Editors' Overview

The 48th issue of the *International Productivity Monitor* sees an enlargement of the editorial team of the publication with Paul Schreyer joining as an Editor. Paul recently retired from the position of Chief Statistician at the OECD and is now the Research Director at the Economics Statistics Centre of Excellence (ESCoE) at King's College London. He has made major contributions to the productivity literature and we are delighted that he has joined the team.

The issue contains a symposium in UK productivity issues, with articles on the post-2007 productivity slowdown, regional productivity disparities, public sector productivity measurement and de-industrialization and the productivity slowdown. The issue also contains an article on the impact of Artificial Intelligence on productivity, and a review article on a recent volume on productivity measurement issues.

We live in the age of Artificial Intelligence (AI), considered by many the latest General Purpose Technology (GPT). A key question going forward is whether AI will have an impact on productivity similar to past GPTs. In the lead article in this issue, **Francesco Filippucci**, **Peter Gal**, **Katharina Laengle**, **Matthias Schief**, and **Filiz Unsal** from the OECD discuss the opportunities and risks of AI for productivity. Their approach is to relate aggregate AI productivity gains to three drivers, potential gains from AI at the task level, the economy-wide exposure to AI, and the AI adoption rate. They provide estimates of these drivers for G7 countries. The authors conclude that AI could raise US total factor productivity growth 0.4-0.7 percentage points per year over the next decade, but less in other G7 economies.

The persistent slowdown in UK productivity growth since the mid-2000s has become one of the most pressing economic challenges facing the country. Despite extensive research, there is still no consensus on its root causes, timing, or the reasons for the UK's underperformance relative to peers. The four articles in this symposium on the UK productivity puzzle offer complementary perspectives on this complex issue, ranging from macroeconomic trends and structural shifts to regional disparities and public service performance.

The first article, by **Josh Martin** from the Bank of England and King's College London, offers a comprehensive statistical review of the UK productivity slowdown. He argues that the deceleration began before the 2008 financial crisis and has been driven primarily by a decline in total factor productivity. Martin emphasizes that the slowdown is broad-based across industries, with particularly sharp declines in manufacturing and finance. He also highlights the importance of measurement challenges and structural shifts, such as the rise of intangible assets and environmental constraints, in shaping the UK's productivity trajectory.

The second article, by **Reitze Gouma** at the University of Groningen, and **Philip McCann** and **Raquel Ortega-Argilés** at the University of Manchester, critically examines recent revisions to regional productivity data by the UK Office for National Statistics. While the new data suggest a narrowing of regional disparities and a potential shift toward convergence, the authors caution that these findings may be artefacts of data inconsistencies, particularly in London. They argue that the apparent reversal of long-standing divergence trends is difficult to reconcile with economic fundamentals and may reflect temporary distortions during the pandemic.

Richard Prothero from the UK Office for National Statistics provides a response to the article. He agrees with the article's conclusion that one should wait for additional years of data before reaching a definitive viewpoint on whether UK regional productivity growth is converging or diverging.

In the third article, **Richard Heys** from the Office for National Statistics focuses on public service productivity, an often-overlooked component of the broader productivity picture. Drawing on a recent review by the UK Statistics Authority, Heys outlines methodological innovations that better capture quality-adjusted outputs in health, education, and other public services. These improvements suggest that public services may have contributed more to productivity growth than previously thought.

The final article in this symposium by **Paul Fisher** of the National Institute of Economic and Social Research Research (NIESR), provides a long-run structural interpretation of the slowdown, arguing that it is a natural consequence of economic maturity and deindustrialization. Drawing on historical data, Fisher reflects on the long-term shift toward a service-dominated economy where productivity gains are harder to measure and achieve. He calls for a rethinking of investment policy, emphasising digital infrastructure, human capital, and the green transition, as a means to revive growth and raise living standards.

Researchers face huge challenges in measuring productivity. The recent volume *The Measures of Economics: Measuring Productivity in an Age of Technological Change*, edited by Marshall Reinsdorf and Louise Sheiner from the Brookings Institution, sheds new light on this topic by laying out the conceptual issues and identifying ways forward. In the final article, **Chad Syverson** from the University of Chicago provides an overview of the volume. He notes that while there has been progress in productivity measurement, there remains much to do. He is however optimistic because the conceptual underlayment of ideal productivity measurement means that we know where the holes are, which can direct our efforts to where work is needed.

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Opportunities and Risks of Artificial Intelligence for Productivity

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Abstract

This article reviews recent evidence and projections on the impact of Artificial Intelligence (AI) on productivity growth, with a focus on G7 economies. Drawing on OECD work and related studies, it synthesizes a range of estimates, suggesting that AI could raise annual total factor productivity (TFP) growth by around 0.3–0.7 percentage points in the United States over the next decade. Projected gains in other G7 economies are up to 50 per cent smaller, reflecting differences in sectoral composition and assumptions about the relative pace of AI adoption. The article compares alternative modeling approaches and explores key mechanisms underpinning these projections. It also discusses risks —such as market concentration, algorithmic collusion, and Baumol effects as well as upside potentials related to innovation, skills, and trade integration through AI-driven efficiency gains.

Reviving sluggish productivity growth is a crucial issue for most advanced economies (Goldin *et al.*, 2024; André and Gal, 2024). This article discusses the potential of Artificial Intelligence (AI) to significantly impact productivity and growth in the medium term, drawing on previous OECD work (Filippucci *et al.*, 2024a, 2024b and forthcoming) as well as other recent literature. Using the framework in

1 The authors are grateful for comments on and contributions to various previous works that fed into this article by Christophe Andre, Manuel Betin, Flavio Calvino, Alain De Serres, Jonathan Haskel, Asa Johansson, Cecilia Josa-Lasinio, Tomasz Kozluk, Alvaro Leandro, Giuseppe Nicoletti, Paul Peltier, Alvaro Pereira and Daniel Rock. The views expressed in this article are solely those of the authors and should not be interpreted as those of the Organization for Economic Co-operation and Development (OECD) or its member countries. Filiz Unsal is the Head of Structural Policy Research Division, OECD. Peter Gal is a Senior Economist and Deputy Head of Structural Policy Research Division, OECD. Francesco Filippucci, Katharina Laengle and Matthias Schief are Junior Economists in the Structural Policy Research Division, Economics Department at the OECD. Emails: francesco.filippucci@oecd.org, peter.gal@oecd.org, katharina.laengle@oecd.org, matthias.schief@oecd.org and filiz.unsal@oecd.org.

these studies, we first provide an assessment of the predicted contribution of AI to growth in aggregate total factor productivity (TFP) growth over the next decade in G7 economies. We then review the risks and opportunities that could cause the impact of AI on productivity growth to vary, either amplifying or reducing it.

Our references for the expected impact of AI on productivity are the headline projection in Filippucci *et al.* (2024a) and (Filippucci *et al.*, forthcoming), which estimates that AI could contribute between 0.3 and 0.7 percentage points to annual aggregate TFP growth in the United States over the next decade.[2]

The predicted impacts across different scenarios are highest in the United States, followed by the United Kingdom, Germany, Canada, France and Italy, and lowest in Japan. These figures indicate that Generative AI will likely be an important source of aggregate productivity growth over the next 10 years but also clarify that the expected gains from the current generation of AI technologies may not be extraordinary.[3] For comparison, the latest technology driven boom linked to information and communication technologies (ICT) has been estimated to have contributed up to 1-1.5 percentage points to annual TFP growth in the United States during the decade starting in the mid-1990s (Byrne *et al.*, 2013; Bunel *et al.*, 2024).

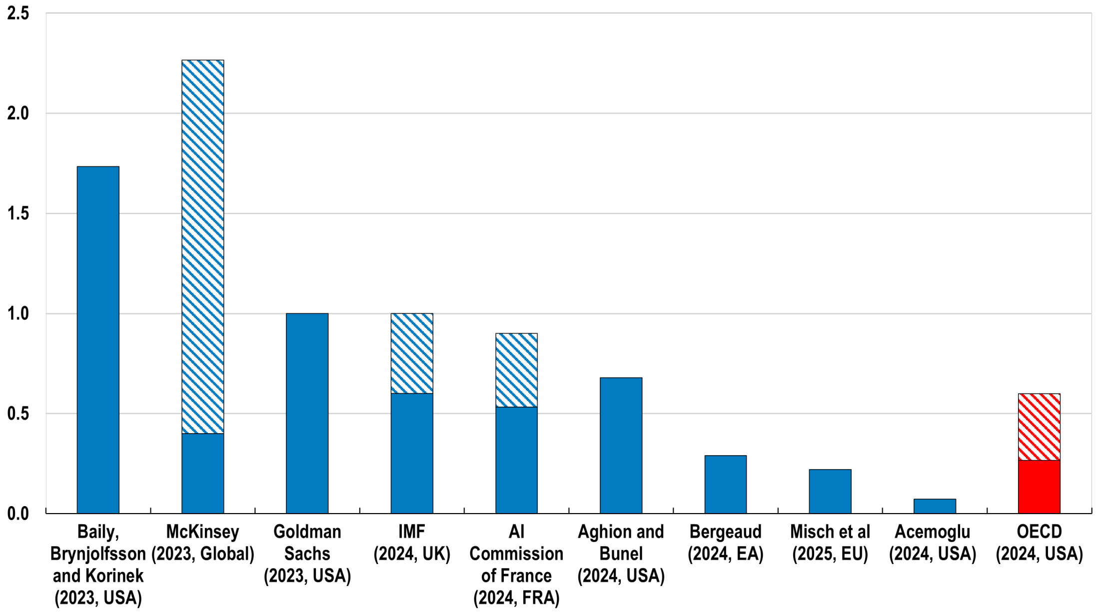
These growth projections are larger than those provided by Acemoglu (2024) but also significantly smaller than some of the more bullish predictions of other authors that have been widely discussed (see Chart 1). For instance, Briggs and Kodnani (2023) give an optimistic view based on their large aggregate productivity growth estimates, amounting to around 1 percentage point TFP boost per year. In contrast, the assessment by Acemoglu (2024) is more cautious. Using a task-based aggregation framework and Hulten's (1978) theorem, he suggests that AI will only allow 0.07 percentage points of additional TFP growth per year. Aghion and Bunel (2024) and Misch *et al.* (2025) use the framework in Acemoglu (2024) but rely on different assumptions from the literature to arrive at numbers that are in between but closer to the optimistic end of the spectrum (around 0.7 percentage points boost to TFP).

AI's impact on productivity and its development trajectory entail both upside and downside risks. On the downside, anti-competitive outcomes in the provision of AI can hamper access to affordable, high-quality AI services (André *et al.*, 2025; Filippucci *et al.*, 2024b; OECD, 2024). We also highlight concerns around AI-powered business models that exploit behavioural biases or enable tacit price col-

2 Filippucci *et al.* (2024a) lays out the conceptual framework to gauge the aggregate productivity gains from AI, building on Acemoglu (2024), and Filippucci *et al.* (forthcoming) updates the results based on more recent evidence on AI adoption rates.

3 Further breakthrough innovations in AI technology are possible and could lead to greater gains over our projection horizon. Future technological developments may also alter the nature of AI technology and how it interacts with capital and labour to generate productivity gains, especially if significant progress towards Artificial General Intelligence is realized (Trammell and Korinek, 2023). While forecasting the pace and trajectory of technological advancement in AI is clearly of great importance, it goes beyond the scope of this article.

Chart 1: AI's Predicted Aggregate TFP Gains Across Different Studies (in percentage points, annualized)



Note: When the source presents a range of estimates as the main result, the lower and upper bounds are indicated by dashed areas. In cases where modelling predictions primarily focus on labour productivity, TFP is obtained using simple assumptions about the aggregate capital multiplier (Acemoglu *et al.*, 2023; Aghion *et al.*, 2017; Bergeaud, 2024). The estimates refer to the countries shown in brackets.
Sources: See references at the end of the article; for Goldman Sachs (2023), the underlying reference is Briggs and Kodnani (2023); for IMF (2024) the underlying reference is Rockall *et al.* (2025); for OECD, the underlying reference is Filippucci *et al.* (2024a).

lusion (OECD, 2018 and 2021), as well as broader risks such as the misuse of AI in malicious activities (Acemoglu, 2024; OECD, 2025) and the threat of Baumol's growth disease, where the relative rise of non-AI impacted, low-productivity growth sectors dampen overall GDP growth (Filippucci *et al.*, 2024a; Baqaee and Farhi, 2019; Nordhaus, 2008). On the upside, AI can drive productivity gains through faster research, innovation and hence technological progress (Aghion *et al.*, 2017; Calvino *et al.*, 2025b); by fostering skill development (Cheon *et al.*, 2025; Mollick *et al.*, 2024); and by boosting trade through lower trade costs and transmitting efficiencies along global value chains (WTO, 2024).

In what follows, we first explain and compare our conceptual framework to other approaches regarding the modelling of the impact of AI on aggregate productivity growth. In section two, we then review micro-level drivers of productivity gains in this framework, discuss our interpretation of the available empirical evidence, and the assumptions we will derive from this evidence. Next, we examine several aspects that are outside of our framework that can constitute upside and downside risks to our quantitative assessment. Important questions around AI, such as the implications for inequality or the consequences of further advances in AI technology towards Artificial General Intelligence (AGI) are deliberately kept outside the scope of this article.

