combination of two factors: older workers (on average with lower levels of education) being replaced by younger workers (with higher levels of education) and the effect of existing workers upgrading their skills over time. For example, the LFS data shows that:

- Those in possession of graduate qualifications (postgraduate and first degrees) represented around 25% of the workforce aged 21-30 in 2000, but 40% of those aged 21-30 in 2019 (i.e. younger cohorts in the same age band are now more educated);
- The cohort of workers who were aged 21-30 in 2000 have also significantly upgraded their skills over time, as the proportion with higher level qualifications moved from 25% in 2000 to 41% for those aged 40-49 in 2019 (i.e. the same cohort observed 19 years later)[41];

[41] As a comparison only 21% of workers aged 40-49 in 2000 were in possession of graduate qualifications

More generally, and across all age bands, individuals with postgraduate and first degrees made up just above one fifth (22%) of those employed between 2001 and 2007 but almost 35% between 2014 and 2019. In contrast, those with a Level 2 qualification or lower made up 33% of those employed in the final time period, which represents a decline of more than one quarter compared to the initial time period (when the share was around 45%).

Figure 11: Labour income shares, by qualification level

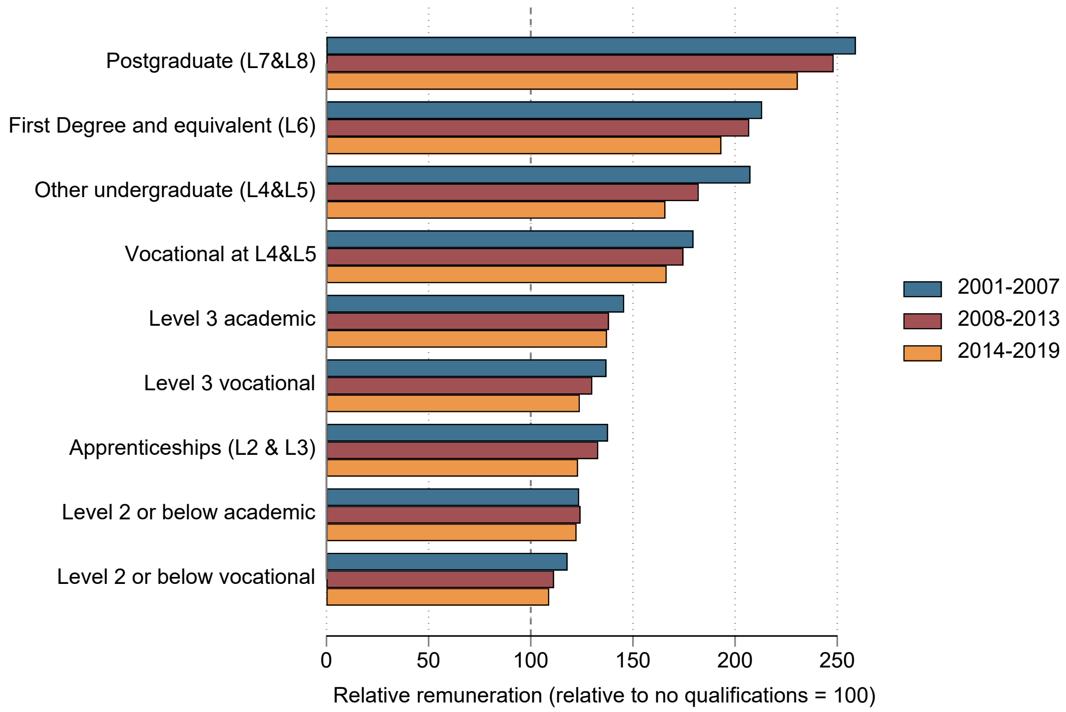


Sources: LFS and London Economics' calculations

There has also been a similar shift in the share of total labour income (i.e. pay bill) paid to those with higher level qualifications, as presented in Figure 11, which was driven by the increase in their employment shares (rather than an increase in their relative remuneration, as shown in Figure 12). In fact, the proportion of total pay bill paid to those with graduate or postgraduate qualifications increased from around a third (34%) in the first time period to 47% in the last time period. This increase is mirrored by a 9 percentage point fall in the pay bill share paid to those with Level 2 qualifications and below (falling from an average of slightly less than one third of total income share (32%) between 2001 and 2007 to less than a quarter between 2014 and 2019 (23%)).

Figure 12 presents changes in relative remuneration across qualification levels. Relative remuneration compares the average hourly wage for those in possession of different highest qualifications to the hourly wage for those with no formal qualifications in a given time period (which is an index set to 100). As shown in Figure 12, the gap between the remuneration for those individuals with higher level qualifications and those with no qualifications declined across the time periods considered. For example, the relative remuneration of those with postgraduate degrees fell from an index value of 259 between 2001 and 2007 to 231 between 2014 and 2019, while for those in possession of a first degree, the relative remuneration declined from an index value of 213 (first sub-period) to 191 (final sub-period). Moreover, workers with other undergraduate qualifications (at level 4 and 5) saw their hourly wage relative to the those with no formal qualifications fall by over 20% from an index value of 208 to 162 over the same time period. On the other hand, the relative remuneration for those with qualifications at Level 2 and below shows limited variation over time (relative to those with no formal qualifications) as shown at the bottom of Figure 12.

Figure 12: Relative remuneration, by qualification level



Sources: LFS and London Economics' calculations

Note: The remuneration by qualification level shows the average remuneration of a given qualification level group within a subperiod relative to the average remuneration of those with no qualifications (=100) within the same subperiod. For example, a group with a relative remuneration of 200 earns, on average, double of the average remuneration of those with no qualifications (within the same subperiod).

The decline in the relative remuneration of higher level qualifications over time is likely to be driven by a combination of the following factors:

- The expansion in the proportion of the labour force holding higher level qualifications (as shown by the rise in employment shares for this group) and the associated decline (suggesting diminishing returns)[42] in the unadjusted wage premium (compared to those with no qualifications); and

- The repeated above inflation uprating in the National Minimum Wage which mostly affected individuals with qualifications at Level 2 and below.

5.2 Growth accounting results

The following sections present the results of the growth accounting analysis, which disaggregates contributions to GVA growth across different inputs (or factors). The results are reported at the national, industry, and regional level.

Throughout the analysis, **GVA growth** represents the annual average change in Gross Value Added (GVA), while **labour productivity growth** represents the annual average change in **GVA per labour hour**. Due to the assumption of constant returns to scale, the contribution of labour composition and total factor productivity remains unchanged irrespective of whether we consider overall GVA growth or growth in GVA per labour hour, while the contribution of capital input to growth in GVA per labour hour is expressed as **capital deepening** (capital per labour hour).

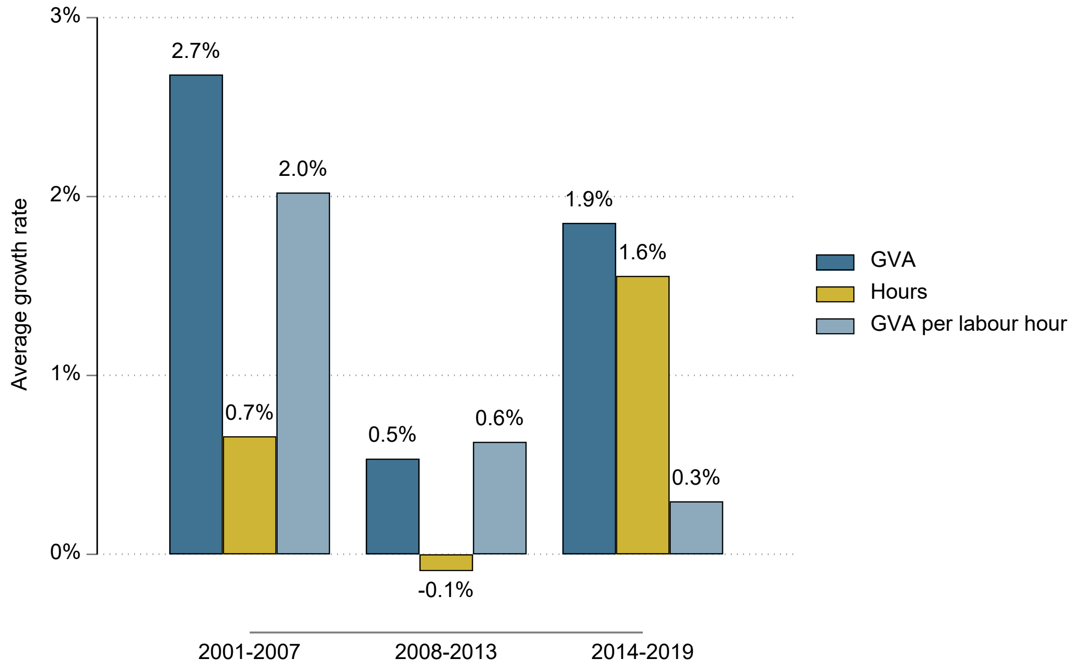
5.2.1 Growth accounting: aggregate results

Growth in GVA, hours worked and labour productivity (GVA per labour hour)

Figure 13 presents annual average GVA growth across the three time periods, the annual growth rate in hours worked and labour productivity growth (GVA per labour hour). Average GVA growth in the first time period was around 2.7% per annum, while annual growth in hours averaged at 0.7% per annum, meaning that annual growth in labour productivity was around 2% per annum on average between 2001 and 2007.

[42] For example, see research published by HESA (https://www.hesa.ac.uk/news/22-10-2019/return-to-degree-research) showing a reduction in the 'graduate premium' for graduates versus non graduates for younger cohorts.

Figure 13: Average annual growth in GVA, hours and GVA per labour hour (labour productivity)



Sources: LFS, ONS, and London Economics' calculations

The decline in usual hours worked across the economy in the second time period (between 2008 and 2013, previously illustrated in Figure 9) is reflected in the negative change in hours shown in Figure 13. The (weak) annual growth in overall GVA observed in the second time period (around 0.5% per annum), associated with this slight decline in hours worked (-0.1% per annum) resulted in a modest increase in labour productivity (around 0.6% per annum).

In the third and final time period (between 2014 and 2019), overall GVA growth rebounded to 1.9% per annum. However, the increase was driven almost entirely by an increase in hours worked (around 1.6% per annum), rather than an increase in labour productivity (GVA per hour worked only increased by approximately 0.3% per annum).

Further analysis of the contribution of hours worked – by qualification level – is presented in section 5.2.2.

Decomposing changes in labour productivity

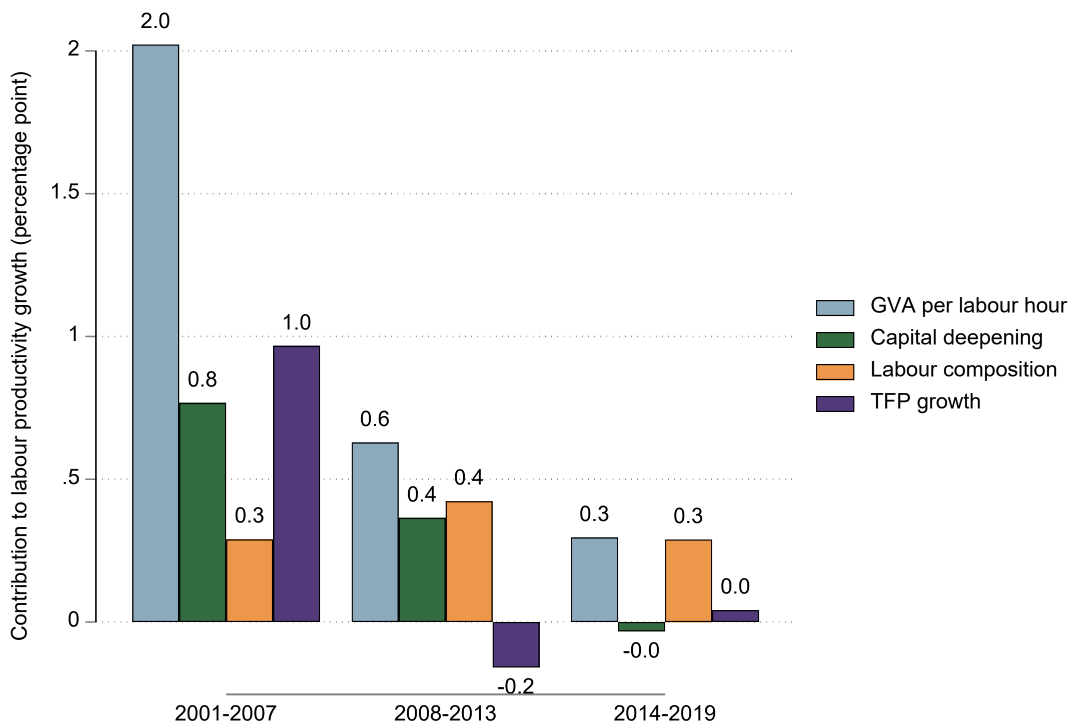
Changes in productivity growth (i.e. GVA per labour hour) can be further decomposed into **changes in capital deepening** (i.e. capital per labour hour**), labour composition** (i.e. Quality Adjusted Labour Index (QALI) minus changes in hours worked), and **Total Factor Productivity** growth, as presented in Figure 14.

Labour composition

The contribution of changes in **labour composition** to labour productivity growth was relatively stable across the three time periods, rising slightly from 0.3 percentage points to 0.4 percentage points between the first (pre-2008) and second time period (2008-13) before returning to 0.3 percentage points in the third time period (2014-19). Although averages across time periods inevitably mask annual variation in contributions, the annual contribution of growth in the labour composition variable ranges between -0.04 percentage points (in 2017) and 0.71 percentage points of productivity growth (in 2012).

As a result, the contribution of labour composition changes to productivity growth was relatively stronger in the period covering the 2008 Financial Crisis (when TFP growth was negative), but also in the period 2014-19 (when there was a negligible contribution of both capital deepening and TFP to labour productivity growth).

Figure 14: Decomposition of contributions to labour productivity growth, by time period (percentage points)



Sources: LFS, ONS, and London Economics' calculations
Note: contributions of capital deepening, labour composition, and TFP may not sum exactly to GVA per labour hour due to rounding of individual factor contributions

Capital deepening

The contribution of growth in capital deepening fell across the three time periods from an annual average contribution of 0.8 percentage points of labour productivity between 2001 and 2007 to 0.4 percentage points in the second time period and (effectively) zero between 2014 and 2019 (in particular, there were four consecutive years of negative contributions of capital deepening were observed between 2012 and 2015). We present additional information on the impact of capital deepening in Figure 15.

As shown in Table 3, the fall in capital deepening growth is driven by capital growth falling faster than hours growth immediately after the Financial Crisis, and then increasing at a slower rate than hours growth in the subsequent recovery. Specifically, capital deepening is defined as capital per labour hour, so growth in capital deepening is driven by growth in capital (positively) and by growth in hours worked (negatively). Table 3 Illustrates the average growth rates (for each time period) for capital (overall), capital deepening, and hours worked. Consistent with Figure 14, capital deepening growth falls across the three time periods. Capital deepening growth fell from 1.9% per annum in the 2001-2007 period to 0.9% per annum in the 2008-2013 period. This is driven by capital growth falling faster (2.6% per annum to 0.8% per annum) than hours growth (0.7% per annum to -0.1% per annum). Further falls in capital deepening growth (to -0.1% per annum between 2014 and 2019) were the result of capital growth increasing at a slower rate (by 0.7 percentage points (from 0.8% per annum to 1.5% per annum)) than hours growth (by 1.7 percentage points (from -0.1% per annum to 1.6% per annum)) between the second and third time periods.

Table 3: Capital deepening, capital, and hours growth rates across time periods

	2001-2007	2008-2013	2014-2019
Capital growth	2.6%	0.8%	1.5%
Hours growth	0.7%	-0.1%	1.6%
Capital deepening growth	1.9%	0.9%	-0.1%

Sources: LFS, ONS, and London Economics' calculations

Note: The time period averages reported in this table are growth rates, not contributions, and would need to be multiplied by the relevant factor shares to reproduce the contributions to labour productivity growth. Capital deepening growth and hours growth may not add up exactly to capital growth due to rounding.

