

# Diagnosing the UK productivity slowdown: which sectors matter and why?

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## Abstract

This paper explores the slowdown in labour productivity growth in the UK and other advanced economies by decomposing its growth into contributions from different sectors of the economy, looking at both within-industry productivity growth and labour reallocation between sectors. We find that the within-industry contribution is the main source of the slowdown. Comparing trends pre- and post-2008, the aggregate productivity slowdown can be attributed largely to the manufacturing sector and the information and communication (ICT) sector. Disaggregating further, the UK productivity growth slowdown can be attributed mainly to transport equipment and pharmaceuticals within manufacturing, and computer software and telecommunications within ICT. Strikingly, these are advanced, high value-added sectors considered to be strengths of the UK economy. Looking across other advanced economies, our results confirm that manufacturing and ICT sectors are the main drivers of the slowdown, to differing degrees. Part of the explanation for the slowdown in in these sectors may relate to the underlying question of how to construct deflators for a modern economy when technological and structural changes are leading to large relative price shifts. The structure and supply chains of the key slowdown sectors also merit further investigation.

## 1 | INTRODUCTION

The ‘puzzle’ of the productivity slowdown has been explored extensively. This paper extends this body of work by decomposing the aggregate productivity statistics into the different sectors and subsectors in order to see whether the slowdown has been dispersed across the economy or

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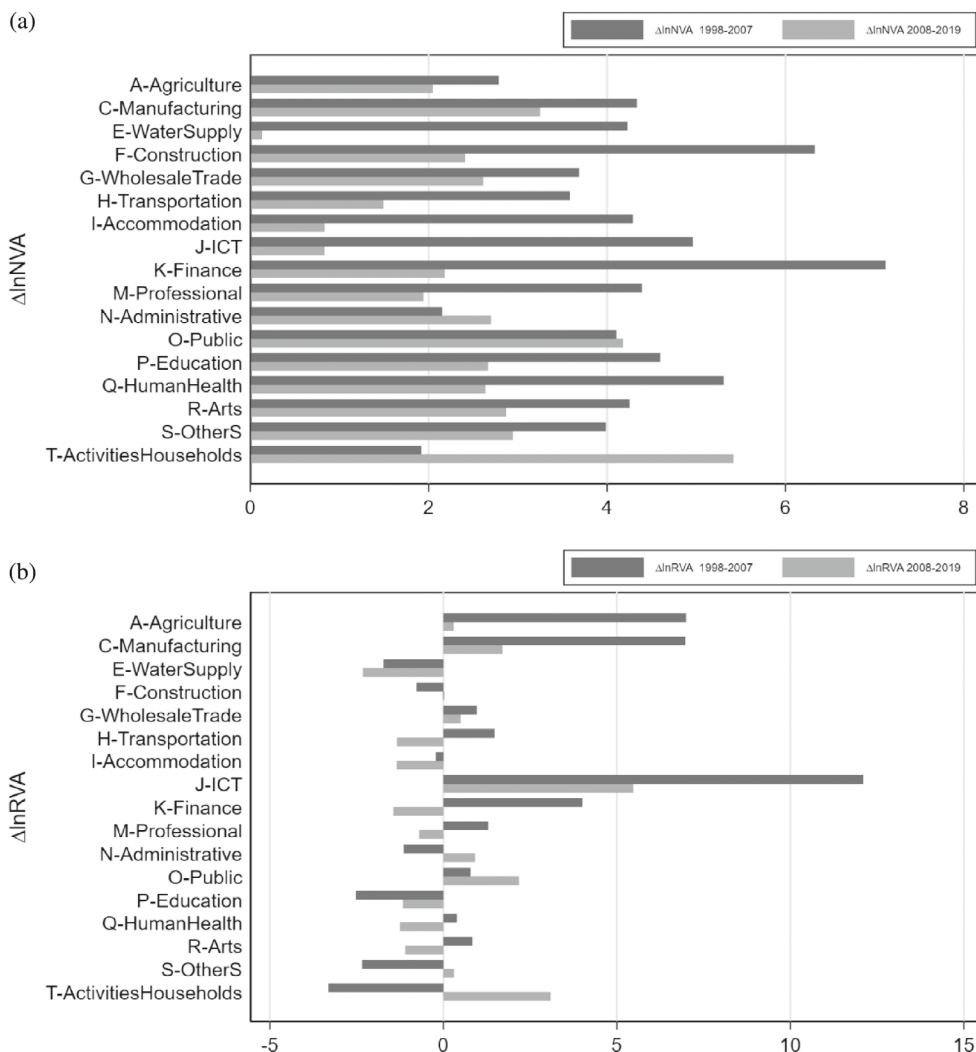
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become more concentrated. One of the questions often raised in discussions of the slowdown is to what extent it reflects specific sectoral slowdowns or, rather, shifts in activity from high- to low-productivity sectors. We find that the main contribution to the slowdown is within the manufacturing sector and the information and communication (ICT) sector, and within these in certain subsectors such as pharmaceuticals and software generally considered to be among the leading industries in the economy.

The term ‘productivity’ itself has a meaning in everyday use that differs from its specific meaning in economics. For example, in business, the variable of interest will often be engineering efficiency, or perhaps revenue or value-added per hour worked in current price terms, whereas economists are interested in real terms output or value-added per hour (i.e. revenue or value-added deflated by a price index). This is because deflating by a price index removes general inflationary effects to give a measure (in constant prices) closer to an economic welfare measure: deflators are constant utility constructs (e.g. Diewert and Gordon 1996). The intuitive way to think about the deflation exercise is as separating the quantity of something sold from its price; how many haircuts or apples are bought and sold is more relevant to economic progress than how many dollars or pounds are involved in the transaction. Yet for aggregate economic measurement, the ‘real’ quantities need to be added together; and as apples, haircuts, cars and all the myriad other products are counted in different volume units (and indeed the volume units are not obvious in many services, such as accountancy or software), they are all converted into monetary terms for the purposes of aggregation. Real GDP is thus a money metric of economic welfare or utility (Hillinger 2002), not a straightforward measure of quantity. Schelling (1958) is referring to this when he states: ‘[W]hat we call “real” magnitudes are not completely real; only the money magnitudes are real. The “real” ones are hypothetical.’

As economic statistics are often generated from collecting data in terms of money revenues, the price–quantity split is then constructed by deflating revenues by a price index (industry-level deflators are constructed from product prices). In moving from current price revenue or value-added per hour to the real terms labour productivity figures in which economists are interested therefore requires using an appropriate price index to deflate current price value-added. Similarly, in moving from aggregate labour productivity to individual sectoral-level measures, there are choices to be made in calculating labour productivity: is current price output to be deflated using a separate output price index for each sector, or should nominal value-added simply be adopted when estimating? In moving from gross output to value-added, similarly, the most appropriate input price deflators will differ between sectors. A further choice concerns how to weight the sectors of the economy to add them up to the aggregate level: should the weights use their share in total revenues, or volume or employment shares instead? When sectoral relative prices are changing, these will differ substantially (e.g. Abdirahman *et al.* 2022). The weights, therefore, have an important meaning in the analysis of the sectoral contributions to aggregate labour productivity growth.

For an initial look, we show in Figure 1(a), the growth rate of current price value-added per hour worked ( $\Delta \ln NVA$ ), and in Figure AI 1 of Online Appendix I, current price value-added per hour worked (in levels) in the UK, a basic productivity metric of key interest to business and policymakers, shaping perceptions of which parts of the economy are the success stories. The figures omit real estate, mining and utilities, which all have substantially higher current price value-added per hour, due to their distinctive features. After these, finance and manufacturing have the highest current price value-added per hour (Figure AI 1), and for both, the decrease in gradient post-2007 is visually evident; indeed, there has been an absolute decline for finance (industry K in Figure 1(a)). Slowdowns are also readily visible for professional, scientific and technical activities (industry M), and wholesale and retail trade (industry G). We test for a break in trend (log change) between 1998–2007 and 2008–19 in Table AI 1 of Online Appendix I, confirming



**FIGURE 1** Growth rates in (a) current price value-added per hour ( $\Delta \ln NVA$ ), and (b) growth rates in real value-added per hour ( $\Delta \ln RVA$ ), 1998–2007 and 2008–19. *Notes:* The growth rate is calculated in log change, where we take the logarithms for both nominal and real value-added as  $\ln NVA$  and  $\ln RVA$ , respectively. Nominal value-added per hour is measured by using the all-industry current price value-added divided by total hours worked. There are 20 industries making up the whole economy sector (A–T, see text for more details). We exclude mining and quarrying, electricity, gas, steam and air conditioning supply, and real estate activities. Real gross value-added per hour is measured by using total gross value-added in chain volume measure divided by the total hours worked based on the new double-deflated data updated since 30 September 2021 by the ONS. See ONS (2021) for more details. *Source:* Authors’ calculations by using `bb2102industrialanalysis` and `gdpolowlevelaggregates2021q3` data series from the ONS.

that water supply (industry E), construction (industry F), information and communication (industry J), professional and scientific (industry M), education (industry P), and human health (industry Q) experienced a statistically significant slowdown (at the 5% level) in *current* price terms during the post-crisis period.

Yet the picture is different when we turn to the *deflated* or ‘real terms’ value-added per hour, where the revenue series for each sector is deflated by a sector-specific output price deflator.

Again, we show in Figure 1(b) the growth rate of real value-added per hour worked ( $\Delta \ln RVA$ ) and the level rebased to 1997 = 100 in Figure AI 1 (bottom) of Online Appendix I. The labour productivity of the ICT sector has grown substantially in real terms over the entire period (industry J in Figure 1(b)), and both manufacturing (industry C) and agriculture (industry A) have grown too. Other sectors experienced either modest productivity growth or some decline. As our focus is explaining the slowdown after the mid-2000s, we test for a break in growth rates for 1998–2007 compared to 2008–19; the results in Table AI 2 of Online Appendix I reveal that both manufacturing and ICT nevertheless experienced the most significant slowdowns in real value-added per hour growth (at the 1% statistical significance level) over the post-crisis period. Other industries, including wholesale and retail trade, financial services, administrative services and public administration, have also grown significantly more slowly in the period 2008–19 compared to 1998–2007.

These charts nevertheless do not answer the question about the role played by reallocation of activity from high to low productivity sectors and the pure within-sector productivity contribution. To answer this question, previous studies have explored the trend differences (before and after 2008) using different decomposition approaches (see, for instance, Fabricant 1942; Maddison 1952; Tang and Wang 2004; McMillan and Rodrik 2011; De Vries *et al.* 2012; Diao *et al.* 2019; Moussir and Chatri 2020; Voskoboynikov 2020; De Vries *et al.* 2021).

Although the recent empirical literature, such as Harris and Moffat (2017),<sup>1</sup> Crafts and Mills (2020), and Goodridge *et al.* (2018),<sup>2</sup> confirms the UK productivity slowdown, this paper updates prior research on UK labour productivity by using recent Office for National Statistics (ONS) statistics that have incorporated double deflation for the first time, that is, deflating inputs and outputs separately.<sup>3</sup> In Section I, we clarify how the aggregate data and sectoral data relate to each other in a diagnostic exploration of the UK productivity slowdown through the lens of sectoral decomposition, discussing the role played by different weights used in deflating nominal value-added. We consider issues raised by the existing sectoral decomposition approaches such as generalized exactly additive decomposition (GEAD) employed in Tang and Wang (2004).<sup>4</sup> In this paper, we adopt the Tornqvist method, which has also been used in Goodridge *et al.* (2018) and Goodridge and Haskel (2022), as it allows output prices and production functions to differ across sectors, and we are interested in sectoral differences. We then decompose labour productivity growth into within and reallocation components through each sector.

For the period since 2008 compared with the prior 10 years, we find that shifts between sectors play little role in accounting for the aggregate labour productivity slowdown in the UK, although they do have a small negative effect on productivity when the real estate sector (whose output is mainly imputed rent) is excluded from the calculation. Our data and results (Sections II and III) show that manufacturing and ICT are the sectors that have experienced the biggest labour productivity slowdowns. Furthermore, we find that the within-sector slowdowns are attributable mainly to transport equipment and pharmaceuticals in manufacturing, and to computer software and telecommunications in ICT. Strikingly, these are among the sectors generally considered to be success stories in the UK.

For comparison, we set out two alternative decomposition methods, the shift-share method and GEAD, in Online Appendix II. The reallocation effects seem to be relatively more important to the aggregate slowdown using the GEAD approach, whereas the shift-share method suggests that it is relatively unimportant, which is similar to what we find under the Tornqvist approach. The alternative methods therefore highlight the importance of weights in the decomposition exercise. We suggest that the choice of weights and output price deflators, as well as omitted quality change, therefore play a part in the story.

In order to see how the UK compares with other countries, we also look in Section IV at 12 other countries, including Japan, the USA, and several European economies for 1998–2015, using the EU KLEMS database. Specifically, we are interested in whether or not the same

sectors contribute to the (smaller) productivity slowdowns in those countries. The results are of further diagnostic interest in trying to pinpoint both the main drivers of the aggregate slowdown and the UK's worse performance than comparator countries. We find that the reallocation term contributes little to explaining the slowdown, and the within-industry contribution is the driver in 12 advanced economies. In these countries, too, the manufacturing and ICT sectors account for most of the slowdown in labour productivity growth. The decomposition exercise does not allow us to control for other observed and unobserved drivers of the slowdown, so it should be interpreted with caution. However, in Section V, we test the robustness of the analysis by using a difference-in-differences (DiD) approach, which confirms that the manufacturing and ICT sectors experienced productivity growth statistically and significantly lower post-2008, by 5.699 percentage points in 2008–19 for the UK, and by 2.268 percentage points in 2008–15 for all 13 countries.

Our work is related to the recent papers by Tang and Wang (2004), McMillan and Rodrik (2011), De Vries *et al.* (2012, 2015, 2021), Diao *et al.* (2019), Moussir and Chatri (2020), and Voskoboynikov (2020).<sup>5</sup> Tang and Wang (2004) adopt the GEAD method and find that the aggregate labour productivity growth gap between Canada and the USA during 1987–98 was driven by the within-industry contribution in manufacturing and service sectors. Using data from the UK, France and the USA during the COVID period (2020 and 2021Q1), De Vries *et al.* (2021) find that the reallocation effects until 2019 were slightly negative for the USA, the UK and France, and all countries saw a decline in within-industry productivity growth since 2011. Relative to these earlier results, our paper adopts a different decomposition approach that relaxes the assumption of an identical production function and relative prices across industries, whereas in McMillan and Rodrik (2011), De Vries *et al.* (2012, 2015), Diao *et al.* (2019) and Moussir and Chatri (2020), the absolute differences in productivity weighted by industry employment shares in the previous period are used. While De Vries *et al.* (2021) provide useful comparisons with different decomposition methods, their main focus is on the shift-share method, and they use data from the UK that pre-date the implementation of double deflation, discussed further below. We also consider the whole economy, not just the market sector.<sup>6</sup>

Our results provide an alternative lens on the productivity ‘puzzle’ compared to taking a firm-level perspective. A number of papers, such as Andrews *et al.* (2019), Autor *et al.* (2020), Coyle *et al.* (2022a) and Linarello and Petrella (2017) use decompositions such as that provided by Olley and Pakes (1996) to identify a trend towards increased productivity dispersion among firms, with the highest-productivity firms pulling further ahead of the rest. Others find that economic structure such as supply chain networks (Carvalho and Gabaix 2013), or other non-linearities such as returns to scale (Baqae and Farhi 2019), can account for some part of the observed aggregate productivity trends. While this strand of firm-level literature provides valuable insights, there are different insights to be gained from looking through the lens of sectoral decomposition (even though some of the firm-level dynamics will be captured in the ‘within’ component of these).

We find that there are distinctively different sectoral patterns, suggesting that the classification of firms to sectors, albeit imperfect, provides useful information. This is consistent with an emerging finding in the literature that there is growing productivity dispersion among firms *within* certain sectors, such that the sectoral identity of firms is material due to industry-specific dynamics such as shocks, idiosyncratic frictions or bursts of innovation (Asker *et al.* 2014; Cunningham *et al.* 2021; Garner *et al.* 2021). In a work in progress, we are looking at patterns of UK firm-level productivity within the sectors that we find here account for much of the productivity slowdown. What is more, a sectoral approach puts the spotlight on the role of input and output price deflators in understanding aggregate economic dynamics, as discussed below. The firm-level lens cannot explore this issue.