Conceptual Framework

An Economic View of AI Systems: Inputs and Outputs

According to the OECD,

"*an AI system is a machine-based system that, for explicit or implicit objectives, infers from the input it receives how to generate outputs —such as predictions, content, recommendations, or decisions —that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment*" (OECD, 2023c).[4]

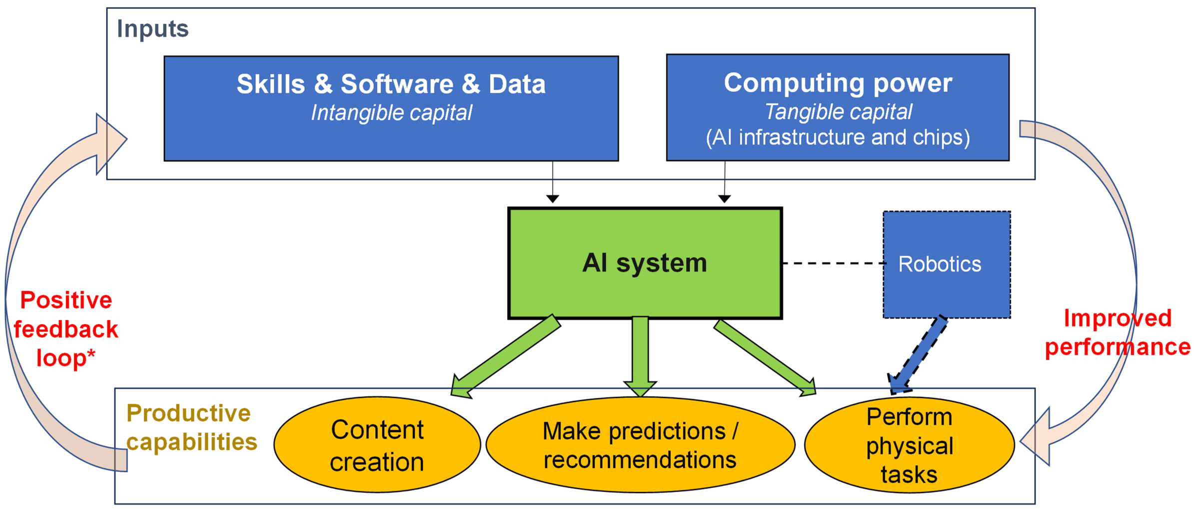
Building on this definition, and given this article's focus on productivity implications of AI, we propose conceptualizing AI systems as a form of production technology, combining various inputs to generate productive capabilities (Figure 1). These capabilities then allow AI-using firms to increase their productivity by improving their production processes and other business activities. For instance, AI as a content creator can be employed in the audiovisual and broadcasting sector to more efficiently generate animations and graphics for videos, harnessing industry-specific tangible and intangible capital (e.g. studios, network infrastructure, expertise, reputation) alongside labour (e.g. graphic designers, journalists). In this context, "more efficiently" means that identical input quantities can produce superior-quality outputs (e.g. visuals that are more engaging or enjoyable for the audience) or a higher volume of output (e.g. creating more videos of equivalent quality employing the company's labour and capital, in the same amount of time).

The operations of AI systems rely on a few key intangible and tangible assets, often complementary to each other (Corrado *et al.*, 2021). Among intangible inputs, skills are critical (e.g. highly trained IT engineers, programmers and data scientists). Another critical input is software, in the form of AI models. Such software often requires vast quantities of data , which is the third key intangible component. Data can take various forms and can enter the system at various phases: either during the development phase of AI, which typically requires large-scale training data used prior to deployment, or for its actual use phase (post-deployment), when additional data may be used by the AI model to execute a query.

Turning to physical (tangible) inputs, the most important inputs are computing power and connectivity. Advanced AI systems require top performance semiconductor chips or specialized computing infrastructure not only during the initial, mostly developmental phase (pre-deployment), but also in actual operation,

4 Other definitions in the literature are focused on the comparison with human capabilities. For instance: "AI is a loose term used to describe a range of advanced technologies that exhibit human-like intelligence including machine learning, autonomous robotics and vehicles, computer vision, language processing, virtual agents, and neural networks." (Furman and Seamans, 2019) or "AI is an umbrella term that refers to a computer system that is able to sense, reason, or act like a human." (Brynjolfsson *et al.*, 2025). Recent work jointly carried out by computer scientists and economists writes: "Artificial intelligence (AI) refers to the science and engineering of building digital systems capable of performing tasks commonly thought to require intelligence, with this behaviour often being learned rather than directly programmed" (Sastry *et al.*, 2024).

Figure 1: AI as a Production Technology (provided by upstream firms)



Note: *Positive feedback loop refers mostly to the training, pre-deployment phase. For ease of exposition regarding the main economic features and implications of AI systems, the terminology may differ from reports with a more technical focus, notably OECD (2023b).
Source: Author's elabouration, building on OECD, 2023b, and Sastry *et al.*, 2024.

during the use phase (post-deployment).[5] Maintaining such high computing power requires an intensive use of energy, another critical input. Finally, high-speed connectivity is necessary especially for performing user-model interactions during final use of AI (i.e. inference phase).

The output of AI systems is a set of productive capabilities. Current AI systems can carry out or assist with cognitive tasks, such as creating content (text, program code, visuals, etc.) or with taking decisions based on sophisticated predictions, recommendations and optimization (Agrawal *et al.*, 2023b). When combined with robotics – machines equipped with sensors and fine motor capacities, including not only humanoid robots but automated assembly lines – they can also perform physical tasks, as in the case of autonomous vehicles.

Based on their functioning and outputs, a useful distinction can be made between more recent Generative AI on the one hand, and prediction, optimization or decision-oriented AI on the other hand. We call the latter non-Generative AI, often referred to pre-Generative AI or predictive AI. Non-Generative AI primarily relies on explicit algorithms and probabilistic models to make low-dimensional predictions and recommendations, based on more

5 See Russo *et al.* (2025) for a discussion and measurement of cloud compute capacity relevant for AI.

simple machine learning models. Generative AI systems are instead mainly designed to produce more complex and multi-dimensional output, i.e. content, such as text, program code, images, videos, or sounds in response to natural (human) language queries, or prompts. Large Language Models (LLMs) fall under this category, with ChatGPT by Open AI being a key example. Generative AI systems are enabled by the "transformer" architecture developed in 2017, which are more efficient than their predecessors (recurrent neural networks) because they can process natural language input in parallel rather than merely in sequence, thus effectively reducing training and computing time. This breakthrough allowed for exponential increases in scale and complexity, with the most refined models featuring billions of parameters.[6]

As shown in Figure 1, most current AI systems are characterized by a positive feedback-loop, that is, self-improvement capacity or learning that can lead to better performance. On the one hand, self-improvement may occur while being trained, that is optimizing and fine tuning the model parameters without yet changing the basic design of the AI model itself (e.g., pricing algorithms). On the other hand, sometimes this process occurs continuously, while in actual use (technically called inference phase). A distinct future possibility is that self-improvement of AI becomes so important that it leads to a singularity or Artificial General Intelligence (AGI), which is usually defined as an AI that surpasses human-level intelligence on nearly all cognitive domains.

AI as a Production Technology for Users

While Figure 1 outlines the key inputs for the production of AI technologies, a related yet distinct question concerns how these technologies influence the production of goods and services in industries that have integrated AI into their production processes. Following recent technological developments, a distinction emerged in the AI value chain, with upstream firms specializing in developing AI technology, particularly increasingly powerful and complex foundational models, while downstream firms adopt these technologies to enhance their productivity (André *et al.*, 2025).[7]

For downstream firms, the primary cost is the initial investment needed to successfully integrate AI in their production processes (e.g. curating firm-specific data and acquiring skills to tailor and apply AI tools), which can result in slower adoption rates. In turn, the marginal user costs of AI appear to be very low relative to prospective gains, with the quality-adjusted cost of AI falling fast (André *et al.*, 2025). Hence in the next section, we model the impact of AI on downstream firms as a pure produc-

6 As an additional distinction, some Generative AI models are considered "foundation" models, given their broad applicability in a range of fields, as opposed to tailor-made models targeting a specific task. Besides sophisticated text and software programme code, foundation models can produce sounds, images or video.

7 In addition, a set of intermediaries often leverages foundational models to develop more specific AI-powered services, for instance customer service bots, search engines, collabouration tools, etc.

Table 1: Comparing AI to Selected Previous General Purpose Technologies (in percentage points, annualized)

	Steam Engine and Electricity	**Computers and Internet**	**Artificial Intelligence**
Nature of Tasks Primarily Affected	Physical	Cognitive routine and communication	Broad range of cognitive and complex
Autonomy & Self-Improvement	Cannot operate independently from humans	Limited autonomy but not self-improving	Potentially autonomous and self-improving
A Method of Invention	No	Yes	Yes

Source: Adapted from Filippucci *et al.* (2024a), building on Lipsey *et al.* (2005) and Agrawal *et al.* (2023a).

tivity shock that augments the efficiency of the users' production function, allowing firms to produce more output for a given amount of inputs.

In particular, and in contrast to some of the previous literature, we view AI as a transformative technology that can improve the joint productivity of labour and capital inputs, i.e. as a technology that increases total factor productivity (TFP). In other words, in our view, AI should not be seen merely as a tool for reducing labour costs, but instead jointly enhancing the productivity of workers and the capital used in production (e.g. computers, office equipment, office space). For instance, the AI-driven time savings in writing tasks documented in Noy and Zhang (2023) imply reductions not only in labour input but also in the use of capital services per completed task. Therefore, we conclude that AI-induced time savings can be interpreted as total factor productivity gains.[8] Furthermore, it cannot be ruled out that AI improves even gross-output based TFP, by increasing the efficiency of how intermediate inputs are combined with capital and labour. This could occur, for example, if AI optimizes production chains, facilitates trade and supply chains (Ahn *et al.*, 2024), or boosts sales through improved marketing and customer service (Hartmann *et al.*, 2023; Guerron-Quintana *et al.*, 2024; Ni *et al.*, 2024).

The Impact of AI on Aggregate Productivity

The rapid advancement of AI has sparked debate about its potential to be a technology that significantly impacts aggregate productivity growth. Historically, these technologies are often the so-called general-purpose technologies (GPTs), defined by three key characteristics: (1) *pervasiveness*, i.e. widespread adoption across diverse industries; (2) *continuous improvement*, i.e. ongoing improvements in performance and capabilities and; (3) *innovation spawning*, i.e. the ability to stimulate innovation in products and processes (Lipsey *et al.*, 2005).

A number of studies evaluates the possibility that AI can be considered a GPT and provide general support for the idea based on emerging evidence, although note that AI is yet to be fully rolled out (Baily *et al.*, 2025; Agrawal *et al.*, 2023a; Calvino

8 Supporting evidence comes from the US Census Business Trends and Outlook Survey (BTOS) AI Supplement, which reported that by early 2024, the share of firms using AI to "perform operations previously performed by existing equipment or software" was roughly three-quarters of those using it to "perform tasks previously done by employees," suggesting AI enhances the productivity of both labour and capital.

et al., 2025b). Table 1 compares the characteristics of AI to previous GPTs, highlighting the potential of AI to become a GPT capable of significantly impacting aggregate productivity in the future. While AI targets a different set of outputs and tasks than previous GPTs, primarily affecting cognitive and complex functions rather than physical or routine cognitive ones, these outputs and tasks represent a broad and growing share of economic activity today.[9] In addition, AI possesses a high degree of autonomy, self-improvement potential, and can become a "method of invention", given its ability to generate and test ideas.

Given AI's strong potential as a GPT, an emerging literature formally discusses the aggregate productivity implications of AI. It can be divided into two broad strands: one is mostly theoretical and focuses on the potential implications of continued advances in AI technology for long-term productivity growth (over several decades), the other is focused on the nearer term (up to 10 years or so) and draws more directly on existing evidence of the productivity gains from using current generation AI technology.

Papers on the long-term growth implications of AI typically operate with aggregate production functions and focus on how AI could transform the growth process, also —or primarily —through impacting research and innovation. In particular, Trammell and Korinek (2023) discuss how transformative AI explore scenarios that could lead to sharply accelerating, "explosive" economic growth. Nordhaus (2021) and Aghion *et al.* (2017) similarly explore the possibility of explosive growth (i.e. singularities) and also discuss the limiting factors that could prevent such a scenario. They emphasize that growth may be constrained by a Baumol growth disease type effect if parts of the economy remain largely unaffected by AI even though they are producing goods and services that are essential (i.e. face strong demand).In this case, the sectors with the lowest productivity gains are expected to grow as a share of nominal GDP, thereby reducing the aggregate importance of productivity gains that AI may achieve in other sectors. A common feature of all papers on the long-run implications of AI is that they emphasize the potential productivity gains that could arise under continued technological advances in AI rather than quantifying the productivity gains that could be achieved with current AI technology.

In contrast, the second strand of the literature starts from the fast-growing body of empirical evidence on the performance gains from adopting available AI solutions at the individual worker or firm level, and asks how such microeconomic gains might translate to aggregate productivity growth over the next decade. Answering this question requires a suitable conceptual framework that clarifies what elements need to be considered in such a micro-to-macro approach. An influential contribution in this literature is Acemoglu (2024) who proposes

9 The range of tasks influenced by AI could expand even further when combined with complementary technologies such as robotics (Filippucci *et al.*, 2024a).

Table 2: Comparison of Modelling Choices on Impact of AI on Productivity

	Goldman Sachs (2023)*	Acemoglu (2024)	Aghion and Bunel (2024)	Filippucci *et al.* (2024a)
I Assumption about AI				
Micro-level productivity gains / cost savings from AI**	30%	27% labour cost savings	27–40% labour cost savings	30% productivity gains (total cost savings)
Exposure to AI	About two-thirds of all jobs	20% Based on Eloundou *et al.* (2024)	18.5–68% Based on Eloundou *et al.* (2024), Gmyrek *et al.* (2023), Pizzinelli *et al.* (2023)	12%–50% (sector specific; averaging approx. 35%). Building on Eloundou *et al.* (2024)
Adoption rate of AI	About 50%	23% Based on cost effectiveness, following Svanberg *et al.* (2024)	23–80% Based on Svanberg *et al.* (2024), Besiroglu and Hobbhahn (2022)	23% or 40% Based on previous GPT adoption speed and current sectoral adoption rates
II Mechanisms captured in the framework				
Reallocation across sectors explicitly modelled?	Partially***	No	No	Yes
Cross-sectoral links explicitly modelled?	No	No	No	Yes
Distributional consequences modelled?	No	Yes	No	No
Innovation	Not considered	Not considered	Not considered	Not considered

Notes: * Goldman Sachs (2023) refers to Briggs and Kodnani (2023).
** Based on the following assumptions: 7% of all workers are displaced and find new employment; all other workers remain in their current jobs but become more productive; the structure of the economy (sectoral composition, prices, etc.) does not adjust.
*** Based on micro-level studies that identify task-level gains from using LLMs.
Source: Filippucci *et al.* (2024a). For a more detailed discussion, see section 2 in Filippucci *et al.* (2024a).

to gauge the aggregate productivity gains from AI by adopting a task-based model of production and leveraging Hulten's aggregation theorem (Hulten, 1978). Specifically, Acemoglu suggests computing the aggregate productivity gain from AI over the next decade as the product of three numbers: (1) the potential productivity gain in "AI exposed" tasks, that is, in tasks that can be performed more productively with the help of AI; (2) the value-added share of AI exposed tasks; and (3) the AI adoption rate in AI exposed tasks.

Even within this second strand of the literature, studies have reached different conclusions regarding the size of the aggregate gains from AI. Acemoglu (2024) finds that AI-driven productivity gains will be trivial in the aggregate, amounting to a cumulative increase in aggregate TFP of only 0.7 per cent over a 10-year period. In contrast, Filippucci *et al.* (2024a) and Aghion and Bunel (2024) arrive at substantially larger growth predictions by following the same, or similar, strategy, but considering less restrictive assumptions on AI-driven micro gains, exposure, and adoption compared to those in Acemoglu (2024). These papers find aggregate productivity gains on the order of 0.24-1.3 percentage points per year over the next decade. Bergeaud (2024) finds similarly large numbers for a range of European economies.