Total factor productivity (TFP)

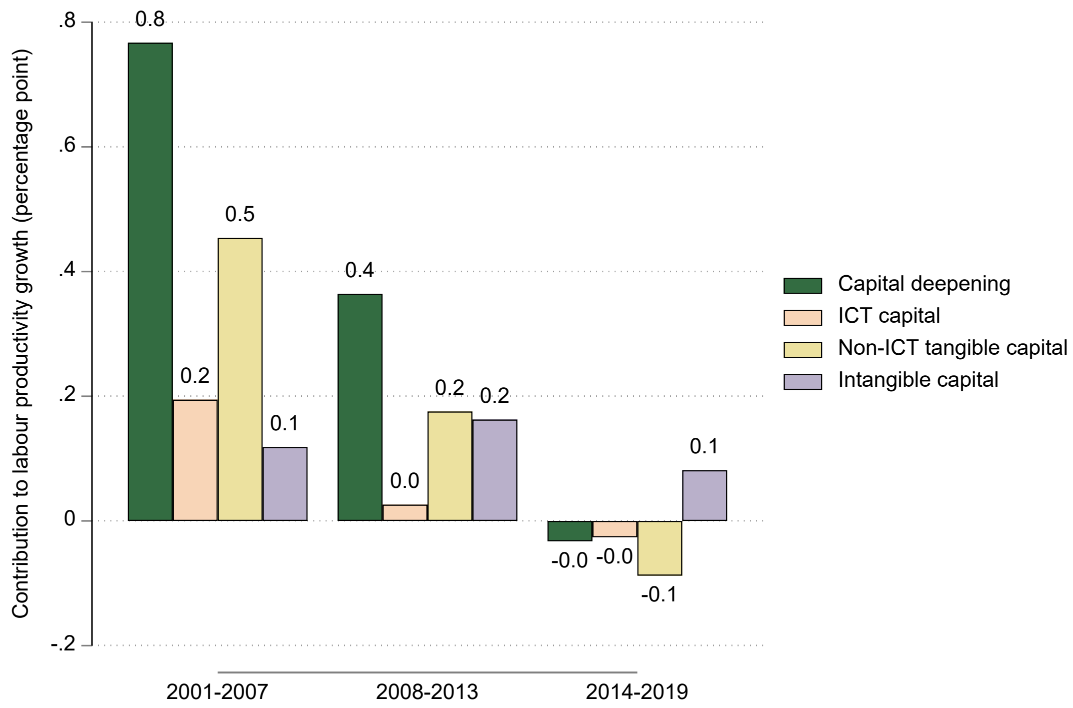
TFP growth is calculated as a **residual** in the growth accounting methodology (i.e., it explains the share of change in labour productivity not accounted for by capital deepening or changes in labour composition, and it is normally attributed to a more efficient use of resources or the adoption of new production technologies. As a result, the contribution of TFP growth depends on the growth rate of labour productivity and the growth rate of labour and capital inputs.

In the pre-2008 period, labour productivity growth was especially strong (at 2% per annum) and TFP explained around half of total growth in labour productivity. In the period after the 2008 Financial Crisis, labour productivity growth was quite sluggish (at 0.6% per annum), while the labour and capital inputs contributed around 0.4% per annum, resulting in negative TFP growth (average at -0.2% per annum). Finally, in the period post-2014, growth in labour productivity further declined to 0.3% per annum with TFP accounting for a negligible contribution (with the labour composition contributing for 0.3 percentage points alongside a zero contribution associated with capital input).

Further information on capital deepening

Figure 15 further decomposes the contribution of capital deepening to labour productivity growth across different types of capital: ICT capital, non-ICT tangible capital, and intangible capital. The contributions of ICT capital and non-ICT tangible capital follow a similar trend to capital deepening across all time periods. Both ICT capital and non-ICT tangible capital contributions fell across the three time periods, with annual contributions of 0.2 percentage points and 0.5 percentage points of labour productivity in the first time period, respectively, decreasing to small negative contributions in the third time period. However, the contribution of **intangible capital** is more stable across the three time periods, with average annual contributions of 0.1, 0.2, and 0.1 percentage points during the three time periods. While only accounting for a small proportion of capital deepening contribution between 2001 and 2007, intangible capital is responsible for almost half of capital deepening contributions between 2008 and 2014. Further, it almost offsets the negative contributions of ICT and non-ICT tangible capital between 2014 and 2019.

Figure 15: Decomposing the contribution of capital deepening to labour productivity growth, by time period (percentage points)



Sources: LFS, ONS, and London Economics' calculations

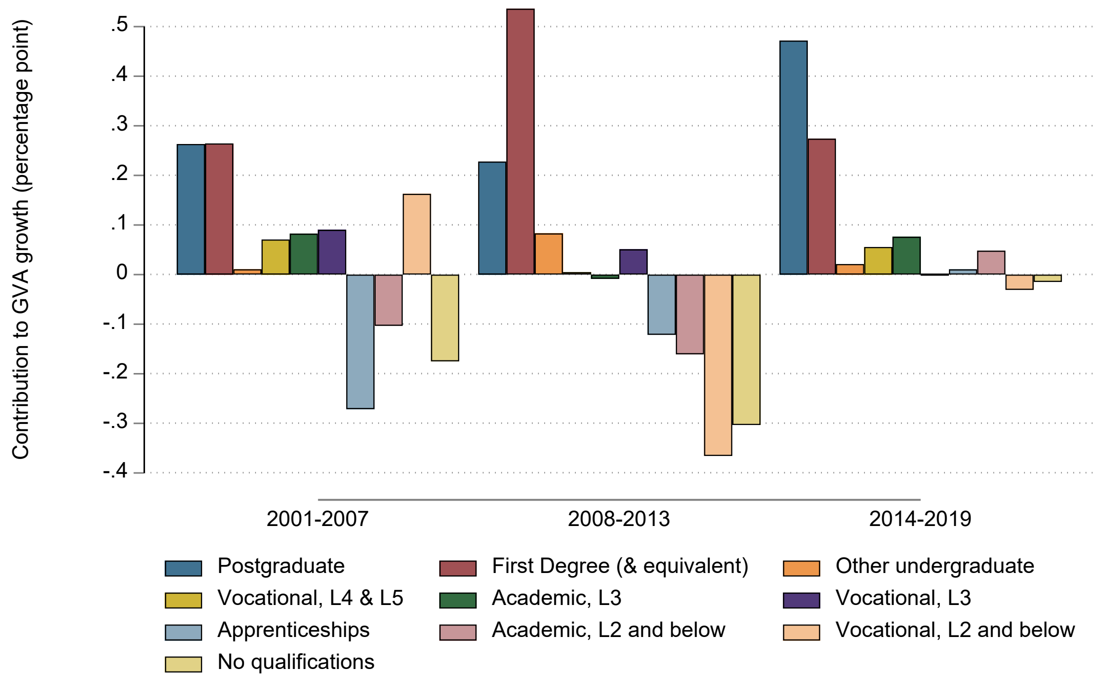
5.2.2 Growth accounting broken down by qualification levels

Hours worked by qualification level

Next, we break down the contribution of changes in hours (Figure 16) and labour composition (Figure 17) across different qualification levels. Consistent with the descriptive statistics in the previous section that identified a shift in total hours worked from lower-level to higher level qualification groups, there is a positive contribution to overall GVA growth of hours worked from higher level qualification groups[43], and a negative contribution from lower-level qualification groups (except for Level 2 and below vocational qualifications in the first time period). In particular, negative changes in hours worked by those with lower-level qualifications were particularly strong in the second time period, while they were more stable (on average) in the third time period.

[43] The spike in the hours worked by those with 'First Degree' qualifications in the middle time period is also driven by a change in the Labour Force Survey data collection in 2011, with all individuals in possession of foreign qualifications at degree level and above (first degree and equivalent or higher level) being assigned first degree as highest qualification. From 2015, it is possible to identify separately those in possession of higher degree achieved outside the UK.

Figure 16: Contribution of hours change to GVA growth, by qualification level and time period (percentage points)



Sources: LFS, ONS, and London Economics' calculations

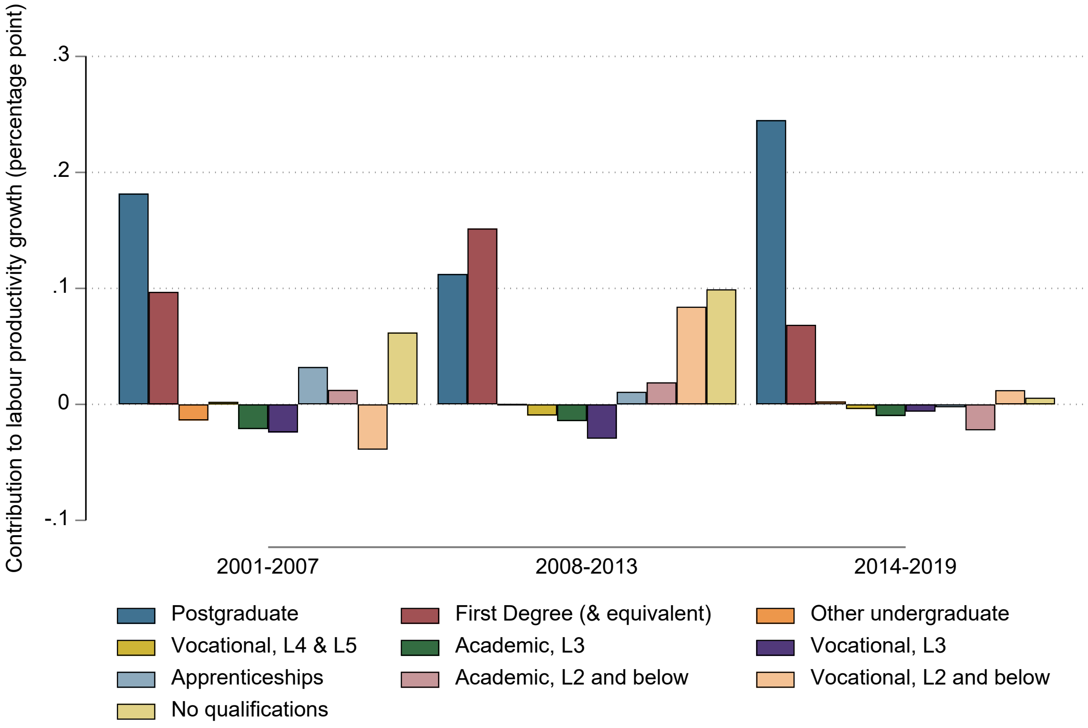
Labour composition and qualification levels

Figure 17 presents the contribution of labour composition changes to labour productivity growth (GVA per hour worked), disaggregated across qualification levels. Large and positive contributions from postgraduate and first degree (and equivalent) qualification levels drive overall labour composition contributions across the three time periods.

One exception is the positive contribution from those with no qualifications in the first and second time period, along with the vocational qualifications at Level 2 and below in the second time period[44]. Contributions from other qualification groups are generally much smaller and often negative across the three time periods.

[44] The positive contribution of labour composition changes for lower-level qualification groups is a result of the large negative changes in hours shown in Figure 16 for the 2008-2013 period and the fact that income shares for these qualifications are lower than their hours share (as they have a lower remuneration compared to higher level qualifications). Both QALI and hours change were strongly negative for these qualifications in the 2008-2013 period, but changes in QALI were smaller in absolute value to changes in hours (as they are weighted by the (smaller) income share while changes in hours are weighted by the hours share), resulting in a positive contribution of labour composition to GVA per hour growth in the period (see the derivation in Box 3).

Figure 17: Contribution of labour composition change to labour productivity growth, by qualification level and time period (percentage points)



Sources: LFS, ONS, and London Economics' calculations

5.2.3 Change in hours and labour composition: robustness checks

The findings presented so far in this section for changes in hours worked and labour composition were developed using the pooled Quarterly Labour Force Survey between 2000 and 2019, and were based on usual weekly hours worked in the main job[45] and hourly pay[46]. To test the robustness of these estimates, we also used alternative measures on hours and wages available in the LFS, as well as using the corresponding measures from the Annual Population Survey[47] (the APS only reports information on highest qualification starting from 2013).

This alternative definition of hours used is based on actual hours worked in main and second job in the reference week[48] and the associated weekly pay[49]. These variables were used to construct the alternative measures for changes in hours worked and labour contribution in order to check the robustness of the main estimates presented in the previous sections. Due to data availability, the robustness check was undertaken using

[45] LFS variable TTUSHR 'Total usual hours worked in main job (including overtime)'
[46] LFS variable HOURPAY 'Average gross hourly pay'
[47] The APS uses data combined from 2 waves of the LFS, collected on a local sample boost
[48] LFS variable SUMHRS 'Total actual hours worked in main and second job'
[49] GRSSWK 'Gross weekly pay in main job' and GRSSWK2 'Gross weekly pay in second job'

the LFS for the entire period and the Annual Population Survey for the most recent time period only (2014-2019)[50].

The resulting findings are illustrated in Table 4, with the first LFS column showing the main results used in the analysis (based on usual weekly hours). As presented in Table 4, the results are highly consistent across all columns, showing that the findings are robust to changes in definitions of hours and wages, as well as using the APS instead of the LFS. A partial exception is the contribution of labour composition to labour productivity growth using APS actual hours between 2014-2019, which stands at around 0.15 percentage points, compared to slightly less than 0.3 percentage points for all other estimates. Also, compared to the LFS estimates using usual hours, the LFS estimates using actual hours worked declined slightly less during the Financial Crisis, and recovered at a faster rate.

Clearly, it should be noted that these averages may mask differences in year-to-year changes. However, when calculating the change per annum over each time period results seem highly consistent across measures and data sources considered. These results are also generally consistent with previous findings for the UK (presented in section 3.1) and with ONS published information[51], although there are some differences in the magnitude of the estimates. In particular, any discrepancy with findings from previous research (for example BEIS (2015) showing contribution of labour composition around 0.5 for the periods 2002-2007 and 2008-2013) are likely to be mainly driven by differences in the methodological approach (e.g. whether GDP or GVA is used, whether looking at the whole economy or market sector only, the definitions of hours used, the granular approach used to construct QALI etc.) and the edition of the quarterly LFS used (as for example weights have been updated over time).

Despite the limitations discussed in this section, these findings provide consistent evidence of the contribution of skills to UK productivity growth.

[50] A further caveat associated with the standard version of the Annual Population (End User Licence) is that it does not allow to distinguish between first and foundation degrees, so the qualification classification used was slightly different from the main analysis.
[51] See here and related publications.

Table 4: Changes in hours and labour composition using alternative measures, by time period

Time period	Change in	LFS		APS	
		Usual weekly hours	Actual weekly hours	Usual weekly hours	Actual weekly hours
2001-2007	Hours	0.7%	0.7%	.	.
	Labour composition (LC)	0.5%	0.5%	.	.
	Contribution of LC to labour productivity growth	0.3pp	0.3pp	.	.
2008-2013	Hours	-0.1%	0.1%	.	.
	Labour composition (LC)	0.7%	0.7%	.	.
	Contribution of LC to labour productivity growth	0.4pp	0.4pp	.	.
2014-2019	Hours	1.6%	1.5%	1.4%	1.4%
	Labour composition (LC)	0.5%	0.5%	0.5%	0.3%
	Contribution of LC to labour productivity growth	0.3pp	0.3pp	0.3pp	0.1pp

Sources: LFS, APS, ONS, and London Economics' calculations
Note: Information on highest qualification not available in the APS before 2013.
pp=percentage points. See footnotes for variable definitions

5.2.4 Growth accounting: results by industry

Figure 18 to Figure 21 present the growth accounting results across industries, decomposing labour productivity (GVA per labour hour) growth, broken down by the relative contributions from capital deepening, labour composition, and TFP growth. Trends in factor contributions to productivity growth differ considerably across industries, but mostly follow the changes observed at the national level in terms of trends over time.