## 2 | DECOMPOSITION METHODS

### 2.1 | Aggregate and sectoral labour productivity growth

In this paper, we use the Tornqvist decomposition as it allows output prices to differ across sectors/industries, separating productivity growth into within and reallocation components. We show results based on two alternative methods—the shift-share and generalized exactly additive decomposition—in Online Appendix II.<sup>7</sup> In the Tornqvist framework, the sum of real-terms sectoral labour productivity growth weighted by value-added in this approach will not be equal to growth in aggregate value-added per hour calculated using an aggregate deflator. But as we are interested in the performance of the different sectors, it is the most appropriate choice. We use estimates of industry real gross value-added ( $V_i$ ) to construct aggregate real gross value-added ( $V$ ) through a weighted sum of log changes in industry gross value-added:

$$\Delta \ln V \equiv \sum_i \bar{\omega}_i \Delta \ln V_i, \quad (1)$$

where

$$\omega_i = v_i / \sum_i v_i \quad (2)$$

and

$$\bar{\omega}_i = 0.5 (\omega_{it} + \omega_{it-1}). \quad (3)$$

Equation (1) says that the log change in real aggregate gross value-added  $V$  is the weighted aggregate of the log changes in industry real gross value-added  $V_i$ , and the weight  $\omega_i$  is the share of industry  $i$  in nominal gross value-added  $v$ . We are using two-period average weights as a Divisia index  $\bar{\omega}_i$ . Since aggregate total worked hours  $H$  can be estimated as a simple sum of industry hours

$$H = \sum_i H_i, \quad (4)$$

we can obtain aggregate labour productivity per hour by taking the change in log of  $H$  as

$$\Delta \ln(V/H) = \Delta \ln V - \Delta \ln H, \quad (5)$$

and so the industry labour productivity growth can be defined as

$$\Delta \ln(V_i/H_i) = \Delta \ln V_i - \Delta \ln H_i. \quad (6)$$

To define aggregate labour productivity growth from the industry data, we can then implement a share-weighted sum over industries  $i$  as

$$\Delta \ln(V/H) \equiv \sum_i \bar{\omega}_i \Delta \ln(V_i/H_i). \quad (7)$$

### 2.2 | Sectoral decomposition

To distinguish within-industry productivity growth from reallocation or structural change, following Fabricant (1942) and extending De Vries *et al.* (2012) and Goodridge *et al.* (2018), we start

by noting that since the weighted sum of within productivity growth in each sector in equation (7) produces an estimate of aggregate labour productivity growth that is different to the estimate from equation (5), we can obtain the whole economy sector-level reallocation term ( $R$ ) as the difference between the two:

$$\Delta \ln(V/H) = \sum_i \bar{\omega}_i \Delta \ln(V_i/H_i) + R. \quad (8)$$

The second term in equation (8) is the term that measures the contribution of labour reallocation across industries, being positive (negative) when activity moves from less (more) to more (less) productive industries. However, equation (8) does not allow us to examine the contribution of each component from subsector to industry labour productivity growth. As in De Vries *et al.* (2012),<sup>8</sup> we therefore break down industry  $i$  into subsectors  $j$ , and calculate

$$\Delta \ln(V_i/H_i) = \sum_{j \in i} \bar{\omega}_j \Delta \ln(V_j/H_j) + R_i, \quad (9)$$

where

$$\omega_j = v_j / \sum_j v_j \quad (10)$$

and

$$\bar{\omega}_j = 0.5 (\omega_{jt} + \omega_{j,t-1}). \quad (11)$$

Here, the subscript  $j$  refers to any subsector, for example, food products, beverages, and tobacco in Manufacturing (in which  $j = 1, 2, \dots, n$ ), and  $R_i$  is derived from the change in value-added weighted labour productivity growth of subsectors  $j$ , with the share of current price value-added  $v_{ij}$  in subsector  $j$  in industry  $i$  as weights  $\omega_j$ , and a residual term measuring the reallocation within industries across subsectors  $j$ . The  $\omega_i$  in equation (2) is the average share of an industry  $i$  in overall nominal value-added, whereas the  $\omega_j$  in equation (10) is the average share of a subsector  $j$  in an industry  $i$ . Substituting equation (11) into equation (9) produces a new reallocation effect, as well as a new within-industry contribution effect, of labour moving within an industry  $i$  across subsectors. We apply this decomposition to the high-level sectors of the whole economy, and subsequently to subsectors of some of these.

### 3 | DATA

We use sector- and subsector-level data on nominal value-added, real value-added (double-deflated in the statistics) and labour input (total hours worked). We use the double-deflated ONS data for the UK, first published in October 2021. The ONS provides two-digit Standard Industrial Classification 2007 (SIC07) level data, dividing the whole UK economy into 20 (A–T) sectors, aggregated from 97 industries.<sup>9</sup> A major change introduced by the ONS through double deflation was a lower output price deflator for telecommunications services, raising that sector’s real output and consequently raising input prices and reducing real output for sectors that are users of telecommunications services as an input, to an extent depending on the share of these services and other intermediates in sectoral gross value-added. Double deflation thus raised the published output and productivity of the ICT and manufacturing sectors (Martin 2021; see chart in Figure AV 1 of Online Appendix V). This makes our finding that

these rapid productivity growth and high value-added sectors account for large contributions to the post-2008 slowdown all the more striking.

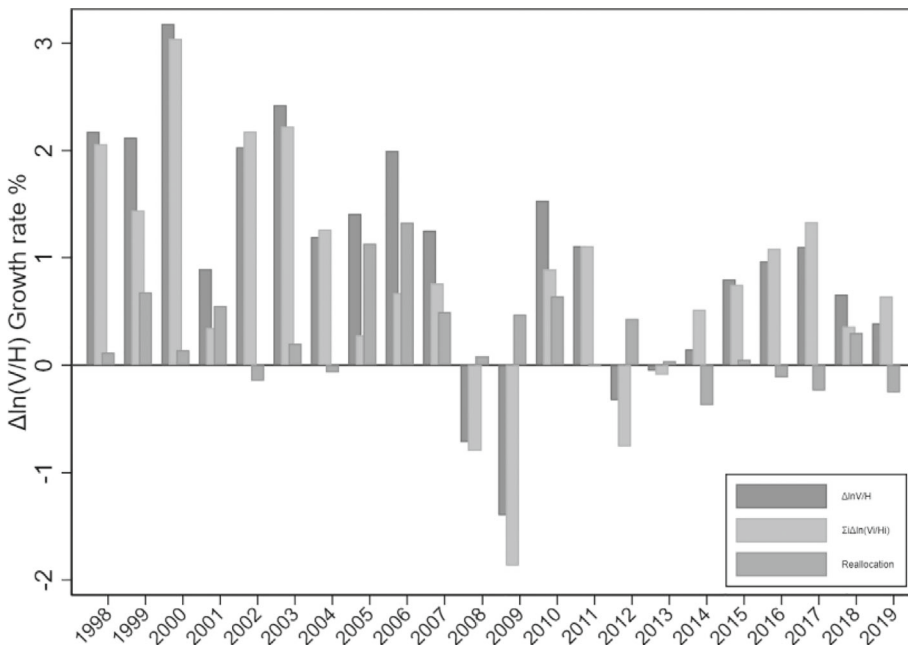
The second data source comes from the EU KLEMS national accounts database, with the Vienna Institute for International Economic Studies (WIIW)<sup>10</sup> release, 2019 version (Stehrer *et al.* 2019).<sup>11</sup> We select data for the USA, Japan, France, Belgium, the Netherlands, Denmark, Germany, Greece, Italy, Portugal, Austria and Sweden, and removed the categories public administration, defence, education, human health and social work activities, arts, entertainment, recreation, other services and service activities, etc., and activities of extraterritorial organizations. This database provides comprehensive coverage of all the variables needed.<sup>12</sup>

We look at the periods 1998–2019 for the UK, and 1998–2015 for international comparison. Data for the 2020–21 period are removed due to the disruption caused by the global pandemic. Over this entire period, there have been shifts in the relative shares of sectors in total gross value-added, including phenomena such as outsourcing of some activities to other firms, and perhaps also the ‘Baumol’ phenomenon (Nordhaus 2008). When such shifts reclassify activities to a different sector, they will be captured in the reallocation term.

## 4 | UK RESULTS

### 4.1 | Baseline results

Figure 2 and Table 1 show the aggregate labour productivity growth for the whole economy  $\Delta \ln(V/H)$ , and the separated terms as the weighted sum of industry labour productivity  $\sum_i \tilde{\omega}_i \Delta \ln(V_i/H_i)$  (i.e. the pure within-sector contribution) and the aggregate reallocation effect  $R$  estimated from equation (8). For the whole period 1998–2019, on average, Table 1 shows that the aggregate labour productivity growth  $\Delta \ln(V/H)$  was 1.04% per year, the weighted sum of labour



**FIGURE 2** Growth in real terms whole economy labour productivity 1998–2019. *Notes:* This graph plots the aggregate sector-level  $\Delta \ln(V/H)$ ,  $\sum_i \tilde{\omega}_i \Delta \ln(V_i/H_i)$  and  $R$  based on all 20 industries. *Source:* Authors’ calculations.



**TABLE 1** Labour productivity growth, whole economy, 1998–2019

	$\Delta \ln(V/H)$ (1)	$\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$ (2)	$R$ (3)
Whole economy (20 industries)	1.040%	0.792%	0.248%
Whole economy (industry L excluded)	0.818%	1.020%	−0.202%
Whole economy (industries O, P, Q excluded)	0.978%	0.810%	0.168%

*Notes:* Data are average growth rates per year for 1998–2019 based on equation (8). Industry L represents real estate activities, O represents public administration, P represents education, and Q represents human health.

**TABLE 2** Labour productivity growth, whole economy ( $\Delta \ln(V/H)$ ,  $\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$ ,  $R$ ), 1998–2008 versus 2008–2019

	$\Delta \ln(V/H)$ (1)	$\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$ (2)	$R$ (3)
Whole economy (20 industries)			
1998–2008	1.632%	1.222%	0.409%
2008–2019	0.350%	0.263%	0.086%
Whole economy (industry L excluded)			
1998–2008	1.502%	1.738%	−0.236%
2008–2019	0.048%	0.216%	−0.168%
Whole economy (industries O, P, Q excluded)			
1998–2008	1.719%	1.316%	0.403%
2008–2019	0.179%	0.233%	−0.053%

*Notes:* Data are average growth rates per year for 1998–2019 based on equation (8). Industry L represents real estate activities, O represents public administration, P represents education, and Q represents human health.

productivity growth  $\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$  was 0.792% per year, and the reallocation term  $R$  was 0.248% per year. The slowdown since 2008 for the whole economy is apparent from the chart in Figure 2, with the within-sector productivity growth component being negative in 2008 and 2009, and relatively small afterwards. Also evident is the relatively small part played by reallocation post-2008.

To explore the slowdown, Table 2 looks separately at 1998–2008 and 2008–19. Focusing on column (1) of Table 2, overall average productivity growth rates for the periods 1998–2008 and 2008–19 were 1.632% and 0.350%, respectively. Columns (2) and (3) decompose these into the contributions from within productivity growth and labour reallocation during the two periods. It shows that about a quarter (i.e.  $(0.086 - 0.409)/(-1.282)$ ) of the slowdown is explained by reallocation, and about three-quarters (i.e.  $(0.263 - 1.222)/(-1.282)$ ) of the slowdown has occurred within industries.

It is worth noting the difference in aggregate labour productivity growth, as well as the within and reallocation effects, when the real estate sector (L) is excluded. As highlighted in ONS (2019), the output of industry real estate is mainly imputed rents for owner-occupiers of housing, while labour input (mainly estate agents) is small. As can be seen in Table 1, excluding imputed rental reduces aggregate productivity growth by 0.22 percentage points (from 1.040% to 0.818%), increases the within component, and reduces the average reallocation effect by 0.45 percentage points so that it becomes negative rather than positive (i.e. 0.248% to −0.202%), thus

also changing the role of reallocation between the two sub-periods (see also, for instance, Riley *et al.* 2018).

Imputed rent is a return to capital, largely reflecting the appreciation of land values (Nguyen and Johansson 2022), so there are strong conceptual reasons to exclude it from consideration of labour productivity. We also show results with the public sector omitted. While these services present well-known distinctive conceptual and measurement challenges, we include them in the decomposition nevertheless.

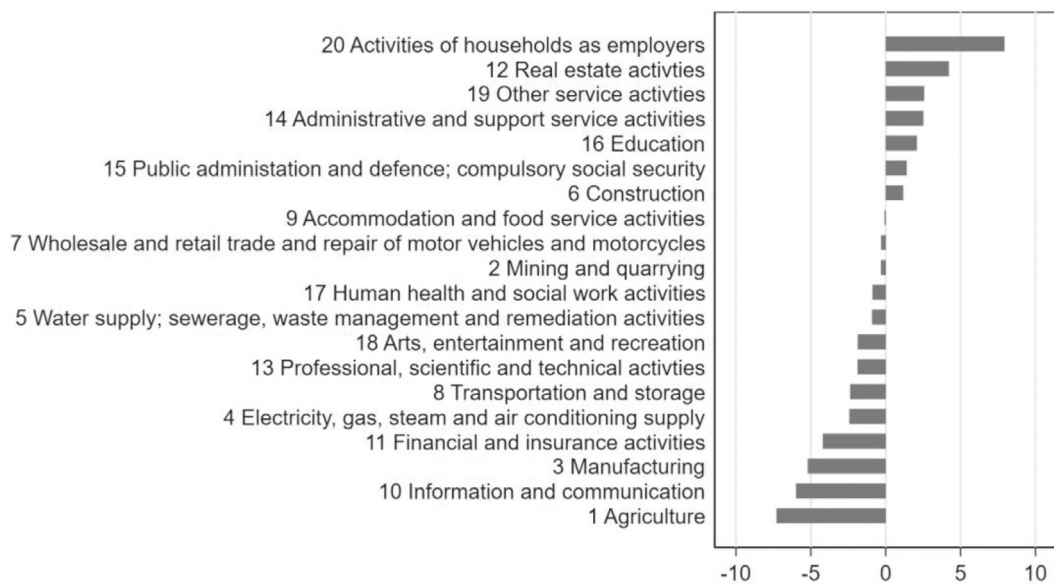
Turning to the sectors, Table 3 and Figure 3 look at the disaggregation for the whole period 1998–2019, pre-crisis (1998–2007) and post-crisis (2008–19). The sectors recording the fastest productivity growth over the whole period were ICT and manufacturing. However, comparing columns (2) and (3) of Table 3, agriculture (–7.296%), information and communication (–5.986%), manufacturing (–5.211%), financial and insurance activities (–4.205%), and electricity, gas, steam and air conditioning supply (–2.427%) were the five sectors recording the largest productivity slowdown between the two sub-periods. Figure 3 presents data for contributions of the nominal value-added-weighted within-sector labour productivity growth for each industry ranked by the slowdown in growth rates  $\Delta(\bar{\omega}_i \Delta \ln(V_i/H_i))$  between the two periods. For example, the slowdown in manufacturing  $\Delta(\Delta \ln V_i/H_i)$  is –5.211% (2008–19 versus 1998–2008), which

**TABLE 3** Labour productivity growth by sector

		$\Delta \ln(V_i/H_i)$		
		1998–2019	1998–2008	2008–2019
Industry breakdown A–T		(1)	(2)	(3)
A	Agriculture	3.625%	8.112%	0.814%
B	Mining and quarrying	–5.687%	–5.773%	–6.098%
C	Manufacturing	3.845%	6.522%	1.311%
D	Electricity, gas, steam and air conditioning supply	0.193%	1.152%	–1.275%
E	Water supply; sewerage, waste management and remediation activities	–2.345%	–1.959%	–2.870%
F	Construction	–0.394%	–1.233%	–0.070%
G	Wholesale and retail trade and repair of motor vehicles and motorcycles	0.498%	0.449%	0.144%
H	Transportation and storage	–0.002%	1.271%	–1.100%
I	Accommodation and food service activities	–0.282%	–0.245%	–0.330%
J	Information and communication	8.260%	11.460%	5.474%
K	Financial and insurance activities	0.971%	3.005%	–1.200%
L	Real estate activities	–1.663%	–3.808%	0.399%
M	Professional, scientific and technical activities	0.158%	1.105%	–0.776%
N	Administrative and support service activities	0.062%	–1.358%	1.150%
O	Public administration and defence; compulsory social security	1.656%	0.991%	2.388%
P	Education	–1.406%	–2.557%	–0.484%
Q	Human health and social work activities	–0.292%	0.042%	–0.849%
R	Arts, entertainment and recreation	–0.301%	0.635%	–1.232%
S	Other service activities	–0.926%	–2.307%	0.253%
T	Activities of households as employers	1.116%	–3.121%	4.806%

Notes: Data are average growth rates per year for 1998–2019.