In Filippucci *et al.* (2024a) as well as its empirical extension to G7 economies in Filippucci *et al.* (forthcoming), we contributed to this debate in several ways. First, we reviewed a larger body of evidence regarding the task-level gains from AI and also considered a broader set of scenarios for AI exposure and AI adoption. Second, we went beyond the aggregation strategy proposed in Acemoglu (2024) to explore the possibility that the aggregate gains from AI may be constrained by a Baumol growth disease type drag if the productivity gains are limited to only a few sectors in the economy. Specifically, we followed a two-step aggregation strategy, in which we first applied the framework in Acemoglu (2024) to derive estimates of the sectoral gains from AI. This step revealed large sectoral variation in the expected gains from AI. In a second step, we then used a multi-sector GE model (borrowing from Baqaee and Farhi (2019)) to illustrate how differential productivity growth across sectors might give rise to a Baumol growth disease type effect. This aggregation strategy also allowed us to discuss how the size of the Baumol effect depends on the cross-sectoral elasticity of substitution in demand and the degree to which factors can be reallocated across sectors. Table 2 compares the key assumptions and modelling choices in Filippucci *et al.* (2024a) with several closely related papers in the literature.

In this article, we build on Filippucci *et al.* (2024a) and extend the results to other G7 economies (Filippucci *et al.*, forthcoming). In doing so, our main focus is cross-country differences in exposure and adoption rates rather than the implications of sectoral reallocation. We also discuss additional upside and downside risks to our projections that could arise inside and outside our conceptual framework.

AI and Aggregate Productivity in G7 Economies

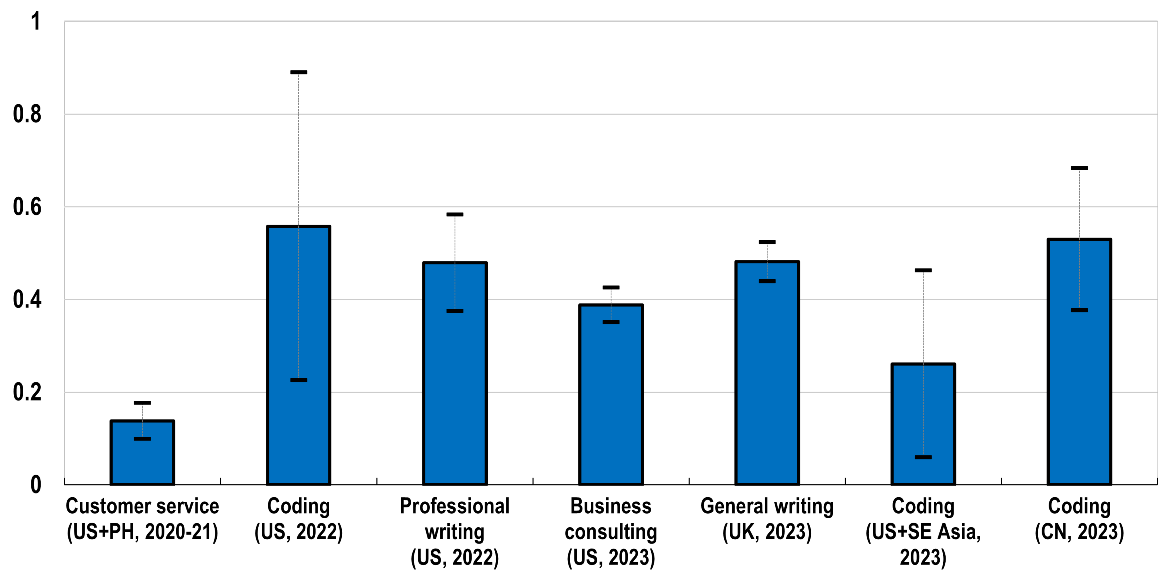
We follow the approach in Acemoglu (2024) to arrive at aggregate productivity impacts from AI. This approach allows relating aggregate gains from AI to three drivers that have an empirical underpinning and thus can be used for quantifying the gains: understanding and measuring the potential gains from AI at the task level; estimating the economy-wide exposure to AI; and predicting AI adoption rates in the economy over the next decade. Below, we discuss each of these determinants separately.

Task-level Productivity Gains

Filippucci *et al.* (2024a) review existing studies that estimate task-level productivity gains thanks to the use of Generative AI. These micro-level studies are often conducted as controlled experiments, lending strong credibility to the estimated effects, and cover a range of activities, such as customer services activities, software development, or professional writing and business consulting tasks. The estimates indicate that the effect of AI tools on worker performance range from 14 per cent, for example in customer service assistance, to 56 per cent, for example in coding, as shown in Chart 2.

In particular, Brynjolfsson *et al.* (2025) exploited the staggered adoption over time of AI-based support to customer service employees in business process software developer companies in 2020-2021, finding a large and significant increase in the number of case resolutions per worker (labelled

Chart 2: Task-level Productivity Gains from Generative AI



Note: The graph shows the productivity gains reported in different studies, together with 95 per cent confidence intervals. In parentheses, the reference country and year of the studies are shown.
Source: Filippucci *et al.* (2024a).

as Customer-service, 2020-21 on Chart 2). Another study estimated the effect of AI coding assistants on software developers, finding an extremely high and significantly positive effect on the number of coding tasks completed (Coding —2022; Peng *et al.*, 2023). Finally, the advent of Chat-GPT spurred a number of randomized controlled experiments estimating its effect on workers, finding a large and significant positive effect of the AI technology: on the speed and quality of professional writing tasks (Professional writing – 2022; Noy and Zhang, 2023), business consulting performances (Business consulting – 2023; Dell'Acqua et al., 2023), and time and quality of writing tasks for a sample of workers (General writing – 2023; Haslberger *et al.*, 2023).[10]

One concern is that these studies were carried out in contexts where performance gains are most promising and may not extend to other business contexts and when AI is used at scale in real-life environments. However, it is important to note that for our purposes we need to come up with an estimate of the average potential productivity gain in AI-exposed tasks, not the average gain in any task. Still, to remain conservative, we will assume a 30 per cent micro-level gain, which is close to the average of the three most precise estimates and excludes studies on coding, where the productivity gains from AI may be particularly large.

More recent OECD research spans an

10 A number of studies have also examined the firm-level impact of pre-generative AI technologies, albeit without relying on experimental or quasi-experimental methods. These studies generally report positive and statistically significant effects (Figure A.1 in the Appendix), suggesting relatively substantial task-level productivity gains and exposure already from pre-generative AI in specific contexts.

even broader range of findings from the rapidly growing literature (Calvino *et al.*, 2025b). In language translation, Lyu *et al.* (2023) show significant improvements in generative AI's performance, while Merali (2024) finds that enhanced AI capabilities allow translators to work faster, produce better outputs, and earn more, especially benefiting lower-skilled translators. In medical imaging, AI can deliver useful predictions, even if radiologists still hesitate to fully trust these AI-generated predictions (Mullainathan and Obermeyer, 2019). In legal contexts, AI helps summarize complex judgments (Deroy *et al.*, 2024), correctly assess simple questions about legal issues and interpretation (Choi and Schwarcz, 2023; Schwarcz *et al.*, 2025) but also improve judicial decisions (Kleinberg *et al.*, 2018). In some of these instances, the gains from AI are of comparable magnitude to the ones in Chart 1 or even larger (Schwarcz *et al.*, 2025).[11]

The Exposure of Tasks to AI by Sectors

Although AI can assist with a broad array of tasks, as discussed earlier, these account for only a portion of total economic activity. To quantify to what extent AI can potentially impact tasks, tasks are categorized based on whether they are exposed to AI. A task is exposed to AI if it can be performed more effectively with the help of AI. Acemoglu (2024) and Filippucci *et al.* (2024a) rely on estimates of task-level exposure to AI from Eloundou *et al.* (2024).[12] This article evaluates for each task in the detailed US-based occupational database O*NET whether it can be performed at least 50 per cent faster with the help of AI or with AI integrated with additional software.

We distinguish between two different measures of exposure. The first measure, which we label baseline exposure, is based on the median estimate from Eloundou *et al.* (2024). Note that this estimate relies only on what were Large Language Models (LLM) capabilities at the time of their study, in 2023, and thus excludes subsequent and future improvements in AI.[13] Therefore, our second measure accounts of AI exposure with *expanded capabilities* fully considers as AI-exposed those tasks where additional software could be developed on top of LLMs, reducing the time it takes to complete the task by at least half. We interpret this measure as a more

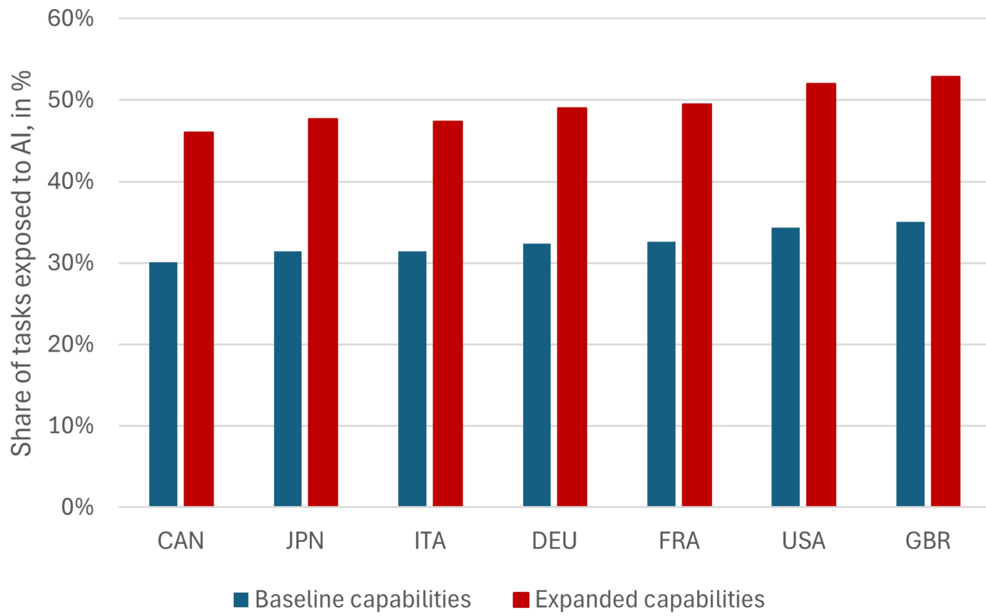
11 Firm-level evidence on pre-generative AI suggest gains that appear to be of a smaller magnitude, similar to the gains from other ICT technologies, although causal identification is more challenging than in the experimental settings at the task level – see Figure A.1 in the Appendix.

12 An alternative, earlier measure is developed by Felten *et al.* (2021) which shows strong correlation with Eloundou *et al.* (2024)

13 Eloundou *et al.* (2024) refer to their median estimate as the measure.

14 Eloundou *et al.* (2024) also offer a third exposure measure, which they label "automation index" and which is meant to capture whether a work activity can be autonomously performed by AI. Specifically, this more restrictive exposure measure requires that LLMs can complete at least 90 per cent of the task autonomously. It is this exposure measure that is used in Acemoglu (2024), which partly explains why he finds smaller productivity gains from AI compared to Aghion and Bunel (2024) or Filippucci *et al.* (2024a).

Chart 3: AI Exposure in G7 Countries



Note: This chart reports the average share of tasks exposed to AI across G7 economies. Country-level averages are obtained by mapping granular task-level exposure from Eloundou *et al.* (2024) (relying on LLM capabilities as of 2023) to occupations within different sectors. This approach distinguishes the occupational composition of 43 sectors (ISIC Rev. 4) which are aggregated to the country-level using respective 2019 pre-pandemic value added shares of different sectors. Due to a lack of data, the occupational composition of industries in Japan is assumed to be the same as in the G7 average.
Source: Filippucci *et al.* (2024a).

forward looking one, more likely to capture average exposure over our projection horizon.[14]

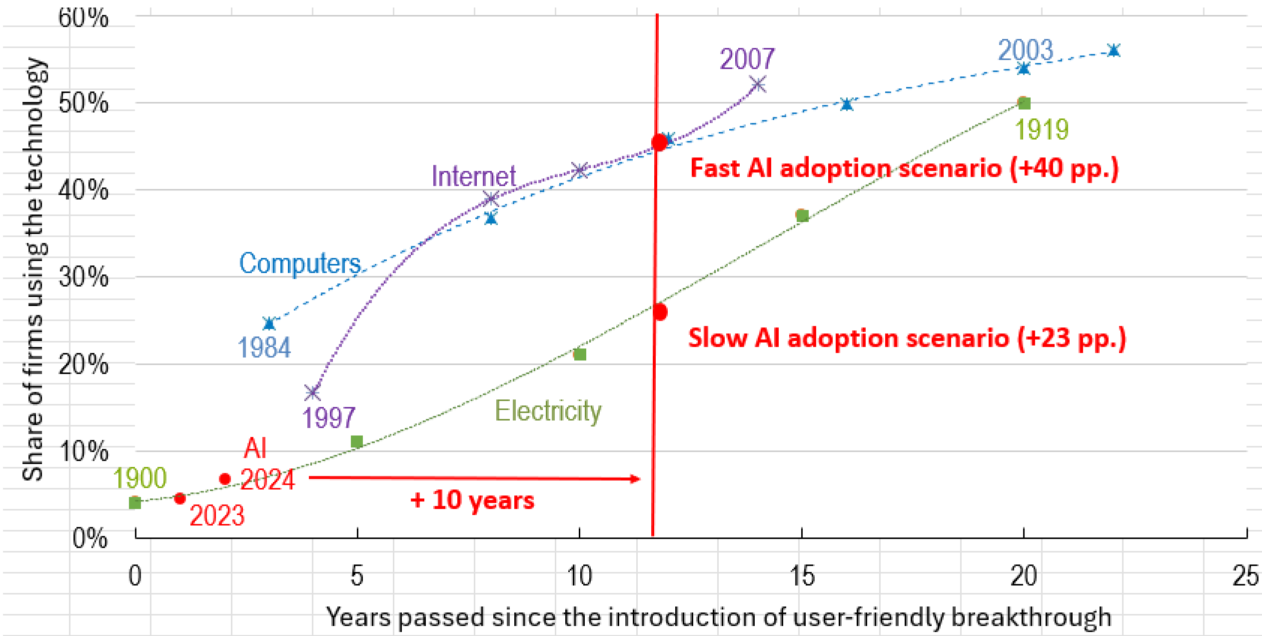
Starting from task-level estimates, we calculate the average AI exposure of detailed occupations based on the O*NET dataset. For each G7 country, we then aggregate occupations into industries and compute aggregate exposure, weighting each industry by its value-added share in the national economy. Chart 3 presents the resulting country-specific estimates of AI exposure, ranging between 30 and 35 per cent for baseline AI capabilities and around 50 per cent for expanded AI capabilities. These are substantial figures but far from covering the whole economy.