Introduction

When interpreting the results, it should be considered that some sectors are relatively labour intensive, while other sectors are relatively capital intensive. In the growth accounting methodology, factor shares[52] are multiplied by the change in the input to generate the contribution to productivity growth, so they play a significant part in

[52] Labour shares are published by the ONS and available at the following link

explaining why labour (or capital) contribution may be higher in some sectors. The two sectors standing out as capital intensive[53] were Real estate activities (Sector L) where the capital share ranged between 93% and 95% and Agriculture and energy (Sectors ABDE), where the capital share ranged between 66% and 74%. Sector K (Financial and insurance activities) was also relatively capital intensive, with the capital share ranging between 43% and 49% in the period considered.

On the other hand, O: Public administration (Sector O), Education (P), Health and social services (Q), Transport and Storage (H) were relatively labour intensive (with the labour factor share around 80%, although declining slightly over time),

Table 5: Labour factor shares, by sector and sub-period

Industry	2001-2007	2008-2013	2014-2019
ABDE: Agriculture and energy	25.9%	29.1%	34.1%
C: Manufacturing	68.4%	66.7%	63.3%
F: Construction	65.8%	66.0%	61.8%
G: Wholesale and retail trade	69.0%	72.2%	71.5%
H: Transport and storage	82.7%	82.9%	80.8%
I: Accommodation and food services	72.8%	76.6%	78.7%
J: Information and communication	62.2%	60.3%	61.5%
K: Financial and insurance activities	57.4%	53.7%	50.6%
L: Real estate activities	5.2%	7.1%	7.2%
M: Professional and technical activities	70.3%	65.4%	65.8%
N: Administrative and support services	66.9%	67.8%	65.5%
O: Public administration	82.6%	80.1%	78.4%
P: Education	82.6%	80.1%	78.4%
Q: Health and social services	82.6%	80.1%	78.4%
RS: Arts, entertainment, and recreation	76.2%	75.7%	71.1%
Total	59.8%,	59.9%,	58.5%

Sources: ONS, and London Economics' calculations

Note: Under constant returns to scale the capital factor share may be calculated as (*1 – labour factor share*)

[53] Under the assumption of constant returns to scale, the capital factor share may be calculated as (*1 - labour factor share*).

Contributions of capital deepening by sector

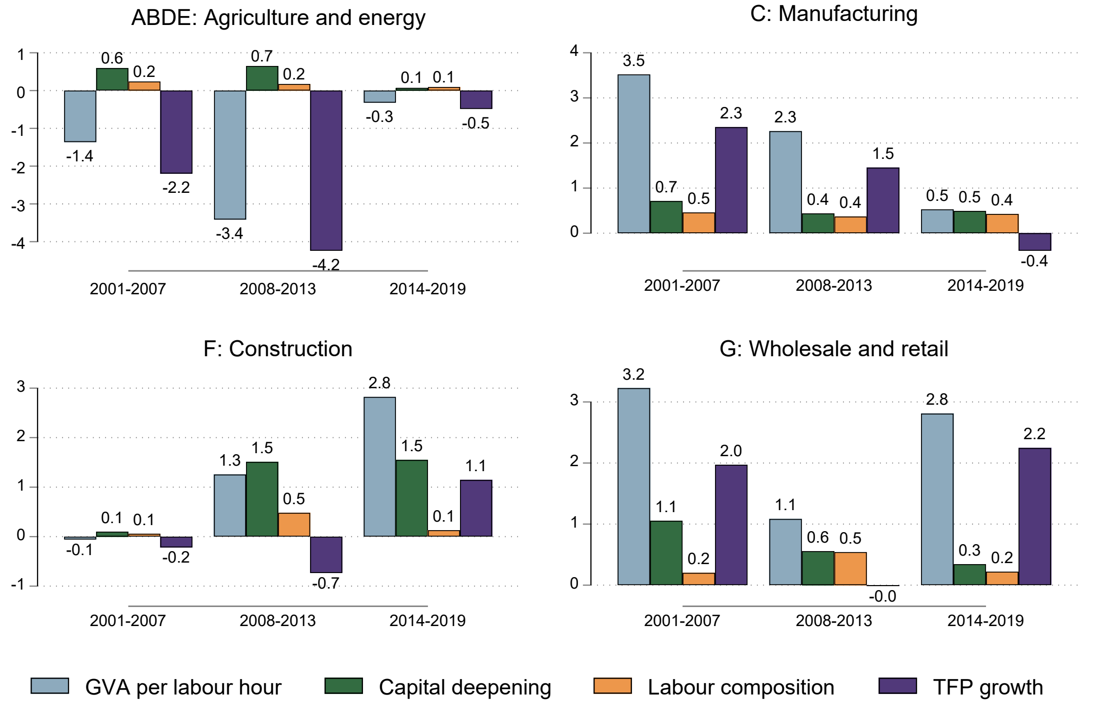
The most significant capital deepening contributions to productivity growth were identified in the Construction industry (Sector F). Despite a limited contribution in the first time period, capital deepening contributed to productivity growth by 1.5 percentage points after 2008. Other significant contributions of capital deepening occurred between 2000 and 2007 in both the Wholesale and Retail trade (Sector G) and the Information and Communication sector (Sector J), respectively. In particular, the average annual contribution of 2.1 percentage points in the Information and Communication sector is the largest average contribution of capital deepening in any time period in the sample. In contrast, the decline of capital deepening in contributing to productivity growth in Real estate activities (Sector L) was the greatest across all sectors in all three time periods. In particular, the contribution in the decline in capital deepening was the equivalent of -3.3 percentage points of productivity growth in the second time period.

Table 6: Contribution of capital deepening to productivity growth, by industry (percentage points)

Industry	2001-2007	2008-2013	2014-2019
ABDE: Agriculture and energy	0.6	0.7	0.1
C: Manufacturing	0.7	0.4	0.5
F: Construction	0.1	1.5	1.5
G: Wholesale and retail trade	1.1	0.6	0.3
H: Transport and storage	0.8	0.3	0.2
I: Accommodation and food services	-0.2	-0.7	-0.1
J: Information and communication	2.1	0.3	-0.1
K: Financial and insurance activities	0.1	0.4	-0.7
L: Real estate activities	-1.3	-3.3	-1.7
M: Professional and technical activities	1.0	-0.2	-0.5
N: Administrative and support services	1.0	-0.9	1.8
O: Public administration	-0.2	0.8	0.0
P: Education	0.6	0.4	0.2
Q: Health and social services	0.1	-0.1	0.0
RS: Arts, entertainment, and recreation	0.7	0.4	-0.2

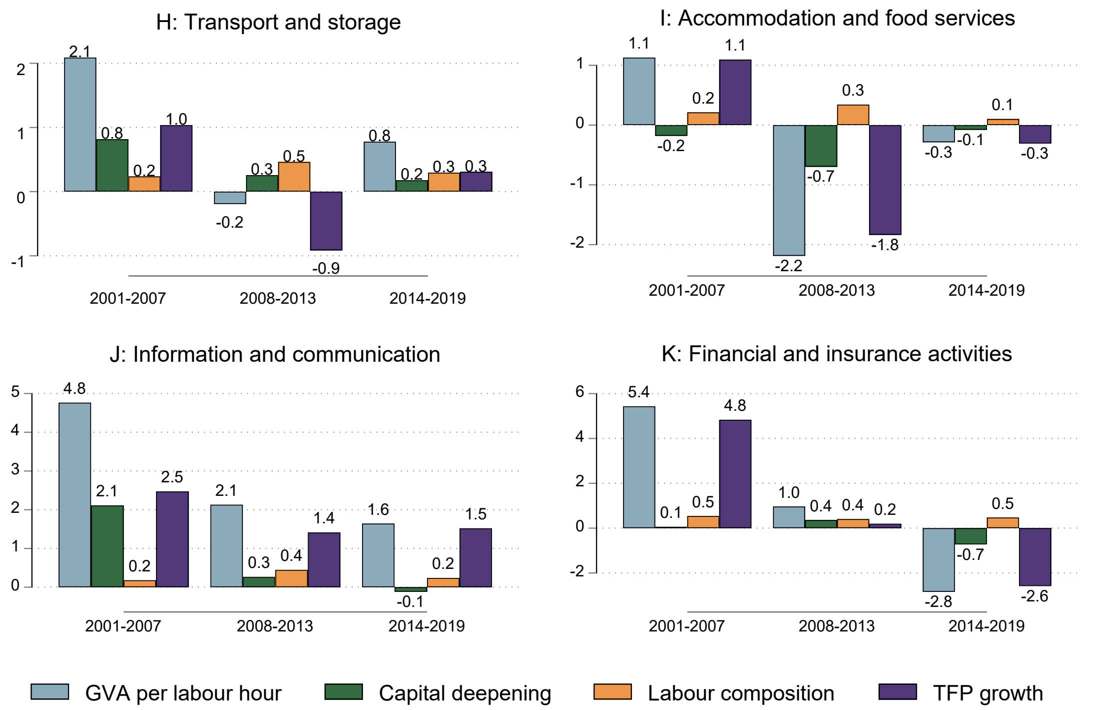
Sources: ONS, and London Economics' calculations

Figure 18: Growth accounting results by industry (sectors ABDE, C, F and G), by time period (percentage points)



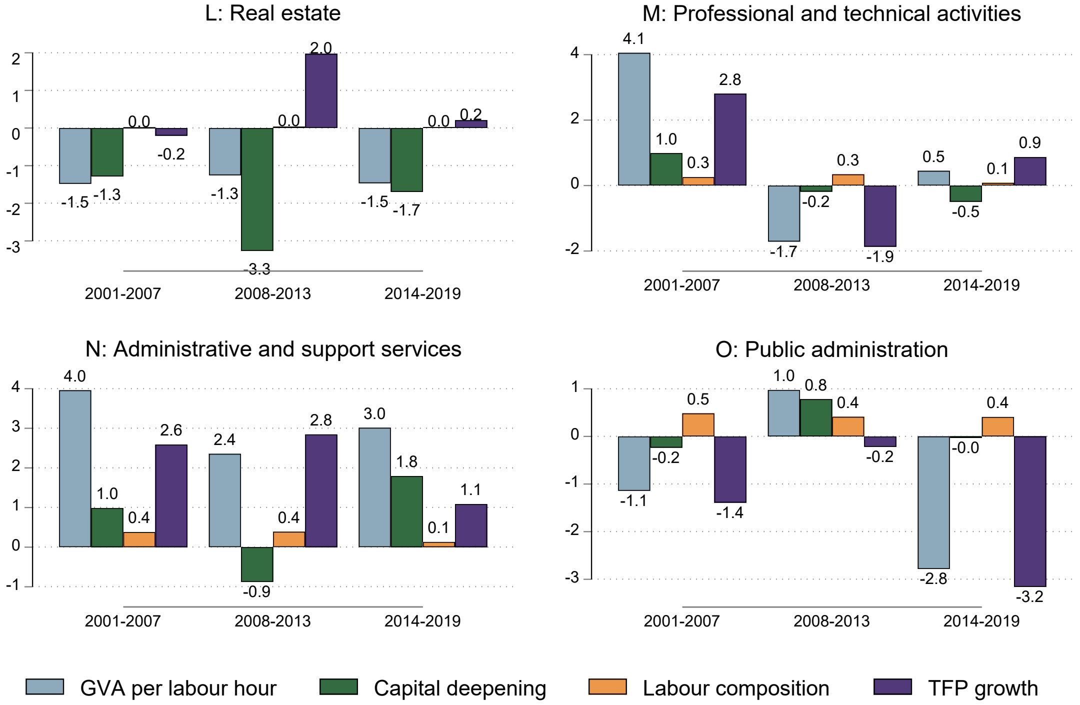
Sources: LFS, ONS, and London Economics' calculations

Figure 19: Growth accounting results by industry (sectors H, I, J, and K), by time period (percentage points)



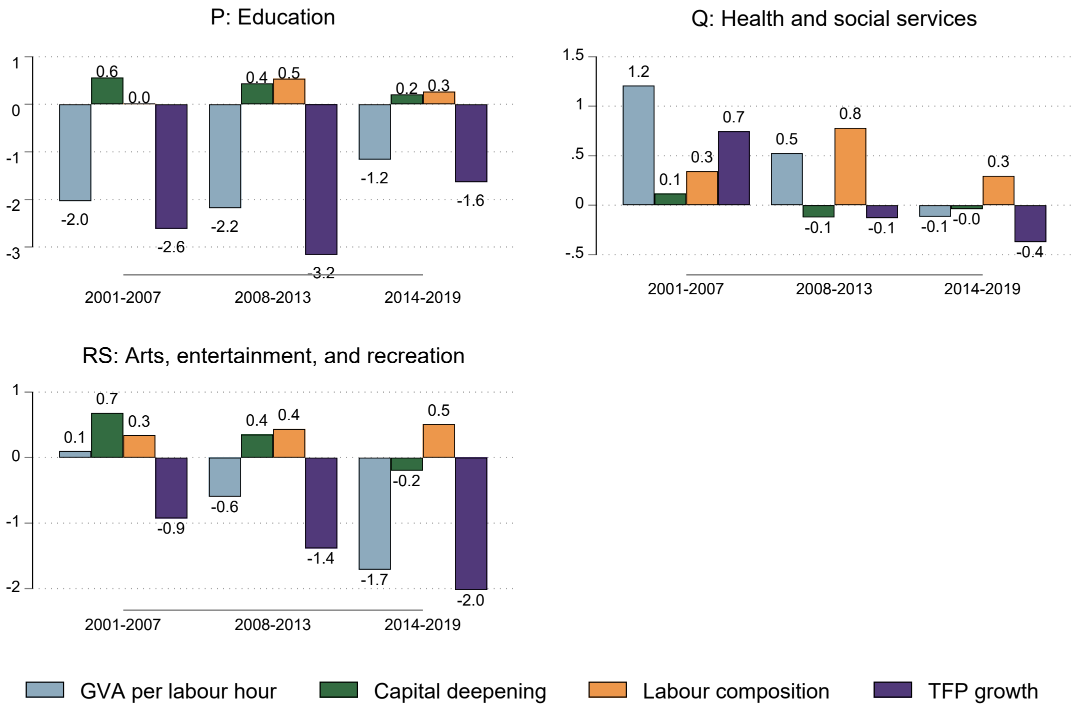
Sources: LFS, ONS, and London Economics' calculations

Figure 20: Growth accounting results by industry (sectors L, M, N, and O), by time period (percentage points)



Sources: LFS, ONS, and London Economics' calculations

Figure 21: Growth accounting results by industry (Sector P, Q, RS), by time period (percentage points)



Sources: LFS, ONS, and London Economics' calculations

Contribution of changes in labour composition by sector

The contribution of changes in **labour composition** to growth in labour productivity are more consistent across time and across industries, reflecting its stability across time at the national level. The estimates range between zero and 0.8 percentage points across industries and time periods, illustrating a degree of general consistency. This is also shown in Table 7, which reports the contribution of changes in the labour composition across industries and time periods. It should be noted that the estimated contribution of labour composition depends both on the change in labour composition for a given sector and the factor share for that sector[54].

In particular, the contribution of labour composition to productivity growth was particularly strong in the Manufacturing sector (Sector C), in Financial and Insurance services (Sector K), in the Public Administration sector (Sector O) and Arts, Entertainment, and Recreation sectors (Sectors RS), all consistently ranging between 0.4 and 0.5 percentage points. The contribution of labour composition was also particularly strong in Health and social services (sector Q) in the second time period (0.8 percentage points).

On the other hand, the contribution of labour composition to productivity growth was generally lower in the Agriculture and Energy sector (Sectors ABDE) (between 0.1 and 0.2 percentage points) and Real estate activities (Sector L) (negligible contribution across the entire period). In the case of Real estate activities, this was driven by a particularly low labour factor share (between 5% and 7%).

[54] For example the labour factor share is quite high for sectors O, P and Q (around 0.8) and quite low for sectors B (around 0.2) and L (less than 0.1), see Table 5.