Source: Authors' calculations.



**FIGURE 3** Industry labour productivity slowdown. *Notes:* Data show slowdowns for each industry, where each bar is  $\Delta(\ln V_i/H_i) = \Delta \ln V_i/H_i^{2008-2019} - \Delta \ln V_i/H_i^{1998-2008}$ . *Source:* Authors’ calculations.

consists of a contribution from within-sector productivity of  $-5.226\%$  and a slowdown due to the labour reallocation term of  $0.015\%$ ; similarly, the slowdown in ICT is  $-5.986\%$ , which consists of a slowdown from within-sector productivity growth of  $-5.933\%$  plus a slowdown from the labour reallocation term of  $-0.053\%$ .<sup>13</sup> The reallocation components are small.

Having looked at the productivity pattern across sectors, we now repeat the exercise as above and move to the next level of disaggregation for two of the sectors displaying the biggest slowdowns, namely manufacturing and ICT. The results are shown in Table 4 and Figure 4. There are 13 subsectors in manufacturing, and six in ICT industries.

Table 4 reveals five subsectors where labour productivity growth ( $\Delta \ln(V_j/H_j)$ ) turns negative during the post-crisis period 2008–19: three in manufacturing, namely machinery and equipment n.e.c. (not elsewhere classified)  $-0.117\%$ , basic pharmaceutical products and pharmaceutical preparations  $-0.188\%$ , and other manufacturing, repair and installation of machinery and equipment  $-0.138\%$ ; and two in information and communication, namely computer programming, consultancy and related activities  $-0.316\%$ , and information service activities  $-0.400\%$ . There are other subsectors with significant slowdowns, albeit not turning negative in the second period, and no subsectors experiencing an increase. The only subsectors not to experience much of a ‘within’ slowdown are chemicals and coke/refined petroleum products.

Figure 5 shows the contribution to the slowdown from each subsector’s within component in manufacturing (Figure 5(a)) and in the information and communication industry (Figure 5(b)). About 60%  $(1.017 + 0.737 + 0.586 + 0.807)/5.211$  of the slowdown in manufacturing overall is attributable to transport equipment, machinery and equipment, computer and electronics manufacture, and basic pharmaceuticals. For the ICT industry, telecommunications and computer programming contribute about 69% of the labour productivity slowdown. It is striking that the most pronounced slowdowns occurred in some industries considered to be UK success stories, and with high nominal value-added per hour, such as autos (in transport equipment), pharmaceuticals and telecommunications.

What about the reallocation between the subsectors? Figure 6 confirms that the reallocation contribution is small although positive on average in manufacturing and ICT.

TABLE 4 Within labour productivity growth  $\bar{\omega}_j \Delta \ln(V_j/H_j)$  IN MANUFACTURING AND ICT

	$\bar{\omega}_j \Delta \ln(V_j/H_j)$		$\Delta(\bar{\omega}_j \Delta \ln(V_j/H_j))$	
	1998–2019 (1)	1998–2008 (2)	2008–2019 (3)	Slowdown (3) minus (2)
<b>Manufacturing subsectors</b>				
Food products, beverages and tobacco	0.272%	0.530%	0.048%	−0.481
Textiles	0.373%	0.528%	0.193%	−0.335
Wood and paper products	0.391%	0.595%	0.267%	−0.328
Coke and refined petroleum products	0.021%	−0.048%	0.083%	0.131
Chemicals and chemical products	0.369%	0.389%	0.384%	−0.005
Basic pharmaceutical products	0.108%	0.618%	−0.188%	−0.811
Rubber and plastics products	0.271%	0.349%	0.145%	−0.204
Basic metals and fabricated metal products	0.234%	0.306%	0.204%	−0.102
Computer, electronic and optical products	0.546%	0.850%	0.263%	−0.587
Electrical equipment	0.142%	0.280%	0.046%	−0.234
Machinery and equipment n.e.c.	0.286%	0.620%	−0.117%	−0.737
Transport equipment	0.371%	0.879%	−0.138%	−1.017
Other manufacturing; repair	0.277%	0.459%	0.069%	−0.390
<b>Information and communication subsectors</b>				
Publishing activities	0.650%	1.271%	0.065%	−1.206
Motion picture, video and TV programme	0.147%	0.349%	0.004%	−0.345
Programming and broadcasting activities	−0.057%	0.129%	0.065%	−0.064
Telecommunications	7.174%	8.313%	5.869%	−2.444
Computer programming	0.707%	1.643%	−0.316%	−1.959
Information service activities	−0.162%	−0.041%	−0.400%	−0.359

Source: Authors' calculations.

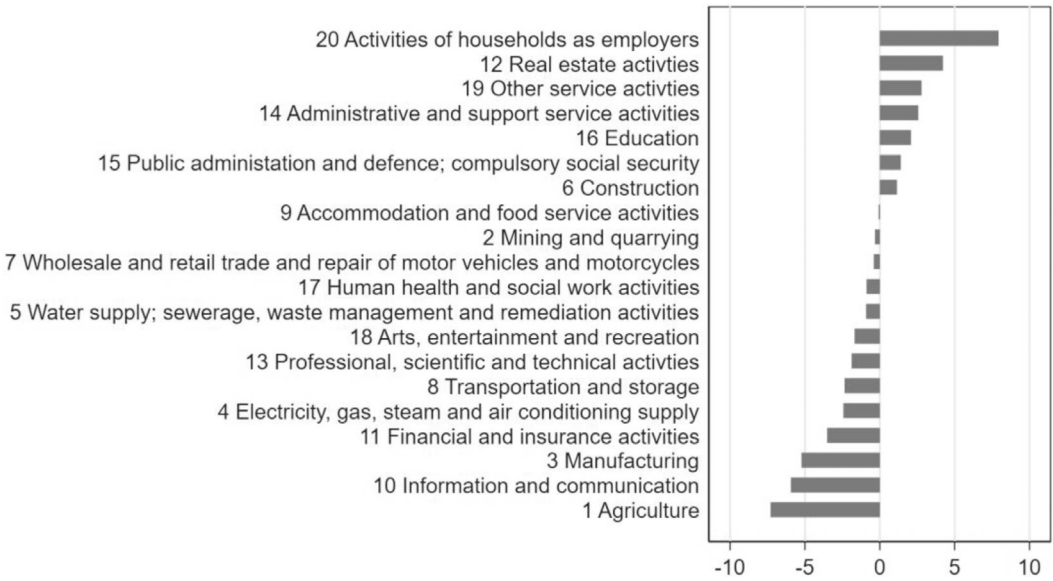
## 4.2 | Sectoral decomposition and structure dynamics

### 4.2.1 | Firm-level dynamics

One question raised by the sectoral decomposition exercise is whether going directly to firm-level dynamics would offer clearer insights. As noted above, the sectoral patterns contain much information and may reflect common market dynamics or shocks that would not be evident by looking at the population of individual firms as a whole. Here, we show how a common firm-level analysis—the Olley and Pakes (1996) framework, adopted recently by, for example, Melitz and Polanec (2015), and Linarello and Petrella (2017)—compares with our industry-level analysis.

Following Olley and Pakes (1996), we generate whole-economy aggregate labour productivity  $\phi$  (defined as log changes) corresponding to the weighted average of industries' labour productivity  $\rho_i$  (defined as real gross value-added/hours in log changes), where the weights  $w_i$  are the two period weighted share of the industry  $i$  nominal gross value-added (i.e. a Divisia index). That is, at time  $t$ ,

$$\phi_t = \sum_A^T \rho_{it} w_i. \quad (12)$$



**FIGURE 4** Within-industry labour productivity slowdown. *Notes:* Data show slowdowns for each industry, where each bar is  $\Delta(\bar{\omega}_i \Delta \ln(V_i/H_i)) = \bar{\omega}_i \Delta \ln(V_i/H_i)^{2008-2019} - \bar{\omega}_i \Delta \ln(V_i/H_i)^{1998-2008}$ . *Source:* Authors’ calculations.

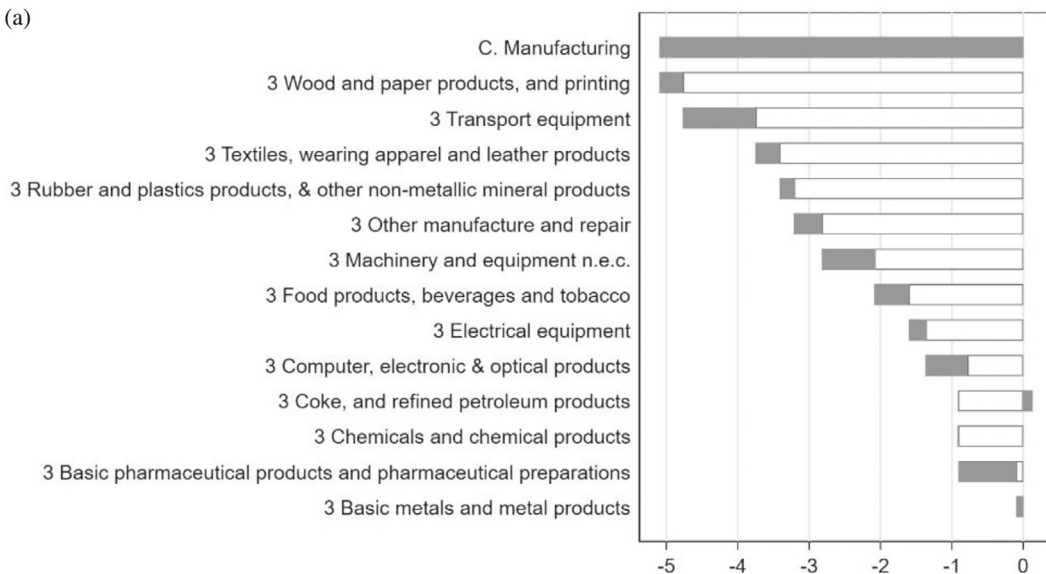
Aggregate labour productivity  $\phi_t$  can then be decomposed as the sum of the unweighted average industry labour productivity and the covariance between industry productivity and the share of industry nominal gross value-added:

$$\phi_t = \bar{\rho}_t + cov(\rho_{it}, w_i) = \bar{\rho}_t + \sum_A^T (\rho_{it} - \bar{\rho}_t) (w_i - \bar{w}_t), \tag{13}$$

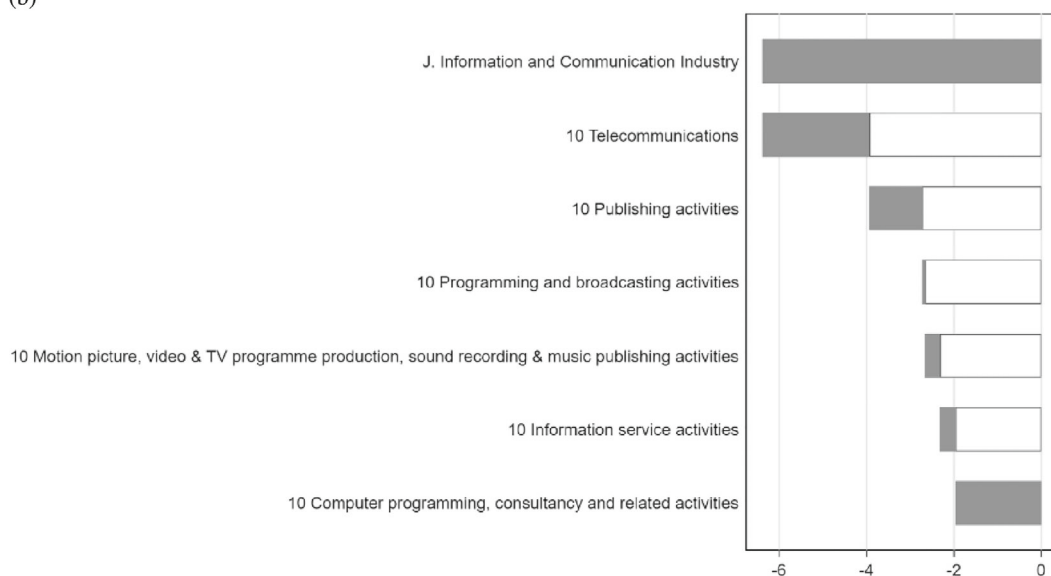
where  $\bar{\rho}_t = \left( \sum_A^T \rho_{it} \right) / n$  is the unweighted industry labour productivity mean, and  $\bar{w}_t$  is the mean market share (mean nominal gross value-added). The covariance term  $cov(\rho_{it}, w_i)$  is referred to as the static Olley–Pakes (OP) covariance. This decomposition allows us also to distinguish between the efficiency gains deriving from a reallocation of resources towards the most productive firms (measured by the increase in the OP covariance), and those arising from the productivity growth of individual firms (captured by the changes in the average productivity term). The former component has been found to explain the largest share of the observed productivity gains.

As shown in Tables 5 and 6, first, the average whole economy labour productivity growth rate is lower as calculated by the OP methodology than by the Tornqvist approach. However, the efficiency gains derived from a reallocation of resources towards the most productive firms, measured by  $cov(\rho_{it}, w_i)$ , are relatively large compared to the reallocation term captured by our Tornqvist method. Second, on the other hand, the industry productivity growth 1998–2019 captured by the changes in the average productivity term ( $\bar{\rho}_t$ ) is lower than that provided by the Tornqvist approach. Third, in either method, we find evidence of productivity slowdown post-2008, and both show a similar slowdown contribution from the reallocation term (by  $-0.323$  percentage points in Tornqvist, and  $-0.349$  percentage points in OP). In a work in progress, we are exploring firm-level dynamics within sectors, but conclude here that there is useful insight from the Tornqvist sectoral decomposition to bring to bear on that exercise.

(a)



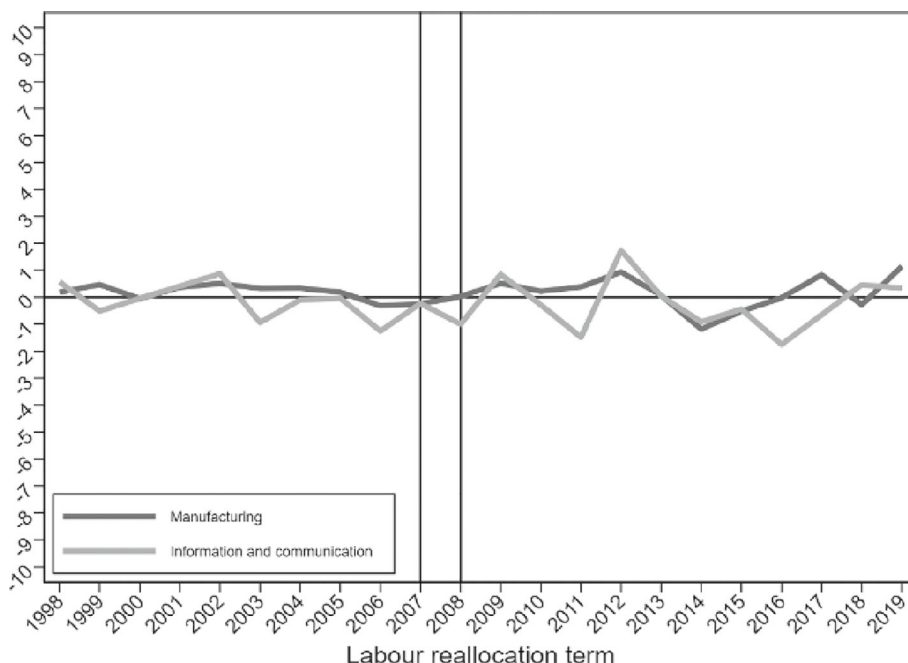
(b)



**FIGURE 5** Subsectors within labour productivity slowdown: (a) manufacturing; (b) information and communication. *Notes:* Data show slowdowns for each industry, where each bar is  $\Delta(\bar{\omega}_j \Delta \ln(V_j/H_j)) = \bar{\omega}_j \Delta \ln(V_j/H_j)^{2008-2019} - \bar{\omega}_j \Delta \ln(V_j/H_j)^{1998-2008}$ . *Source:* Authors' calculations.

