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 both at 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 largely be attributed to the manufacturing and the information and communication sectors. Disaggregating further, the UK productivity growth slowdown can be mainly attributed to transport equipment and pharmaceuticals within manufacturing, and computer software and telecommunications within information and communication. 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 information 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.

Keywords: Productivity, Decomposition, Manufacturing, Information and Communication

JEL: O47, L16, L60, L86

INTRODUCTION

The 'puzzle' of the productivity slowdown has been extensively explored. This paper extends this body of work by decomposing the aggregate productivity statistics into the different sectors and sub-sectors in order to see whether the slowdown has been dispersed across the economy or 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 and information and communication sectors, and within these in certain sub-sectors 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) was referring to this when he stated: "[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 economists are interested in 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 (top panel) the growth rate of current price value added per hour worked ($\Delta lnNVA$) and in Figure AI 1 in 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 figure omits real estate, mining and utilities, which all have substantially higher current price value added per hour, due to their distinctive features. After these, finance (brown) and manufacturing (blue) 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 (Figure 1 the top panel, industry K). 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 2008-2019 in Appendix I Table AI 1, confirming that Water supply (industry E), Construction (industry F), Information 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 (bottom panel) the growth rate of real value added per hour worked ($\Delta lnRVA$) and the level rebased to 1997=100 in Figure AI 1 (bottom). The labour productivity of the information and communication sector has grown substantially in real terms over the entire period (bottom panel, industry labelled J), and both manufacturing (C) and agriculture (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 2008-2019; the results in Appendix

I Table AI 2 reveal that both manufacturing and information communication 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 2008-2019 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, Erumban, Timmer, Voskoboynikov, and Wu, 2012; Diao, McMillan, and Rodrik, 2019; Moussir and Chatri, 2020; Voskoboynikov, 2020; De Vries, Erumban, and van Ark, 2021).

Although the recent empirical literature, such as Harris and Moffat (2017),[1] Crafts and Mills (2020), and Goodridge, Haskel, and Wallis (2018),[2] confirms the UK productivity slowdown, this paper updates prior research on UK labour productivity by using recent ONS statistics that have incorporated double deflation for the first time, that is deflating inputs and outputs separately.[3] In Section 2, we clarify how the aggregate data and the 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).[4] In this paper we adopt the Tornqvist method, which has also been used in Goodridge, Haskel, and Wallis (2018), 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 3 and 4) show that manufacturing and information and communication are those that have experienced the biggest labour productivity slowdowns. Furthermore, we find that the within-sector slowdowns are mainly attributable to transport equipment and pharmaceuticals in manufacturing, and to computer software and telecommunications in information and communication. 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 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 UK compares with other countries, we also look in Section 5 at 12 other countries including Japan, the US, 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 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 information and communication 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 6 we test the robustness of the analysis by using a difference-in-difference approach, which confirms that the manufacturing and information and communication sectors experienced productivity growth statistically and significantly lower post-2008, by 5.699 percentage points in 2008-2019 for the UK, and by 2.268 percentage points in 2008-2015 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), de Vries, Timmer, and de Vries (2015), Diao et al. (2019), Moussir and Chatri (2020), Voskoboynikov (2020), and De Vries et al. (2021).[5] Tang and Wang (2004) adopt the GEAD method and find that the aggregate labour productivity growth gap between Canada and the United States during 1987-1998 was driven by the within-industry contribution in manufacturing and service sectors. Using data from the UK, France and the US during the COVID period (2020 and 21-Q1), De Vries et al. (2021) find that the reallocation effects until 2019 were slightly negative for the US, 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), De Vries et al. (2015), Diao, McMillan, and Rodrik (2019), and Moussir and Chatri (2020) the absolute differences in productivity weighted by industry employment shares in the previous period is 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 predate the implementation of double deflation, discussed further below. We also consider the whole economy, not just the market sector.[6]

Our results provide an alternative lens on the productivity 'puzzle' compared to taking a firm-level perspective. A number of papers such as Criscuolo, Andrews, and Gal (2019), Autor, Dorn, Katz, Patterson, and Van Reenen (2020), Coyle et al. (2022), and Linarello and Petrella (2017) use decompositions such as that provided by Olley and Pakes (1996) to identify a trend toward 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 (Baqaee 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).