Cross-country variation arises from differences in the structure of economic activity – industries such as ICT, finance, and professional services, which are more exposed to AI, contribute more to value added in some countries than in others – and to a lesser extent from variation in the occupational composition within industries, as some countries have a higher incidence of AI-intensive roles (e.g., coders, translators, or accountants) in specific industries. Overall, the differences in exposure among G7 countries are such that the most exposed country reports levels approximately 15 per cent higher than the least exposed one.

Projected AI Adoption Rates

Aggregate productivity gains from AI can only be realized if AI technology is ac-

Chart 4: AI Adoption Paths Following Previous General Purpose Technologies



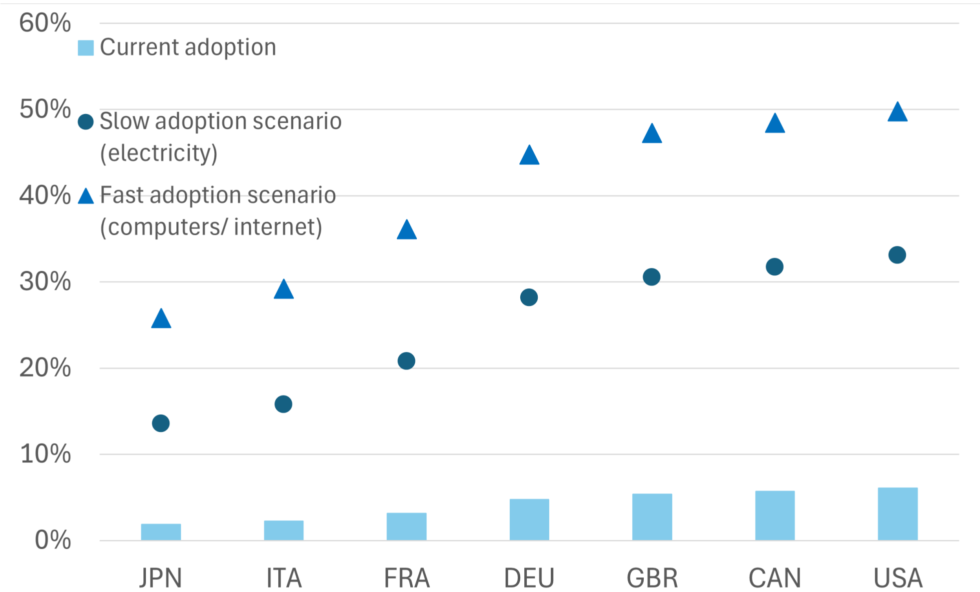
Source: adapted from Filippucci, Gal and Schief (2024), building on United States Census (internet and computers) and Woolf (1987) for electricity adoption of businesses and United States Census Bureau, Business Trends and Outlook Survey (BTOS) for AI adoption.

tually used i.e. adopted, by firms. Hence, to assess the economy-wide magnitude of these gains, we need to project the economy wide AI adoption rate into the future. Consistent with the literature, we aim at predicting productivity gains over a 10-year projection horizon and therefore project AI adoption rates of the next decade.

The rate at which AI applications will spread throughout the economy depends on many different factors, such as their user-friendliness, their cost effectiveness, the need for complementary investments, the availability of data centers and other types of infrastructure, the general degree of business dynamism, or even cultural factors shaping the readiness of workers to embrace AI tools. Predicting AI adoption rates over the next decade is therefore a challenging task. That said, it can be instructive to consider the historical experience with previous major GPTs, such as electricity, computers, or the internet. Chart 4 shows the adoption rates among firms for these technologies in the United States during the first 10 years after a user-friendly breakthrough becomes available (taken to be the appearance of ChatGPT in the case of AI). According to this historical experience, adoption rates can be expected to rise by approximately 23 to 40 percentage points over a 10-year period.

Given the considerable uncertainty around future adoption rates, we consider two scenarios. Our slow adoption scenario of a 23 percentage point increase is in line with the relatively slow adoption path of an earlier technology, electricity. In contrast, our rapid adoption scenario is in line with the adoption path of digital technologies in the workplace such as computers and the internet. Acemoglu (2024) also assumed

Chart 5: AI Adoption Among Firms in 2024 and Projections for 2034, in Per cent per year



Note: This chart presents the current AI adoption and its projected increase across G7 countries within 10 years. Predictions are based on extrapolations of comparable current AI adoption rates, derived through data harmonisation and out-of-sample predictions with digital infrastructure quality and skills as determinants. Extrapolations are in line with previous General Purpose Technologies electricity (slow adoption scenario) and computers/ internet (rapid adoption scenario).
Source: Authors' calculations (Filippucci *et al.*, forthcoming).

a 23 per cent adoption rate adoption over 10 years (compared to approximately zero in the base year) based on an argument about the cost-effectiveness of a specific AI technology (computer vision), reported in Svanberg *et al.* (2024). Incidentally, we note that our 40 percentage point adoption increase scenario approximately coincides with a more optimistic scenario in Svanberg *et al.* (2024) that allows for improvements in the cost effectiveness of the technology.

To analyse the productivity implications of AI for countries other than the United States, these future AI adoption rate projections (shown in Chart 4) need to be adapted to the context of other countries. Our projections are based on comparable current AI adoption rates across G7 countries, derived through data harmonisation and by relying on key fundamental determinants of adoption (digital infrastructure quality and skills) to capture adoption capacity. The estimates for current AI adoption rates for each country are then extrapolated using the two scenarios of AI adoption: a slow and a rapid adoption pathway, following an S-shaped adoption path which was observed for previous major technologies (Hall, 2009; Geroski, 2000; Tankwa *et al.*, 2025, building on Griliches, 1957 and Rogers, 1962). This implies an accelerating speed of adoption in the initial diffusion phase of the technology, followed by a slowdown later on as adoption reaches a saturation level. Chart 5 shows the predicted increase in AI adoption across G7 economies between 2024 and 2034.

Even the rapid adoption scenario of a 40 percentage point increase in 10 years could seem relatively conservative in light of the fact that AI is generally considered a particularly user-friendly technology. On the other hand, systemic adoption of AI in the core business functions of firms may still require substantial complementary investments in a range of intangible assets, including data, managerial practices, and organization (Agrawal *et al.*, 2022). Such investments are not only costly but also require experimentation and learning-by-doing, which may slow down adoption.

Another risk to these scenarios is that they focus on a single, economy-wide adoption rate, implicitly assuming it is homogenous across economic activities. In practice, however, firms and workers who carry out economic activities with stronger AI exposure may also be more likely to adopt AI as they may find it more profitable to integrate AI in their business processes, given the higher returns associated with higher exposure. A positive relationship between adoption and exposure would increase the share of AI-exposed tasks in the overall economy where AI is adopted, compared to our situation focusing only on overall adoption rates. This in turn would lead to larger aggregate gains than presented here.

Aggregate Productivity Gains

In the preceding sub-sections, we have discussed our best estimates of the average task-level productivity gains that might be achieved in AI-exposed tasks, the share of AI-exposed tasks within economies, and the likely AI adoption rates. This sub-section addresses the question of how to use these estimates to derive the implied aggregate productivity gains. This is not a trivial task, because productivity shocks at the microeconomic level also cause changes in the structure of the economy (e.g. reallocation of factors across sectors, changes in the input-output structure of the economy, changes in relative output prices), which all potentially matter for aggregate productivity growth.

In a seminal contribution, Hulten (1978) showed that aggregate productivity gains can, to a first order, be approximated as an appropriately weighted sum of the microeconomic productivity changes. The theorem applies in any competitive economy with constant returns to scale, irrespective of underlying structural features of the economy, such as the network of input-output linkages or the elasticities of substitution in production and consumption.[15] In this spirit, we follow Acemoglu (2024) and leverage Hulten's theorem to approximate aggregate TFP gains over the next decade as a simple multiplication of our estimates for micro gains, current AI exposure, and the projected increase in AI adoption over the next ten years. The cor-

15 Hulten's theorem is an implication of the envelope theorem. Intuitively, because equilibrium allocations in a competitive economy correspond to the solution of the social planner's problem, small changes in allocations around the equilibrium have only negligible effects on aggregate productivity, and the aggregate impact of micro-level productivity shocks reflect the Lagrange multipliers on the resource constraints. If the micro units are firms or sectors and production features input-output linkages and if productivity gains are measured as gross output-based TFP growth, then a micro unit's weight is the ratio of its gross sales to GDP and the sum of these (Domar) weights can exceed one. In our setting, the micro units are tasks and we do not model input-output linkages between tasks. In this case, the weights are given by the micro units' value-added shares.

responding formula reads as follows.

$$\begin{aligned}&\mathit{Aggregate\ Productivity\ Growth}_{c,[t,t+10]}\\&= \mathit{Micro\ Level\ Gains}\\&\times \mathit{Exposure}_c \times \Delta \mathit{Adoption\ Rate}_{c,[t+10]}\end{aligned}$$

Chart 6 shows the resulting projections of aggregate productivity gains from AI across G7 economies annualized over a 10-year time horizon. Predictions on the contribution of AI to annual TFP growth over the 10-year time horizon differ significantly across G7 economies and scenarios. Across countries, these range from 0.11 to 0.27 percentage points under the slow adoption scenario, and from 0.34 to 0.66 percentage points under the rapid adoption and expanded capabilities scenario. Cross-country differences across these projections reflect country differences regarding the occupational composition within sectors, to a lesser extent, and more importantly, the sectoral value-added shares and projections of AI adoption rates more importantly.

Upside and Downside Risks for AI Productivity Projections

There are several reasons why the growth projections in Chart 6 could overstate or understate the productivity gains from AI. While some of these reasons have been discussed in the context of the aggregation framework in the previous sections, other reasons go beyond this framework and are discussed below.

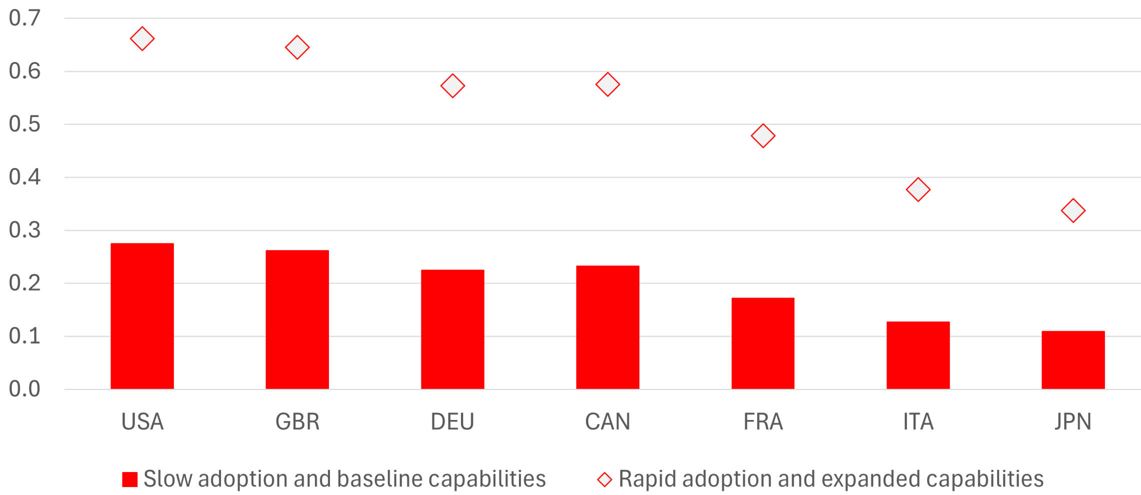
AI's Impacts on Innovation and Research

The projected productivity gains in Chart 6 could understate the true gains from AI to the extent that additional productivity gains can result from broader AI-driven innovations in organizational structures and business models. Such gains would not be observed at the level of individual tasks but would emerge in the productive reconfiguration of the interlinkages between existing work tasks or in the creation of entirely *new* tasks.

More generally, AI could improve the process of research and innovation. Aghion *et al.* (2017) emphasize that AI will not only affect the production function of goods and services, but also the "idea production function". If AI can increase the rate of technological progress, the productivity gains over the next decade could be larger than what we predicted. Aghion *et al.* (2017) and Trammell and Korinek (2023) discuss the possibility that such a scenario leads to explosive growth in the medium term, while also pointing to possible limiting factors, such as Baumol's growth disease (discussed below).

There is empirical evidence of AI increasing the productivity of researchers and boosting innovation. Calvino *et al.* (2025b) review the existing literature and show that generative AI accelerates innovation in academia and the private sector. Specifically, it supports research by helping humans develop novel ideas or by executing research tasks and freeing up time, which allow researchers to focus on those tasks that require human expertise. AI patents are cited by follow-on innovations in a broad number of application areas, supporting the general-purpose nature of AI as a technology, and there is evidence of positive feedback loops from follow-on innovation back to generative AI innova-

Chart 6: Projected Aggregate TFP Gains from AI Over a Decade in G7 Countries (in percentage points, annualized)



Source: Adapted from Filippucci *et al.* (forthcoming)

tion, supporting the notion that AI could trigger a virtuous cycle of continuously increasing productivity growth (Calvino *et al.*, 2025a).

At the same time, AI-driven technological developments may not always contribute positively to welfare – some may increase measured productivity while reducing social value. For instance, AI could enable the creation of "bad" tasks – such as manipulative advertising or addictive digital content – that generate revenue at the cost of well-being (Acemoglu, 2024). Moreover, malicious applications, including AI-enabled cyberattacks, could destroy value and undermine economic performance. Longer-term concerns include the possibility of advanced AI systems with self-improvement capabilities outpacing human control and raising existential safety risks (Nordhaus, 2021; Jones, 2023; Bostrom, 2014; Suleyman and Bhaskar, 2023). These scenarios, though speculative, underscore the importance of aligning AI development with societal goals and closely monitoring potentially harmful developments, as highlighted by ongoing initiatives such as the OECD.AI Incidents and Hazards Monitor (OECD, 2025).

Baumol's Growth Disease

The projected TFP gains shown in Chart 6 are derived under the assumption that sectoral GDP shares remain unaffected by AI-driven productivity growth. This aggregation approach can lead to an overestimation of the aggregate gains from AI if the sectors with the fastest productivity growth shrink as a share of GDP. Historically, sectors experiencing faster productivity growth have in fact tended to see decreases in their GDP shares (driven by declines in relative output prices and employment shares), thus reducing aggregate productivity growth – a phenomenon known as Baumol's growth disease (Baumol, 1967; Nordhaus, 2008).

Traditionally, Baumol's growth disease is discussed in the context of the rising GDP share of low-productivity growth services. Although AI-driven productivity growth may benefit some of the sectors that have experienced limited productivity growth in the past, the mechanisms underlying Baumol's growth disease should still apply. In particular, if demand for the output of the least AI-augmented sectors is relatively price-inelastic, then the expenditure share on these sectors would grow. As Aghion *et al.* (2017) note, AI-driven growth may then be constrained "not by what we do well but rather by what is essential and yet hard to improve."