#### 4.2.2 | Entry and exit

A further issue is how much difference firm entry and exit might make to the sectoral decomposition results. While our decomposition framework outlines the growth components from within industry and reallocation between industries, we treat implicitly firms' entry and exit as part of the within-industry contribution. To see how firms' entry, exit and survival could potentially affect the overall pattern, we implement some firm-level evidence provided by Coyle *et al.* (2022b).<sup>14</sup> Figure 7(b) displays the post-2008 pattern of firms' entry, exit and stay (survivors/incumbents).



**FIGURE 6** Labour reallocation  $R_i$  within manufacturing and ICT industries. *Notes:* Labour reallocation term  $R_i$ , where  $i$  refers to manufacturing or ICT. A positive term implies movement of labour from a low-productivity subsector towards a high-productivity subsector within either manufacturing or ICT, respectively. *Source:* Authors’ calculations.

**TABLE 5** Labour productivity growth, whole economy, 1998–2019, using the tornqvist method

	$\Delta \ln(V/H)$ (1)	$\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$ (2)	$R$ (3)
1998–2019			
Whole economy	1.040%	0.792%	0.248%
1998–2008			
Whole economy	1.632%	1.223%	0.409%
2008–2019			
Whole economy	0.350%	0.263%	0.086%
Whole economy implied productivity gap	-1.282 p.p.	-0.960 p.p.	-0.323 p.p.

*Notes:* Data are average growth rates per year for 1998–2019 based on equation (8). Percentage points is abbreviated to p.p.

We also plot the firm-level labour productivity measure (defined as gross value-added/employees with revenue weights) to check if entry and exit might contribute in a systematic way (Figure 7(a)). The chart shows that incumbents largely dominate the evolution of labour productivity growth over time.

Another check is provided by ONS firm-level analysis, with results shown in Table 7. These also provide a similar pattern of within-industry contribution to our decomposition framework.

TABLE 6 Labour productivity growth, whole economy, 1998–2019, using Olley and Pakes (1996)

	$\phi_t$ (1)	$\bar{\rho}_t$ (2)	$\text{cov}(\rho_{it}, w_{it})$ (3)
1998–2019			
Whole economy	0.793%	0.416%	0.377%
1998–2008			
Whole economy	1.224%	0.689%	0.535%
2008–2019			
Whole economy	0.265%	0.079%	0.186%
Whole economy implied productivity gap	−0.959 p.p.	−0.610 p.p.	−0.349 p.p.

Notes: Data are average growth rates per year for 1998–2019 based on equations (12) and (13).

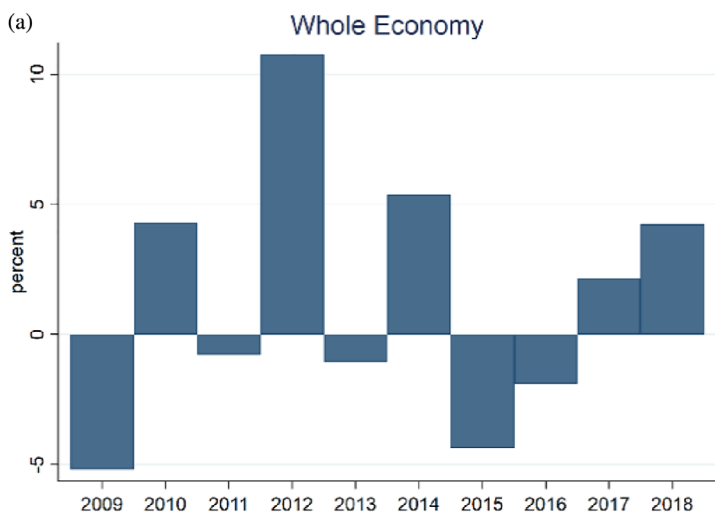
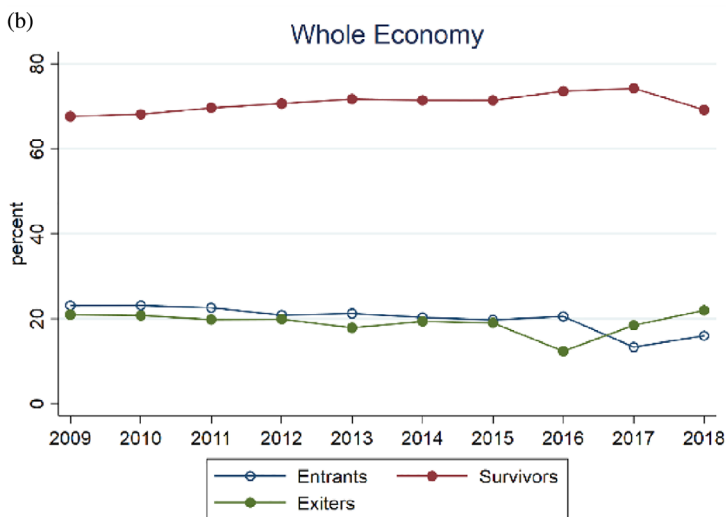


FIGURE 7 Average labour productivity growth, entry, exit and survive post-2008. Notes: We gather data from the ONS Annual Business Survey (ABS) firm-level secure database 2008–19. (a) The bar chart represents the aggregate growth rate of labour productivity (revenue-weighted), defined as the sum of real gross value-added divided by the number of employees through each firm. (b) Firms’ entry, exit, and survive rates are presented as 100%. Source: ONS ABS firm-level data and authors’ calculations.



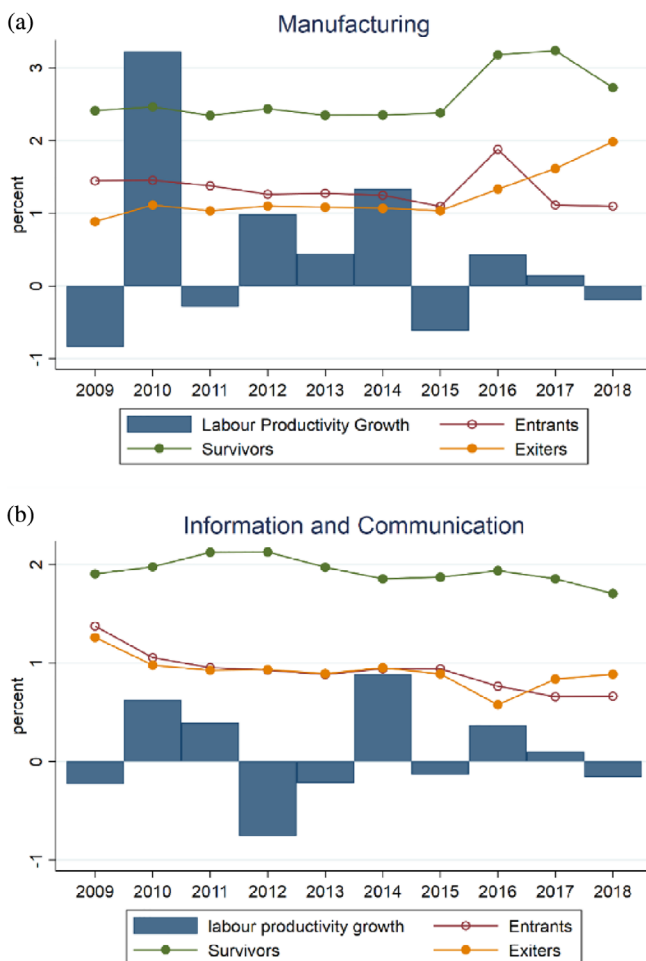


**TABLE 7** ONS firm-level aggregate productivity versus tornqvist sectoral-level aggregate productivity growth, whole economy, 1999–2007

	$\Delta \ln(V/H)$ (1)	$\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$ (2)	$R$ (3)
Tornqvist equation (8)	1.833%	1.355%	0.478%
ONS firm-level aggregation	2.220%	1.420%	0.800%

*Notes:* Data are average growth rates per year for each period based on equation (8) and ONS calculations. We select the period 1999–2007 in order to be consistent with the ONS report. Of 1.420% (the within-industry growth component from the firm-level aggregation), about 0.17% is attributed to small firms within industry contributes, and about 0.46% is attributed to the within growth from net entry and exit inside industry based on the firm-level aggregation. We find similar results for the post-period. Source: ONS experimental statistics on firm-level capital stocks, total factor productivity, and aggregate productivity decompositions based on the Annual Business Survey (available online at <https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/articles/firmleveltotalfactorproductivitymeasuresfromtheannualbusinesssurveyuk1998to2019/august2022>, accessed 29 December 2022).

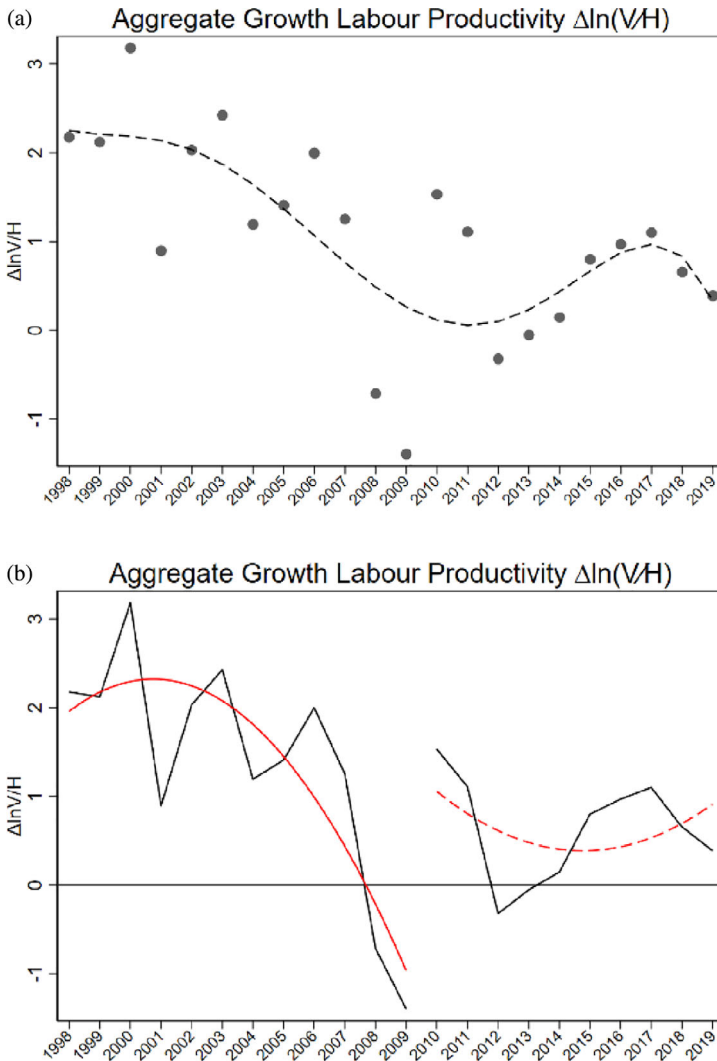
**FIGURE 8** Firms’ entry, exit and survive post-2008 (2009–18). *Notes:* We gather data from the ONS ABS database based on all firms within manufacturing and ICT. The bar charts represent the growth rate of labour productivity, defined as the sum of gross value-added divided by the number of employees through each firm (revenue weighted aggregated). *Source:* ONS ABS firm-level data and authors’ calculations.



As a further check, we look at those firms within manufacturing and ICT industries. Figure 8 indicates that between 2016 and 2017, there was more firm entry than exit. However, the number of incumbents always outweighs the number of exits and entrances.

### 4.2.3 | Structural non-linearities

Finally, we consider the need to take into account non-linearities in the productivity decomposition due in particular to the network structure of the economy and microeconomic shocks (e.g. Carvalho and Gabaix 2013; Baqaee and Farhi 2019). First, we implement the non-linearity concept from the literature based on our labour productivity growth measure. Here, we set out the UK evidence, but include international evidence in Online Appendix V (Figure AV 2). We first fit our data using a smooth local polynomial function and then implement a quadratic line through the period 1998–2019. Figure 9 demonstrates both inverse-U (1998–2009) and U-shape (2009–19) patterns alongside our labour productivity growth rate.



**FIGURE 9** The non-linearity of labour productivity growth. *Notes:* (a) Smooth local polynomial function. (b) Separated trends before and after 2008. *Source:* ONS and authors' calculations.

We introduce a quadratic term of the within component ( $\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)^2$ ) into equation (8). Table 8 provides a comparison with and without taking into account non-linearity. While we note that the within component shown in column (2) is the same as it is in the linear framework, the quadratic term also enters with a considerable contribution to the overall labour productivity growth rate. Thus the non-linearity term does have a significance influence on the reallocation term shown in column (4).

The sectoral-level fluctuations could be the result of many microeconomic shocks (Carvalho and Gabaix 2013). At the sectoral level, such microeconomic shocks are not observed. Therefore we look at whether a fundamental volatility taking into account the variation in TFP and all microeconomic shocks can track back to our aggregate labour productivity growth rate. If aggregate shocks come in large part from microeconomic shocks, then aggregate volatility should track fundamental volatility. If our aggregate labour productivity growth pattern has a trajectory similar to that of the fundamental volatility measure, then that should imply that our decomposition framework at least contains information about microeconomic shocks.

For a robustness check, we first plot the trajectory of sectoral volatility versus aggregate labour productivity growth. In so doing, we construct a measure of sectoral-level

TABLE 8 Non-linear sectoral-level aggregate productivity growth, whole economy, 1998–2019

	$\Delta \ln(V/H)$ (1)	$\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$ (2)	$\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)^2$ (3)	R (4)
Linear	1.040%	0.792%	—	0.248%
Non-linear	1.040%	0.792%	0.306%	-0.058%

Notes: Data are average growth rates per year for each period based on equation (8) and an inclusion of a quadric term  $\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)^2$ .

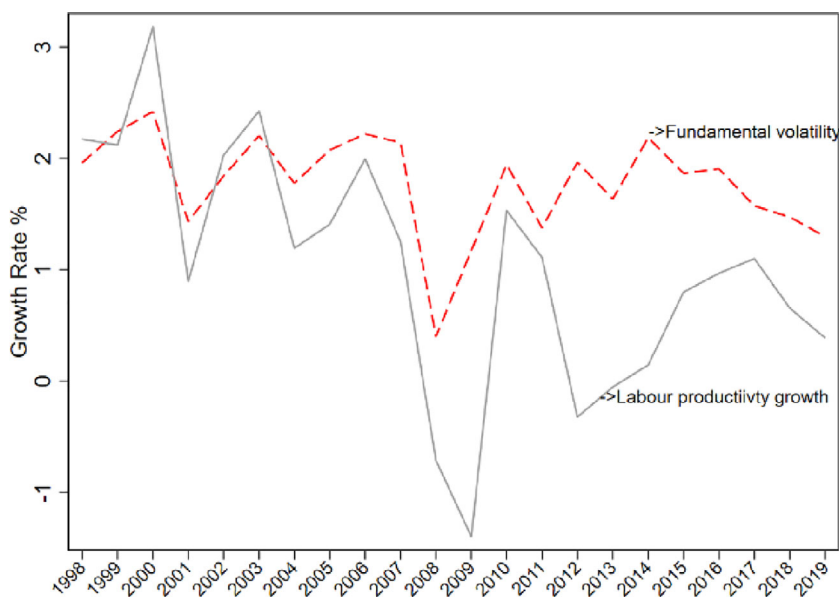


FIGURE 10 UK labour productivity growth pattern versus sectoral volatility. Source: ONS and authors' calculations.

fundamental volatility proposed by Domar (1961), Hulten (1978) and Jones (2011), and implemented by Carvalho and Gabaix (2013). The fundamental volatility is measured as

$$\sigma_{ft} = \sqrt{\sum_{i=1}^n \left( \frac{S_{it}}{GDP_t} \right)^2 \sigma_i^2},$$

where  $S_{it}/GDP_t$  are the weights that capture the impact of microeconomic shocks through each industry (Domar 1961; Hulten 1978). Here,  $\sigma_i^2$  is the variance of the total factor productivity (TFP) in the industry.<sup>15</sup> Figure 10 shows the results. We find that the trajectory of our aggregate labour growth pattern is similar to the fundamental volatility measure. We conclude that our decomposition framework, at least to a reasonable degree, accommodates the structural change of the economy.