Table 7: Contribution of labour composition changes to productivity growth, by industry and time period (percentage points)

Industry	2001-2007	2008-2013	2014-2019
ABDE: Agriculture and energy	0.2	0.2	0.1
C: Manufacturing	0.5	0.4	0.4
F: Construction	0.1	0.5	0.1
G: Wholesale and retail trade	0.2	0.5	0.2
H: Transport and storage	0.2	0.5	0.3
I: Accommodation and food services	0.2	0.3	0.1
J: Information and communication	0.2	0.4	0.2
K: Financial and insurance activities	0.5	0.4	0.5
L: Real estate activities	0.0	0.0	0.0
M: Professional and technical activities	0.3	0.3	0.1
N: Administrative and support services	0.4	0.4	0.1
O: Public administration	0.5	0.4	0.4
P: Education	0.0	0.5	0.3
Q: Health and social services	0.3	0.8	0.3
RS: Arts, entertainment, and recreation	0.3	0.4	0.5

Sources: LFS, ONS, and London Economics' calculations

These trends are likely to reflect the underlying distributions and trends in skills and relative remuneration in each sector, as well as labour factor shares across different sectors. For example, sectors showing positive contribution of labour composition are generally associated with a significant increase in the share of workers with undergraduate and postgraduate qualifications over time, or by a relatively small decline in the relative remuneration for these qualifications (or a combination of both).

However, it is not necessarily straightforward to identify the main drivers of the overall contribution of labour composition to productivity growth as the analysis uses ten different qualification categories (capturing both academic and vocational qualifications at different levels), each with different levels and trends in relative remuneration and share of hours worked. Also, factor shares may vary considerably across sectors and have a significant impact on the contribution to labour composition to productivity growth.

A few examples are presented below, focusing on postgraduate and first degree qualifications, but these trends may not capture the variety of underlying changes across different qualifications and time periods. For example, the proportion of hours worked by individuals holding a postgraduate degree in the Manufacturing sector was particularly low in the first time period (only 3.3%) but almost doubled by the final time period (6.5%). However, this was substantially below the national average (12.6%). The proportion of hours worked by individuals with postgraduate qualifications in Financial and Insurance services also rose significantly over time (from 6% to 15% in the first and final sub-periods respectively), while the proportion of those having a first degree as highest qualification grew from 20% to 33%. At the same time, the relative remuneration in the third period was similar to that observed in the first period, compared to a decline more generally.

The Professional Services sector (which showed a small but constant contribution of labour composition to productivity growth) is characterised by an increase in the share of hours worked by those with postgraduate qualifications (from 9% to 15%), and from 23% to 30% in the share of hours worked by those with first degree qualifications, but also with above average decline in the relative remuneration for both categories (for example the relative remuneration for postgraduate qualifications declined quite strongly from an index value of 277 to 229 between the first and the third period)[55].

Total factor productivity growth by industry

As a residual term in the growth accounting methodology (explaining the part of labour productivity growth not accounted for by changes in labour and capital inputs), there is significant variation in TFP contribution to labour productivity growth. In fact, TFP growth contribution was particularly large in the Information and Communication sector (Sector J), with average annual contributions of 2.5, 1.4, and 1.5 percentage points across the three time periods. TFP growth contributions were also relatively high in the administrative and support services sector (Sector N), with high average annual growth rates in the three time periods (2.6, 2.9, and 1 percentage points respectively). TFP growth was also particularly strong in the Financial and Insurance sector (Sector K) between 2000 and 2007 (almost 5 percentage points), reflecting the boom in the sector before the 2008 crisis, while it declined to zero in 2008-2013, and then turned negative after 2014.

The contribution of TFP growth to productivity growth is also consistently negative in several other industries, including in public administration (Sector O), education (Sector P), and arts, entertainment, and recreation (Sectors RS). The smallest TFP growth ‘contributions’ are observed in agriculture and energy (Sectors ABDE), with average annual contributions of -2.0 and -4.2 percentage points in the first two time periods.

[55] Moreover, sector L is characterised by a very low labour factor share (less than 0.1, see Table 5), which also explains the constant but low contribution of labour composition to productivity growth in that sector.

5.2.5 Growth accounting: results by region

The figures in Table 8 present the results of the growth accounting methodology by region. It should be noted that, given the experimental nature of regional-level capital estimates, caution should be exercised when interpreting these results. Also, it was only possible to construct the regional changes in capital stock up to 2018 (instead of 2019 as with the rest of the analysis). Further, national-level factor shares were used with components of regional productivity growth. Moreover, the approach used to construct changes in labour composition was tailored for the regional analysis. As a consequence, the methodological approach used to construct regional growth accounting differs to some extent to the main approach used to construct the national and sector growth accounting (see sections A2 and A3 in the Appendix for more details). Hence, results may not be fully consistent with the results presented in the previous sections.

Contribution of capital deepening to productivity growth, by region

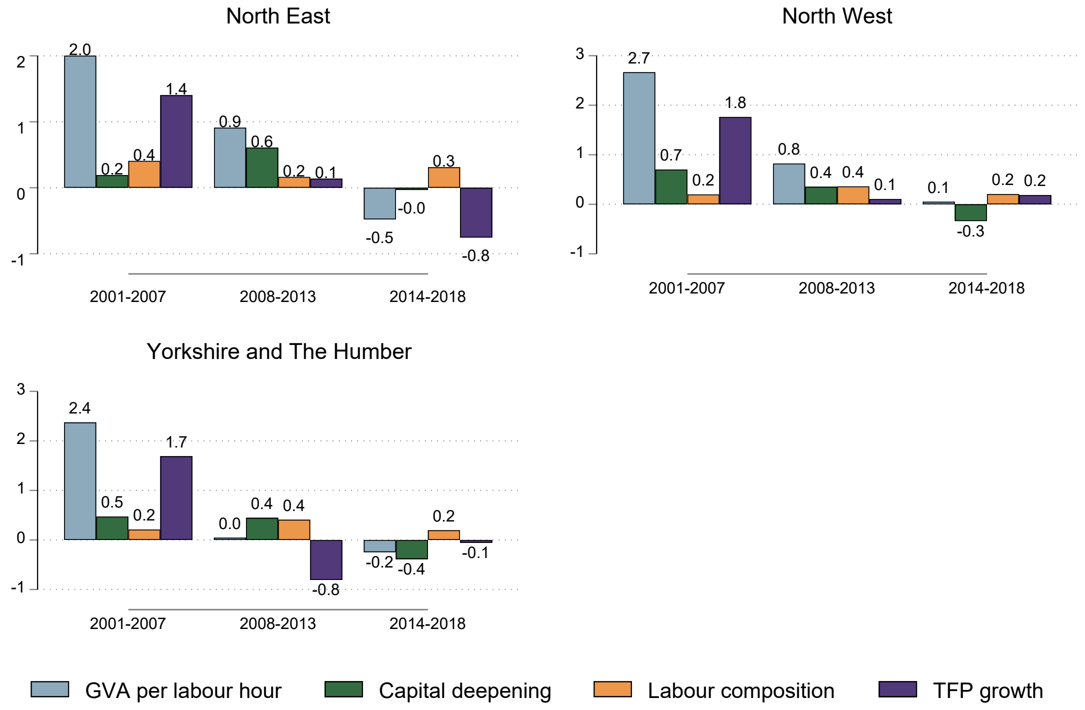
The contribution of capital deepening to productivity growth was positive for all regions in the first two time periods considered (with the exception of the London area, which recorded a -0.3 percentage point contribution in the 2008-13 period). However, the contribution of capital deepening mostly turned negative in the period after 2014 (explaining the national trends).

Table 8: Contribution of capital deepening to productivity growth, by region and time period (percentage points)

Region	2001-2007	2008-2013	2014-2018
North East	0.2	0.6	0.0
North West	0.7	0.4	-0.3
Yorkshire and the Humberside	0.5	0.4	-0.4
East Midlands	0.6	0.2	-0.2
West Midlands	0.6	0.4	-0.4
East of England	0.7	0.1	0.0
London	0.4	-0.3	-0.5
South East	0.7	0.2	0.1
South West	0.5	0.2	-0.4
England	0.6	0.2	-0.2
Wales	0.2	0.5	-0.3
Scotland	0.3	0.3	0.1
Northern Ireland	0.5	0.4	0.8

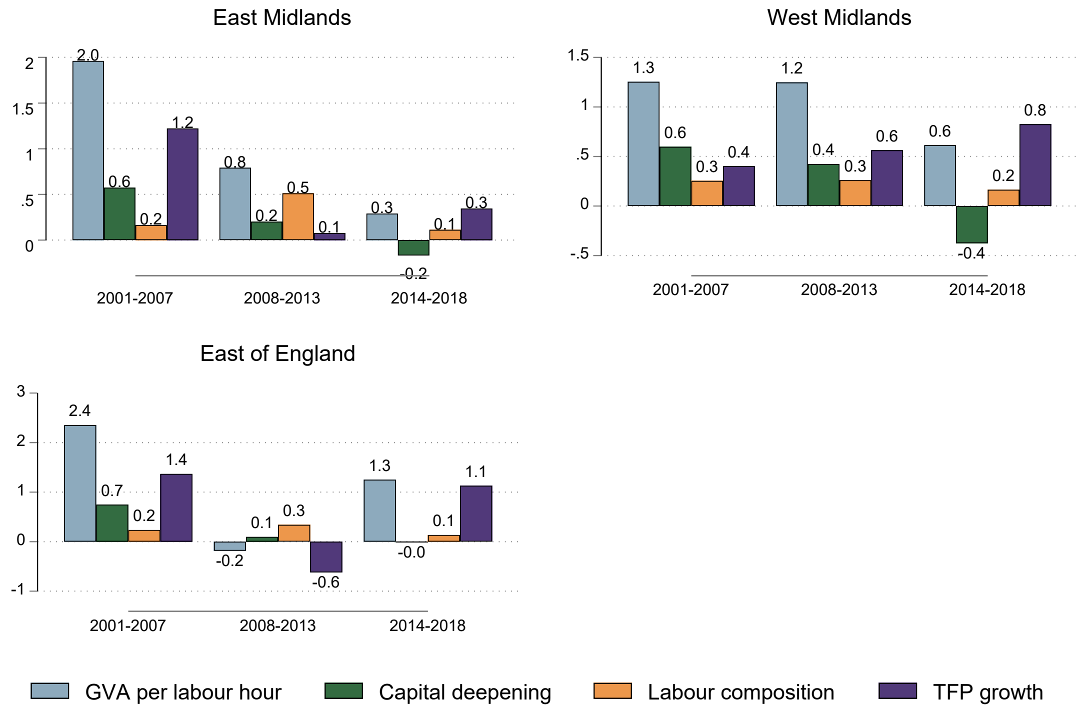
Sources: ONS, and London Economics' calculations
Note: Data on regional capital deepening available up to 2018 and based on an experimental approach

Figure 22: Growth accounting results by region (North East, North West, and Yorkshire and the Humber) and time period (percentage points)



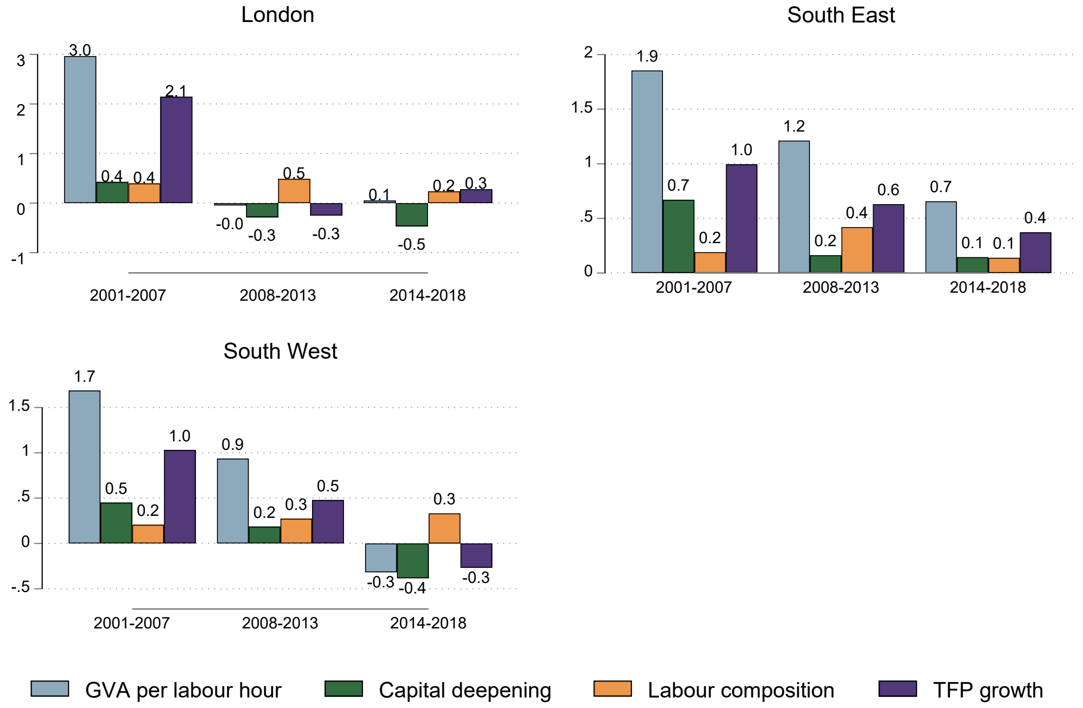
Sources: LFS, ONS, and London Economics' calculations
Note: Data on regional capital deepening available up to 2018 and based on an experimental approach

Figure 23: Growth accounting results by region (East Midlands, West Midlands, and East of England) and time period (percentage points)



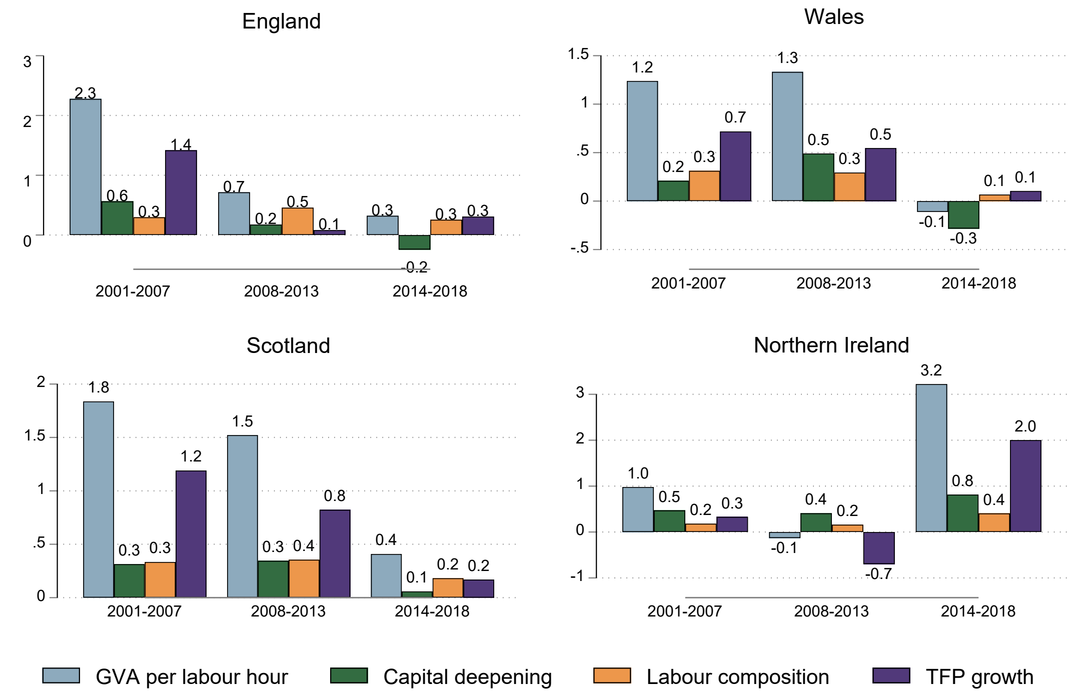
Sources: LFS, ONS, and London Economics' calculations
Note: Data on regional capital deepening available up to 2018 and based on an experimental approach

Figure 24: Growth accounting results by region (London, South East, and South West) and time period (percentage points)



Sources: LFS, ONS, and London Economics' calculations
Note: Data on regional capital deepening available up to 2018 and based on an experimental approach

Figure 25: Growth accounting results by home nation and time period (percentage points)



Sources: LFS, ONS, and London Economics' calculations
Note: Data on regional capital deepening available up to 2018 and based on an experimental approach

Contribution of labour composition changes to productivity growth, by region

A similar cross cutting theme identified in the results at the national-level, industry-level, and regional-level is the relative stability of the contribution of changes to the labour composition. All average annual contributions of labour composition to productivity growth at the regional level range between 0.1 percentage points and 0.5 percentage points, across all time periods and regions. In particular, labour contribution was quite strong (around 0.4 percentage points) in the North East and London area in the pre-2008 period, in the London area and the East Midlands in the second time period (around 0.5 percentage points); and in Northern Ireland (0.4 percentage points), North East and the South West between 2014 and 2018 (around 0.3 percentage points).