For 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 burts 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's 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.

I. DECOMPOSITION METHODS

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 Appendix II.[7] 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:

(1) $$\Delta lnV \equiv \sum_i \bar{\omega}_i \, \Delta lnV_i$$

where

(2) $$\omega_i = {}^{v_i}/_{\sum_i v_i}$$

and

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

Eq. (1) says 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 ω_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

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

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

(5) $$\Delta \ln (V/H) = \Delta lnV - \Delta lnH$$

and so the industry labour productivity growth can be defined as:

(6) $$\Delta \ln (V_i/H_i) = \Delta lnV_i - \Delta lnH_i$$

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

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

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 Eq. (7) produces a different estimate of aggregate labour productivity growth to the estimate from Eq.(5), we can obtain the whole economy sector level reallocation term (R) as the difference between the two:

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

The second term in Eq. (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, Eq. (8) does not allow us to examine the contribution of each component from sub-sector to industry labour productivity growth. As in De Vries et al. (2012),[8] we therefore breakdown industry i into sub-sectors j, and calculate the following:

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

where

(10) $$\omega_j = {}^{v_j}\!\big/_{\sum_j v_j}$$

and

(11) $$\bar{\omega}_j = 0.5(\omega_{jt} + \omega_{jt-1})$$

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

III. DATA

We use sector and sub-sector 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 Office National Statistics (ONS) data for the UK, first published in October 2021. 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.[9] A major change introduced by 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 GVA. Double deflation thus raised the published output and productivity of the ICT and manufacturing sectors (ONS 2021 – see chart in Appendix V Figure AV 1). 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 EU KLEAM national account dataset, with the Vienna Institute for International Economic Studies (WIIW)[10] release 2019 version (Stehrer, R., Bykova, A., Jäger, K., Reiter, O. and Schwarzhappel, 2019).[11] We select data for the US, Japan, France, Belgium, Netherland, 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 dataset provides comprehensive coverage of all the variables needed.[12]

We look at the periods 1998-2019 for the UK, and 1998-2015 for international comparison. Data for the 2020-2021 period is 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 GVA, 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.

IV. UK RESULTS

BASELINE RESULTS

Figure 2 and Table 1 show first the aggregate labour productivity growth for the whole economy $\Delta\ln(V/H)$ (grey bars), and the separated two terms as the weighted sum of industry labour productivity $\sum_i \bar{\omega}_i \Delta\ln(V_i/H_i)$ (i.e., the pure within-sector contribution) and the aggregate reallocation effect R estimated from Eq. (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 productivity growth $\sum_i \bar{\omega}_i \Delta\ln(V_i/H_i)$ was 0.792% per year, and the reallocation term R 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 (red bars) post-2008.

To explore the slowdown, Table 2 looks separately at 1998-2008 and 2008-2019. Focusing on column (1) of Table 2, overall average productivity growth rates for the periods 1998-2008 and 2008-2019 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 ((0.086-0.409)/-1.282) of the slowdown is explained by reallocation, and about three quarters ((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 the ONS 2019 Labour Productivity Report, 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, Riley, Rincon-Aznar, and Samek, 2018, for instance).

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 (2008-2019). The sectors recording the fastest productivity growth over the whole period were information and communication and manufacturing. However, comparing columns (2) and (3) in 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% (2008-2019 vs. 1998-2008), which consists of a contribution from within-sector productivity of minus 5.226% and a slowdown due to the labour reallocation term of 0.015%; similarly the slowdown in information and communication is minus 5.986%, which consists of a slowdown from within-sector productivity growth of minus 5.933% plus a slowdown from the labour reallocation term of minus 0.053%.[13] 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 information and communication. The results are shown in Table 4 and Figure 4. There are 13 sub-sectors in manufacturing and six in information and communication industries.

Table 4 reveals five sub-sectors where labour productivity growth ($\Delta\ln\,(V_j/H_j)$) turns negative during the post-crisis period 2008-2019; three in manufacturing, namely machinery and equipment n.e.c, (-0.117%), basic pharmaceutical products and pharmaceutical preparations (minus 0.188%), and other manufacturing, repair and installation of machinery and equipment (minus 0.138%); and two in information and communication, computer programming, consultancy and related activities (minus 0.316%), and information service activities (minus 0.400%). There are other sub-sectors with significant slowdowns, albeit not turning negative in the second period, and no sub-sectors experiencing an increase. The only subsectors not to experience much of a 'within' slowdown are chemicals and coke/refined petroleum products.