We next regress each growth component constructed by equation (8) on the measure of sectoral-level fundamental volatility. Table 9 summarizes the results. We find high statistical and economic significance of  $\sigma_{ft}$  on the aggregate labour productivity growth rate and within component (at the 1% significance level). The  $R^2$  value is around 0.43 for the growth rate and 0.24 for the within contribution. We do not find evidence supporting an association between reallocation and volatility, so again these results suggest that our framework captures to a reasonable degree the structural shocks.

#### 4.2.4 | Relative price effects

It is clear that the choice of weights could significantly affect both the within and reallocation components in any decomposition exercise. For this reason, we provide findings based on two alternative methods—the shift-share and GEAD—in Online Appendix II. The shift-share method uses relative number of employees as the weight for each industry, whereas GEAD applies the product of relative price and employees as the weight for each industry. The Tornqvist decomposition accommodates relative price shifts between sectors, but the price effect is currently hidden in the reallocation term. Coyle *et al.* (2022c) find that the price effect indeed contributes to the evolution of labour productivity growth in the UK, and specifically that the reallocation term becomes smaller once relative price changes are isolated. To the best of our knowledge, there are no prior examples of isolating this effect based on the Tornqvist framework. In an extension of the GEAD framework, following Diewert (2015), the price effects can be isolated from the other components as follows:

TABLE 9 UK growth components and sectoral-level volatility

	$\Delta \ln(V/H)$ (1)	$\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$ (2)	R (3)
$\hat{a}$ (constant)	-1.379** (0.687)	-1.060 (0.761)	-0.318 (0.397)
$\hat{b}$ (sectoral-level volatility)	1.403*** (0.369)	1.095*** (0.409)	0.308 (0.213)
$R^2$ (fraction explained)	0.431	0.235	0.051

Notes: Regression of each labour productivity growth component on sectoral fundamental volatility:  $y_t = a + b\sigma_{ft} + \eta_t$ , where  $y_t$  refers to  $\Delta \ln(V/H)$ ,  $\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$  and R.

$$\begin{aligned}
 g(X_t) &= \sum_i X_{t-1}^i \frac{P_{t-1}^i L_{t-1}^i}{P_{t-1} L_{t-1}} \frac{X_t^i - X_{t-1}^i}{X_{t-1}^i} + \sum_i X_{t-1}^i \left( \frac{P_t^i L_t^i}{P_t L_t} - \frac{P_{t-1}^i L_{t-1}^i}{P_{t-1} L_{t-1}} \right) \\
 &+ \sum_i X_{t-1}^i \left( \frac{P_t^i L_t^i}{P_t L_t} - \frac{P_{t-1}^i L_{t-1}^i}{P_{t-1} L_{t-1}} \right) \frac{X_t^i - X_{t-1}^i}{X_{t-1}^i} = \sum_i s_{t-1}^i \frac{X_t^i - X_{t-1}^i}{X_{t-1}^i} \\
 &+ \sum_i s_{t-1}^i \frac{p_t^i - p_{t-1}^i}{p_{t-1}^i} + \sum_i s_{t-1}^i \frac{l_t^i - l_{t-1}^i}{l_{t-1}^i} + \sum_i s_{t-1}^i \frac{X_t^i - X_{t-1}^i}{X_{t-1}^i} \frac{p_t^i - p_{t-1}^i}{p_{t-1}^i} \\
 &+ \sum_i s_{t-1}^i \frac{X_t^i - X_{t-1}^i}{X_{t-1}^i} \frac{l_t^i - l_{t-1}^i}{l_{t-1}^i} + \sum_i s_{t-1}^i \frac{l_t^i - l_{t-1}^i}{l_{t-1}^i} \frac{p_t^i - p_{t-1}^i}{p_{t-1}^i} \\
 &+ \sum_i s_{t-1}^i \frac{X_t^i - X_{t-1}^i}{X_{t-1}^i} \frac{p_t^i - p_{t-1}^i}{p_{t-1}^i} \frac{l_t^i - l_{t-1}^i}{l_{t-1}^i},
 \end{aligned}$$

where  $p_t^i = P_t^i/P_t$  is the industry  $i$  price relative to the aggregate,  $l_t^i = H_t^i/H_t$  is the labour input share (hours worked), and  $s_{t-1}^i = p_{t-1}^i V_{t-1}^i / \sum_i p_{t-1}^i V_{t-1}^i$  is the share of industry nominal value-added with industry  $i$  price weight at  $t - 1$ . Rearranging, we get

$$\begin{aligned}
 g(X_t) &= \underbrace{\sum_i s_{t-1}^i g(X_t^i)}_{\text{pure within}} + \underbrace{\sum_i s_{t-1}^i g(p_t^i)}_{\text{relative price changes}} + \underbrace{\sum_i s_{t-1}^i g(l_t^i)}_{\text{labour input reallocation}} \\
 &+ \underbrace{\sum_i s_{t-1}^i g(X_t^i) g(p_t^i) + \sum_i s_{t-1}^i g(X_t^i) g(l_t^i) + \sum_i s_{t-1}^i g(l_t^i) g(p_t^i) + \sum_i s_{t-1}^i g(X_t^i) g(p_t^i) g(l_t^i)}_{\text{other interaction effects}}.
 \end{aligned} \tag{14}$$

Equation (14) expresses the aggregate percentage growth rate of labour productivity decomposed into four components. The first component,  $s_{t-1}^i g(X_t^i)$ , is the contribution of ‘pure’ within labour productivity growth in industry  $i$ . The second component,  $s_{t-1}^i g(p_t^i)$ , is the contribution of relative price changes between sectors. The third component,  $s_{t-1}^i g(l_t^i)$ , is labour input reallocation. The last component consists of four interaction terms. The weights are the industry shares of aggregate nominal value-added (using an aggregate deflator). As can be seen in Table 10, both within and reallocation terms are now smaller than in the standard GEAD framework.

## 5 | COMPARISON WITH OTHER ADVANCED ECONOMIES

Having identified some high-value sectors as being of particular interest in terms of their contribution to the slowdown in the UK, we next explore how the productivity decomposition for the UK compares to some other economies. The similarities and differences will shed light on

**TABLE 10** Labour productivity growth, whole economy, 1998–2019

	$g(X_t)$	$\sum_i s_{t-1}^i g(X_t^i)$	$\sum_i s_{t-1}^i g(p_t^i)$	$\sum_i s_{t-1}^i g(l_t^i)$	
	Total	Within	Price	Labour	Interaction terms
	(1)	(2)	(3)	(4)	(5)
Standard GEAD: Whole economy	1.125	0.369	—	0.756	—
Extension of GEAD: Whole economy	1.125	0.369	0.460	0.406	-0.110

*Notes:* Data are average growth rates per year for 1998–2019 based on equation (1). Industry L is real estate activities, O is public administration, P is education, and Q is human health. Columns (2)–(5) sum to column (1) for each row, subject to rounding. Column (5) reports the sum of the interaction terms; these are  $-0.037 - 0.086 + 0.013 - 0.0002$  for 20 industries,  $-0.039 - 0.077 + 0.014 - 0.0001$  for 19 industries, and  $-0.043 - 0.097 + 0.014 - 0.0001$  for 17 industries.

potential drivers of productivity.<sup>16</sup> We use equations (8) and (9) to carry out the decomposition exercise for an additional 14 economies for 1998–2015 using the data as described above.

Table 11 (based on equation (8)) shows that the US economy experienced the highest productivity growth, and Italy, Greece, Japan and Portugal the weakest, during the entire period 1998–2015. The average reallocation term is negative for the USA and France, which implies that labour was moving from more productive to less productive industries during 1998–2015, while Japan and the UK have a positive contribution from labour reallocation. Nevertheless, the reallocation term is relatively small in all countries, and is negative for all countries once real estate is excluded. Finding the reallocation term to be small is consistent with McMillan and Rodrik (2011), and Moussir and Chatri (2020), who also find that labour reallocation made

**TABLE 11** Growth in Whole Economy ( $\Delta \ln(V/H)$ ,  $\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$ ,  $R$ ), 1998–2015

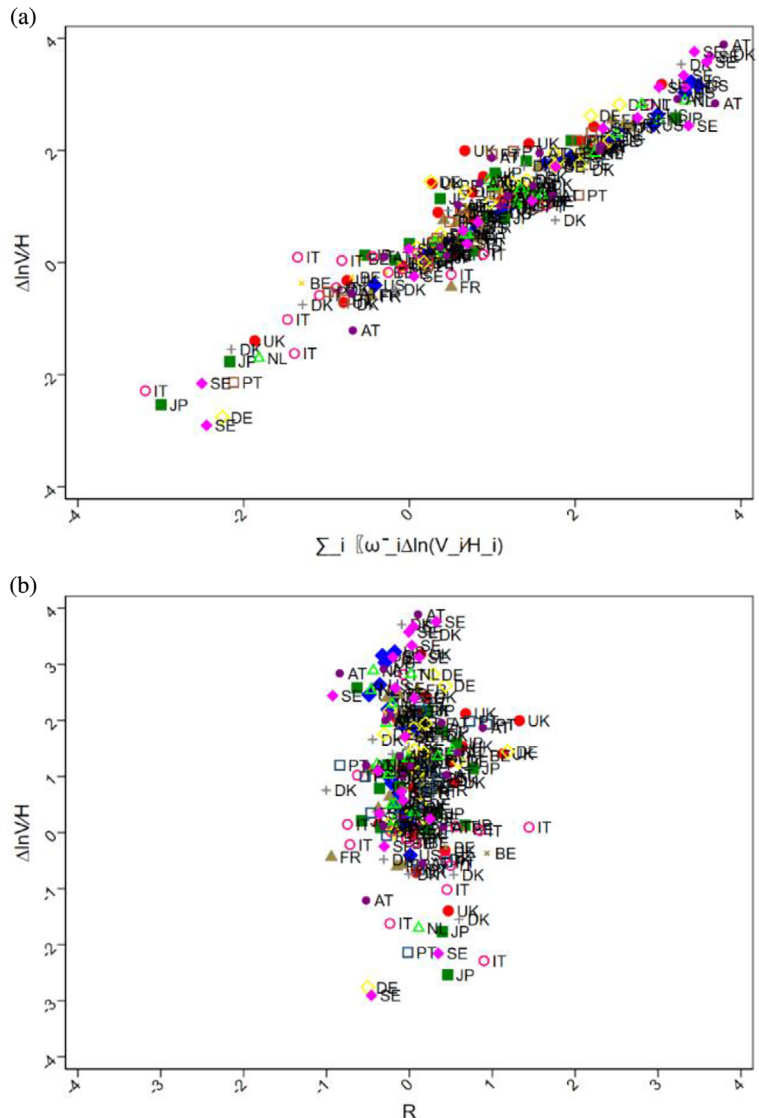
	$\Delta \ln(V/H)$ (1)	$\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$ (2)	$R$ (3)
Whole economy (20 sectors)			
UK	1.098%	0.778%	0.319%
USA	1.549%	1.709%	-0.160%
Japan	0.616%	0.537%	0.079%
France	1.068%	1.150%	-0.081%
Belgium	0.781%	0.619%	0.161%
Netherlands	1.242%	1.362%	-0.120%
Denmark	1.113%	1.009%	0.103%
Germany	0.888%	0.892%	-0.003%
Italy	0.060%	-0.065%	0.125%
Portugal	0.696%	0.625%	0.071%
Austria	1.308%	1.328%	-0.019%
Greece	0.127%	-0.576%	0.703%
Sweden	1.522%	1.626%	-0.103%
Whole economy (industry L excluded)			
UK	0.863%	1.057%	-0.193%
USA	1.504%	1.746%	-0.242%
Japan	0.556%	0.662%	-0.106%
France	1.067%	1.116%	-0.048%
Belgium	0.819%	0.822%	-0.003%
Netherlands	1.262%	1.412%	-0.149%
Denmark	1.079%	1.011%	0.068%
Germany	0.912%	1.038%	-0.125%
Italy	0.005%	-0.062%	0.068%
Portugal	0.697%	0.641%	0.056%
Austria	1.297%	1.325%	-0.028%
Greece	-0.347%	-0.212%	-0.134%
Sweden	1.639%	1.776%	-0.137%

*Notes:* Data are average growth rates per year for 1998–2015, as decomposition of labour productivity in per hour terms based on equation (8). We remove industries public administration, defence, education, human health and social work activities, arts, entertainment and recreation, other services and service activities, and activities of extra-territorial organizations and bodies from our aggregation exercise. Industry L represents real estate activities.

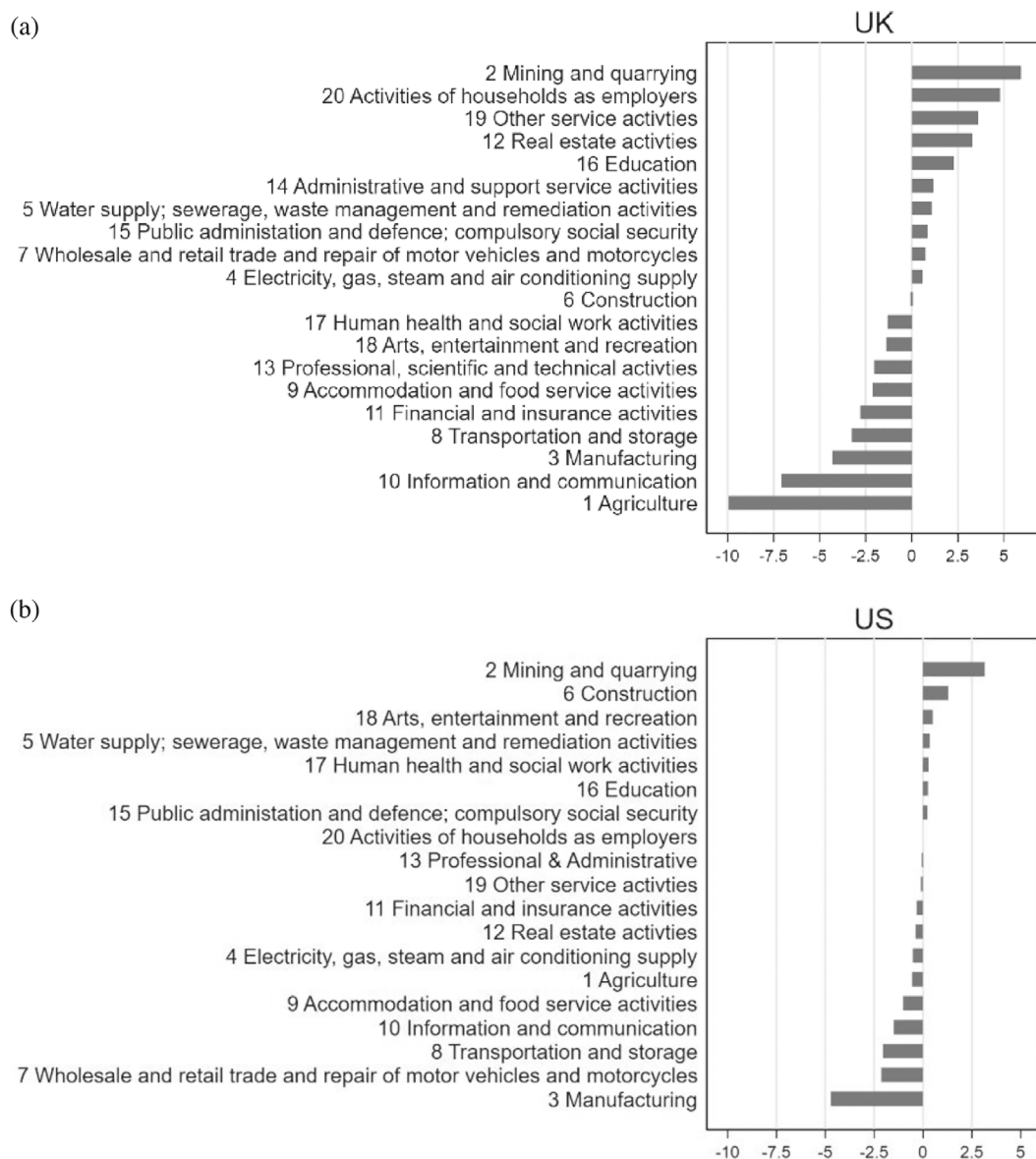
Source: ONS, EU KLEMS national accounts data files, and authors' calculations.

very little contribution to productivity performance in high-income countries during the period 1990–2005. In Figure 11, we show the correlation between aggregate labour productivity growth and the within and reallocation terms, confirming that there is indeed a positive and linear correlation between aggregate growth  $\Delta \ln(V/H)$  and the within contribution  $\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$ , but no pattern between the aggregate growth  $\Delta \ln(V/H)$  and reallocation  $R$ .