Filippucci *et al.* (2024a) analyze how sectoral heterogeneity in AI-driven productivity gains may give rise to a Baumol effect over the medium term. Using a multi-sector general equilibrium model, they show that the size of the effect depends on sectoral productivity patterns, demand elasticities, and whether factors of production can be easily reallocated across sectors. Under their most pessimistic scenarios, a Baumol effect could reduce AI's aggregate productivity gains by up to one-third.

J-curve Dynamics

As with previous GPTs, generative AI may experience a productivity paradox, where improvements in productivity are not immediately apparent. Realising these gains often require additional, complementary investments in a range of intangible assets such as workforce skill enhancement, organizational restructuring, data, software or innovation in general. Some of these complementary assets are not fully captured yet in standard official statistics (e.g. National Accounts) (Brynjolfsson *et al.*, 2021). This leads to a productivity J-curve, characterizing the adoption of a new General Purpose Technology: in the early phase of adoption, both capital inputs and output are under-measured due to unaccounted intangible investments, leading to an underestimation of productivity improvements. In the later phase, once the complementary investments begin to bear fruit but remain unmeasured, measured productivity may be overstated, as output gains are attributed to technology alone rather than to prior investment.

Competition

AI could further complicate existing competition issues in digital markets and introduce new market failures that threaten its anticipated productivity benefits. Competition concerns may emerge both upstream in the supply of AI and downstream in its user applications that risk undermining productivity growth by limiting access to AI technologies and reinforcing market concentration (Filippucci *et al.*, 2024b; OECD, 2024).

Especially with the advent of Generative AI (LLMs and image generators, etc.), the upstream market of AI, i.e. AI development, depends on a complex value chain involving computing infrastructure, vast datasets, and specialized expertise, where economies of scale and network effects can lead to market concentration and barriers to entry (Nicoletti *et al.*, 2023). Larger datasets and computing power boost AI performance —a dynamic known as "scaling laws" (Kaplan *et al.*, 2020) —giving an advantage to established firms with proprietary resources and infrastructure (CMA, 2023). However, open-source models and supportive policies around data access and infrastructure could counteract these trends by fostering competition and inclusion. Despite concerns about concentration, the market for foundation models currently shows signs of dynamism, with a growing number of models, suppliers, and improving performance at decreasing costs (André *et al.*, 2025).[16]

The use of AI can also raise significant competition concerns downstream, particularly when AI-powered business models exploit consumer biases or personalize pricing in non-transparent ways. Such practices can manipulate consumer choices, promote low-quality products (Calo, 2013), or enable discriminatory pricing, especially in opaque online markets (OECD, 2018). AI recommender systems may reinforce market concentration by boosting attention to already-dominant products (Calvano et al., 2023), while "killer acquisitions" of emerging firms by incumbents can further limit market contestability. These trends risk stifling innovation and slowing AI adoption in less competitive sectors. Additionally, AI systems may facilitate tacit or algorithmic collusion, especially in pricing, by enabling autonomous coordination among firms without explicit agreements (OECD, 2021).

Trade and Global Access

In the context of international trade, AI presents both upside and downside risks. The benefits of AI for trade are not automatic, and access to AI itself faces downside risks if trade in digital services – including AI provided services – or ICT assets become fragmented. Indeed, limited cross-border access to competitively priced and high-quality AI tools could hold back AI adoption of companies outside countries that develop such advanced AI models, and could also restrict innovation on the developer's front. Moreover, trade restrictions on hardware components that are critical for AI training and inference, e.g. advanced semiconductors, could create bottlenecks that stifle technological progress.

On the upside, AI has the potential to lower trade costs and stimulate trade flows by reducing non-tariff barriers such as adapting to regulatory complexity and differences or to language obstacles. AI tools can automate summarizing legal and regulatory documents, enhance translation accuracy, and streamline compliance processes —developments that are particularly beneficial for small and medium-sized enterprises (SMEs), which often lack the resources to overcome such barriers (Rubinova and Sebti, 2021). These advancements can make trade more inclusive and efficient. Moreover, AI-driven productivity gains can ripple through global value

16 For instance, André *et al.* (2025) find that the capabilities of the large language model that showed the highest performing on industry benchmark tests in March 2023 (GPT-4 by OpenAI) are achieved by open source models in February 2025, which are accessible on the cloud at less than one-hundredth of the price that OpenAI charged two years ago. The finding that this segment of the AI market seems more dynamic than initially feared is also consistent with the conclusions of Hagiu and Wright (2025), although it is important to stress that these are still early days when market players experiment with different business models.

chains (GVCs) via improved process planning, better quality intermediates, and lower input costs, ultimately benefiting both producers and consumers across borders (WTO, 2024).

Impact on Skill Development

Generative AI is also reshaping human capital development – an essential engine of long-term growth – by enhancing learning, re-skilling, and problem-solving in both educational and workplace environments (OECD, 2023a). In particular, AI personalizes instruction and delivers outsized gains for lower-proficiency learners (Cheon *et al.*, 2025; Mollick *et al.*, 2024). It can also enable students to complete tasks more efficiently (Zhang *et al.*, 2024; Urban *et al.*, 2024) and may function as an on-demand subject-matter expert and search tool for educators and learners (Kestin et al., 2024). Finally, it can also provide cost-effective tutoring in low-resource settings (Henkel *et al.*, 2024; De Simone *et al.*, 2025). These developments could provide indirect productivity benefits from AI through improving human capital. On the other hand, skill acquisition in the schooling system may be hampered if AI tools end up having long-term negative effects on skill acquisition, and they are nonetheless used to obtain short-run benefits by students.

Concluding Remarks

This article has reviewed the potential impact of Artificial Intelligence (AI) on productivity growth, with a focus on medium-term projections for G7 economies. Drawing on recent OECD work and related literature, we discussed how AI—particularly generative models—could become a major driver of total factor productivity (TFP) growth over the next decade. Benchmark estimates suggest that AI may contribute between 0.3–0.7 percentage points to annual TFP growth in the United States, with somewhat lower but still substantial impacts expected in other G7 economies. These effects, while smaller than those observed during the ICT boom, are significant in the context of persistently sluggish productivity growth.

Despite these promising projections, several important sources of uncertainty remain. First, the macroeconomic impact of AI will depend critically on adoption dynamics —both the speed and breadth of diffusion across firms and sectors—as well as the ability of laggard firms to catch up. Second, the full productivity benefits of AI are likely to hinge on complementary investments in intangible assets, such as data infrastructure, skills, and organizational adaptation, much of which remains unmeasured in national statistics.

Moreover, AI may generate risks that could dampen or delay its productivity-enhancing effects. These include rising market concentration in AI supply chains, potential abuses of market power, algorithmic collusion, and uses of AI that prioritizes automation over quality or welfare. Broader societal risks—including misinformation, loss of trust, and misalignment between AI systems and human objectives—could also slow down adoption and trigger policy responses that restrict diffusion.

Future research should aim to better quantify the general equilibrium implications of AI adoption, develop more robust cross-country adoption metrics, and assess how various policy levers—from competition enforcement to digital infrastructure investment— shape outcomes. Given the pace of technological progress and the magnitude of the stakes involved, deepening the empirical and theoretical understanding of AI's productivity effects remains an urgent task.

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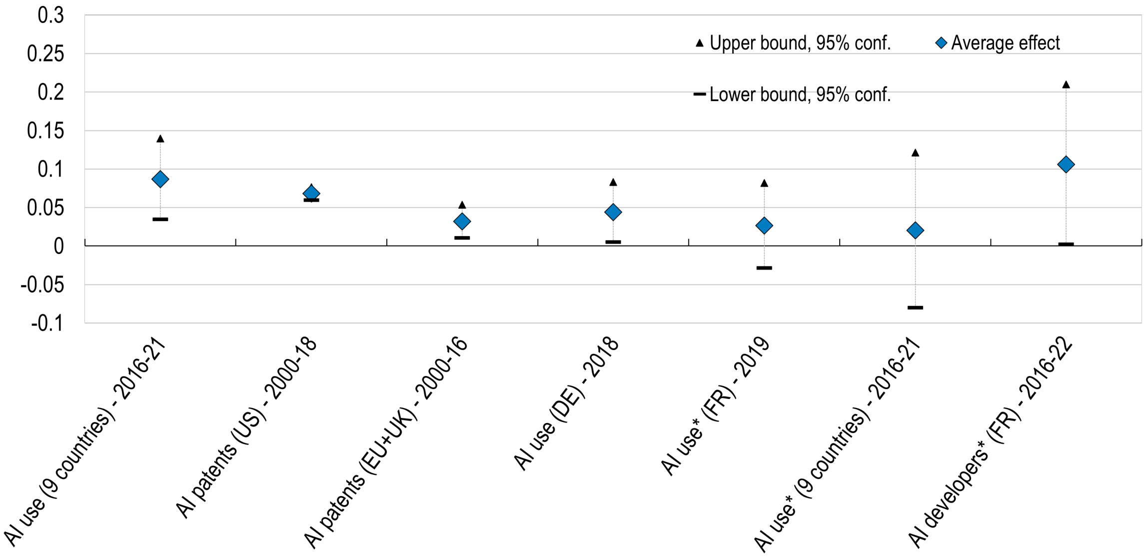
Figure A.1: The Relationship Between AI and Productivity at the Worker Level: Selected Estimates from the Literature



Notes: Firm-level studies focusing on pre-Generative AI. "AI use" is a 0-1 dummy obtained by firm surveys, while AI patents refers either to a 0-1 dummy for having at least 1 patent (US study) or to the number of patents in firms (for the EU+UK study, where the average number is 0.48 with 2.6 standard deviation, so that firms cumulating more than one patents are relatively few). Two of the estimates in the panel ("9 countries, 2016-21") relate to the same study (Calvino and Fontanelli, 2023), but the second estimate controls for other ICT technology use and thus better isolates the marginal impact of AI. Given that the study reports separate estimates for all 9 countries, the median estimate across countries is shown on the Figure. *Controlling for other ICT technologies.
Source: Filippucci *et al.* (2024b).

The UK Productivity Slowdown: A Review of Timing, Magnitude, and Drivers

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Abstract

Labour productivity growth in the UK has been historically slow since around the time of the 2008 global financial crisis. This slowdown has prompted extensive policy interest and research effort, with still little consensus. This article reviews the literature on the UK productivity slowdown, and presents new evidence on its timing, magnitude and drivers. On timing, I argue that underlying productivity growth began slowing before 2008. Aggregate productivity growth in 2007 was propped up by unusually fast growth in the finance and insurance industry, and absent this effect would have flatlined from mid-2006. On magnitude, I suggest the slowdown was a little smaller than typical estimates. Using a pre-slowdown period covering multiple full business cycles gives a better pre-slowdown trend growth rate. Excluding particular industries does not materially alter the trends. On drivers, I suggest that the UK may be more affected by some measurement issues and macroeconomic trends than other advanced economies. Notably the UK has decarbonised quicker than most other advanced economies, which may drag on measured productivity more in the UK than elsewhere. I also update growth accounting analyses using the latest data, broadly confirming findings in recent studies. I conclude with recommendations for UK productivity measurement.

There is a large and long literature on UK productivity, and in particular its perceived weakness. Studies of weak UK productivity relate to at least three different notions: a low level of UK productivity relative to other countries; slow

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growth in UK productivity relative to other countries; and a slowdown in productivity growth relative to previous UK experience. Mason *et al.* (2018) document research over many decades on the UK productivity performance, notably on the lower level of UK productivity relative to other advanced economies. Fisher (2024 and 2025) argues that productivity growth has been slowing across advanced economies, including the United Kingdom, for several decades.

This article is concerned with the apparent sharp slowdown in productivity growth in the United Kingdom in the 2000s and 2010s, which is often interpreted to have started with the 2008 global financial crisis and associated economic downturn. This slowdown has been known as the "productivity puzzle" and has garnered significant research and policy attention in the United Kingdom ever since. The Royal Statistical Society labelled the 0.3 per cent average annual increase in UK productivity in the decade or so since the financial crisis as its "UK Statistic of the Decade" in 2019.

Despite the considerable attention paid to this productivity growth slowdown, there is no consensus on its causes. Perhaps more surprising, there is also disagreement on when the slowdown started, and how big it has been. Data revisions over time have altered findings and perceptions, and some views prevail despite new and improved data that suggest otherwise. There are also limitations to current UK economic measurement that hamper productivity analysis.

This article provides a review of the literature on the UK productivity slowdown, with a focus on empirical studies, presents evidence on the timing, size, and drivers of the slowdown, using the latest data, and suggests fruitful avenues to develop UK productivity analyses.

The main findings are as follows.

Timing – The slowdown started before the global financial crisis (GFC), contrary to common perception. Aggregate productivity growth was driven predominantly by the finance and insurance industry in 2007, and absent this contribution it would have already clearly begun slowing in 2006. While it seems likely that the global financial crisis and associated downturn exacerbated the productivity slowdown, underlying productivity growth had already slowed before then.

Magnitude – As the data have evolved over time, notably following the introduction of double deflation in the official UK data in 2021, estimates of the UK productivity slowdown have been revised downward. Using a pre-slowdown period covering multiple full business cycles (e.g. 1976-2006), rather than a shorter period dictated by data availability, a reasonable pre-slowdown rate of trend growth in output per hour worked is 1.9-2.1 per cent for the whole economy and 2.2-2.4 per cent for the market sector – a little lower than typical estimates in the current literature. On this basis, I find a slowdown of roughly 1.5 percentage points per year for the whole economy and 2.0 percentage points per year for the market sector.

Drivers – Based on the latest data and other studies using the post-2021 UK data, the productivity slowdown looks less exceptional relative to other advanced countries. The UK labour productivity slowdown appears to be: (i) mainly driven by a slowdown in TFP, (ii) also partly driven by a slowdown in capital accumulation, especially of tangible assets, (iii) widespread across industries, and (iv) with a particularly large slowdown in manufacturing. These features are broadly in common with other advanced economies. Other macro trends, notably environmental and industrial, may drag on UK productivity more than in other economies.

This article does not consider the impact of the coronavirus pandemic or the period since. At the time of writing, official data suggest declines in UK productivity in 2023-24, potentially consistent with a further slowdown in productivity growth. However, significant uncertainties exist with official labour market data due to a sharp decline in response rates to the UK Labour Force Survey, a key data source. Given that the true trends in productivity are unclear, and data uncertainties abound, this period is left to future studies.