Table 9: Contribution of labour composition changes to productivity growth, by region and time period (percentage points)

Region	2001-2007	2008-2013	2014-2018
North East	0.4	0.2	0.3
North West	0.2	0.4	0.2
Yorkshire and the Humberside	0.2	0.4	0.2
East Midlands	0.2	0.5	0.1
West Midlands	0.3	0.3	0.2
East of England	0.2	0.3	0.1
London	0.4	0.5	0.2
South East	0.2	0.4	0.1
South West	0.2	0.3	0.3
England	0.3	0.5	0.3
Wales	0.3	0.3	0.1
Scotland	0.3	0.4	0.2
Northern Ireland	0.2	0.2	0.4

Sources: LFS, ONS, and London Economics' calculations
Note: Data on regional capital deepening available up to 2018 and based on an experimental approach

Total factor productivity by region

TFP growth is more variable across time periods and regions, with the largest average annual contributions identified in London (2.1 percentage points), the North West and Yorkshire and the Humber (around 1.7-1.8 percentage points) between 2001 and 2007 (during the years of rapid growth before the Financial Crisis). As already observed for the national and industry-level analysis, TFP growth contributions follow a cyclical pattern, with many regions experiencing negative TFP growth contribution in the second time period that includes the recession induced by the Financial Crisis. The lowest TFP growth contributions during the second time period occurred in Yorkshire and the Humber (-0.8 percentage points), Northern Ireland (-0.7 percentage points), and in the East of England (-0.6 percentage points). In the third and final time period, TFP growth was highest in Northern Ireland (2 percentage points).

5.3 Decomposing the gaps in productivity levels: comparison across countries

Box 8: International comparison results - summary

How to interpret these findings

- The analysis here is **experimental** and **largely descriptive**.
- The results presented below should be treated as **indicative** and **not be compared directly with findings from other research.** There are several reasons for this:
    - Using **alternative data sources** may lead to different findings. This analysis uses different data sources from its closest comparative research (Broadberry and O'Mahoney, 2004).
    - There is **limited existing literature** to compare the findings to – again, the Broadberry and O'Mahoney analysis provides the closest comparison but there is no more recent literature to compare to. This means we cannot test the validity of these results, especially where trends appear to have changed.
    - The analysis shows **significant volatility** between the two years analysed which we wouldn't expect to see in productivity performance, which tends to change slowly over time. Given this volatility, we should exercise some caution in the conclusions drawn from these findings.

Capital and relative earnings per hour and share of hours worked (Table 10, Table 11 and Table 12)

- **Capital per hour worked** is significantly lower for the UK compared with the other countries of interest.
- In 2015, **capital per hour worked** is estimated to be 36% higher in the US and 60-67% higher in Germany and France, respectively.
- **Relative earnings per hour** is estimated to be higher for the UK compared to France and Germany (but lower compared to the US) for both upper secondary and tertiary education.

Decomposition of labour productivity results (Table 13 and Table 14)

- **Capital differences** make up the largest component of the productivity gap between the UK and all three countries analysed.
- For France and Germany, **the skills gap appears to have closed,** though this is subject to caveats mentioned.
- Compared to the United States, the UK **still has a skills gap**.

Previous analysis

Previous literature has investigated the gap in productivity levels (instead of productivity growth) between the UK and other countries, such as the US, Germany or France (Broadberry and O'Mahony, 2004; De Boer, 2002; O'Mahony and Van Ark, 2003). According to these estimates, in 2002 labour productivity was nearly 30% higher in the United States than in the UK, 27.5% higher in Germany, and more than 30% higher in France (Broadberry and O'Mahony, 2004). Nearly all of the labour productivity advantage identified in France and Germany (compared to the United Kingdom) appears to be as a result of **differences in physical capital** (explaining around three quarters of total productivity gap) and **skills** (between 16%-23% of total productivity gap), while the productivity advantage identified for the US compared to the UK was mainly attributed to higher **total factor productivity** (Broadberry and O'Mahony, 2004). A previous study from De Boer (2002) found similar results when looking at the productivity gap between the UK and these same three countries, with **physical capital explaining around 80% of the gap with France and Germany** (with skills explaining between 12% and 19%) and **physical capital and TFP almost equally explaining the gap with the US**.

Findings

In this section, we have tried to replicate and update these estimates using productivity levels for the UK, the US, France and Germany. As in previous studies, the UK's productivity gap with other countries can be decomposed in a similar way to the growth accounting approach. However, it should be noted that results presented in this section do not use the same data sources used for previous analyses so may not be directly comparable. Also, due to data availability, the latest year for which the information was consistently available across all data series and countries was 2015. Moreover, we tried to use data sources available across all countries considered (in particular using relative earnings from the OECD, also covering the United States), but it is important to remember that the results are sensitive to the data sources used.

The approach does not directly explain differences in productivity or factor input levels across countries, but simply compares ratios in the relevant variables using the UK as base (set to 100). All results should be interpreted as purely descriptive and subject to the caveats described throughout this section. The methodology and data sources used are presented in detail in Annex A4 in the Appendix.

The productivity gap is presented in Table 13, and shows that productivity gap per hour worked was around 22%-24% in 2015 compared to the US, France and Germany (in line with previous findings although slightly lower when looking at the comparison with the US). To provide some additional context, we show the level of capital stock per hour (Table 10), the remuneration by qualification group relative to those with below secondary education (Table 11), and the share of hour worked across qualification groups (Table 12). In all instances the value for the other countries is expressed relative to the UK (indexed to 100).

As identified in previous analyses, capital per hour worked is significantly lower for the UK compared with the other countries of interest. Specifically, in 2015, capital per hour worked is estimated to be 36% higher in the US and 60-67% higher in Germany and France, respectively.

Relative remuneration (compared to the baseline ISCED 0-2) was higher for the UK compared to France and Germany in 2015 (but lower compared to the US) for both upper secondary and tertiary education.

Table 10: Capital per hour (UK = 100)

	2010	2015
US	134	136
France	155	167
Germany	155	160

Source: Bick et al. (2019)

Table 11: Relative earnings per hour (below secondary education = 100)

		2010	2015
Upper secondary or post-secondary non-tertiary (ISCED 3-4)	**UK**	**143**	**128**
	US	142	139
	France	115	117
	Germany		122
Tertiary (ISCED 5-8)	**UK**	**227**	**187**
	US	238	230
	France	168	174
	Germany		173

Sources: Bick et al. (2019), OECD, LE calculations
Note: Results for Germany are unavailable in 2010 due to missing relative earnings data

The share of hours worked for those with below upper secondary qualifications (ISCED 0-2) was around 15% for the UK in 2015 (in line with Germany, but higher than France and the US), while the proportion with tertiary education was around 50% in 2015, which was slightly lower than the US share, but higher than the share observed for France and Germany (both having a higher share of hours worked by individuals in the ISCED 3-4 (upper secondary or post-secondary non-tertiary qualifications) category).

Table 12: Share of hours worked across qualification groups

		2010	2015
Below upper secondary (ISCED 0-2)	**UK**	**17.8%**	**14.8%**
	US	7.1%	6.9%
	France	8.9%	8.3%
	Germany	21.0%	14.5%
Upper secondary or post-secondary non-tertiary	**UK**	**37.4%**	**35.0%**
	US	44.1%	41.7%
	France	57.5%	58.0%
	Germany	43.4%	43.1%
Tertiary	**UK**	**44.8%**	**50.2%**
	US	48.8%	51.4%
	France	33.6%	33.6%
	Germany	35.6%	42.4%

Sources: Bick et al. (2019), OECD, and LE calculations
Note: Results for Germany are unavailable in 2010 due to missing relative earnings data

Table 13 provides the results of the decomposition in 2010 and 2015. Results for Germany are unavailable in 2010 due to missing relative earnings data. Results for 2000 from Broadberry and O'Mahony (2004) are presented in Table 14 by means of a comparison, but such a comparison should be treated with caution due to the different data used in their analysis. It should be noted that using different data sources (e.g., OECD, Eurostat, EU KLEMS, the Conference Board) may lead to different results.

Table 13 shows that the UK's productivity gap (the percentage difference between other country's GDP per hour worked and the UK's) to the US, France, and Germany has remained in excess of 20%. However, the composition of the productivity gap differs between the two analyses. The gap in skills between the UK and US is estimated to contribute a large proportion of the productivity gap between the two countries. The gap in skills in 2015 accounts for 10.4 percentage points out of the 23.7 percent difference between UK and US labour productivity. However, residual TFP accounts for a far lower proportion of the productivity gap, especially compared to 2000. Across all three years analysed, capital per hour differences account for more than half of the productivity gap between the UK and the US, France and Germany. This suggests that the productivity gap between the UK and these countries can primarily be explained by differences in capital.

Table 13: Decomposition of labour productivity levels relative to the UK

		2010	2015
US	**Labour Productivity**	**18.3%**	**23.7%**
	of which (percentage point contribution from each factor):		
	Capital	11.9	12.6
	Skills	4.2	10.4
	TFP	2.2	0.7
France	**Labour Productivity**	**11.2%**	**23.8%**
	of which (percentage point contribution from each factor):		
	Capital	18.5	22.3
	Skills	-16.4	-5.9
	TFP	9.1	7.4
Germany	**Labour Productivity**	**-**	**22.5%**
	of which (percentage point contribution from each factor):		
	Capital	-	20.1
	Skills	-	-6.2
	TFP	-	8.6

Sources: London Economics based on OECD, Bick et al. (2019), Bergeaud et al. (2020), The Conference Board (2021) for 2010 and 2015

Note: Results for Germany are unavailable in 2010 due to missing relative earnings data.

Table 14: Broadberry and O'Mahoney results for 2000

		2000
US	**Labour Productivity**	**37.4%**
	of which (percentage point contribution from each factor):	
	Capital	12.5
	Skills	1.6
	TFP	24.3
France	**Labour Productivity**	**22.1%**
	of which (percentage point contribution from each factor):	
	Capital	16.8
	Skills	5.1
	TFP	0.3
Germany	**Labour Productivity**	**24.7%**
	of which (percentage point contribution from each factor):	
	Capital	18.1
	Skills	4.1
	TFP	2.6

Sources: Broadberry and O'Mahony (2004)
All values expressed relative to the UK

In particular, differences in capital per hour make up almost all the UK's productivity gap to both France and Germany. Analysis for 2010 and 2015 suggests that there is no gap in skills between the UK and France and Germany, with the UK's advantage in skills reducing the productivity gap by 5.9 and 6.2 percentage points to France and Germany, respectively. This suggests that relatively low capital intensity, relative to France and Germany, is preventing the closing of the productivity gap. If the contribution of skills were not so substantial in the UK, the productivity gap would be even greater.

As already mentioned, this analysis is subject to significant caveats:

- The information had to be collated from various data sources, with potentially different measurement errors and biases. However, cross-country consistency was ensured as we used the same source for a given data series across all countries (e.g. the source for GDP is the same across all countries considered).
- Using alternative data sources may lead to different findings. In particular Table 27 in the Appendix shows results using relative remuneration from Eurostat (Structural Earnings Survey), which yields similar results for France to those

presented here, but a positive skills gap for Germany versus the UK (compensated by a negative gap in TFP). Clearly no Eurostat information is available for the US.

- There is limited existing literature to compare the findings to – the Broadberry and O'Mahoney analysis provides the closest comparison but there is no more recent literature to compare to. Therefore, it is difficult to confirm whether these results are repeatable.
- The analysis only looks at two specific years, 2010 and 2015, and therefore does not track change in productivity performance between years. Given this, there is significant volatility between the two years which we wouldn't expect to see in productivity performance, which tends to change slowly over time because capital and labour inputs change slowly over time.
- We do not have enough data to draw conclusions about specific trends over time. This analysis can only be said to be descriptive of the productivity decomposition in 2010 and 2015.

6. Econometric results

Box 8: Econometric results - summary

The econometric approach estimates the impact of a given change in the composition of the labour and capital inputs on overall GVA growth and productivity growth. The overall change in the labour input (the **Quality Adjusted Labour Input** (QALI)) can be broken down into its two constituent components: **changes in hours worked** and **changes in labour composition (i.e. labour quality)**:

- The econometric analysis suggests that **changes in QALI are positively associated with GVA growth** over the entire period of analysis (2001-2019), with **a 1% increase in QALI associated with a 0.10% growth in overall GVA**;
- Breaking down changes in QALI into changes in hours and labour composition over the entire period (2001-2019), the results suggest that **the effect of changes in hours worked on GVA growth is quantitatively similar to the aggregated QALI coefficient (0.09%)** and statistically significant, while the point estimate for **labour composition** is larger in magnitude (0.26), but statistically insignificant. Hence, despite these results, it is not possible to say with complete certainty whether hours or labour composition were the main drivers of GVA growth;
- The impact of a given increase in the **capital input on GVA growth was positive** and ranged between 0.06% to 0.08% across different types of capital (although the point estimates were not always statistically significant).

As with the Growth Accounting modelling approach, the aggregate econometric results indicate that both labour and capital inputs have a positive impact on GVA growth.

Disaggregated analysis

The baseline model was interacted with time dummies (to capture any differential effect before and after the 2008 financial crisis), as well as introducing a variable identifying higher-level qualifications (at first degree or equivalent level and above).

- The disaggregated results show that the effect of QALI was strong for higher level qualifications between 2001 and 2007 but then declined substantially after 2008;
- The point estimates for labour composition were substantially higher for the pre-2008 period (compared to the post 2008 period), and higher for higher-level qualifications (compared to lower-level qualifications); however, the results were never statistically significant;
- Numerous alternative specifications were explored at the disaggregated level; however, results were rarely statistically significant due to the limited sample sizes.

Although there may be many explanations for these findings, one potential explanation may be that the demand-side of the economy was more able to absorb and utilise increases in the more highly qualified labour input pre 2008, while the reverse was true after 2008 (e.g, linked to the relative availability of jobs at different qualification levels).

This section reports the results of the econometric analysis, which estimates the relationship between the growth rates of inputs and growth in GVA and labour productivity (GVA per hour). In addition to the aggregate results, results are presented for the analysis using industry-time observations (15 industries over 19 years), while the results using region-time observations are presented in Annex A7[56]. All the caveats underlying the analysis are presented in Section 4.2[57].

Aggregate results for GVA growth

Table 15 presents the results of the baseline econometric analysis, which estimates the impact of growth in capital (across capital types) and labour inputs (QALI) on GVA growth. Columns 1, 2, and 3 present the baseline results using Ordinary Least Squares, random effects, and fixed effects models, respectively.

Impact of Quality Adjusted Labour input (QALI) on GVA growth

The estimated impact of QALI changes on GVA growth is positive, statistically significant, and consistent across the specifications, with point estimates of 0.09 or 0.1 across the three specifications. As the variables used in the analysis are changes in log-transformed values, the coefficient estimates can be interpreted as **elasticities**. For example, a point estimate of 0.1 suggests that a 1% change in the labour input (QALI) is associated with a 0.1% change in GVA. In our sample, the average annual change in QALI is 1.4% per annum over the entire period of analysis. Therefore, multiplying the average annual change in QALI (1.4% per annum) by the estimated coefficient of 0.10 provides an implied average labour contribution to annual GVA growth that is around 0.14 percentage points.