To save space, Figure 12 shows the decomposition in average labour productivity growth for 1998–2008 and 2008–15 across all 20 sectors for the UK and the USA.<sup>17</sup> There is a slowdown in average productivity growth in manufacturing (except for Denmark and Italy; see Figure 13) and information and communication in each country. Although somewhat less pronounced in Japan, Belgium and Portugal than in the other countries, manufacturing is the main contributor to the growth slowdown:  $-4.721\%$  for the USA,  $-4.310\%$  for the UK,  $-1.327\%$  for France,  $-2.868\%$  for the Netherlands,  $-2.060\%$  for Germany,  $-2.809\%$  for Austria,  $-3.585\%$  for Greece, and  $-4.910\%$  for Sweden. The ICT sector also contributes to the overall productivity slowdown



**FIGURE 11** Industry labour productivity  $\Delta \ln(V/H)$ , within productivity  $\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$  and reallocation  $R$  across countries, 1998–2015. *Notes:* Data show correlation between aggregate productivity  $\Delta \ln(V/H)$  and within productivity  $\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$ , and between within productivity  $\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)$  and reallocation  $R$ . We remove Greece (as it is an outlier country) for visualization purposes. Figure AIV 1 of Online Appendix IV provides results for 21 countries.

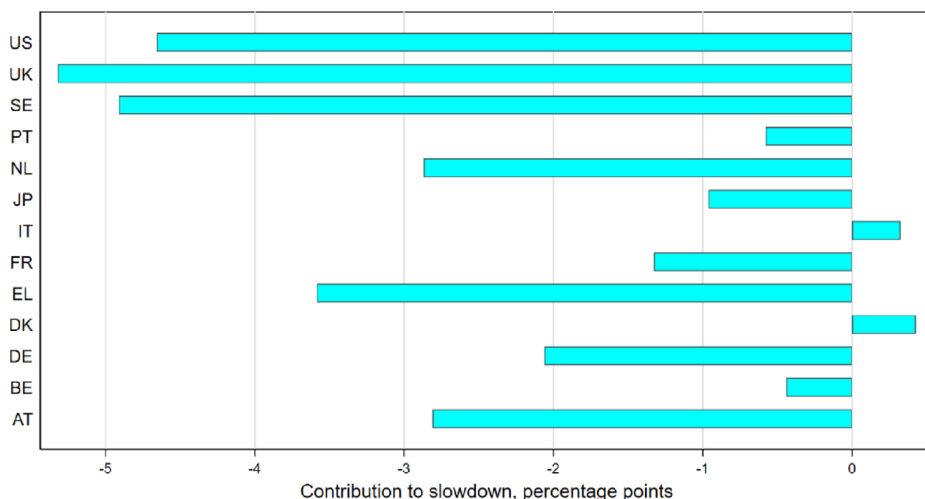


**FIGURE 12** Sectoral contributions to labour productivity slowdown, UK and USA, 1998–2015. *Notes:* Data show slowdowns for each industry, where each bar is  $\Delta(\Delta \ln V_i/H_i) = \Delta \ln V_i/H_i^{2008-2015} - \Delta \ln V_i/H_i^{1998-2008}$ . The other countries are shown in Figure AIII 1 of Online Appendix III. *Source:* ONS, EU KLEMS database and authors' calculations.

in all economies (except Denmark), although it is relatively smaller in Belgium (−0.906%) and France (−0.810%) than in other countries.

There are some differences across countries in the ranking of the sectors contributing to the overall productivity slowdown. For instance, the slowdown is attributable mainly to wholesale trade (−2.125%) and transport and storage (−2.039%) in the USA, electricity (−15.327%) and mining (−14.801%) in Japan, and electricity (−6.536%) and other service activities (−3.416%) in France (see Figure 12, and Figure AIII 1 of Online Appendix III). Which industries in the UK are doing better compared to other countries? Figure 12 shows that the better-performing sectors





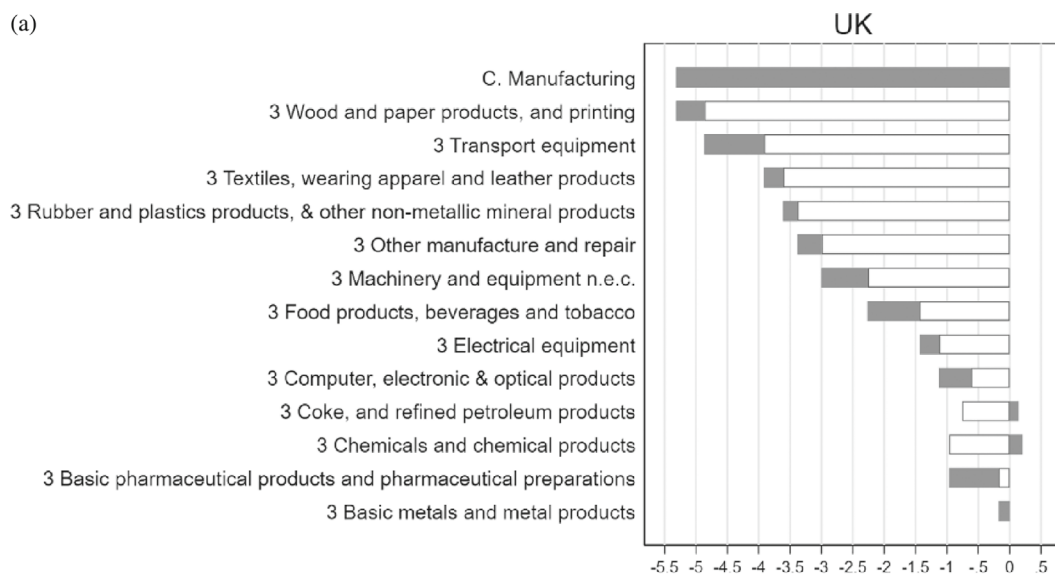
**FIGURE 13** Contribution to slowdown from manufacturing industry across countries, 1998–2015. *Notes:* Data show slowdown contribution from manufacturing for each country. *Source:* ONS, EU KLEMS database and authors' calculations.

include mining and quarrying (5.910%), activities of households as employers (4.781%), other service activities (3.617%), real estate (3.278%) and education (2.305%).

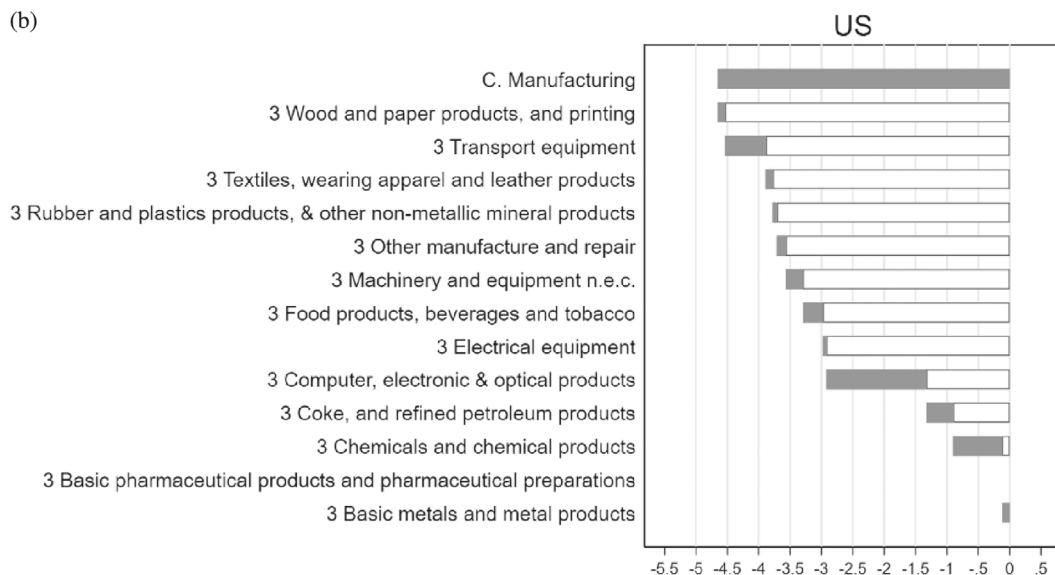
We next decompose manufacturing into 13 subsectors. Figure 14 shows the results. Overall, the transport equipment subsector shows a somewhat similar picture, contributing notably to the decline across all economies. However, the pattern for other subsectors differs across countries. Another notable pattern is that chemicals and computers in the USA have post-2008 growth rates of  $-0.785\%$  and  $-1.594\%$ , respectively, which account for almost one-half and one-third of the US manufacturing productivity slowdown. While these two subsectors perform relatively better in the UK compared to the USA, in the UK the computer subsector makes a substantial negative contribution. The pharmaceutical subsector also shows different patterns across countries; the UK shows the biggest slowdown in pharmaceuticals, but productivity growth in this subsector accelerates in Japan, Germany, Denmark, Italy, the Netherlands and Greece (see Figure AIII 2 of Online Appendix III).

Overall, as Figures 12 and 13 show, the slowdown occurs 'within' sectors rather than reflecting reallocations of labour between sectors, although the reallocation that occurs is negative. The productivity slowdown is common across these 13 advanced economies, and in all of them the decompositions show that the high value-added sectors of manufacturing and ICT make a notable contribution to the slowdown. While there is variation among these countries, there is enough consistency for certain subsectors to warrant further investigation: information and communication, and within manufacturing, transport equipment, computer and electronics manufacture, and pharmaceuticals. Our results suggest that there is likely a mixture of common global drivers of the productivity slowdown and UK-specific factors in the same sectors accounting for a relatively greater slowdown. There are broadly two competing hypotheses about productivity slowdown: one is that there is a paucity of new innovations (e.g. Bloom *et al.* 2020); the other is that there are delays in adopting new technologies leading to a 'J-curve' phenomenon in measured productivity (Brynjolfsson *et al.* 2021). The decompositions do not validate either but rather point to how to refine attempts to address them; further work could include investigating the variance of the within component across the 13 countries and 27 sectors as a starting point, to leverage cross-country differences.

(a)



(b)



**FIGURE 14** Subsectors within labour productivity slowdown, 1998–2008 versus 2008–15, manufacturing industry. *Notes:* Data show slowdowns for each industry, where each bar is  $\Delta(\bar{\omega}_j \Delta \ln(V_j/H_j)) = \bar{\omega}_j \Delta \ln(V_j/H_j)^{2008-2015} - \bar{\omega}_j \Delta \ln(V_j/H_j)^{1998-2008}$ . To save space, we have moved other countries into Figure AIII 2 of Online Appendix III. *Source:* ONS, EU KLEMS database and authors’ calculations.

## 6 | ROBUSTNESS CHECKS

### 6.1 | Difference-in-differences estimates

As a final robustness check to examine whether the two sectors definitively account for the labour productivity slowdown in the UK and the other countries, we carry out a DiD exercise. We adopt a general two-way fixed effects with DiD estimator to test for a difference in mean labour

productivity growth rates between the two sub-periods as follows:

$$\bar{\omega}_i \Delta \ln(V_i/H_i) = \alpha + \gamma MIT + \beta Post + \delta MIT \cdot Post + \varphi d_t + \varepsilon_{i,t}, \quad (15)$$

where  $\bar{\omega}_i \Delta \ln(V_i/H_i)$  is the pure within-industry labour productivity contribution estimated by equation (9),  $Post$  is a dummy equal to 1 if  $t > 2008$  and 0 otherwise,  $MIT$  is an indicator equal to 1 if industry  $i$  is either manufacturing or ICT, and 0 otherwise,  $d_t$  is a year fixed effect, and  $\varepsilon_{i,t}$  is a zero mean error term. As in Stiroh (2002), the coefficient  $\alpha$  captures the mean within-industry labour productivity contribution for industries excluding manufacturing and ICT (i.e. industries in the control group) in the period prior to 2008,  $\alpha + \gamma$  is the mean within-industry labour productivity contribution for treated industries prior to 2008,  $\beta$  measures acceleration/deceleration for control industries after 2008 (including  $t = 2008$ ), and  $\beta + \delta$  is then the acceleration/deceleration for treated industries after 2008. The notation highlights that  $\delta$  is the differential labour productivity growth contribution of manufacturing and ICT industries relative to others. We cluster robust standard errors at the industry (for the UK) and country–industry pair level (for worldwide) to allow for arbitrary forms of serial correlation and heteroscedasticity.

Table 12 reports the results; columns (1) and (2) are for the UK 20 industries (A–T) 1998–2019, and columns (3)–(6) are for worldwide comparison 1998–2015.<sup>18</sup> Column (1) reports simple OLS estimates and shows that the manufacturing and ICT industries experienced an economically and statistically significant lower labour productivity growth compared to other

**TABLE 12** Labour productivity growth post-2008

	Within industry labour productivity growth $\sum_{j \in i} \bar{\omega}_j \Delta \ln(V_j/H_j)$					
	UK 1998–2007 versus 2008–19			Worldwide 1998–2007 versus 2008–15		
	(1)	(2)	(3)	(4)	(5)	(6)
MIT	9.420*** (1.997)		4.112*** (0.364)	4.169*** (0.479)		
Post	–0.002 (1.421)	–0.002 (1.419)	–0.0676 (0.598)	–0.233 (0.503)	–0.245 (0.504)	–0.233 (0.503)
MIT * Post	–5.699*** (0.823)	–5.699*** (0.822)	–2.227*** (0.481)	–1.975*** (0.598)	–1.967*** (0.599)	–2.268*** (0.605)
Constant	1.932 (1.658)	2.874* (1.420)	0.228 (0.375)	0.364 (0.352)	0.823** (0.321)	0.823** (0.320)
R-squared	0.104	0.052	0.018	0.037	0.017	0.018
Number of countries	1	1	21	13	13	13
Number of industries	20	20	19	19	19	19
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	No	No	No	No
Country–industry fixed effects	No	No	No	No	Yes	Yes
Regroup DK	No	No	No	No	No	Yes
Observations	440	440	8034	3952	3952	3952

*Notes:* This table reports the estimates based on the model specification in equation (14). The dependent variable is  $\sum_{j \in i} \bar{\omega}_j \Delta \ln(V_j/H_j)$ . Columns (1), (3) and (4) are OLS; columns (2), (5) and (6) are the two-way fixed effect estimates. Column (6) regroups manufacturing and ICT industries into control for Denmark since the slowdown in Denmark was not caused mainly by the two industries. See Figure AIII 1 in Online Appendix III for more details. Columns (3)–(6) combine ‘professional, scientific and technical activities’ and ‘administrative and support service activities’ into one industry, given by the EU KLEMS database. Robust standard errors are clustered at industry and country–industry pair, respectively, reported in parentheses.

\*, \*\*, \*\*\* represent 10%, 5%, 1% significance levels, respectively.

industries post-2008 (i.e. *MIT · Post*). When industry fixed effects are accounted for (column (2)), the point estimate remains negative and statistically significant at the 1% level. The next four columns report the cross-country comparison. When 21 countries<sup>19</sup> are included in the sample, column (3) shows that both the manufacturing and ICT sectors exhibit a negative within-industry labour productivity contribution 2.227 percentage points lower than other industries post-2008. When focusing on only the 13 countries discussed above, columns (4) and (5) still suggest that the treatment group's labour productivity growth was 1.97 percentage points lower than the control group post-2008. Column (6) regroups manufacturing and ICT sectors into the control group for Denmark as a robustness check, as there they do not contribute much to accounting for the overall productivity slowdown (see Figure AIII 1 of Online Appendix III). However, the regrouping does not change the overall pattern; manufacturing and ICT remain significant and contribute negatively to the aggregate labour productivity, with estimated coefficient  $-2.268$  at the 1% significance level.