In Figure 5, the top panel shows the contribution to the slowdown from each sub-sector's within component in manufacturing (top panel) and in the information and communication industry (bottom panel). 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 information and communication 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 sub-sectors? Figure 6 confirms that the reallocation contribution is small although positive on average in manufacturing and information and communication.

SECTORAL DECOMPOSITION AND STRUCTURE DYNAMICS

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 ϕ (defined as log changes) corresponding to the weighted average of industries' labour productivity ρ_i (defined as real gross value added/hours in log changes), where the weights w_i are the two period weighted share of industry i's nominal gross value added (i.e., a Divisia index). That is, at time t:

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

Aggregate labour productivity ϕ_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:

(13) $$\begin{aligned}\phi_t &= \bar{\rho}_t + cov(\rho_{it}, w_i)\\ &= \bar{\rho}_t + \textstyle\sum_A^T (\rho_{it} - \bar{\rho}_t)(w_i - \bar{w}_t)\end{aligned}$$

where $\bar{\rho}_t = {}^1\!/_n \sum_A^T \rho_{it}$ 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 and 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 of all, 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 $cov(\rho_{it}, w_i)$ is relatively large compared to the reallocation term captured by our Tornqvist method. 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 the one provided by the Tornqvist approach. Thirdly, in either method, we find evidence of productivity slowdown post-2008, and both show a similar slowdown contribution from the reallocation term (by minus 0.323 p.p. in Tornqvist and minus 0.349 p.p. 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.

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, McHale, Bournakis, and Mei (2022).[14] In Figure 7 the right hand panel displays the post-2008 pattern of firms' entry, exit, and stay (survivors/incumbents). We also plot the firm-level labour productivity measure (defined as GVA/employees with revenue weights) to check if entry and exit might contribute in a systematic way (left-hand panel). 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.

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.

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 Appendix V (Figure V2). 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 (2009-2019) patterns alongside our labour productivity growth rate.

We introduce a quadratic term of the within-component ($\sum_i \bar{\omega}_i \Delta \ln(V_i/H_i)^2$) into Eq. (8) above. 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. The non-linearity term, thus, 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 similar trajectory as the fundamental volatility measure, then it should imply that our decomposition framework at least contains information about microeconomic shocks.

To do so as 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 fundamental volatility proposed by Domar (1961), Hulten (1978), Jones (2011), and implemented by Carvalho and Gabaix (2013). The fundamental volatility is measured as $\sigma_{ft} = \sqrt{\sum_{i=1}^{n}(\frac{S_{it}}{GDP_t})^2\sigma_i^2}$, where $\frac{S_{it}}{GDP_t}$ are the weights that capture the impact of microeconomic shocks through each industry (Domar,1961; Hulten, 1978). The σ_i^2 is the variance of the total factor productivity (TFP) in the industry[15]. 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 Eq. (8) on the measure of sectoral level fundamental volatility. Table 9 summarises the results. We find high statistical and economic significance of σ_{ft} on the aggregate labour productivity growth rate and within component (at the 1% significance level). The R^2 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.

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 Generalized Exactly Additive Decomposition (GEAD, henceforth) in Appendix II. The shift-share method uses relative number of employees as the weight for each industry, whereas the 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, Mei, and Hampton (2022) 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:

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

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 $s_{t-1}^i = \frac{p_{t-1}^i V_{t-1}^i}{\sum_i p_{t-1}^i V_{t-1}^i}$ is the share of industry nominal value added with industry i price weight at $t-1$. Rearranging, we get

$$
\begin{aligned}
g(X_t) = & \underbrace{\sum_i s_{t-1}^i g(X_t^i)}_{\text{Pure Within}} + \underbrace{\sum_i s_{t-1}^i g(p_t^i)}_{\text{Relative Price Changes}} + \underbrace{\sum_i s_{t-1}^i g(l_t^i)}_{\text{Labour Input Reallocation}} \\
& + \underbrace{\sum_i s_{t-1}^i g(X_t^i) g(p_t^i) + \sum_i s_{t-1}^i g(X_t^i) g(l_t^i) + \sum_i s_{t-1}^i g(l_t^i) g(p_t^i) + \sum_i s_{t-1}^i g(X_t^i) g(p_t^i)\, g(l_t^i)}_{Other\ Interaction\ Effects}
\end{aligned}
$$

(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 $s_{t-1}^i g(p_t^i)$ is the contribution of relative price changes between sectors. The third $s_{t-1}^i g(l_t^i)$ 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.