The article proceeds as follows. Section 1 reviews the literature on the UK productivity slowdown, starting with cyclical and short-term explanations, before turning to structural and global explanations. Section 2 considers whether the UK productivity growth slowdown started before 2007, as often argued for the United States and other countries, drawing especially on industry-level data. Section 3 estimates the magnitude of the slowdown, by first establishing a pre-slowdown rate of trend productivity growth using a time period determined by economic arguments rather than data availability. This section also considers whether the exclusion of any "unusual" industries would alter the findings. Section 4 explores the drivers of the slowdown by first analyzing the latest data, then considering UK-specific measurement issues, and then considering macroeconomic drivers. Section 5 concludes with some suggestions for measurement to enhance UK productivity analysis.

Literature Review

In reviewing the literature on the UK productivity growth slowdown, it seems that the focus and understanding evolved over time. This section is structured roughly chronologically: first, studies exploring cyclical and short-term drivers and narratives; second, studies considering structural drivers (in the United Kingdom and internationally); and finally, more recent studies which consider the UK slowdown in the context of a global slowdown.[2]

Cyclical and Short-Term Explanations

The productivity growth slowdown became apparent somewhat after the 2008-2009 economic downturn precipitated by the global financial crisis. The outcome for productivity from the 2008-2009 downturn could have been: (i) a one-off hit to the level, with subsequent catch-up growth and return to trend; (ii) a one-off hit to the level, with no catch-up but return to

2 For overviews of a range of arguments for the UK productivity slowdown written at different times, see Grice (2012), Patterson (2012), Disney *et al.* (2013), Barnett *et al.* (2014), Bryson and Forth (2015), Haldane (2017), McCann (2018), Heys (2020), and Chadha and Samiri (2024).

trend growth; or (iii) a permanent impact on trend productivity growth. Most observers at the time expected the first possibility.

Given rigidities in the labour market (especially in Europe) and normal labour hoarding (given costs of hiring and firing for firms), economic activity typically falls faster than employment in recessions. As such, measured labour productivity tends to fall at the start of recessions in the United Kingdom (and Europe, though less so in the United States), before recovering as activity recovers and employment adjusts with a lag. As such, the initial fall in UK labour productivity in 2008 was not a puzzle.

However, the hit to real output in 2008 was larger and more persistent than in previous recessions, while the response of employment was slower and smaller (Disney *et al.*, 2013: Chart 3.2), and similarly the rise in unemployment was less than might have been expected. Taken together, this led labour productivity to begin to look unusually weak from around the start of 2009.[3]

In the early literature on this productivity slowdown, cyclical explanations were predominant, in line with the expectation of a return to trend productivity growth. Three common lines of enquiry were: (i) mismeasurement, notably of output; (ii) labour hoarding and capacity utilization; and (iii) reallocation effects across industries.

Measurement is always a challenge, but economic turning points may be harder to measure well, so mismeasurement was a concern shortly after the 2008-2009 economic downturn. Dale (2011) noted that the Monetary Policy Committee at the time expected GDP to be revised up over 2008-2011, which would raise measured productivity and reduce the productivity growth slowdown somewhat.[4]

Goodridge *et al.* (2013) considered another aspect of mismeasurement: the revision to the National Accounts guidelines to treat research and development (R&D) expenditure as capital investment.[5] They suggested that if a wider set of intangibles (beyond just R&D) were treated as investments, cumulative GDP growth between 2008 and 2012 would be revised up by 1.6 percentage points (roughly 0.3 percentage points per year), since the omitted intangibles component was less weak than measured GDP. However, this adjustment is small in the context of the productivity slowdown, is based on a much wider set of intangible assets than are currently included in GDP, and measurement of intangibles remains challenging.

Data revisions over time have increased post-GFC labour productivity growth somewhat, and decreased pre-GFC labour productivity growth a little, both con-

3 The Bank of England's August 2009 Inflation Report was the first to note that productivity was unusually weak relative to previous recessions.

4 Grice (2012) and Patterson (2012) provide reviews of the data underpinning productivity statistics at the time, including comparisons of nominal GDP growth with tax revenues.

5 The UK annual national accounts update in 2014 (Blue Book 2014) was the first to be consistent with the European System of Accounts (ESA) 2010, which capitalized R&D.

tributing to reducing the magnitude of the estimated productivity growth slowdown. Table 1 shows successive data vintages of average annual growth in UK output per hour worked, before and after the 2008-09 downturn and the slowdown as the difference between them (an equivalent table using output per worker is in the Appendix[6]). By Blue Book 2015 the data had settled down to a picture similar to what we have today, in part due to data revisions (mostly to GDP) and in part due to a longer post-GFC period. But even with improved measurement, the productivity growth slowdown clearly remains (UK measurement is discussed further in Section 4).

On labour hoarding and capacity utilization, Blundell *et al.* (2014) and Pessoa and van Reenen (2014) argue for the role of real wage flexibility in the productivity slowdown. If real wages are flexible, then firms can adjust to the decline in demand by reducing real wages rather than reducing hours or headcount. Thus, more real wage flexibility could have enabled firms to retain their workforce to a greater extent without excessively damaging their profitability, but with the result of lower labour productivity. This could explain relatively strong employment, weak productivity, and weak wage growth. In turn, cheaper labour relative to capital might reduce business investment and lead to capital shallowing, further reducing labour productivity.

Composition and reallocation effects act on aggregate productivity growth at all times, but may be particularly important during and after economic downturns. Broadbent (2012) notes that resources (notably capital, but also labour) are slow to reallocate across industries, leaving the economy temporarily mismatched, resulting in lower output per unit of input, and higher price pressures in some industries. A related narrative of "zombie firms" emerges here: historically low interest rates and bank forbearance allow unproductive firms to remain in business for longer than they otherwise would (or should), which hampers the productivity-enhancing effects of firm exit and reallocation of resources to more productive firms.

All these arguments likely played some role in the early years of the slowdown. But the longer that weak productivity growth continued, the clearer it became that trend growth had slowed, rather than just a one-off impact.[7] Business surveys on capacity utilization returned to normal around 2013-14, suggesting firms no longer had too much labour, and business investment was back towards trend in 2015. In light of this, it seems the early literature searching for cyclical drivers was overtaken, and so attention turned to structural drivers of the persistent weak growth rates.

Structural Explanations

From around 2014, the failure of productivity growth to recover motivated a transition from cyclical to structural explana-

6 Online Appendix for this article can be found at csls.ca/ipm/48/UK_productivity_slowdown_appendix.pdf

7 Resources will eventually be reallocated to their most profitable uses; Broadbent (2012) notes that could even lead to a period of above-trend productivity growth, something which has not occurred.

Table 1: UK Output per Hour Worked Growth Estimates, by Data Vintages

Vintage	Release	Last Year of Post-GFC Period	Pre-GFC (1997–2007)	Post-GFC (2010–latest/2019)	Slowdown (Post-GFC minus Pre-GFC)	Memo: Latest Estimate of Post-GFC Period
BB12	Jul-12	2011	2.5	1.1	1.4	0.9
BB13	Jul-13	2012	2.4	-0.5	2.9	0.3
BB14	Oct-14	2013	2.2	-0.1	2.3	0.1
BB15	Oct-15	2014	2.2	0.3	2.0	0.2
BB16	Jul-16	2015	2.2	0.2	2.0	0.2
BB17	Oct-17	2016	2.1	0.3	1.8	0.3
BB18	Jul-18	2017	2.2	0.4	1.8	0.5
BB19	Oct-19	2018	2.3	0.5	1.9	0.5
BB20	Oct-20	2019	2.2	0.4	1.9	0.5
BB21	Oct-21	2019	2.0	0.6	1.4	0.5
BB22	Oct-22	2019	2.0	0.5	1.5	0.5
BB23	Oct-23	2019	2.2	0.5	1.7	0.5
BB24	Oct-24	2019	2.2	0.5	1.7	0.5

Source: ONS (various vintages), author's calculations.
Notes: Update and modification of Table 1 from Martin and Mackenzie (2021), which went up to BB21. In this version the post-GFC period is adjusted to be growth from 2010 (i.e. first year of growth is 2011) to the latest year available or 2019. "Latest estimate of post-GFC period" uses ONS data from May 2025. An equivalent table for output per worker is Table A1 in the Appendix. Growth rates are compound annual averages.

tions. Barnett *et al.* (2014) provide a comprehensive assessment of a range of explanations up to that point, distinguishing between cyclical and more persistent factors. This experience was common across developed countries, so the literature on structural explanations for the productivity slowdown is less UK-specific (see Goldin *et al.* 2024, for an international review). Williams *et al.* (2025) present results of a survey of UK productivity experts on the explanations for the slowdown in question.

Another motivation for the change in course was the availability, from around this time, of data allowing more comprehensive assessment of productivity growth in the post-GFC period in the United Kingdom: growth accounting, and firm-level microdata.

Growth accounting decomposes growth in output (usually GVA) into growth of appropriately weighted inputs of labour and capital, and total factor productivity (TFP) as the residual. Labour inputs are usually measured as compositionally adjusted measures of hours worked (accounting for the changing mix of workers across education, age, and sex groups), and capital inputs are usually measured as capital services (accounting for the changing mix of the capital stock across assets and industries). This framework can be re-arranged to decompose growth in output per hour worked into the contributions of labour composition, capital services per hour worked (capital deepening, or capital shallowing), and TFP. In theory, TFP aims to measure efficiency and technology, though in practice it can also capture anything else that goes unmeasured, and mismeasurement.

As early as 2014, the prevailing view has been that the slowdown in UK labour productivity growth was caused by a slowdown in TFP growth. Goodridge *et al.* (2014) found that the shortfall in labour produc-

8 This paper is appropriately titled "The UK productivity puzzle is a TFP puzzle", which has become a stylised

tivity between 2007 and 2011, relative to the 2000-2007 trend, could be fully 'explained' by a slowdown in TFP growth.[8] More accurately, since TFP is a residual rather than an explanation, they found that labour composition and capital shallowing did not explain the labour productivity growth slowdown. Almost all growth accounting analyses of the United Kingdom since then have made a similar finding. Goldin *et al.* (2024:Table 14) provide a useful summary of the sign and magnitude of contributions to the labour productivity slowdown of ICT and non-ICT capital inputs, labour composition, and TFP across a range of studies. They report a large contribution of TFP in all the UK studies they consider, typically a small contribution from capital (more so non-ICT capital), and no clear contribution from labour composition.

Table A4 in the Appendix summarizes a range of estimates of TFP growth resulting from growth accounting studies of the UK productivity slowdown. Average growth rates of TFP in the pre-slowdown period (variously defined) are typically around 1–1.2 per cent per year for the whole economy, or 1.2–1.5 per cent per year for the market sector. In the slowdown period, TFP growth is typically found to be around zero, or slightly negative, for both the market sector and whole economy. Thus, a considerable slowdown in TFP growth is a consistent finding.

Labour composition (LC) is usually found to continue to grow at much the same pace in the slowdown and pre-slowdown periods, consequently contributing nothing to the slowdown in labour productivity growth. Indeed, some measures find an improvement in LC after 2007, which 'worsens' the productivity puzzle (an improvement in LC should, other factors equal, increase labour productivity growth). That said, there are many labour-relevant factors that LC measures do not account for, such as on-the-job training. Rincon-Aznar *et al.* (2015) find a very small role for a slowdown in training in explaining the labour productivity slowdown.[9]

By contrast, the role of capital is more debated. First, ONS measures of capital stocks and capital services were significantly revised in 2019 following a substantial review of the methods and assumptions and an improved statistical processing system (ONS, 2019). These revisions made capital services for the market sector appear weaker around 2009-2013 than in previous estimates, adding to the estimated role of capital shallowing in explaining the productivity slowdown. Several more recent studies have found that a slowdown in capital deepening (or in the extreme capital shallowing) capital shallowing can explain around a third of the labour productivity growth slowdown (Martin and Mackenzie, 2021; Goodridge and Haskel, 2023).

Second, the scope of capital varies across studies, notably by whether a broader set of intangible assets (beyond those included as assets in the National Accounts) are included. Studies that include these addi-

fact.

9 It is also worth noting inconsistencies in LC measures across datasets and vintages of datasets.

tional intangibles as capital assets (such as Goodridge *et al.* 2014, 2018; and studies using data from EUKLEMS) can be seen to be moving some sources of TFP growth into the contribution of capital and therefore out of TFP. Studies in Table A4 that adjust for additional intangibles tend to find slightly lower pre-slowdown growth in TFP (and slightly larger contributions from capital deepening accordingly), but a negligible effect in the slowdown period. Where studies split capital into different types (e.g. Van Reenen and Yang, 2024; Bontadini *et al.* 2024); van Ark *et al.,* 2024), they tend to find a larger role for capital shallowing of tangible assets than intangible assets.

Finally, the interpretation of capital deepening as an independent driver of labour productivity growth has been challenged by Fernald and Inklaar (2022). They argue that the capital stock is endogenous to TFP, and so the slowdown in TFP growth endogenously slows capital accumulation. They re-arrange the growth accounting framework such that capital is expressed not relative to labour (hours worked), but relative to output, such that it is changes in the capital-output ratio that determine the contribution of capital to labour productivity growth. In this formulation, capital contributes little (independently of TFP) to labour productivity growth or the productivity slowdown in the United Kingdom.

To shed more light on the slowdown in TFP growth, some articles turned to growth accounting by industry. Riley *et al.* (2018) is a thorough example of this approach (see also Tenreyro, 2018, and Kierzenkowski *et al.*, 2018). Based on growth accounting analysis across 15- and 59-industry breakdowns in the market sector, Riley *et al.* (2018) confirmed that the labour productivity slowdown was widespread and driven by TFP across most industries, suggesting macroeconomic drivers. Of the more detailed industries, they identified the financial services and telecommunications services industries as the two largest contributors to the slowdown, followed by retail, mining and quarrying, electricity supply, and manufacturing of pharmaceuticals. In all of these (and indeed most other detailed industries), they found TFP to be the main driver. They note that several of the industries contributing most to the aggregate slowdown are subject to particular measurement challenges.

Industry data also permits the decomposition of aggregate productivity growth into contributions from within-industry growth and changes in industry composition (known as reallocation effects, or between-effects). There are several decomposition methods, and the results depend also on the level of industry aggregation used; for instance, growth within manufacturing includes the contribution of reallocation between detailed manufacturing industries. However, across a range of studies using different aggregation levels and decomposition methods, reallocation effects across industries have consistently been found to play a minor role in the UK productivity slowdown (Riley *et al.* 2018; Goodridge *et al.* 2018; Goodridge and Haskel, 2023; Coyle and Mei, 2023).

The second key data source was firm-level microdata, which became available covering the post-GFC period around 2014, leading to a range of firm-level analyses of the productivity slowdown. An important data source for this sort of analysis in the UK is the Annual Business Survey (ABS).[10] The cross-sectional ABS data were combined together into a panel dataset known as the Annual Respondents Database (ARD) which has been extensively used for UK firm-level productivity analysis. A major benefit of firm-level analysis is the ability to explore the role of firm entry and firm exit, and re-allocation effects across incumbent firms.