To see if the pattern is driven mainly by either manufacturing or ICT, we examine the following: (i) the treatment group includes only manufacturing; (ii) the treatment group includes only ICT. We show the results in Tables 13 and 14. Overall, while the baseline results are statistically robust to the two alternatives, we now find that the ICT industry contributes to more of a slowdown compared to the manufacturing industry ( $-1.9$  to  $-1.7$  at 5% and 1% significance levels for manufacturing, versus  $-2.5$  to  $-2.1$  at 5% and 1% significance levels for ICT). This finding is consistent with our UK evidence shown in Figure 5, where information and communication is

**TABLE 13** Labour productivity growth post-2008 (manufacturing versus others)

	Within industry labour productivity growth $\sum_{j \in i} \bar{\omega}_j \Delta \ln(V_j/H_j)$					
	UK 1998–2007 versus 2008–19			Worldwide 1998–2007 versus 2008–15		
	(1)	(2)	(3)	(4)	(5)	(6)
M	6.910*** (0.702)		3.635*** (0.507)	3.219*** (0.540)		
Post	0.348 (1.442)	0.348 (1.440)	-0.091 (0.618)	-0.348 (0.503)	-0.361 (0.504)	-0.355 (0.502)
M * Post	-5.489*** (0.810)	-5.489*** (0.809)	-1.897*** (0.499)	-1.751** (0.676)	-1.743** (0.676)	-1.998*** (0.679)
Constant	1.742 (1.715)	2.105 (1.482)	0.249 (0.387)	0.377 (0.359)	0.566* (0.330)	0.566* (0.329)
R-squared	0.052	0.042	0.013	0.021	0.015	0.015
Number of countries	1	1	21	13	13	13
Number of industries	19	19	18	18	18	18
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	No	No	No	No
Country–industry fixed effects	No	No	No	No	Yes	Yes
Regroup DK	No	No	No	No	No	Yes
Observations	418	418	7614	3736	3736	3736

*Notes:* This table reports the estimates based on the model specification in equation (14). The dependent variable is  $\sum_{j \in i} \bar{\omega}_j \Delta \ln(V_j/H_j)$ . Columns (1), (3) and (4) are OLS; columns (2), (5) and (6) are the two-way fixed effect estimates. Column (6) regroups manufacturing and ICT industries into control for Denmark since the slowdown in Denmark was not caused mainly by the two industries. See Figure AIII 1 in Online Appendix III for more details. Columns (3)–(6) combine ‘professional, scientific and technical activities’ and ‘administrative and support service activities’ into one industry, given by the EU KLEMS database. Robust standard errors are clustered at industry and country–industry pair, respectively, reported in parentheses.

\*, \*\*, \*\*\* represent 10%, 5%, 1% significance levels, respectively.

**TABLE 14** Labour productivity growth post-2008 (ICT versus others)

	Within industry labour productivity growth $\sum_{j \in i} \bar{\omega}_j \Delta \ln(V_j/H_j)$					
	UK 1998–2007 versus 2008–19			Worldwide 1998–2007 versus 2008–15		
	(1)	(2)	(3)	(4)	(5)	(6)
ICT	11.930*** (0.702)		4.590*** (0.446)	5.120*** (0.642)		
Post	–0.206 (1.475)	–0.206 (1.473)	–0.070 (0.626)	–0.247 (0.523)	–0.260 (0.524)	–0.252 (0.524)
ICT * Post	–5.910*** (0.810)	–5.910*** (0.809)	–2.557*** (0.768)	–2.199** (0.913)	–2.191** (0.913)	–2.526*** (0.927)
Constant	2.217 (1.700)	2.845* (1.464)	0.242 (0.391)	0.433 (0.366)	0.733** (0.337)	0.733** (0.337)
R-squared	0.100	0.046	0.014	0.032	0.014	0.015
Number of countries	1	1	21	13	13	13
Number of industries	19	19	18	18	18	18
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	No	No	No	No
Country–industry fixed effects	No	No	No	No	Yes	Yes
Regroup DK	No	No	No	No	No	Yes
Observations	418	418	7614	3736	3736	3736

*Notes:* This table reports the estimates based on the model specification in equation (14). The dependent variable is  $\sum_{j \in i} \bar{\omega}_j \Delta \ln(V_j/H_j)$ . Columns (1), (3) and (4) are OLS; columns (2), (5) and (6) are the two-way fixed effect estimates. Column (6) regroups manufacturing and ICT industries into control for Denmark since the slowdown in Denmark was not caused mainly by the two industries. See Figure AIII 1 in Online Appendix III for more details. Columns (3)–(6) combine ‘professional, scientific and technical activities’ and ‘administrative and support service activities’ into one industry, given by the EU KLEMS database. Robust standard errors are clustered at industry and country–industry pair, respectively, reported in parentheses.

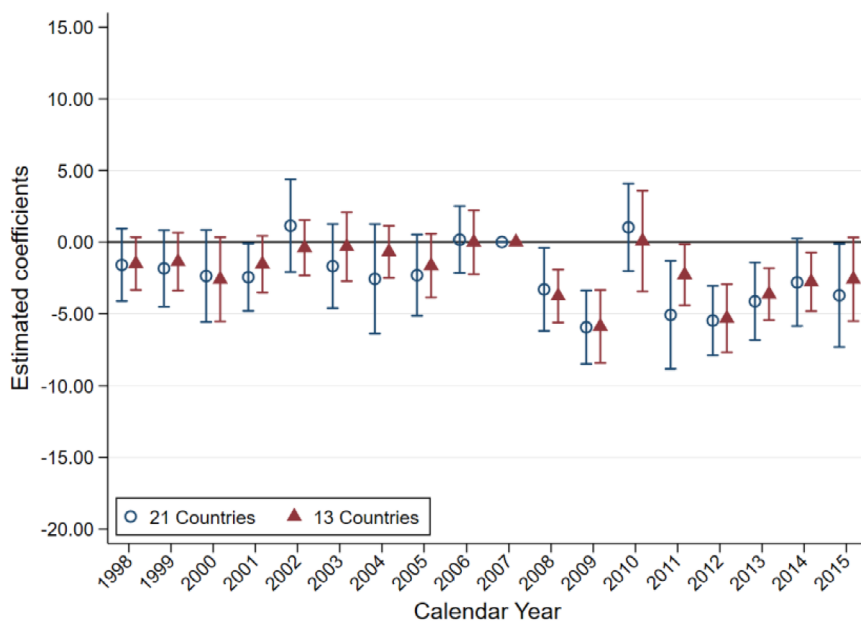
\*, \*\*, \*\*\* represent 10%, 5%, 1% significance levels, respectively.

highlighted as the industry that contributes most to the labour productivity slowdown. We find the same pattern for the international sample.<sup>20</sup>

We next extend our static DiD estimates from equation (15) by breaking down the average treatment effect across each year to capture the accumulated dynamics of the within-sector productivity contribution as well as to examine the assumption of a common trend in the prior period. The specification is identified as

$$\bar{\omega}_i \Delta \ln(V_i/H_i) = \sum_{k=1998}^{2007} \pi_k \text{PreMIT} + \sum_{m=2008}^{2015} \phi_m \text{PostMIT} + \varphi d_t + \varepsilon_{j,t}, \quad (16)$$

where *PreMIT* is a dummy taking value 1 if an observation pertains to calendar year  $k$  and is in treatment group (manufacturing and ICT industries) and 0 otherwise, and *PostMIT* is a dummy taking value 1 if an observation pertains to calendar year  $m$  and is in treatment group (manufacturing and ICT industries) and 0 otherwise. We normalize 2007 to be the reference year. This specification thus allows us to further examine if there was any pre-existing difference in trends between the control and the treated industries. Figure 15 shows the results. Reassuringly, the coefficients on the *PreMIT* dummy variables are not significantly different from zero for all years prior to 2008, confirming a lack of pre-existing differential trends between treated and control industries. After 2008, manufacturing and ICT experience a significant slowdown in their



**FIGURE 15** DiD estimates of the labour productivity slowdown. *Notes:* In this exercise, we study the dynamic within productivity growth difference before and after the 2008 financial crisis between MIT (treated group) and other industries (control group) across countries, 1998–2015. The figure plots the baseline estimates of the yearly DiD coefficients, together with their 95% confidence intervals. Year and country–industry pair fixed effects are controlled for throughout the specifications. We regroup manufacturing and ICT industries into a control group for Belgium and Denmark based on column (6) of Table 12. Robust standard errors are clustered at country–industry pair level, respectively, reported in parentheses.

within-sector contributions, such that by 2009 and 2012, they have about 6% lower within-sector labour productivity growth compared to other sectors.

## 6.2 | External shocks

Here, we try to explore whether a shift in productivity performance across sectors post-2008 is related to potential external shocks. Starting with the UK, to calculate the within component’s variance, we run a linear regression (following equation (15)) that includes industry and time fixed effects for 1998–2019. We extract the residual, which is thus all factors not explained by the industry fixed effects and time fixed effects, potentially including factors such as external finance or import competition shocks.

Results are reported in Table 15. One immediate finding is that the within component in manufacturing is lower compared to any other industries (except professional, scientific and technical activities, education, and human health and social work activities). The ICT industry also has a low unexplained variation in the data.

To explore whether external shocks might contribute to this finding, first we look at import and export data for the two key slowdown industries (Figure 16). Manufacturing has a consistent trade deficit, and while the ICT sector has a surplus, both import and export trends slow down after 2008. Drawing on Coyle *et al.* (2022b), we also look at the relative number of total employees for each firm and year (Figure 17). Figure 18 shows that foreign multinational enterprises (MNEs) and UK domestic-owned firms have almost identical trends in firm-level revenue based total factor productivity (TFPR). The ICT industry seems to be different from manufacturing, as we do not find a clear pattern for either foreign MNEs or MNE-acquired firms.

**TABLE 15** Within component  $\sum_{j \in I} \tilde{\omega}_j \Delta \ln(V_j/H_j)$  VARIANCE DECOMPOSITION BY UK INDUSTRY

		UK (%)
A	Agriculture	2.310
B	Mining and quarrying	1.896
C	Manufacturing	0.156
D	Electricity, gas, steam and air conditioning supply	1.951
E	Water supply; sewerage, waste management and remediation activities	0.328
F	Construction	0.240
G	Wholesale and retail trade and repair of motor vehicles and motorcycles	0.187
H	Transportation and storage	0.274
I	Accommodation and food service activities	0.154
J	Information and communication	0.277
K	Financial and insurance activities	0.415
L	Real estate activities	0.163
M	Professional, scientific and technical activities	0.096
N	Administrative and support service activities	0.156
O	Public administration and defence; compulsory social security	0.195
P	Education	0.102
Q	Human health and social work activities	0.083
R	Arts, entertainment and recreation	0.290
S	Other service activities	0.189
T	Activities of households as employers	2.048

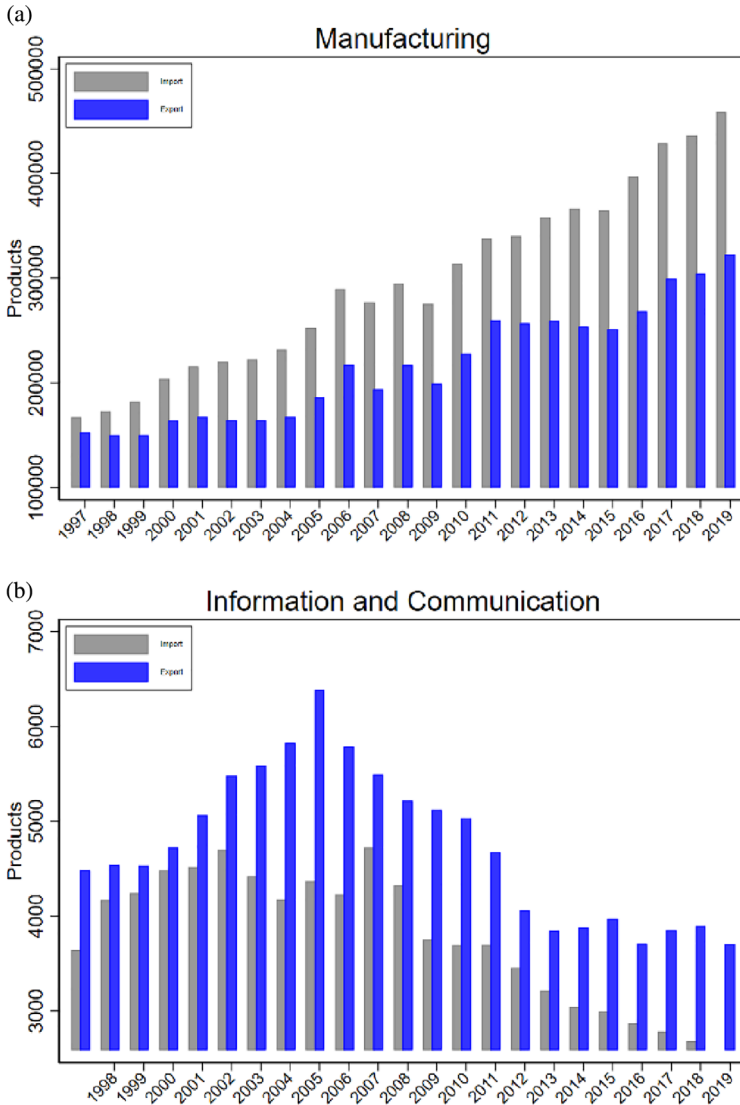
*Notes:* Data are variances of within component  $\sum_{j \in I} \tilde{\omega}_j \Delta \ln(V_j/H_j)$  obtained through the specification  $within_{it} = \alpha + Treat + Post + Treat * Post + F_i + F_t + \varepsilon_{it}$ , where  $F_i$  and  $F_t$  are the industry and time fixed effects, and  $within_{it}$  refers to the within component  $\sum_{j \in I} \tilde{\omega}_j \Delta \ln(V_j/H_j)$  for 1998–2019. We extract the residual from the regression, and then collect the variance afterwards. *Source:* Authors' calculations.

These pieces of evidence are suggestive of a potential role for external shocks in explaining the productivity slowdown in these sectors, meriting further investigation.

## 7 | DISCUSSION

This has been an era of substantial technological change, reflected in large declines in output prices in some sectors over 1998–2019. One example is the telecommunications subsector of ICT. Improvements to the UK's telecoms output deflator suggest that it declined by between 37% and 96% between 2010 and 2017 (Abdirahman *et al.* 2022), and a revised deflator adopted by the ONS (Martin 2021) captures a price decline that shows up in the large rise in its real value-added per hour, as illustrated in Figure 1. However, there appears to be a puzzle: why then does telecommunications appear as the one of the biggest contributors to the slowdown in 'within' labour productivity growth in the UK ICT sector—and indeed, why does ICT overall appear to be one of the bigger contributors to the aggregate slowdown? Figure 1 shows nominal growth in value-added per hour slowing post-2007, but it also shows consistently high real value-added per hour post-2007.