V. 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 potential drivers of productivity.[16] We use Eqs. (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 Eq.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 US and France, which implies that labour was moving from more productive to less productive industries during 1998-2015, while Japan and 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 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.

Figure 12 shows the decomposition in average labour productivity growth between 1998-2008 and 2008-2015 across all 20 sectors for each country.[17] There is a slowdown in average productivity growth in manufacturing (except Denmark and Italy, see Figure 14) and information and communication in each. Although somewhat less pronounced in Japan, Belgium, and Portugal than in the other countries, manufacturing is the main contributor to the growth slowdown with minus 4.721% (US) and minus 4.310% (UK), minus 1.327% (France), minus 2.868% (Netherlands), minus 2.060% (Germany), minus 2.809% (Austria), minus 3.585%(Greece), and minus 4.910% (Sweden), respectively. The information and communication sector also contributes to the overall productivity slowdown in all economies (except Denmark), although it is relatively smaller in Belgium (-0.906%) and France (-0.810%) than other countries.

There are some differences across countries in the ranking of the sectors contributing to the overall productivity slowdown. For instance, the slowdown mainly is attributable to wholesale trade (minus 2.125%) and transport and storage (minus 2.039%) in the US; electricity (minus 15.327%) and mining (minus 14.801%) in Japan; and electricity (minus 6.536%) and other service activities (minus 3.416%) in France (see Figure 12 and Figure AIII 1 in Appendix III). Which industries in the UK are doing better compared to other countries? Figure 12 shows that the better-performing sectors include mining and quarrying (5.910%), activities of households as employers (4.781%), other service activities (3.617%), education (2.305%), and real estate (3.278%).

We next decompose manufacturing into 13 sub-sectors. Figure 14 shows the results. Overall, the transport equipment sub-sector shows a somewhat similar picture, contributing notably to the decline across all economies. However, the pattern for other sub-sectors differs across countries. Another notable pattern is that chemicals and computers in the US have post-2008 growth rates of minus 0.785% and minus 1.594%, respectively, which account for almost two-quarters and one-third of the US manufacturing productivity slowdown. While these two sub-sectors perform relatively better in the UK compared to the US, in the UK the computer sub-sector 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 sub-sector accelerates in Japan, Germany, Denmark, Italy, Netherlands, and Greece (see Appendix III Figure AIII 2).

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 information and communication make a notable contribution to the slowdown. While there is variation among these countries, there is enough consistency for certain sub-sectors to warrant further investigation: information and communication, and, within manufacturing, transport equipment, computer and electronics manufacture, and pharmaceuticals. Our results suggest 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, Jones, Van Reenen, and Webb, 2020); the other is that there are delays in adopting new technologies leading to a 'J-curve' phenomenon in measured productivity (Brynjolfsson, Rock, and Syverson, 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.

VI. ROBUSTNESS CHECKS

DIFFERENCE-IN-DIFFERENCE 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 difference-in-difference exercise. We adopt a general two-way fixed effects (TWFE) with difference-in-difference estimator to test for a difference in mean labour productivity growth rates between the two sub-periods as follows:

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

where $\bar{\omega}_i \Delta \ln(V_i/H_i)$ is the pure within industry labour productivity contribution estimated by Eq. (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 information communication industry 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 α captures the mean within-industry labour productivity contribution for industries excluding manufacturing and information (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, β measures acceleration/deceleration for control industries after 2008 (including $t = 2008$), $\beta + \delta$ is then the acceleration/deceleration for treated industries after 2008. The notation highlights that δ is the differential labour productivity growth contribution of manufacturing and information and communication 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) for worldwide comparison 1998–2015.[18] The first column reports simple OLS estimates and shows that the manufacturing and information and communication industries experienced an economically and statistically significant lower labour productivity growth compared to other 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[19] are included in the sample, column (3) shows that both manufacturing and information and communication sectors exhibit a negative within-industry labour productivity contribution 2.227 percentage points lower than other industries post 2008. When focusing only on 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) re-groups manufacturing and information and communication 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 in Appendix III). However, the regrouping does not change the overall pattern; manufacturing and information remain significant and negatively contribute to the aggregate labour productivity, with estimated coefficient -2.268 at the 1% significance level.