Impact of capital on GVA growth

The estimated coefficients for capital are positive and generally range between 0.03 and 0.1 depending on the type of capital and the specification used, but it is normally smaller in magnitude, and less often statistically significant, across the three specifications. To test whether the lack of statistical significance may be due to the disaggregation into

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[56] Due to data limitations it was not possible to disaggregate by both industry and region at the same time. Hence, industries (and regions separately) are the units of observations for the econometric analysis and no sub-industry analysis was undertaken.

[57] It should be noted that in the growth accounting analysis, factor shares are imposed (derived from the labour share in a given industry, which is defined as being the percentage of that industry's factor costs (sum of the compensation of employees and the gross operating surplus) for which the compensation of employees is responsible), while the capital share is defined as (*1 - labour share*).
In the econometric analysis the coefficients (i.e. the equivalent of the factor shares in growth accounting) are estimated econometrically across all UK industries over the period 2001-2019 and can be interpreted as the average effect on productivity of raising the labour and capital input by a given amount (e.g. 1%). In the analysis we include time and industry specific fixed effects, which enable us to control for unobserved sources of heterogeneity affecting productivity. Hence, the results from the two approaches may not be directly comparable.

different capital input components (also associated with a relatively small sample size), we also estimated the same specification aggregating the capital input variables into a single variable. Results are presented in Table 28 in the Appendix and show a positive and highly statistically significant estimate of 0.17 for the random effects specification[58].

Table 15: Baseline econometric results

Dependent variable: GVA growth (by industry)

	(1) **Δ QALI**	**(2)** **Δ QALI**	**(3)** **Δ QALI**
Δ ICT capital	0.08***	0.07**	0.07***
	(0.03)	(0.03)	(0.03)
Δ Non-ICT tangible capital	0.08	0.08	0.07
	(0.08)	(0.08)	(0.09)
Δ Intangible capital	0.10**	0.06	0.03
	(0.04)	(0.05)	(0.05)
Δ QALI	0.10**	0.10**	0.09*
	(0.05)	(0.05)	(0.05)
Constant	0.00	0.04	0.27***
	(0.02)	(0.03)	(0.09)
Specification	OLS	RE	FE
R-squared	0.37	0.35	0.16
Observations	285	285	285
Sample	Industry	Industry	Industry

*Standard errors clustered at the industry level in parentheses. Additional controls: year dummies and age structure of the workforce. OLS: Ordinary least squares; RE: Random effects; FE: Fixed effects. *** p<0.01, ** p<0.05, * p<0.1*

The Hausman specification test was used to determine the **relative suitability** of the random and fixed effects models for further analysis[59]. There is statistically insignificant

58 In the Appendix we also present the regression interacting growth rates in the different types of capital and the Quality Adjusted Labour Index. There is some evidence of a positive effect of the interaction of ICT capital and QALI.

59 This was implemented in STATA using *hausman*, a general implementation of Hausman's (1978) specification test, which compares an estimator $\hat{\theta}_1$ that is known to be consistent (the fixed effects estimator in our case) with an estimator $\hat{\theta}_2$ that is efficient (the random effects estimator) under the assumption being tested. Under the Hausman test considered we were unable to reject the null hypothesis

difference between the random and fixed effects estimates, so the Hausman test recommends the use of the efficient estimator (random effects) over the consistent estimator (fixed effects). In the remainder of the analysis we present results relative to the **random effects** specification.

Understanding the role of changes in labour composition and changes in hours

Table 16 decomposes the impact of changes in QALI into changes in labour composition and changes in hours. Column 1 reproduces the random effects specification estimates of Column 2 of Table 15, while Column 2 of Table 16 decomposes the impact of QALI into the impact of changes in labour composition and hours across the entire time period of the analysis (2001-2019).

Table 16: Disaggregating the labour input into labour composition and hours
Dependent variable: GVA growth (by industry)

	(1) **Δ QALI**	**(2)** **Δ LC and Δ Hours**
Δ ICT capital	0.07*	0.07*
	(0.04)	(0.04)
Δ Non-ICT tangible capital	0.08	0.08
	(0.10)	(0.10)
Δ Intangible capital	0.06	0.06
	(0.04)	(0.04)
Δ QALI	0.10***	
	(0.04)	
Δ Labour composition		0.26
		(0.19)
Δ Hours		0.09**
		(0.04)
Constant	0.04	0.04
	(0.03)	(0.03)
Specification	Random effects	Random effects
R-squared	0.36	0.36
Observations	285	285
Sample	Industry	Industry

*Standard errors clustered at the industry level in parentheses. Additional controls: year dummies and age structure of the workforce. *** p<0.01, ** p<0.05, * p<0.1*

While the point estimate of the impact of changes in labour composition (0.26) is greater than that for changes in changes in hours (0.09), the former is a noisy estimate and has a

that the estimator $\hat{\theta}_2$ is indeed an efficient and consistent estimator of the true parameters and, hence, used the random effects model as our preferred specification.

very large standard error (and it is not statistically significant)[60]. **The estimate of changes in hours is positive and significant** (at the five percent significance level)[61].

Breaking down the role of changes in labour composition and hours by qualification level

The labour input variables (QALI, labour composition, and hours) can be further disaggregated across qualification groups, as shown in Table 17. Qualification levels are assigned to one of two aggregated qualification groups: upper-level and lower-level qualifications. The upper qualification group includes those who hold a postgraduate degree or a first degree (and equivalent), while the lower qualification group includes all other qualification levels.

[60] The analysis was also replicated using regional data. However, the noisy estimates reflect the potential problems with the experimental regional capital data. Baseline results of the regional-level analysis are presented in Table 28 and Table 29 in Annex A7. The impact of a given change in QALI or labour composition at a regional level is positive and statistically significant given the large standard errors.
[61] This implies that raising the usual weekly hours worked in the economy by 10% (e.g. from a weekly total of 1,000 million hours to 1,100 million) would be associated with an increase of 1.3% in GVA, corresponding to around £22 billion in 2018 prices (as the average GVA over the period was about £1,680 billion).

Table 17: Disaggregating by qualification group (2001-2019)
Dependent variable: GVA growth (by industry)

	(1) Δ QALI	(2) Δ LC and Δ Hours
Δ ICT capital	0.07*	0.07*
	(0.04)	(0.04)
Δ Non-ICT tangible capital	0.08	0.08
	(0.10)	(0.10)
Δ Intangible capital	0.06	0.07*
	(0.04)	(0.04)
Δ QALI (upper)	0.12***	
	(0.05)	
Δ QALI (lower)	0.08	
	(0.07)	
Δ Labour composition (upper)		0.60
		(0.53)
Δ Labour composition (lower)		0.13
		(0.30)
Δ Hours (upper)		-0.04
		(0.18)
Δ Hours (lower)		0.09
		(0.07)
Constant	0.04	0.03
	(0.03)	(0.03)
Specification	Random effects	Random effects
R-squared	0.35	0.36
Observations	285	285
Sample	Industry	Industry

*Standard errors clustered at the industry level in parentheses. Additional controls: year dummies and age structure of the workforce.*** p<0.01, ** p<0.05, * p<0.1*

Column 1 of Table 17 shows the impact of a given change QALI across the two aggregated qualification groups. The point estimates of 0.12 and 0.08 for the upper and lower qualification groups (respectively) are positive, but only the impact of the upper qualification group is statistically significant (to the one percent significance level). Both are similar to the estimated impact of aggregated QALI of 0.1 presented in Column 1 in Table 16 and the difference between the two is statistically insignificant.

However, decomposing changes in QALI into changes in labour composition and changes in hours exposes significant differences between the qualification groups. Column 2 of Table 17 presents the estimates of the impact of changes in labour composition and changes in hours by qualification group. **The impact of a given change in the labour composition for the upper qualification group is larger than that for the lower upper qualification group, although not statistically significant**. The estimate suggests that a 1% change in labour composition of the upper qualification group is associated with a 0.6% change in GVA growth. The average annual change in labour composition for the upper qualification group is 0.36%, so the implied average annual contribution to GVA growth is 0.22%. The impact of changes in labour composition for the lower qualification group is not statistically different from zero. The impact of an increase in hours for both the lower and higher-level qualifications groups is insignificantly different from zero.

Breaking down the role of changes in labour composition and hours by time period

The baseline analysis provides an average estimate across the entire period between 2001 and 2019. However, this estimate may mask differences across time periods, and the recession following the Financial Crisis of 2008 provides a potential break in the sample timeline. Allowing for different coefficient estimates pre- and post-recession allows for the analysis of the impact of labour changes in different labour market environments.

Table 18 shows the estimates of the impact of changes in QALI, labour composition, and hours on GVA growth before and after the recession. Two binary variables are interacted with the labour variables: ‘Pre-2008’ takes a value of one in the years up to but not including 2008 (and zero otherwise), and ‘Post-2008’ takes a value of one from 2008 and onwards[62].

Column 1 presents the impact of changes in QALI before and after 2008, standing at 0.11 before 2008 and 0.09 from 2008 onwards (with the difference between the two estimates being statistically insignificant and only the impact before 2008 is statistically significant).

However, there are large differences before and after 2008 when changes in QALI are decomposed into changes in labour composition and changes in hours, as shown in Column 2. **The impact of a change in the labour composition is large (although not statistically significant) before 2008**. The coefficient of 0.64 and an average labour composition change of 0.45 before 2008 imply an average labour composition contribution of 0.29 percentage points to GVA growth before 2008.

This estimated impact becomes insignificantly different from zero from 2008 onwards. This result suggests that the impact of a given change in labour composition, for example due to an increase in the proportion of the workforce in possession of a university degree, significantly decreased since 2008. However, this is not the same as suggesting that labour composition changes have slowed (in fact labour composition changes

[62] We also tried using 2009 and 2010 as cut-off points to define the time periods for the analysis and the results were broadly similar.

increased from 0.49% a year before 2008 to 0.58% from 2008 and onwards as shown in Figure 9 in the growth accounting section).

Table 18: Disaggregating by time period
Dependent variable: GVA growth (by industry)

	(1) Δ QALI	(2) Δ LC and Δ Hours
Δ ICT capital	0.07*	0.08**
	(0.04)	(0.04)
Δ Non-ICT tangible capital	0.08	0.08
	(0.10)	(0.10)
Δ Intangible capital	0.06	0.09**
	(0.04)	(0.04)
Pre-2008 X Δ QALI	0.11*	
	(0.06)	
Post-2008 X Δ QALI	0.09	
	(0.06)	
Pre-2008 X Δ Labour Composition		0.64
		(0.40)
Post-2008 X Δ Labour Composition		0.06
		(0.27)
Pre-2008 X Δ Hours		0.06
		(0.07)
Post-2008 X Δ Hours		0.09
		(0.07)
Constant	0.03	0.02
	(0.03)	(0.02)
Specification	Random effects	Random effects
R-squared	0.36	0.37
Observations	285	285
Sample	Industry	Industry

*Standard errors clustered at the industry level in parentheses. Additional controls: year dummies and age structure of the workforce. *** p<0.01, ** p<0.05, * p<0.1*

Although it is not entirely clear what is driving this result, one potential explanation could relate to demand-side factors. Essentially, labour composition changes, such as an increase in the proportion of workers who hold university degrees, may not have been met with similar changes in employer demand for workers with those qualifications (potentially reflecting a degree of skills underutilisation). Demand-side changes after the 2008 Financial Crisis may explain why a given change on the supply side may have had a more limited impact on GVA growth. Another explanation may point to a skills mismatch between vacancies that result in skills shortages. Even if the workforce becomes more qualified, if there are difficulties in matching skills between workers and jobs (for example geographical immobility), then employers may still face shortages in skills.

GVA growth is generally insensitive to changes in hour worked, with estimates of the impact of changes in hours worked on GVA growth positive (0.06 and 0.09 before and after 2008) but not statistically significant.

Breaking down the role of changes in labour composition and hours by qualification level and time period

Table 19 interacts the impact of changes in QALI by qualification groups with the dummy identifying the period pre-and-post 2008. Column 1 reproduces the baseline results from Column 1 of Table 15. The estimates in Column 2 suggest that the **impact of a given labour input change from the higher level qualification group is large and positive before 2008, but insignificantly different to zero from 2008 and onwards**. The opposite is true for lower-level qualifications, where GVA growth is more sensitive to changes in lower-level qualification labour inputs after the 2008 Financial Crisis.

Table 19: Disaggregating by qualification group and time period

Dependent variable: GVA growth (by industry)

	(1) **Δ QALI**	**(2)** **Δ QALI**
Δ ICT capital	0.07*	0.07**
	(0.04)	(0.04)
Δ Non-ICT tangible capital	0.08	0.07
	(0.10)	(0.09)
Δ Intangible capital	0.06	0.06
	(0.04)	(0.04)
Δ QALI	0.10***	
	(0.04)	
Pre-2008 X Δ QALI (upper)		0.27*
		(0.16)
Post-2008 X Δ QALI (upper)		0.03
		(0.06)
Pre-2008 X Δ QALI (lower)		-0.01
		(0.08)
Post-2008 X Δ QALI (lower)		0.14
		(0.11)
Constant	0.04	0.03
	(0.03)	(0.03)
Specification	Random effects	Random effects
R-squared	0.36	0.37
Observations	285	285
Sample	Industry	Industry

*Standard errors clustered at the industry level in parentheses. Additional controls: year dummies and age structure of the workforce. *** p<0.01, ** p<0.05, * p<0.1*

These results may suggest that the demand-side of the economy was more responsive to increases in labour input from those with first degrees and postgraduate qualifications before 2008, and more responsive to increases in labour input from those in other educational qualification groups after 2008. This may be driven by the relative availability of jobs across qualification groups. More limited availability of jobs suitable for those higher level qualifications may result in individuals working in jobs that match less well with their skills. This would result in a lower impact on GVA growth of a given change in both the labour composition as well as the QALI of those with higher level qualifications.[63]

This is supported by evidence in the wider labour economics literature. For example, Cribb et al. (2017) find persistent scarring effects on earnings in the UK after recessions. More specifically, Liu et al. (2016) find that demand-side shocks in recessions increase skill-mismatches between skills supplied by university graduates and hiring industries that account for most of the long-term earnings losses associated with a recession (and up to half of the short-term losses).

Results for labour productivity growth

The econometric analysis presented above estimates the relationship between a given change in labour (through QALI, labour composition, and hours) and GVA growth. Table 20 presents the results of econometric analysis that focuses on the relationship between changes in inputs of production and **GVA per hour growth** (labour productivity).

Column 1 presents the baseline specification that includes change in capital per labour hour (by capital type) and change in labour composition. The effect of changes in capital stock per labour hour is always positive and statistically significant across the different types of capital considered and ranges from 0.08 for ICT capital to 0.51 for non-ICT tangible capital.

On the other hand, the impact of a given increase in labour composition on GVA per hour growth (Column 1 of Table 20) is positive but not statistically significant. In Column 2 we show the coefficients for labour composition changes disaggregated by time period (before and after 2008). As with the analysis of the impact of labour inputs on GVA growth, the estimated impact of changes in labour composition on GVA per hour growth is large (even if not statistically significant) before 2008, but negligible after 2008. The estimated coefficient of 0.62 and an average labour composition change of 0.49% before 2008 implies an average annual contribution of 0.3 percentage points of GVA per hour growth.

[63] We also tried to disaggregate further changes in QALI into labour composition and hours, interacted with qualification group and time period but the resulting samples were not large enough to provide meaningful results.

The changing impact on productivity is consistent with the previous interpretation of results concerning GVA growth. The reduced impact of labour composition changes on productivity may arise from demand-side factors. If growth in demand for workers with university degrees falls behind the growth in the supply of workers with those degrees after 2008, then the surplus of workers with degrees may work in occupations where their degrees have a lower impact on productivity growth. The same demand-side factors would have an impact on both GVA and GVA per hour.