Part of the resolution lies in the fact that the within figures in the Tornqvist decomposition use *nominal* value-added shares as weights, and hence the slowdown reflects slower (albeit still

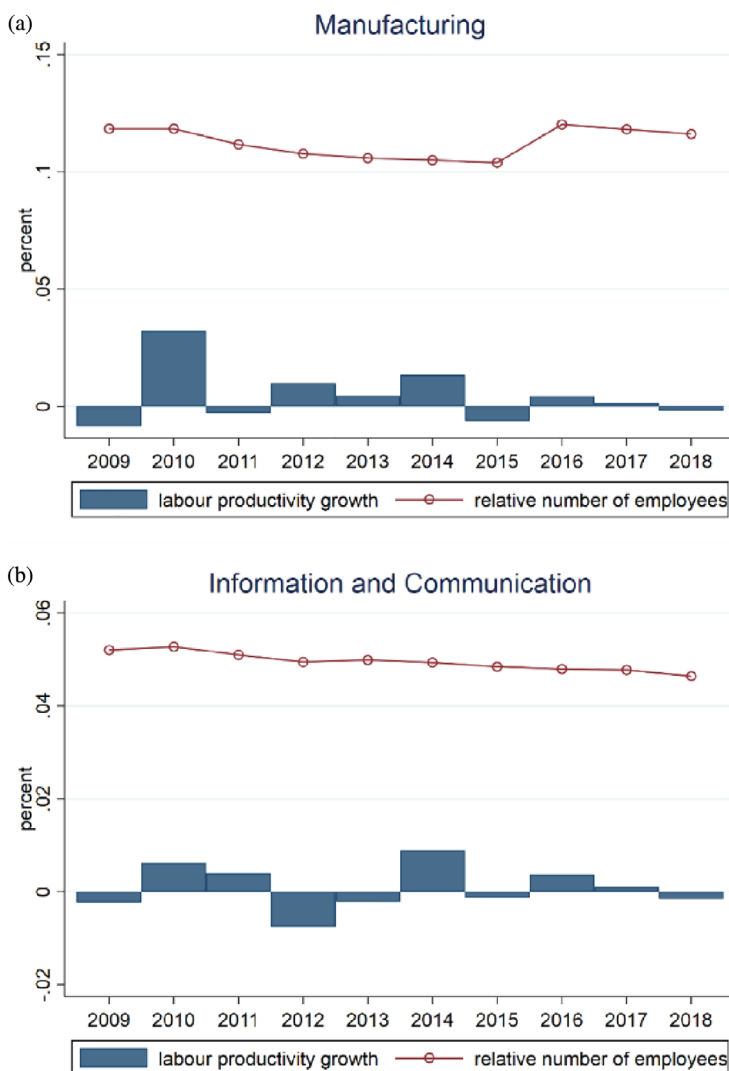


**FIGURE 16** Trade in goods through UK manufacturing and ICT, 1998–2019. *Notes:* Dark grey for exports, and light grey for imports. We use ONS variables P289, P2ON for manufacturing, and P2NA and P3B6 for ICT for the period 1998–2019. *Source:* ONS Trade in Goods and authors' calculations.

quite rapid) revenue growth in the sector. It might seem that using volume weights instead—for example, growth in bytes of data used—would give a ‘truer’ picture of the contribution of telecommunications to productivity growth, but this would be misleading in the sense that user value lies in the content carried by the telecoms network, with value generated by downstream sectors, rather than the volume in terms of number of bytes *per se*. It is not immediately obvious how to think about the changing value of bytes of data over time. Does twice the data lead to twice the money-metric utility? Probably not. There are unresolved questions concerning how to think about price indices for markets whose outputs are complements (such as telecoms and sectors using communications intensively) or those whose products demonstrate significant returns to scale and non-rivalry. One potential avenue to progress on this issue would be to consider prices for bundles of product characteristics using the Lancaster (1966) approach defining utility over characteristics, and expenditure over products, linked through a consumption ‘technology’. Hulten and Nakamura (2022) have suggested recently how this could be developed at the level of aggregate economic measurement, with a price index defined over product characteristics.

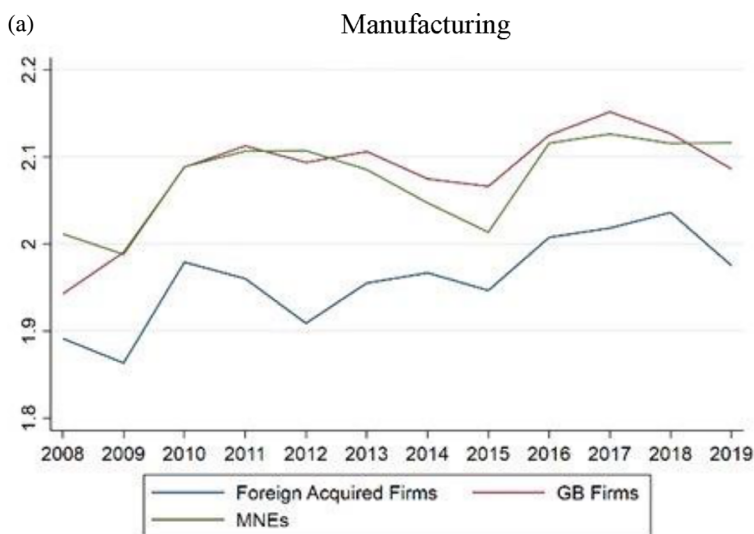


**FIGURE 17** Growth in labour productivity and number of employees post-2008. *Notes:* We access the ONS ABS secure firm-level database and focus on manufacturing and ICT industries. We gather information based on the labour productivity measure (value-added/employees) and number of employees across each firm and year. *Source:* ONS ABS firm-level database and Coyle *et al.* (2022b).

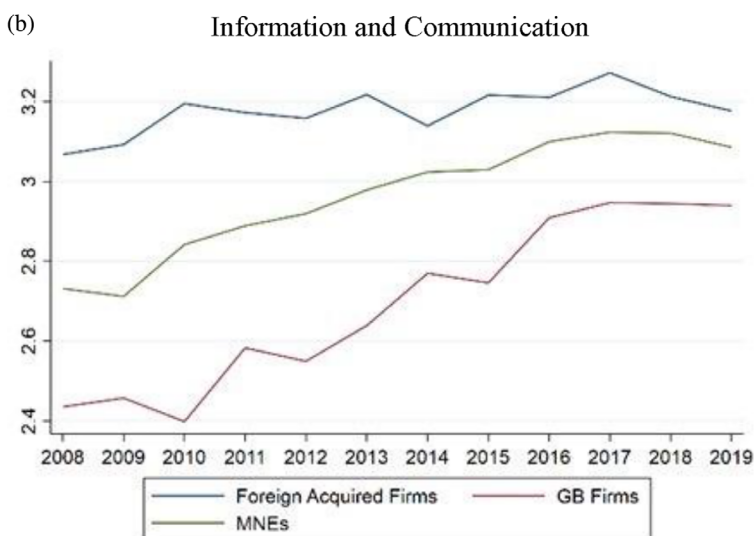


One lesson is that interpreting the results of any decomposition must be done with care. The fundamental issue is that the choice of revenue weights versus volume or employment weights (as in alternative decomposition methods) provides distinct lenses on the economy—as does decomposition at the firm level. For the case of telecommunications, Abdirahman *et al.* (2022) show that the greater the use of volume (in terms of bytes of data) rather than revenue weights, the larger the decline in the deflator, and the faster the growth in real terms output. The difference can be large when there is rapid change in a sector, due in this example to technological shifts such as greater compression, more bandwidth and faster speeds, such that the relationship between volume and revenue shifts. The use of a unit value deflator (which uses pure volume weights) rather than the ONS output price deflator would tell a different productivity story.

In this paper, we adopt the Tornqvist decomposition formula to allow for relative price shifts between different sectors of the economy, while also using two alternative methods to demonstrate the importance of different weights employed in the exercise. We demonstrate that within-sector labour productivity growth is the main source of the slowdown in aggregate labour productivity growth, while labour reallocation between sectors accounts for little. We further show that some other high value-added sectors—transport equipment manufacture (mainly



**FIGURE 18** Firm-level TFPR, 2008–19. *Notes:* We access the ONS ABS secure firm-level database and focus on foreign-acquired, GB-owned firms, and MNEs in manufacturing and ICT industries. *Source:* ONS ABS firm-level database and Coyle *et al.* (2022b).



motor vehicles), pharmaceuticals, and computer, electronic and optical products within manufacturing, and telecommunications and computer programming, consulting and related activities within ICT—experienced the biggest within labour productivity slowdowns in the UK, to a greater extent than other countries.

Looking at 13 (including the UK) advanced economies, the pattern at the sector level is broadly consistent across countries, however. Within manufacturing, there is variation across subsectors but some common elements with slowdowns in within-industry labour productivity growth in transport equipment, pharmaceuticals, and computer and electronics manufacture. Since many of the subsectors in this list are regarded as success stories in the UK and worldwide, it is striking that the productivity slowdown is greatest in some of the most technologically advanced industries.

There are two possible avenues to pursue in exploring the reasons for this pattern. One concerns price deflators: the usual shift-share method, using employment share weights, ensures that the sum of the sectors' labour productivity growth is equal to the aggregate by assuming that relative prices between sectors do not change. The difference compared with the Tornqvist method

used here can be large when there is rapid change in a sector, due for example to technological shifts (such as greater compression, more bandwidth and faster speeds in telecoms) such that the relationship between volume and revenue shifts. Alongside this, our findings call for more detailed investigation of the slowdown subsectors and their supply chains, including across countries, looking more closely at the construction of deflators when discussing aggregate productivity outcomes. Other avenues for progress include using insights from the sectoral results to explore firm- or plant-level data, testing whether there are common structural shifts that can account for the observed more aggregated phenomena.

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## NOTES

<sup>1</sup> Harris and Moffat (2017) find that labour productivity for the whole UK economy by the end of 2014 was 13% lower compared to a potential output per worker level had the pre-2007 trend continued.

<sup>2</sup> Crafts and Mills (2020) find that the current productivity slowdown has resulted in productivity being 19.7% less than the pre-2008 trend path by 2018.

<sup>3</sup> There are three general approaches to calculating gross value-added (GVA): (i) extrapolating GVA from the base period using the volume growth of output; (ii) single deflation, which uses an output price deflator for both output and intermediate consumption; and (iii) double deflation, which deflates output and intermediate consumption separately. Before November 2021, the UK applied single deflation. This is based implicitly on the assumption that output grows at a constant ratio to GVA, which is rarely correct. Since October 2021, the ONS has used double deflation. See Online Appendix VI for more details.

<sup>4</sup> Tang and Wang (2004) adopt the GEAD formula to take into account changes in relative prices. By incorporating price effects into contributions, this approach captures the overall economic significance of different sectors to aggregate labour productivity growth, but not the impact of sectoral real contribution on aggregate labour productivity growth. It has been argued that the generalized exactly additive decomposition approach often produces results being perceived as counterintuitive (de Avillez 2012; Reinsdorf 2015; De Vries et al. 2021).

<sup>5</sup> Other papers using the shift-share method are applied in the developing economy context. For example, McMillan and Rodrik (2011) document large gaps in labour productivity between the traditional and modern parts of the economy such that labour flows from low-productivity to high-productivity activities are a key driver of productivity growth from 1990 to 2005. Focusing on structural transformation, De Vries et al. (2012) similarly find that reallocation of labour across sectors contributes to aggregate productivity growth for China, India and Russia, but not for Brazil, 1993–2004.

<sup>6</sup> While Voskoboynikov (2020) also includes a whole economy sector and finds that structural change is growth-enhancing but decreasingly so over time, the author focuses on only the Russia economy and does not use the Tornqvist decomposition.

<sup>7</sup> Our results confirm that the shift-share method provides similar results for the aggregate productivity growth pattern compared to our current approach. By contrast, the GEAD approach provides divergent results. See Online Appendix II for more details.

<sup>8</sup> As in De Vries et al. (2015), this term can be further decomposed into static and dynamic components of structural change. Diao et al. (2019) argue that the structural change term is often negative and may be difficult to interpret. However, it enables distinctions to be drawn between labour moving to sectors with different levels of productivity, and sectors with different productivity growth rates (De Vries et al. 2021).

<sup>9</sup> The 20 A–T sectors include: A Agriculture, B Mining and quarrying, C Manufacturing, D Electricity, gas, steam and air conditioning supply, E Water supply; sewerage, waste management and remediation activities, F Construction, G Wholesale and retail trade and repair of motor vehicles and motorcycles, 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, scientific and technical activities, N Administrative and support service activities, O Public administration and defence; compulsory social security, P Education, Q Human health and social work activities, R Arts, entertainment and recreation, S Other service activities, T Activities of households and employers.

<sup>10</sup> Stehrer *et al.* (2019) provide and release data sheets for the EU KLEMS database managed by the Vienna Institute for International Economic Studies (WIIW) in 2019. This is different to the version managed by the Luiss Lab of European Economics. The WIIW data run to 2017, with file names such as ‘US\_National-Accounts\_SDB\_2019’ for the USA. (Data can be accessed at <https://euklems.eu/archive-history/download-archive>, accessed 28 December 2022.) Importantly, some crucial data such as total hours worked are missing for some years, countries and industries. Hence we restrict our analysis in the international comparison to focus on 1998–2015. However, we provide robustness for the period 1998–2017.

<sup>11</sup> Note that the LUISS (i.e. EU KLEMS and INTANProd 2021) release provides advances over the EU KLEMS (WIIW 2019), including separate statistics for professional, scientific and technical services (industry labelled M), and administrative and support services (industry labelled N) for all those countries for which data are available. In addition, there is a significant improvement in the data for intangible assets, such as measures of organizational capital, brand, design and training. Although the intangible capital measure is out of the scope of this paper, we provide a comparison between the data that we apply in the current paper and the data released by the LUISS in Online Appendix VII. While we find that the overall pattern is consistent (see Table AVII 1 and Figure AVII 1 in Online Appendix VII), for analysis of the role of intangible capital in industry productivity, the LUISS 2022 data would be needed. See the LUISS update report at [https://euklems-intanprod-lee.luiss.it/wp-content/uploads/2022/02/EUKLEMSINTANProd\\_2021\\_Methods-and-data-description-Rev1.pdf](https://euklems-intanprod-lee.luiss.it/wp-content/uploads/2022/02/EUKLEMSINTANProd_2021_Methods-and-data-description-Rev1.pdf) (accessed 28 December 2022).

<sup>12</sup> As the EU KLEMS data combine professional, scientific and technical activities, and administrative and support service activities, into one industry, we combine these two for the UK in the international comparison.

<sup>13</sup> The reallocation is simply calculated as residual, subtracting the slowdown in  $\Delta \hat{\omega}_i \Delta \ln(V_i/H_i)$  from the slowdown in  $\Delta (\Delta \ln V_i/H_i)$ .

<sup>14</sup> Coyle *et al.* (2022b) focuses on the six slowdown industries identified in this paper. In Coyle *et al.* (2022b), we employ the UK Annual Business Survey firm-level database (secure data access) to estimate the firm-level revenue based total factor productivity (TFPR), industry-level markups, and quantity-based TFP.

<sup>15</sup> The TFP data are collected from the ONS estimates of TFP from the Annual Business Survey: <https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/articles/firmleveltotalfactorproductivitymeasuresfromtheannualbusinesssurveyuk1998to2019/august2022> (accessed 28 December 2022).

<sup>16</sup> Jorgenson and Timmer (2011) highlight that specialization may generate differences across European countries when relatively small countries trade widely, and suggest that it is important to aggregate across European countries as a region rather than nation. While we are aware of this concern, it is worth looking—similar to Kaldor (1961) and Kuznetz (1971)—at how each nation’s labour productivity performs individually, and the differences that may exist across industries. We also provide other European countries’ statistics, including Ireland, Czechia, Estonia, Poland, Romania, Slovenia and Slovakia, in Online Appendix IV.

<sup>17</sup> We keep the USA and the UK in the main context but move other countries into Online Appendix III. In addition, we provide overall growth patterns for 1998–2008 and 2008–15 across the 13 economies in Tables AIII 1 and AIII 2 of Online Appendix III.

<sup>18</sup> However, the time period selection does not drive the results. We provide evidence based on the whole time period 1998–2017 in Table AV 3 of Online Appendix V. We find that the key interested variable ‘Treat\*Post’ remains highly statistically significant at the 1% significance level. Its sign remains negative, indicating that manufacturing and ICT industries indeed cause the overall labour productivity slowdown.

<sup>19</sup> They are the UK, the USA, Japan, France, Belgium, the Netherlands, Ireland, Denmark, Germany, Italy, Portugal, Austria, Czechia, Estonia, Greece, Finland, Sweden, Slovenia, Slovakia, Poland and Romania.

<sup>20</sup> We also examine whether the reallocation component, treated as the dependent variable, could show up some interesting patterns. We repeat the exercise outlined in equation (14), and report results in Table AV 2 of Online Appendix V. Reassuringly, the results are consistent with the finding that the within component is the main contributor rather than the reallocation.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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