To see if the pattern is mainly driven by either manufacturing or information and communication, we examine: (1) the treatment group only includes manufacturing industry; and (2) the treatment group only includes information and communication. We show results in Tables 13 and 14. Overall, while the baseline results are statistically robust to the two alternatives, we now find that the information and communication industry contributes to more of a slowdown compared to the manufacturing industry (minus 1.9-1.7 at 5% and 1% significance levels for manufacturing vs minus 2.5-2.1 at 5% and 1% significance levels for information and communication). This finding is consistent with our UK evidence shown in Figure 5 above where the information and communication is highlighted as the industry that contributes most to the labour productivity slowdown). We find the same pattern for the international sample.[20]

We next extend our static DiD estimates from Eq. (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 follows:

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

where $PreMIT$ is a dummy taking value 1 if an observation pertains to calendar year k and is in treatment group (manufacturing and information industries) and 0 otherwise, $PostMIT$ is a dummy taking value 1 if an observation pertains to calendar year m and is in treatment group (manufacturing and information industries) and 0 otherwise. We normalise 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 information and communication experience a significant slowdown in their within-sector contribution, such that by 2009 and 2012 they have about 6% lower within-sector labour productivity growth compared to other sectors.

EXTERNAL SHOCKS

Here we try to explore at 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 Eq. 15) that includes industry and time fixed-effects through 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 information and communication 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 information and communication sector has a surplus, both import and export trends slow down after 2008. Drawing on Coyle, McHale, Bournakis, and Mei (2022), we also look at the relative number of total employees for each firm and year (Figure 17). Figure 18 shows that foreign MNEs and UK domestic owned firms have almost identical trends in firm-level revenue based total factor productivity (TFPR). The information and communication industry seems to be different from manufacturing, as we do not find a clear patten for either foreign MNEs or MNE acquired firms.

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

VII. DISCUSSION

This has been an era of substantial technological change, reflected in large declines in output prices in some sectors 1998-2019. One example is the telecommunications sub-sector of ICT. Improvements to the UK's telecoms output deflator suggest it declined by between 37% and 96% between 2010 and 2017 (Abdirahman et al., 2020), and a revised deflator adopted by ONS (ONS, 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 information and communication sector – and indeed why does information and communication 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 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, 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 Lancaster (1966) approach defining utility over characteristics and expenditure over products, linked through a consumption 'technology'. Hulten and Nakamura (2022) have recently suggested how this could be developed at the level of aggregate economic measurement, with a price index defined over product characteristics.

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) provide 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 motor vehicles), pharmaceuticals, and computer, electronic and optical products within manufacturing, and telecommunications and computer programming, consulting and related activities withing in information and communication – 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 sub-sectors 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 sub-sectors 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 relative prices between sectors do not change. The difference 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 sub-sectors 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.

ACKNOWLEDGEMENTS

This work was produced using statistical data from ONS. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

We thank Peter Goodridge, Shane Greenstein, Jonathan Haskel, Richard Heys and ONS colleagues, Bart Van Ark and Tony Venables for their helpful comments, Adam Muhtar, and Lucy Hampton for excellent research assistance. We also thank the anonymous reviewers and editor for their extremely helpful and insightful suggestions. Coyle is grateful for funding from the Productivity Institute, ESRC grant number ES/V002740/1, and Mei for funding from the Gatsby Charitable Foundation and the ONS small grant research support ONS2014988.

NOTES

[1] Harris and Moffat (2017) found 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 had continued.
[2] Crafts and Mills (2020) found that the current productivity slowdown has resulted in productivity being 19.7% less than the pre-2008 trend path by 2018.