Table 20: Impact of labour composition changes on GVA per hour growth
Dependent variable: GVA per hour growth (by industry)

	(1) **Δ LC**	**(2)** **Δ LC**
Δ ICT capital	0.08*	0.08*
	(0.04)	(0.04)
Δ Non-ICT tangible capital	0.51***	0.51***
	(0.11)	(0.11)
Δ Intangible capital	0.18**	0.19***
	(0.07)	(0.07)
Δ Labour composition	0.32	
	(0.22)	
Pre-2008 X Δ Labour Composition		0.62
		(0.60)
Post-2008 X Δ Labour Composition		0.16
		(0.60)
Constant	(0.01)	(0.01)
	0.03	0.03
Specification	Random effects	Random effects
R-squared	0.53	0.53
Observations	285	285
Sample	Industry	Industry

*Standard errors clustered at the industry level in parentheses. Additional controls: year dummies and age structure of the workforce. *** p<0.01, ** p<0.05,*

7. Conclusions

Acknowledging that there are externalities to education that have wider economic and social benefits over and above what can be directly observed through labour market outcomes, this report explores the impact of education attainment on the narrower economic outcome of UK productivity growth. Two main methodologies are used: growth accounting and an econometric approach. Both decompose the labour input's impact on growth into contributions from total hours worked in the economy and labour composition. The latter allows for the estimation of the contribution of changes in the composition (or quality) of labour across qualifications, such as changes in the share of hours worked by those with different educational qualifications.

The growth accounting results suggest that the contribution of changes in labour composition towards productivity growth is positive and generally stable across time (around 0.3 percentage points), although it increased slightly to 0.4 percentage points during the period following the 2008 Financial Crisis. These are generally consistent with previous analyses although there are some differences that can be explained by the methodological differences and potential revisions to the LFS data used.

Results vary to some extent across UK regions and sectors of economic activity but generally range between 0.1 and 0.5 percentage points. In particular, the contribution of labour composition to GVA growth appeared to be relatively strong in the Manufacturing sector, Financial and Insurance services and in the Public Administration sector, but also in Health and Social Services and the Arts, Entertainment, and Recreation sectors. At the regional level annual contributions of labour composition were relatively high in the North East (first and last period), London (first two periods) areas and also Northern Ireland (final period).

In the post-2008 period, the labour input was the only input factor making a positive and consistent contribution to growth in GVA per hour growth, as the contribution of the other factors (capital deepening and Total Factor Productivity) declined significantly and became negligible in the period post-2014.

While the growth accounting analysis suggests that changes in labour composition (such as increases in the proportion of the labour force who hold higher level qualifications) have affected GVA growth at a consistent rate across time, the econometric approach seems to suggest that the **impact of the labour input on GVA growth was mostly driven by labour composition before 2008 but mainly by hours worked in the post-2008 period** (although results are not statistically significant). Further research could investigate the long-term impact of the Financial Crisis on skills under-utilisation, or whether other demand or supply-side factors might explain this structural break.

Overall, the evidence presented in this report, together with the findings from recent literature showing the positive effect of educational attainment on labour market outcomes shows that there is a positive effect of skills on wages and labour productivity.

As mentioned previously, both the results from the growth accounting and econometric approaches should be interpreted with appropriate caveats. Both approaches rely on relatively strong assumptions, such as constant returns to scale for the growth accounting approach. Further, both approaches leave a significant proportion of the variation in output and productivity growth in a residual Total Factor Productivity category. Other caveats include the fact that the quality of the Labour Force Survey data has declined in recent years (due to a smaller number of respondents), and the fact that analysis by time period is based on a relatively small number of observations.

Further research could investigate heterogeneity in the impact of changes in post-18 educational attainment, such as the differences in the impact of education across age or gender. In addition, changes in the composition of particular qualifications across time may also be important. For example, the skills obtained from a university degree in a given subject in 2002 may be different to those from a university degree in the same subject in 2022 (such as proficiency in ICT). These trends may also be important in explaining the impact of qualification attainment on UK productivity growth.

Appendix

A1. Data sources used

Table 21: Data sources

Variable	Description	Source
GVA	Gross value added by region and sector (constant prices)	ONS (Link)
Hours worked	Usual weekly hours worked in main job	Labour Force Survey
Hourly wage	Gross hourly wage	Labour Force Survey
Skill composition	Highest qualification	Labour Force Survey
Age structure	Current age of workers	Labour Force Survey
Tangible capital	Split into ICT/non-ICT capital, using regional GFCF and net capital stocks for total UK economy	ONS (Link and Link)
Intangible capital	Net capital stocks	ONS (Link)
Inflation	Consumer Price Index	ONS (Link)
International data	EU KLEMS 2017 release	Link

A2. Availability of capital data

Tangible capital (including ICT)

Previous academic literature has identified the importance of distinguishing between non-ICT capital assets (e.g., machinery, infrastructure) and ICT capital assets (e.g., computers, software) when estimating the determinants of labour productivity growth. Data on capital stock and gross fixed capital formation, disaggregated by asset type, is available at the UK and industry level, but only aggregated gross fixed capital formation is available at the regional level. There is limited information on regional breakdown for gross fixed capital formation[64], but that information is not disaggregated by type of asset (ICT and non-ICT).[65]

Intangible capital

Data on investment in intangible assets provided by the ONS is broken down by high level industry (SIC section), but not currently disaggregated by region. The most recent publication of intangible asset investment from November 2021 contains data up to 2019. Data on intangible assets are also available from INTAN INVEST[66], which contains information on various types of intangible assets by sector until 2017, but not by region. These data contain more types of intangible capital than the data from the ONS, some of which are not included in the ONS estimates of GVA. Using these data with the ONS GVA estimates would be inconsistent, and as a result ONS data is used.

Many studies rely on data from EU KLEMS[67], which provides data on capital by asset type, intangible capital, and output by industry (but not region) for all EU Member States (also available for the United Kingdom up to 2017). To ensure consistency with data for other variables, such as GVA, ONS capital data is used.

One potential proxy for intangible capital data that is available at the regional level is on-the-job training from the ONS. However, the data at the regional level is noisy and potentially a limited proxy for intangible capital, so has been excluded from the analysis.

Estimating regional capital stocks

Constant price net capital stocks (K) for each region-industry are calculated by estimating the initial net capital stock in 2000, and then applying consumption of fixed capital (CFC) and gross fixed capital formation (GFCF) in the following years using PIM:

$$K_t = K_{t-1} - CFC_t + GFCF_t$$

The initial net capital stock for a region-industry is estimated as a weighted share of total net capital stock in the industry across the country:

$$K_{ij2000} = \frac{\sum_t GFCF_{ijt}}{\sum_t GFCF_{Njt}} K_{Nj2000}$$

[64] This information is not part of a standard data series but has been published by the ONS following user requests, the latest of which is available here
[65] The ONS Regional Accounts and Gross Fixed Capital Formation (GFCF) teams were contacted and confirmed that at the time of writing sub-national series were not available for capital (although there may be development in the future).
[66] http://www.intaninvest.net/
[67] https://euklems.eu/

K_{ij2000} is the net capital stock of region i in industry j in 2000, which is estimated as a share of total net capital stock in industry j in 2000, K_{Nj2000}. This share is calculated as the total gross fixed capital formation (by industry j in region i) across the sample timeline (2000 to 2019) as a proportion of total gross fixed capital formation in industry j across all regions across the sample timeline[68].

Consumption of fixed capital (CFC) data was estimated using industry-level CFC data from the ONS[69]. Industry-level CFC was assigned across regions according to the region's share of GFCF in the industry for that year.

Estimating the initial constant price net capital stock, gross fixed capital, and consumption of fixed capital allows for the estimation of region-industry net capital stock.

A3. Detailed growth accounting methodology

Derivation of capital and labour inputs decompositions

Labour input decomposition

Labour input can be decomposed into various labour types, based on skill group. The growth rate of labour input in industry j can be stated as the growth in hours worked by workers of type l ($\Delta lnH_{l,j}$) weighted by the Divisia index of the nominal cost share of labour of type l summed across all labour types:

$$\Delta lnL_j = \sum_l \bar{v}_{L,l,j} \, \Delta lnH_{l,j}$$

The nominal cost share of labour of type l, or the quality-adjusted labour index (QALI) is given by:

[68] Gross fixed capital formation data at the regional level, estimated by the ONS, is presented in current prices. As a result, industry-level price indices are calculated using industry-level estimates of gross fixed capital formation in current and constant prices. These series are estimated using ONS data on net capital stocks and consumption of fixed capital (current and constant price series), where net capital stock is $NetCapitalStock_{t+1} = NetCapitalStock_t + GrossFixedCapitalFormation_t - ConsumptionFixedCapital_t$. This is rearranged to estimate gross fixed capital formation (at current and constant prices), and the price index for each industry and year is calculated as current price gross fixed capital formation divided by constant price gross fixed capital formation. These industry-specific price indices are applied to the regional current price estimates provided by the ONS to estimate constant price regional gross fixed capital formation.

[69] ONS Gross and net capital stocks for total UK economy, by industry and asset (November 2021 release), available at https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/datasets/grossandnetcapitalstocksfortotaleconomybyindustryandassetincurrentpricesandchainedvolumemeasures

$$v_{L,l,j} = \frac{p_{L,l,j} H_{l,j}}{\sum_k p_{L,k,j} H_{k,j}}$$

Where $p_{L,l,j}$ denotes the nominal factor price (i.e., hourly wage) of labour type l in industry j. Thus, it denotes the share of labour compensation in industry j that goes toward labour of type l. The growth rate of labour input $\Delta lnL_{j,t}$ is a Törnqvist volume index of the growth in hours worked weighted by the nominal input share. This means, it can be broken down into a) a labour composition effect and b) a change in hours worked, as follows:[70]

$$\Delta lnL_j = \sum\nolimits_k \bar{v}_{L,k,j}\, \Delta lnH_{k,j} - \Delta lnH_j + \Delta lnH_j$$
$$= \left(\sum\nolimits_k \bar{v}_{L,k,j}\, \Delta lnH_{k,j} - \sum\nolimits_k \bar{v}_{L,k,j}\, \Delta lnH_j\right) + \Delta lnH_j$$
$$= \underbrace{\sum\nolimits_k \bar{v}_{L,k,j}\, \Delta ln\frac{H_{k,j}}{H_j}}_{\Delta lnLC_j} + \Delta lnH_j$$

resulting in:

$$\Delta lnL_j = \Delta lnLC_j + \Delta lnH_j$$

This equation shows that growth in labour input can be decomposed into the impact of labour composition, and the contribution of changes in hours worked. Hence, growth accounting allows for the assessment of the contribution of skill accumulation at different skill levels to total productivity. This requires information on the change in the share of the workforce in different skill groups, as well as the productivity differentials between the different skill groups. If overall hours worked in industry j stay constant, then an increase in growth of labour input can be interpreted as being due to changes in the skills composition of workers, either because (relative) wages change or because hours worked by workers with higher wages increase.

To construct year on year changes in hours, QALI and labour composition and generate the growth accounting results at the **national** and **sectoral** level, information on labour inputs (hours and income shares) were broken down into cells[71] by:

- Qualification group (the 10 different qualification groups used in the analysis and presented in Figure 5)[72]; and

[70] Time subscripts omitted for simplicity.
[71] Although further disaggregation may have been desirable (e.g. by age and gender, as well as a cross-disaggregation with the regional breakdown), that would have resulted in small cell sizes (and a number of empty cells).
[72] Those with highest qualification classified as “No answer” or “Don’t know” were removed from the analysis.

- Sector (15 sectors, as presented in Table 1).

The data did not allow to use the same type of granularity also for the regional growth accounting decomposition (as sample sizes did not allow for a full disaggregation by sector, region and qualification type at the same time), so for the growth accounting analysis at the **regional level** we used the following disaggregation:

- Regions (the 12 ITL1 UK regions);
- Qualification group (5 different qualification groups)[73]; and
- Sector (10 sectors)[74].

As a consequence, the results of the regional growth accounting decomposition may not be fully consistent with the national results.

Capital input decomposition

Similar to the decomposition of the labour input, the input of capital is measured as a Törnqvist volume index of different asset types in industry j as given by:

$$\Delta lnK_j = \sum_l \bar{v}_{K,k,j} \Delta lnK_{k,j}$$

where $K_{k,j}$ denotes the capital stock (in chain-linked volumes) of asset type k in industry j, and $\bar{v}_{K,k,j}$ denotes the **Divisia shares**, defined as:

$$v_{K,k,j} = \frac{p_{K,k,j} K_{k,j}}{\sum_l p_{K,l,j} K_{k,j}} = \frac{p_{K,k,j} K_{k,j}}{p_{K,j} K_j}$$

where $p_{K,k,j}$ denotes the price of capital asset type k in industry j. Capital assets are divided into tangible assets (ICT and non-ICT assets) and intangible assets[75]. Data sources for capital assets by industry and the method used to estimate capital assets by region are outlined in Section A2 in the Appendix.

Based on the estimates of capital stock $K_{k,j,t}$ in real chain-linked series volumes, the **nominal rate of return** in industry j can be estimated as follows:

$$i_{j,t} = \frac{p_{K,j,t} K_{j,t} + \sum_l (p^I_{l,j,t} - p^I_{l,j,t-1}) K_{l,j,t} - \sum_l \delta_{l,j} p^I_{l,j,t} K_{l,j,t}}{\sum_l p^I_{l,j,t-1} K_{l,j,t}}$$

[73] Postgraduate degrees, First degrees, Level 5 and Level 4 (combined), Level 3 (including Apprenticeships), all qualifications at Level 2 and below.

[74] "ABDE: agriculture and energy", "C: manufacturing", "F: construction" , "GHI: Distribution; transport; accommodation and food", "J: information and communication", "K: financial and insurance activities", "L: real estate activities", "MN: professional, scientific/administrative activities ", "OPQ Public administration; education; health", 10"RS:arts, entertainment; other service activities".

[75] Intangible capital is usually divided into R&D, organisational capital and ICT capital. For this analysis intangible capital will not be broken down further into its components.

where $p_{K,j,t}K_{j,t} = v_{K,j}$ (total capital income in industry j). The investment price of asset type k in industry j is given by $p^I_{k,j,t}$, and $\delta_{k,j}$ denotes the depreciation rate of asset of type k. To calculate the price of capital (or **user cost of capital**, which is the price of asset k at which an investor is indifferent between buying and renting it), the equation is given by:

$$p_{K,k,j,t} = p^I_{k,j,t-1} + \delta_{k,j}p^I_{k,j,t} - (p^I_{k,j,t} - p^I_{k,j,t-1})$$

Empirical growth accounting

Taking into account various types of capital assets and skill-adjusted labour, equation 2 (Eq. 2) can be rewritten as:

$$\Delta lnY_{j,t} = \bar{v}_{K,j,t} \textstyle\sum_G \bar{v}_{G,j,t}\, \Delta lnK_{G,j,t} + \bar{v}_{L,j,t}(\Delta lnLC_{j,t} + \Delta lnH_{j,t}) + \Delta lnTFP_{j,t}$$

where G denotes capital inputs tangible ICT-capital, tangible non-ICT capital, and intangible capital. To express equation (2*) in terms of labour productivity (i.e. total output per hour worked), $\Delta lnH_{j,t}$ has to be subtracted from both sides:

$$\begin{aligned} &\Delta lnY_{j,t} - \Delta lnH_{j,t} \\ &= -\Delta lnH_{j,t} + \bar{v}_{K,j,t} \sum_G \bar{v}_{G,j,t} \left(\Delta lnK_{G,j,t} - \Delta lnH_{j,t}\right) + \bar{v}_{K,j,t}\Delta lnH_{j,t} \\ &+ \bar{v}_{L,j,t}\Delta lnLC_{j,t} + \bar{v}_{L,j,t}\Delta lnH_{j,t} + \Delta lnTFP_{j,t} \end{aligned}$$

Using the condition that $\bar{v}_{K,j,t} + \bar{v}_{L,j,t} = 1$ leads to the cancellation of the $\Delta lnH_{j,t}$ terms, resulting in:

$$\Delta ln\frac{Y_{j,t}}{H_{j,t}} = \bar{v}_{K,j,t} \sum_G \bar{v}_{G,j,t}\, \Delta\ln\frac{K_{G,j,t}}{H_{j,t}} + \bar{v}_{L,j,t}\Delta lnLC_{j,t} + \Delta lnTFP_{j,t}$$

This means that labour productivity growth can be decomposed into the change in capital deepening, the amount of capital per hour worked, the change in labour composition capturing the effect of changes in skill levels of workers, and total factor productivity growth (i.e. the residual component of labour productivity growth that is attributed to technological progress).