As with industry-level analysis, there are several different decompositions and approaches possible in firm-level data. Riley *et al.*, (2015) implement several decomposition methods, with varying results. Their preferred approach finds that the slowdown in productivity growth across 2007-2013 (both the 2008-09 fall and subsequent partial recovery) relative to earlier years is driven primarily by a within-firm slowdown, while the contribution of external effects (net entry, and re-allocation between incumbents) was somewhat smaller than pre-GFC. Given that economic downturns might be expected to lead to an increase in creative destruction and reallocation of resources, the lack of increase in the external effects is tentative evidence for impairment in the re-allocation process.

Black *et al.* (forthcoming) updates and extends Riley *et al.*, (2015) with ABS data up to 2022, and improved historical data. The longer post-GFC period enables analysis of productivity change over longer windows (e.g. five-year changes in productivity) which can improve the results given that firm-level data can be noisy. Findings in this study suggest a larger role for reduced between-firm re-allocation effects in explaining the post-GFC productivity growth slowdown, with within-firm and between-firm effects each explaining roughly half of the slowdown, and net entry effects explaining relatively little. That said, they also find considerable variation cross decomposition methods, consistent with Riley *et al.*, (2015), which makes these findings uncertain. Black (2022: Figure 3) suggests that much of the strong pre-GFC growth in manufacturing labour productivity was through a reduction in the number of workers in relatively low productivity firms as manufacturing declined in the UK up to 2008, a pattern that could not be repeated. The Bank of England (2023) notes that manufacturing productivity growth between 1997 and 2007 was unusually strong relative to the period before or after.

Other studies explored which parts of the firm-level productivity distribution saw the largest slowdowns. Here the evidence is mixed. Haldane (2017, 2018) emphasized the "long tail" of low productivity firms in the UK, linked to management practices, technology adoption, and international exposure. While potentially significant for the level of UK productivity, it is not clear that these low productivity firms contributed materially to the slowdown in aggregate productivity growth. While nu-

10 The ABS is conducted with a year's lag, and becomes available to researchers a year after that (e.g. data for 2010 was collected in 2011 and available in 2012).

merous, low productivity firms tend to be small, and thus account for a relatively small share of the UK economy, and so likely contributed little to aggregate productivity growth either before or after the GFC. By contrast, Dacic and Melolinna (2022) show that productivity growth of the 100 largest firms in the UK is significant for aggregate UK productivity outcomes.

Schneider (2018) argued that it was a slowdown among UK frontier firms that contributed most to the aggregate productivity slowdown, using a novel decomposition method and data up to 2014. The findings in Schneider (2018) should be interpreted cautiously for two main reasons. First, firms in the extremes of the productivity distribution (both top and bottom) are more likely the subject of measurement error – firms with extremely high or low measured productivity may have erroneously high or low values for turnover or employment. Especially at the top of the distribution, and when working with sample survey data, these firms can have outsized effects on results. Second, Schneider appears to use a version of the ARD that is missing a large part of the services sector, namely the retail and accommodation and food services industries. This omission is likely the result of errors in the construction of early iterations of the ARD, and may influence the results.

The latest analysis of firm-level productivity using the ABS (as in Black, 2022; ONS, 2024) suggest that it is the 'middle' of the productivity distribution that drove the productivity slowdown (van Ark and O'Mahony, 2023). Contributions to aggregate labour productivity growth from firms in the top 10 per cent of the employment-weighted firm productivity distribution was 0.7 percentage points per year on average between 1998 and 2007, and 0.8 percentage points per year on average between 2011 and 2019. The bottom 50 per cent of the productivity distribution contributed just 0.1 percentage points per year on average in both periods. Firms between the 50th and 90th percentiles contributed 0.6 percentage points per year on average pre-GFC, falling to 0.3 percentage points per year afterwards. However, even at this level of aggregation the year-to-year patterns are noisy (Figure A1 in the Appendix), and the implied productivity growth slowdown in the ABS is much less than that in National Accounts data. Wales (2019) documents a range of other findings on UK productivity from firm-level data.

The UK in a Global Slowdown

Literature in more recent years has sought to put the UK productivity slowdown in a global perspective, motivated by data developments and international events.

Until 2021, official UK GVA and GDP estimates were based on "single deflation" methods, making them inconsistent with international best practice and measures in other countries, and so hampering international productivity comparisons. The ONS implemented "double deflation" for the first time in 2021, leading to major revisions to UK National Accounts and industry GVA data, and improving consistency with other countries. Another major change at the same time was the introduction of a new deflator for telecommunications services (Abdirahman *et al.*

2022). Martin (2021) documents the impact of both changes on UK productivity trends and finds notable changes, with revisions varying substantially by industry. The telecommunications industry saw substantial upward revisions to productivity growth, reducing the degree of slowdown considerably. Many manufacturing industries saw productivity growth revised up in years before the financial crisis, but much less in years after, leading to a larger productivity growth slowdown. Findings in studies using earlier UK industry data therefore may no longer hold.

More recent articles using the latest UK industry data (e.g. Martin and Mackenzie, 2021; Coyle and Mei, 2023; Goodridge and Haskel, 2023) tend to find the largest contributions to the productivity slowdown from manufacturing, ICT, and finance industries. Goodridge and Haskel (2023) suggest that the TFP slowdown is mostly explained by intangible-intensive industries, including the aforementioned selection. These industry patterns are mirrored for the United Kingdom in international datasets.

A range of recent studies compare productivity trends across countries, facilitated by advances in cross-country data, including the EUKLEMS-INTANProd database (see Bontadini *et al.* 2024 for details). Van Reenen and Yang (2024) compare the United Kingdom with the United States, Germany, and France using the 2023-vintage of EUKLEMS-INTANProd. They find a 1.2 percentage point slowdown in annual TFP growth for the UK market sector in 2007–2019 compared with 1995–2007, broadly similar to that for the comparator countries; but a larger slowdown in capital deepening and labour composition than others. Bontadini *et al.* (2024) use the same data, including also an adjustment for the capitalization of additional intangible assets, and find the UK productivity slowdown driven by TFP and capital deepening.[11] Goldin *et al.* (2024) use the 2019-vintage of EUKLEMS and define the slowdown as 2006–2017 relative to 1996–2005. They similarly find a large (albeit common) slowdown in TFP growth and capital deepening, but an unusual slowdown in labour composition in the United Kingdom. It is noteworthy that studies using EUKLEMS datasets have markedly different findings from studies using ONS data (e.g. Goodridge and Haskel, 2024) on the role of labour composition; any differences in labour composition have equivalent differences of the opposite sign for TFP.

These studies tend to find the labour productivity growth slowdown (variously defined) to be larger in the United Kingdom than comparator countries, which is also a common theme in commentary on productivity in UK policy circles. By contrast, Fernald and Inklaar (2022) suggest that the UK productivity slowdown was

11 However, they also offer an alternative interpretation: using an adjusted (lower) pre-slowdown baseline for TFP growth, a more recent comparison period of 2014-2019, and adjusting for "mismeasurement of prices for consumer digital services", they find that the TFP slowdown is much milder at just 0.15 percentage points per year for the UK, and near zero for the United States. The relevance of the mismeasurement adjustment for the UK is unclear, given that these UK data already include the substantially revised telecommunications deflator described in Abdirahman *et al.* (2022).

very similar to that in the United States and northern European countries and that the United Kingdom does not appear unusual in this regard. They argue that the slowdown, common across countries, should be viewed through the lens of conditional convergence, and since the frontier (taken to be the United States) slowed, so too would countries near the frontier (such as the United Kingdom).[12] They argue that any (small) additional slowing in the United Kingdom relative to the slowing at the frontier can be explained by industry-specific issues (e.g. mining) and a small difference in industry structure across countries. Fisher (2024: Figure 5) similarly notes the parallel trends of whole economy labour productivity in the United Kingdom and United States between 2009 and 2019.

Timing of the Slowdown

Many studies assume that the UK productivity slowdown in question started with the Global Financial Crisis (GFC) and the associated economic downturn. The United Kingdom entered recession in 2008 Q2 and saw annual falls in measured labour productivity in 2008 and 2009. It is intuitive and common, therefore, to interpret 2008 as the start of the slowdown and thus the period up to 2007 as the period before the slowdown.

Table A3 provides a summary of growth accounting studies that analyze the UK productivity slowdown. The vast majority use a pre-slowdown period that ends in 2007, in line with the view that the slowdown happened after 2007. The choice of "before" period and "after" period matters for the estimated size of the slowdown, but for now we focus on the timing.

There is a broad consensus that the slowdown in the United States started around 2005 (e.g. Cette *et al.*, 2016; Fernald *et al.*, 2025), and so slowdowns are often defined between pre-2005 and post-2005. This is the case, for instance, in Gordon and Sayed (2019) and Goldin *et al.* (2024). A key motivation here seems to be the end of the ICT-related productivity boom in the United States which ran from the mid-1990s to the mid-2000s (roughly 1995–2005). Gordon and Sayed (2019) note that Europe did not see such a productivity boom pre-2005. Cette *et al.* (2016) argue that productivity slowdown in question happened before the "Great Recession" of 2008–09 both in the United States and Europe, but observe a "sharp break with the [Global Financial] Crisis" for the United Kingdom.

Given the view that US productivity slowed before the GFC, it is worth considering if that might also hold for the United Kingdom. Chart 1 explores the industry contributions to annual growth in aggregate UK output per hour worked in each year between 1998 and 2007. Some remarkable patterns emerge. First, the contribution from the finance and insurance industry (dark brown) alone can almost explain aggregate productivity growth in 2007. From the underlying industry de-

12 Philippon (2022) argues that TFP actually evolves linearly rather than exponentially. In this view, there has been no slowdown in the true additive TFP process, but rather TFP in most advanced economies is now so high that new innovations make only a small additive contribution.

tail, it is the insurance industry which drives this, bouncing back from a particularly weak year in 2006 (note the negative contribution of finance and insurance in 2006); though the other two finance industries also contribute positively in 2007. Second, manufacturing (light green), which had been the engine of productivity growth up to 2006, contributes very little in 2007. At a more detailed level within manufacturing, the drop in contributions is widespread, but due especially to manufacturing of other transport equipment (division 30), e.g. aircraft; manufacturing of computer, electronic, and optical products (26); and manufacturing of food products (10). Third, the remaining "other" industries (dark green) collectively contribute negatively in 2007.

Chart 1 suggests that apparently strong productivity growth in 2007 is something of a mirage, driven by unusually fast growth in the finance and insurance industries, and not matched elsewhere. Table A2 in the Appendix presents some descriptive statistics that attempt to capture the breadth of productivity growth across the economy. Across most metrics, 2007 appears a year of relatively narrow productivity growth—for instance, the unweighted median annual growth in output per hour worked across 78 industries was just 0.1 per cent in 2007, having been near 2 per cent in previous years.

The unusually fast productivity growth in the finance and insurance industries in 2007 may have been driven by mismeasurement, which is notoriously difficult, and perhaps especially so in the run-up to the GFC. Alternatively, measurement may have been appropriate but capturing "bad outputs" associated with unsustainable risk-taking and socially damaging activities that led to the GFC. Better or alternative measures of finance and insurance output and productivity might therefore give an alternative perspective of aggregate productivity growth in the years before the GFC (note the large contribution of the finance and insurance industries in 2005 in Chart 1 as well).

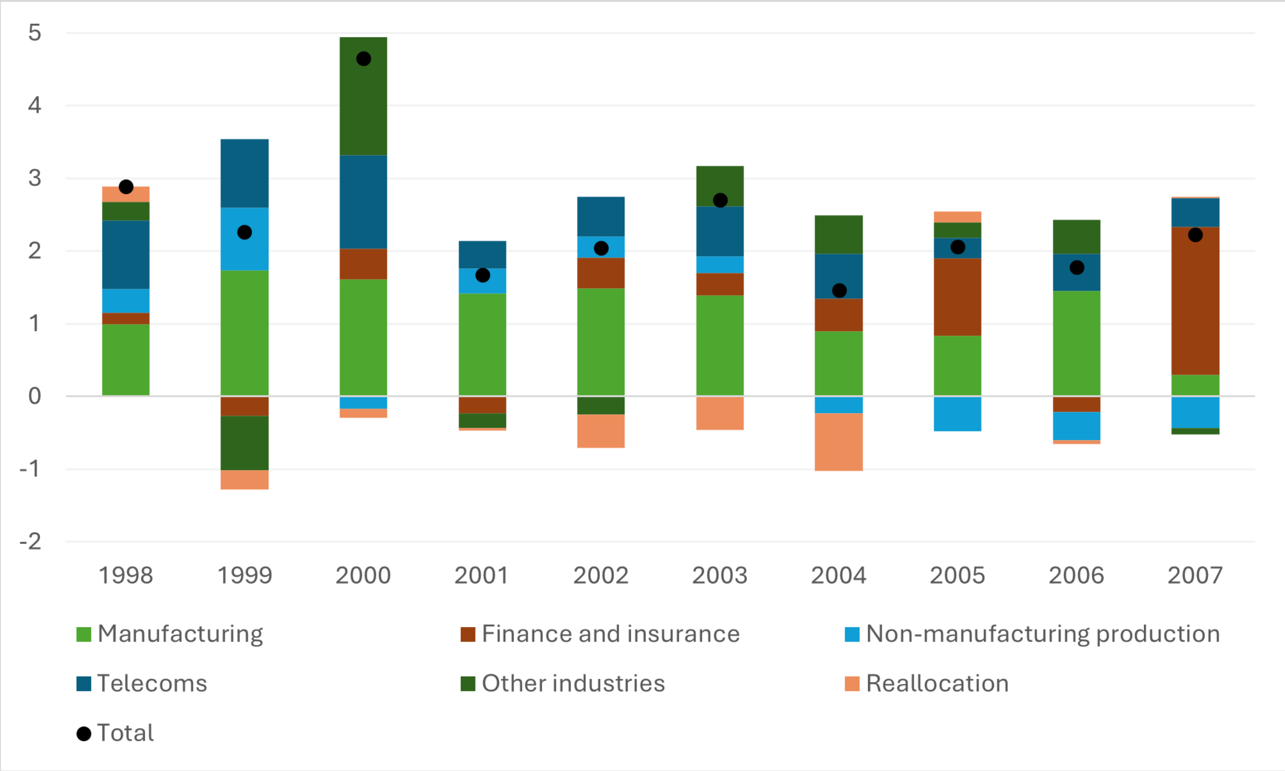
Chart 2 shows output per hour worked for the whole economy including and excluding the finance and insurance industry, indexed to 100 in 1997, to explore the potential impact of alternative measurement of this industry. Consistent with Chart 1, measured productivity peaks in 2006 and falls in 2007 for the series excluding finance and insurance, and goes on to fall in 2008 and 2009, before recovering. By about 2013 the series had more or less re-converged. Using quarterly data (not shown), output per hour worked peaks in 2006 Q2–Q3 for the series excluding the finance and insurance industry, essentially flatlines through to 2008 Q2, before falling. Section 2 considers measures that exclude other industries for various reasons.