[3] There are three general approaches to calculating GVA: (1) extrapolating GVA from the base period using the volume growth of output; (2) single deflation, which uses an output price deflator for both output and intermediate consumption; and (3) double deflation, which separately deflates output and intermediate consumption. Before November 2021, the UK applied single deflation. This is implicitly based on the assumption that output grows at a constant ratio to GVA, which is rarely correct. Since October 2021, ONS has used double deflation. See Appendix VI for more details.
[4] 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 (Avillez, 2012; Reinsdorf, 2015; De Vries et al., 2021)
[5] 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 that labour flows from low-productivity to high-productivity activities are a key driver of productivity growth from 1990-2005. 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.
[6] While Voskoboynikov (2020) also includes whole economy sector and finds that structural change is growth-enhancing but decreasingly so over time, the author only focuses on the Russia economy and does not use the Tornqvist decomposition.
[7] Out results confirm that the shift-share method provides similar results for the aggregate productivity growth pattern compared to our current approach. By contrast, the Generalized Exactly Additive Decomposition approach provides divergent results. See Appendix II for more details.
[8] As in De Vries et al. (2015), this term can be further decomposed into a static and dynamic component 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).
[9] 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, entrainment and recreation, S Other service activities, T Activities of households as employers.
[10] Stehrer, Bykova, Jäger, Reiter, and Schwarzhappel (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 US. (Data can be accessed here: https://euklems.eu/archive-history/download-archive/). 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.
[11] Note that the LUISS (i.e., EUKLEMS and INTANProd 2021) release provides advances over the EUKLEMS (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 of 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 Appendix VII. While we find the overall pattern is consistent (see, Table AVII 1 and Figure AVII 1 in 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 here:
https://euklems-intanprod-llee.luiss.it/wp-content/uploads/2022/02/EUKLEMSINTANProd_2021_Methods-and-data-description-Rev1.pdf
[12] As the EU KLEMS data combines 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.

[13] The reallocation is simply calculated as residual, subtracting the slowdown in $\Delta\bar{\omega}_i\Delta\ln(V_i/H_i)$ from the slowdown in $\Delta(\Delta ln\, V_i/H_i)$).
[14] Our working paper focuses on the six slowdown industries identified in this paper. In Coyle, McHale, Bournakis, and Mei (2022), we employ the UK ABS firm-level dataset (secure data access) to estimate the firm-level revenue based total factor productivity (TFPR), industry-level markups, and quantity based TFP.
[15] The TFP data is collected from the ONS estimates of total factor productivity from the Annual Business Survey:https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/articles/firmleveltotalfactorproductivitymeasuresfromtheannualbusinesssurveyuk1998to2019/august2022
[16] Jorgenson and Timmer (2011) highlight that specialisation 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 at, similar to Kaldor (1963) and Kuznetz (1971), 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 Appendix IV.
[17] To save space, we keep the US and UK in the main context but move other countries into Appendix III. In addition, we provide overall growth patterns between 1998-2008 and 2008-2015 across the 13 economies in Appendix III Tables AIII 1 and AIII 2.
[18] However, the time period selection does not drive the results. We provide evidence based on the whole time period 1998-2017 in Appendix V Table AV 3. We find that the key interested variable "Treat*Post" remains highly statistically significant at the 1% significance level. Its sign remains as negative, indicating that manufacturing and information and communication industries indeed cause the overall labour productivity slowdown.
[19] They are the UK, US, Japan, France, Belgium, Netherlands, Ireland, Denmark, Germany, Italy, Portugal, Austria, Czechia, Estonia, Greece, Finland, Sweden, Slovenia, and Slovakia.
[20] We also examine whether the reallocation component, treated as the dependent variable, could show up some interesting patterns. We repeat the exercise outlined in Eq. (14) and report results in Table AV 2 in Appendix V. Reassuringly, the results are consistent with the finding that the within component is the main contributor rather than the reallocation.

References

Abdirahman, M., Coyle, D., Heys, R. and Stewart, W., 2022. Telecoms Deflators: A story of volume and revenue weights. *Economie et Statistique/Economics and Statistics*, (530-31), pp.43-59.

Asker, J., Collard-Wexler, A. and De Loecker, J., 2014. Dynamic inputs and resource (mis) allocation. *Journal of Political Economy*, *122*(5), pp.1013-1063.

Autor, D., Dorn, D., Katz, L.F., Patterson, C. and Van Reenen, J., 2020. The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, *135*(2), pp.645-709.