Box 9: Decomposing the contribution of the labour input

When looking at the contribution of the labour input to output (GVA) growth, it is possible to refine the standard measure of hours worked and construct a measure accounting for changes in the composition (or quality) of the employed workforce, as well as changes in hours worked by different types of workers (the **Quality-adjusted labour input QALI**), with different levels of productivity (proxied by wages).

$$\Delta QALI = \sum_i \underbrace{\frac{IS_{i,t} + IS_{i,t-1}}{2}}_{\text{Using average income shares (IS) as weights}} * \ln \underbrace{\frac{hours_{i,t}}{hours_{i,t-1}}}_{\text{Change in hours}} + \Delta hours_{i,t}$$

i is the qualification type (skill)

$$\Delta QALI = \Delta\textbf{Labour Composition} + \Delta\textbf{hours}$$

Hence, labour input or QALI can change either due to a change in the total number of hours worked in the UK economy, or due to a change in labour composition, constructed by weighting the hours worked by each skill group by their income share.

Changes in labour composition can be interpreted as the gain in productivity that is either due to a compositional change in hours worked by workers of skill level i relative to overall hours worked; or as the change in (relative) factor prices (i.e., wages per hour worked) that changes the income shares over time. Workers are assumed to be paid their marginal products, hence workers with higher qualifications are assumed to earn higher hourly wages.

Since labour composition is weighted by the income share of each qualification group, it is relatively more affected by changes in the number of hours worked by workers with higher qualifications, as they are paid more. Similarly, if total hours worked remained constant but were worked by more qualified workers, this would also imply a positive contribution of labour composition on output growth.

A4. Decomposition of productivity level gaps – methodology and data

Methodological approach

The methodology used follows the one described by O'Mahony and de Boer (2002). In particular, the difference between the UK's labour productivity and those of other countries can be broken down into contributions from capital, skills, and a residual TFP, following the methodology used. The following equation outlines the decomposition into factors:

$$\ln\left(\frac{y_J}{y_{UK}}\right) = \alpha_{J,UK} \ln\left(\frac{H_J}{H_{UK}}\right) + \left(1 - \alpha_{J,UK}\right) \ln\left(\frac{k_J}{k_{UK}}\right) + \ln\left(\frac{TFP_J}{TFP_{UK}}\right)$$

y_J and k_J are the labour productivity (GDP per hour worked) and capital per labour hour of country J, respectively[76]. $\alpha_{J,UK}$ is the average labour share of income between country J and the UK. H_J measures the skills (or human capital) of country J, which is calculated as the average hourly earnings relative to the average hourly earnings of those in the lowest (educational) qualification category, weighted across qualification groups by their share of total hours worked:

$$H_J = \sum_{S=1,2,3} \frac{w_{Js}}{w_{J1}} l_{Js}$$

$\frac{w_{Js}}{w_{J1}}$ is the ratio between the hourly wage between qualification group S and the lowest qualification group 1 (below upper secondary education) in country J[77]. H_{UK} is calculated in the same way. There are three qualification groups: below upper secondary education (group 1), upper secondary or post-secondary non-tertiary education (group 2), and tertiary education (group 3). l_{Js} is the proportion of total hours worked by those in qualification group S[78].The ratio of TFP between country J and the UK, $\frac{TFP_J}{TFP_{UK}}$, is calculated as a residual:

$$\ln\left(\frac{TFP_J}{TFP_{UK}}\right) = \ln\left(\frac{y_J}{y_{UK}}\right) - \alpha \ln\left(\frac{H_J}{H_{UK}}\right) - (1 - \alpha) \ln\left(\frac{k_J}{k_{UK}}\right)$$

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[76] GDP per hour is calculated using The Conference Board's Total Economy Database (real GDP in 2020 international dollars converted using PPPs) and capital per hour provided by Bergeaud et al. (2020) in 2010 US dollars (PPPs) per hour.
[77] The OECD provides data on relative annual earnings between qualification groups and the lowest qualification group. To convert this into relative hourly earnings, the relative annual earnings are divided by average annual hours (average weekly hours multiplied by 52 weeks, provided by Bick et al. (2019)), and then normalised by the hourly earnings of those in group 1, with below upper secondary education. The hourly earnings of those in group 1 are normalised as 100.
[78] Hours worked per week are calculated by multiplying the employment rate (Bick et al., 2019), average hours worked per week (Bick et al., 2019), and population (OECD), by qualification group. Hours worked per week are used to calculate hours shares across qualification groups.

Data sources used

In Table 22 we present the various data sources used in the analysis.

Table 22: Data sources used in the productivity gap analysis

Variable	Description	Source
GDP	Real GDP in 2020 international dollars converted using PPPs	The Conference Board's Total Economy Database[1]
Capital intensity	$US 2010 ppp per hours	Long Term Productivity Database v2.4 (2020 update)[2] A. Bergeaud, G. Cette and R. Lecat (2016)
Relative remuneration	Relative remuneration by educational attainment (ISCED 0-2=100)	OECD Stats[3]
Employment rates	Employment rates by educational attainment	OECD Stats[3]
Population	Population by educational attainment	OECD Stats[3]
Hours worked	Average annual hours worked by educational attainment (based on national labour force surveys)	Bick, A., Brüggemann, B. and Fuchs-Schündeln, N. (2019)[4] 'Hours Worked in Europe and the United States: New Data, New Answers'

1 https://www.conference-board.org/data/economydatabase/total-economy-database-productivity
2 http://www.longtermproductivity.com/download.html
3 https://stats.oecd.org/
4 https://onlinelibrary.wiley.com/doi/abs/10.1111/sjoe.12344

A5. Supplementary growth accounting analysis

Table 23: Average annual growth rates of capital deepening, capital, and hours by industry and by time period (ABDE – K)

Industry	Component	2001-2007	2008-2013	2014-2019
ABDE: Agriculture and energy	Capital deepening	0.8%	1.0%	0.2%
	Capital	1.0%	1.9%	1.4%
	Hours	0.2%	0.9%	1.3%
C: Manufacturing	Capital deepening	2.3%	1.6%	1.3%
	Capital	-1.2%	-1.9%	1.5%
	Hours	-3.4%	-3.5%	0.2%
F: Construction	Capital deepening	0.4%	4.5%	4.1%
	Capital	3.0%	1.0%	5.4%
	Hours	2.6%	-3.5%	1.3%
G: Wholesale and retail trade	Capital deepening	3.4%	2.0%	1.2%
	Capital	3.2%	0.9%	1.5%
	Hours	-0.2%	-1.0%	0.3%
H: Transport and storage	Capital deepening	4.7%	2.2%	1.0%
	Capital	4.6%	0.8%	1.5%
	Hours	-0.1%	-1.3%	0.5%
I: Accommodation and food services	Capital deepening	-0.7%	-3.0%	-0.3%
	Capital	1.3%	-1.0%	2.2%
	Hours	2.0%	2.0%	2.6%
J: Information and communication	Capital deepening	5.7%	0.7%	-0.3%
	Capital	6.1%	0.6%	2.5%
	Hours	0.4%	-0.2%	2.9%
K: Financial and insurance activities	Capital deepening	0.3%	0.8%	-1.5%
	Capital	1.2%	-0.8%	0.2%
	Hours	0.9%	-1.6%	1.7%

Sources: LFS, ONS, and London Economics' calculations

Notes: Average growth rates for each time period is reported in percentages. Capital deepening growth and hours growth may not add up exactly to capital growth due to rounding of individual components.

Table 24: Average annual growth rates of capital deepening, capital, and hours by industry and by time period (L – RS)

Industry	Component	2001-2007	2008-2013	2014-2019
L: Real estate activities	Capital deepening	-1.3%	-3.5%	-1.8%
	Capital	2.5%	0.2%	0.7%
	Hours	3.8%	3.8%	2.6%
M: Professional and technical activities	Capital deepening	3.4%	-0.6%	-1.5%
	Capital	5.5%	3.5%	1.8%
	Hours	2.1%	4.1%	3.3%
N: Administrative and support services	Capital deepening	2.9%	-2.8%	5.2%
	Capital	4.0%	-1.2%	6.4%
	Hours	1.1%	1.6%	1.1%
O: Public administration	Capital deepening	-1.4%	4.0%	-0.1%
	Capital	1.0%	2.2%	2.0%
	Hours	2.4%	-1.8%	2.1%
P: Education	Capital deepening	3.2%	2.3%	0.9%
	Capital	5.8%	4.9%	2.8%
	Hours	2.6%	2.7%	1.8%
Q: Health and social services	Capital deepening	0.7%	-0.6%	-0.2%
	Capital	3.1%	1.9%	1.4%
	Hours	2.5%	2.5%	1.6%
RS: Arts, entertainment, and recreation	Capital deepening	3.0%	1.4%	-0.7%
	Capital	4.3%	2.5%	2.3%
	Hours	1.2%	1.0%	3.1%

Sources: LFS, ONS, and London Economics' calculations

Notes: Average growth rates for each time period is reported in percentages. Capital deepening growth and hours growth may not add up exactly to capital growth due to rounding of individual components.

Table 25: Average annual growth rates of capital deepening, capital, and hours by region and by time period

Region	Component	2001-2007	2008-2013	2014-2019
North East	Capital deepening	0.5%	1.5%	-0.1%
	Capital	1.7%	0.3%	1.0%
	Hours	1.2%	-1.3%	1.1%
North West	Capital deepening	1.8%	0.9%	-0.8%
	Capital	2.2%	0.3%	1.0%
	Hours	0.4%	-0.6%	1.8%
Yorkshire and the Humber	Capital deepening	1.2%	1.1%	-0.9%
	Capital	2.0%	0.4%	0.9%
	Hours	0.8%	-0.7%	1.9%
East Midlands	Capital deepening	1.5%	0.5%	-0.4%
	Capital	2.0%	0.3%	1.0%
	Hours	0.6%	-0.2%	1.4%
West Midlands	Capital deepening	1.5%	1.1%	-0.9%
	Capital	2.0%	0.4%	1.0%
	Hours	0.5%	-0.7%	1.9%
East of England	Capital deepening	1.9%	0.2%	0.0%
	Capital	2.1%	0.5%	1.2%
	Hours	0.2%	0.3%	1.2%
London	Capital deepening	1.1%	-0.7%	-1.1%
	Capital	1.9%	0.8%	1.6%
	Hours	0.8%	1.5%	2.7%
South East	Capital deepening	1.7%	0.4%	0.3%
	Capital	2.0%	0.4%	1.2%
	Hours	0.3%	0.0%	0.8%
South West	Capital deepening	1.1%	0.5%	-0.9%
	Capital	1.7%	0.3%	1.1%
	Hours	0.6%	-0.2%	2.0%

Sources: LFS, ONS, and London Economics' calculations

Notes: Average growth rates for each time period is reported in percentages. Capital deepening growth and hours growth may not add up exactly to capital growth due to rounding of individual components.

Table 26: Average annual growth rates of capital deepening, capital, and hours by country and by time period

Country	Component	2001-2007	2008-2013	2014-2019
England	Capital deepening	1.4%	0.4%	-0.6%
	Capital	2.0%	0.4%	1.2%
	Hours	0.6%	0.0%	1.7%
Wales	Capital deepening	0.5%	1.2%	-0.7%
	Capital	1.7%	0.3%	0.8%
	Hours	1.2%	-0.9%	1.5%
Scotland	Capital deepening	0.8%	0.9%	0.1%
	Capital	1.8%	0.4%	0.7%
	Hours	1.1%	-0.5%	0.6%
Northern Ireland	Capital deepening	1.2%	1.0%	1.9%
	Capital	2.8%	0.5%	0.8%
	Hours	1.7%	-0.5%	-1.2%

Sources: LFS, ONS, and London Economics' calculations

Notes: Average growth rates for each time period is reported in percentages. Capital deepening growth and hours growth may not add up exactly to capital growth due to rounding of individual components.

A6. Supplementary productivity gap decomposition results

Table 27: Decomposition of comparative labour productivity levels (GDP per hour worked) using earnings from Eurostat (relative to the UK)

		2000	2006	2010	2014
France	**Labour Productivity**	**22.1%**	**16.4%**	**11.2%**	**21.3%**
	of which (percentage point contribution from each factor):				
	Capital	16.8	21.4	18.5	22.2
	Skills	5.1	-12.7	-2.2	-3.2
	TFP	0.3	7.8	-5.0	2.4
Germany	**Labour Productivity**	**24.7%**	**16.2%**	**14.0%**	**21.5%**
	of which (percentage point contribution from each factor):				
	Capital	18.1	21.5	18.6	20.5
	Skills	4.1	-0.9	19.0	13.9
	TFP	2.6	-4.4	-23.5	-12.8

Sources: Broadberry and O'Mahony (2004) for 2000 results, London Economics based on EUROSTAT Structural Earnings Survey, Bick et al. (2019), Bergeaud et al. (2020), The Conference Board (2021) for 2006, 2010 and 2014

Note: The US are not available in the EUROSTAT data

All values expressed relative to the UK

A7. Supplementary econometric results

Table 28: Aggregating capital across types of capital, by industry
Dependent Variable: GVA growth (by industry)

	(1) **Δ QALI**	**(2)** **Δ LC and Δ Hours**
Δ Capital	0.17**	0.17**
	(0.08)	(0.08)
Δ QALI	0.11***	
	(0.04)	
Δ Labour composition		0.16
		(0.17)
Δ Hours		0.11**
		(0.04)
Constant	0.05*	0.05*
	(0.03)	(0.03)
Specification	Random effects	Random effects
R-squared	0.32	0.32
Observations	285	285
Sample	Industry	Industry

*Standard errors clustered at the industry level in parentheses. Additional controls: year dummies and age structure of the workforce. *** p<0.01, ** p<0.05, * p<0.1*

Table 29: Interacting QALI and types of capital, by industry

Dependent variable: GVA growth (by industry)

	(1) Δ QALI
Δ ICT capital	0.07**
	(0.03)
Δ Non-ICT tangible capital	0.07
	(0.09)
Δ Intangible capital	0.09**
	(0.04)
Δ QALI	0.35
	(0.75)
Δ ICT capital x Δ QALI	0.02**
	(0.01)
Δ Non-ICT tangible capital x Δ QALI	-0.02
	(0.04)
Δ Intangible capital x Δ QALI	-0.02
	(0.03)
Constant	0.01
	(0.02)
Specification	Random effects
R-squared	0.37
Observations	285
Sample	Industry

*Standard errors clustered at the industry level in parentheses. Additional controls: year dummies and age structure of the workforce. *** p<0.01, ** p<0.05, * p<0.1*

Table 30: Regional data - baseline econometric results

Dependent variable: GVA growth (by region)

	(1) Δ QALI	(2) Δ QALI	(3) Δ QALI
Δ Capital	-0.23	-0.23	-0.11
	(0.36)	(0.36)	(0.37)
Δ QALI	0.14*	0.14**	0.13
	(0.07)	(0.07)	(0.08)
Constant	-0.12	-0.12	-0.14
	(0.08)	(0.08)	(0.11)
Specification	OLS	RE	FE
R-squared	0.70	0.71	0.59
Observations	216	216	216
Sample	Regional	Regional	Regional

*Standard errors clustered at the industry level in parentheses. Additional controls: year dummies and age structure of the workforce. *** p<0.01, ** p<0.05, * p<0.1*

Table 31: Regional data - labour composition and hours

Dependent variable: GVA growth (by region)

	(1) Δ QALI	(2) Δ LC and Δ Hours
Δ Capital	-0.23	-0.25
	(0.36)	(0.36)
Δ QALI	0.14**	
	(0.07)	
Δ Labour composition		0.07
		(0.16)
Δ Hours		0.16**
		(0.08)
Constant	-0.12	-0.13
	(0.08)	(0.08)
Specification	Random effects	Random effects
R-squared	0.71	0.71
Observations	216	216
Sample	Regional	Regional

*Standard errors clustered at the industry level in parentheses. Additional controls: year dummies and age structure of the workforce. *** p<0.01, ** p<0.05, * p<0.1*

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