Baqaee, D.R. and Farhi, E., 2019. The macroeconomic impact of microeconomic shocks: Beyond Hulten's theorem. *Econometrica*, *87*(4), pp.1155-1203.

Bloom, N., Jones, C.I., Van Reenen, J. and Webb, M., 2020. Are ideas getting harder to find?. *American Economic Review*, *110*(4), pp.1104-44.

Brynjolfsson, E., Rock, D. and Syverson, C., 2021. The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, *13*(1), pp.333-72.

Carvalho, V. and Gabaix, X., 2013. The great diversification and its undoing. *American Economic Review*, *103*(5), pp.1697-1727.

Coyle, D., Lind, K., Nguyen, D. and Tong, M., 2022. *Are digital-using UK firms more productive?* (No. ESCoE DP-2022-06). Economic Statistics Centre of Excellence (ESCoE).

Coyle, D. and Mei, J.C. and Hampton, L., 2022. UK Labour Productivity Dynamics: Relative Price Shifts and Labour Reallocation, *Working Paper*.

Coyle, D. and McHale, J. and Bournakis, I. and Mei, J.C., 2022. Foreign ownership and Productivity Growth at the Firm Level in UK industries. *Working Paper*, University of Cambridge.

Criscuolo, C., Andrews, D. and Gal, P.N., 2019. The best versus the rest: divergence across firms during the global productivity slowdown.

Crafts, N. and Mills, T.C., 2020. Is the UK productivity slowdown unprecedented?. *National Institute Economic Review*, *251*, pp.R47-R53.

Cunningham, C., Foster, L., Grim, C., Haltiwanger, J., Pabilonia, S.W., Stewart, J. and Wolf, Z., 2021. Dispersion in dispersion: Measuring establishment-level differences in productivity.

De Avillez, R., 2012. Sectoral contributions to labour productivity growth in Canada: does the choice of decomposition formula matter?. *International Productivity Monitor*, (24), p.97.

De Vries, G., Timmer, M. and De Vries, K., 2015. Structural transformation in Africa: Static gains, dynamic losses. *The Journal of Development Studies*, *51*(6), pp.674-688.

De Vries, G.J., Erumban, A.A., Timmer, M.P., Voskoboynikov, I. and Wu, H.X., 2012. Deconstructing the BRICs: Structural transformation and aggregate productivity growth. *Journal of Comparative Economics*, *40*(2), pp.211-227.

De Vries, K., Erumban, A. and van Ark, B., 2021. Productivity and the pandemic: short-term disruptions and long-term implications. *International Economics and Economic Policy*, *18*(3), pp.541-570.

Diao, X., McMillan, M. and Rodrik, D., 2019. The recent growth boom in developing economies: A structural-change perspective. In *The Palgrave handbook of development economics* (pp. 281-334). Palgrave Macmillan, Cham.

Diewert, W.E. and Gordon, R.J., 1996. Price and volume measures in the system of national accounts. In *The New System of National Accounts* (pp. 237-297). Springer, Dordrecht.

Diewert, W.E., 2015. Decompositions of productivity growth into sectoral effects. *Journal of Productivity Analysis*, *43*(3), pp.367-387.

Domar, E.D., 1961. On the measurement of technological change. *The Economic Journal*, *71*(284), pp.709-729.

Fabricant, S., 1942. Manufacturing in the National Economy. In *Employment in Manufacturing, 1899-1939: An Analysis of Its Relation to the Volume of Production* (pp. 153-168). NBER.

Garner, C., Russell, M., Bessen, J., Meyer, P.B. and Sveikauskas, L., 2021. Intangible Capital and US Productivity Growth in 61 Industries.

Goodridge, P., Haskel, J. and Wallis, G., 2018. Accounting for the UK productivity puzzle: a decomposition and predictions. *Economica*, *85*(339), pp.581-605.

Goodridge, P. and Haskel, J., 2022. *Accounting for the slowdown in UK innovation and productivity* (No. 022).

Harris, R. and Moffat, J., 2017. The UK productivity puzzle, 2008–2012: evidence using plant-level estimates of total factor productivity. *Oxford Economic Papers*, *69*(3), pp.529-549.

Hillinger, C., 2002. *A General Theory of Price and Quantity Aggregation and Welfare Measurement* (No. 818). CESIFO Working Paper.

Hulten, C.R., 1978. Growth accounting with intermediate inputs. *The Review of Economic Studies*, *45*(3), pp.511-518.
Jones, C.I., 2011. *Misallocation, economic growth, and input-output economics* (No. w16742). National bureau of economic research.
Jorgenson, D.W., Ho, M.S. and Stiroh, K.J., 2005. productivity, Volume 3: information technology and the American growth Resurgence. *MIT Press Books*, *3*.
Jorgenson, D.W. and Timmer, M.P., 2011. Structural change in advanced nations: a new set of stylised facts. *Scandinavian Journal of Economics*, *113*(1), pp.1-29.
Kaldor, N., 1961. Capital Accumulation and Economic Growth. *International Economic Association Series*, pp.177-222.
Kuznetz, S., 1971. Total Output and Production Structure. *Kuznetz.–Cambridge*, *503*.
Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy*, *74*(2), 132–157.
Lewis R (2021) Indicative impact of a new framework including double deflation on industry volume estimates of GDP: Blue Book 2021 https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/articles/impactofdoubledeflationonindustrychainvolumemeasureannualestimates1997to2018/bluebook2021
Linarello, A. and Petrella, A., 2017. Productivity and reallocation: evidence from the universe of Italian firms. *international productivity Monitor*, *32*, pp.116-136.
Maddison, A., 1952. Productivity in an expanding economy. *The economic journal*, *62*(247), pp.584-594.
Martin, J (2021) Impact of double deflation on labour productivity: 1997 to 2018 https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/articles/impactofdoubledeflationonlabourproductivity/1997to2018
McMillan, M.S. and Rodrik, D., 2011. *Globalization, structural change and productivity growth* (No. w17143). National Bureau of Economic Research.
Melitz, M.J. and Polanec, S., 2015. Dynamic Olley-Pakes productivity decomposition with entry and exit. *The Rand journal of economics*, *46*(2), pp.362-375.
Moussir, C.E. and Chatri, A., 2020. Structural change and labour productivity growth in Morocco. *Structural Change and Economic Dynamics*, *53*, pp.353-358.
Hulten, C.R. and Nakamura, L.I., 2022. *Is GDP Becoming Obsolete? The "Beyond GDP" Debate* (No. w30196). National Bureau of Economic Research.
Nguyen, T and Johansson K, (2022). Improving Estimates of Land Underlying Dwellings in the National Balance.
Nordhaus, W.D., 2008. Baumol's diseases: a macroeconomic perspective. *The BE Journal of Macroeconomics*, *8*(1).
Office for National Statistics (2021). Impact of double deflation on labour productivity 1998-2017. https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/articles/impactofdoubledeflationonlabourproductivity/1997to2018
Office for National Statistics (2022). Improving estimates of land underlying dwellings in the national balance sheet UK 2022. https://www.ons.gov.uk/releases/nationalbalancesheetredevelopmentlandunderlyingdwellings
Olley, S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64, 1263–1295.
Reinsdorf, M., 2015. Measuring industry contributions to labour productivity change: a new formula in a chained fisher index framework. *International Productivity Monitor*, (28), p.3.
Riley, R., Rincon-Aznar, A. and Samek, L., 2018. Below the aggregate: a sectoral account of the UK productivity puzzle. *ESCoE Discussion Papers*, *6*.
Schelling, T.C., 1958. The strategy of conflict. Prospectus for a reorientation of game theory. *Journal of Conflict Resolution*, *2*(3), pp.203-264.
Stehrer, R., Bykova, A., Jäger, K., Reiter, O. and Schwarzhappel, M., 2019. Industry level growth and productivity data with special focus on intangible assets. *Vienna Institute for International Economic Studies Statistical Report*, *8*.
Stiroh, K.J., 2002. Information technology and the US productivity revival: what do the industry data say?. *American Economic Review*, *92*(5), pp.1559-1576.
Tang, J. and Wang, W., 2004. Sources of aggregate labour productivity growth in Canada and the United States. *Canadian Journal of Economics/Revue canadienne d'économique*, *37*(2), pp.421-444.
Voskoboynikov, I.B., 2020. Structural change, expanding informality and labor productivity growth in Russia. *Review of Income and Wealth*, *66*(2), pp.394-417.