Taking the evidence from this section together, the productivity slowdown in the United Kingdom probably started before the GFC, with productivity already having slowed in 2007 (before the recession in 2008). However, measurement challenges mean that we should perhaps be cautious not to over-interpret any individual year of data.

Size of the Slowdown

A slowdown in productivity growth is,

Chart 1: Industry Contributions to Annual Growth in Whole Economy Output Per Hour Worked, 1998–2007



Source: ONS (2025), author's calculations.
Notes: Contributions use the Tang and Wang (2004) decomposition, with each industry weighted by its share of nominal GVA in the previous year; the reallocation effect is the residual after subtracting all the within-industry contributions from whole economy growth. Whole economy and real estate industry exclude imputed rental from GVA. Contributions are calculated across 78 industries using ONS data and aggregated. Non-manufacturing production is agriculture, mining and quarrying, energy, and water and waste. Telecoms is industry division 61.

by definition, the difference between some slower rate of growth in a later period relative to some faster rate of growth in an earlier period. We would prefer those "before" and "after" growth rates to be representative of the trend rate of growth, rather than distorted by volatility or idiosyncratic events. Which periods are most suitable for such a calculation?

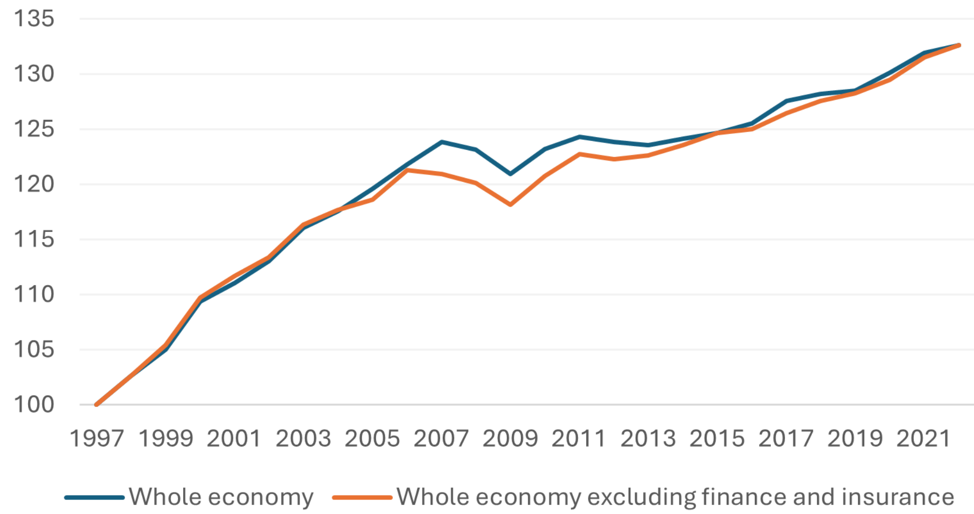
The Pre-Slowdown Trend – The "Before" Period

The choice of period for the trend rate of productivity growth "before" the slowdown should be informed by economic arguments, but has often been dictated instead by data availability and convenience.

Many studies use a "before" period that ends in 2007, aligned with the perceived pre-GFC peak in UK labour productivity. It was mentioned in the previous section that the slowdown likely started just before the 2008 financial crisis and economic downturn, and so the "before" period would be better ended in 2006 than 2007. But the impact on the trend pre-slowdown rate of productivity growth from such a choice will be slight.

Of more significance to the trend rate

Chart 2: Output Per Hour Worked, Whole Economy With and Without the Finance and Insurance Industry, Index 1997=100



Source: ONS (2025), author's calculations.
Notes: "Whole economy excluding finance and insurance" is whole economy GVA minus the GVA of the finance and insurance industry (section K), correctly chain-linked, divided by hours worked with a similar adjustment.

of pre-slowdown productivity growth is the choice of where to start the period. The start of the "before" period is often taken as 1997 (first growth rate in 1998), likely because various official UK data published by the ONS start in 1997, which makes this an easy choice.[13] Tables A3 and A4 in the Appendix show a range of studies on the UK productivity slowdown, many of which use a "before" period that starts in 1997. Other convenient years to start the "before" period include 1995 (the start of UK data in some international datasets)[14], 1990 (the start of some ONS industry GVA data, and a decennial year), and 1970 (the start of the current ONS growth accounting estimates).

However, it would be preferable to choose a period that best establishes the trend rate of productivity growth based on economic principles. Given the known pro-cyclicality of labour productivity estimates (Basu and Fernald, 2001), the trend is likely best measured over a period that

13 For instance, ONS industry productivity estimates start in 1997, which follows because the annual supply and use tables are currently published for years since 1997, and this has been true since 2011 when the ONS moved the National Accounts to the Standard Industrial Classification (SIC) 2007 for the first time. GDP and GVA estimates for years prior to 1997 are given less scrutiny, and so are likely to be less consistent with post-1997 data.

14 For transmission to Eurostat (while the United Kingdom was still a member of the EU), data since 1995 was required for some variables under EU regulations. For the United Kingdom, these were typically compiled as an 'extension' to more comprehensive estimates that started in 1997. As such, many international datasets contain UK data since 1995, though the quality of the 1995 and 1996 data is likely lower than the data from 1997 onwards.

15 An alternative approach would be to use a series that is already adjusted for variations in capacity utilization, such as Fernald (2014) for the United States. There is not such a series for the United Kingdom given challenges measuring capital utilization (see Martin and Jones, 2022, for a discussion).

Table 2: Average Annual Growth of Output per Hour Worked, Various Ranges Prior to Slowdown

Range	Whole Economy		Market Sector	
	Compound Annual Average Growth	Median Annual Growth	Compound Annual Average Growth	Median Annual Growth
Preferred ranges				
1976-2006	2.3	2.3	2.2	2.4
1985-2006	2.1	2.1	2.2	2.2
1994-2006	2.1	2.0	2.4	2.2
2002-2006	1.9	1.8	2.4	2.2
Preferred start dates with ending in 2007				
1976-2007	2.2	2.3	2.2	2.2
1985-2007	2.1	2.0	2.2	2.2
1994-2007	2.1	1.9	2.4	2.1
2002-2007	1.8	1.7	2.3	2.1
Typical ranges				
1995-2005	2.2	2.2	2.7	2.4
1995-2007	2.2	2.0	2.5	2.2
1997-2007	2.2	1.8	2.7	2.4
2000-2007	1.8	1.7	2.3	2.1

Source: ONS (May 2025), author's calculations.
Notes: Year ranges are from the level of productivity in the first year, e.g. 1976–2006 is the growth from 1976 to 2006, with the first growth rate being between 1976 and 1977 (the growth between 1975 and 1976 is not included). Whole economy data from latest labour productivity statistics at time of writing, published May 2025, consistent with Blue Book 2024; market sector data from latest ONS growth accounting estimates at time of writing, published May 2025, consistent with Blue Book 2024.

spans one or more whole business cycles.[15] This could be done peak-to-peak or trough-to-trough, though deviations at peaks and troughs are not always comparable, and may be subject to increased measurement error. Therefore, a period starting and ending at a point where the economy is near balance (i.e. the output gap is near zero and capacity utilization is near normal) is preferable. Additionally, longer periods are likely preferable since the effects of any short-term volatility or measurement error are diluted with longer time periods.

To identify periods when the economy was near balance and so judge a reasonable period to establish trend productivity growth, estimates of the historical output gap and capacity utilization from a range of sources are used, summarized in Pybus (2011). Periods at which the output gap seems near closed include roughly 1976–77, 1985–86, 1994–95, 2002–2003, and 2006.

Table 2 shows average annual growth of output per hour worked between each of these earlier periods and 2006 (taken to be the end period and start of the slowdown, as discussed earlier), for both the whole economy and market sector. For the whole economy, the preferred ranges give similar averages to the typical ranges; but for the market sector, the average growth rates over the preferred ranges are lower than the typical pre-slowdown growth rates used in studies of the UK slowdown, as detailed in Table A3 (some of which are also shown in Table 2). The difference between ending in 2006 and 2007 is slight, but starting in 1995 or 1997 seems to give a trend rate that is too high for the market sector. There are three years of fast labour productivity growth in the late 1990s, which likely cause the pre-slowdown period to be overstated if a short window is used.

An alternative approach, also shown in Table 2, is to take the median annual growth rate across the period. This reduces the influence of unusually fast (or slow) years of productivity growth and gives a better sense of the central tendency of annual growth over the period. These medians accord better with the means over the periods proposed in this article. Taken together, a reasonable pre-slowdown rate of trend growth in output per hour worked is 2.2–2.4 per cent for the market sector and 1.9–2.1 per cent for the whole economy. This is similar to, though slightly lower than, the estimate from Crafts and Mills (2020), who find a trend rate of whole economy output per hour worked growth of 2.3 per cent immediately pre-GFC (and a range from 0.9 per cent to 3.3 per cent per year over the preceding 150 years).

The Slowdown Trend – The "After" Period

For the "after" period, we again wish to choose a period that best represents the trend rate of growth in this slowdown period, rather than being distorted by where we choose to measure it. For this second period in the before–after comparison, it is the start date that is most significant. Some studies start this second period immediately after the end of the "before" period—for instance, 1997–2007 and then 2007–2019. However, given the procyclicality of labour productivity measures, this suffers the same issues as described above. Labour productivity fell in 2008 and fell further in 2009 before recovering strongly in 2010. Taking those three years together gives a reasonable average of 0.3 per cent annual growth, but taking only one or two of those years (e.g. starting in 2008 or 2009) risks biasing the results.

Even starting in 2006, however, causes problems. The GFC caused a large recession by recent historical standards, so even including the whole GFC and downturn period (2008–2010) is arguably not a good reflection of the trend rate of growth in this slowdown period. This is particularly true for TFP, given challenges measuring capital during downturns (see Section 5). It might be preferable, therefore, to start in 2010 (i.e. growth in 2011) and miss the GFC period entirely.

After the 2008–09 downturn there were a series of other shocks that complicate the assessment of trends, especially across countries. The Eurozone debt crisis of 2012–13 likely had some impact on the United Kingdom, but causes particular issues for European country comparisons, leading some authors to split the post-GFC period in two parts (e.g. Bontadini *et al.*, 2024, use 2010–2014 and 2015–2019). The United Kingdom's vote to leave the European Union in 2016 is a UK-specific shock. Impacts on the UK economy likely began immediately given the sharp depreciation of Sterling and stagnation of business investment (Haskel and Martin, 2023). The impacts of Brexit likely built over time, especially so when border controls came into effect in 2020, though the assessment of this is hampered by the concurrent coronavirus pandemic. The pandemic and associated recession in 2020, followed by the Russian invasion of Ukraine in 2022 and surge in inflation in 2022–23, complicate this period further. Data issues also increased during and after the pandemic.

The post-GFC period in the United Kingdom has been marked by substantial growth in employment and hours worked,

Table 3: Average Annual Growth of Output per Hour Worked, Various Ranges for the Slowdown

Range	Whole Economy		Market Sector	
	Compound Annual Average Growth	Median Annual Growth	Compound Annual Average Growth	Median Annual Growth
Preferred ranges				
2006-2019	0.41	0.44	0.37	0.12
2010-2019	0.47	0.44	0.24	0.12
Other ranges				
2007-2019	0.31	0.43	0.25	0.09
2008-2019	0.39	0.44	0.31	0.12
2009-2019	0.60	0.46	0.47	0.15
2010-2016	0.31	0.43	0.13	0.09
2010-2017	0.50	0.44	0.28	0.12

Source: ONS (May 2025), author's calculations.
Notes: Year ranges are from the level of productivity in the first year, e.g. 2006–2019 is the growth from 2006 to 2019, with the first growth rate being between 2006 and 2007 (the growth between 2005 and 2006 is not included). Whole economy data from latest labour productivity statistics at time of writing, published May 2025, consistent with Blue Book 2024; market sector data from latest ONS growth accounting estimates at time of writing, published May 2025, consistent with Blue Book 2024.

driven in part by inward migration. Hours worked in the market sector grew at an average annual rate of 1.8 per cent between 2010 and 2019, faster than any individual year since 1997 and more than twice as fast as the average over any of the pre-slowdown year ranges discussed. Some of this strength in market sector labour input is offset by declining employment in the public sector between 2010 and 2019, such that whole economy labour input growth is somewhat less strong.

Table 3 reports a range of average annual growth rates for the "after" period, in a similar style to Table 2. The unusually strong growth rates in 2010 (recovery from the GFC) and 2017 (footnote 16) drag up the means when included, while periods that start with the low levels of productivity during the financial crisis appear too low (for the whole economy at least). The medians give a better sense of the typical year over this period, which for the market sector is a paltry 0.1 per cent.[16]

Taking the estimates in Table 3 together, a reasonable rate of trend growth in output per hour worked since the slowdown is 0.2–0.3 per cent for the market sector and 0.4–0.5 per cent for the whole economy. It is noteworthy that the market sector has seen slower growth than the economy as a whole, implying yet faster growth for the non-market sector.

Measuring the Trend – Which Industries to Include

There are several industries (sectors) which might be considered peculiar and so omitted from measures of trend productivity growth. Some of these overlap with industries identified by Coyle (2024)

16 The pattern of annual growth in output and hours gives rise to the peculiar result that output per hour worked in 2017 grows by 1.2 per cent in the market sector and 1.7 per cent for the whole economy, while other years in the post-GFC decade do not come close to this. Similarly, MFP is estimated to grow by 1.1 per cent in 2017, while estimated MFP growth in the adjacent four years is negative (in the latest ONS data). This leads the mean to be much higher than the median. However, measurement is never so accurate as to over-interpret a single year, and timing inconsistencies in labour, capital and output data could play a role.

as "hard to measure" in the modern economy, though my choices are dictated not only by measurement. This section discusses the arguments for such exclusions and presents estimates that omit various combinations of these industries.

Government. The most obvious candidate industries for exclusion are perhaps those industries in which the public sector (government) dominates—both because these industries are much less the subject of market forces and because their measurement is challenging. In the National Accounts, non-market output is usually measured by its inputs, which prohibits any measured productivity growth. The ONS is a world leader in measuring government output, using output measures based on activities rather than inputs to a large extent, which allows for change in measured productivity. But measures in the National Accounts do not account for quality change, in the United Kingdom or internationally, making these measures limited (see Heys, 2025, in this issue for discussion of UK public service productivity measures).

In the United Kingdom context, the relevant industries are public administration and defense (section O), education (section P), and health and social care (section Q).[17] Some studies and datasets, for convenience, equate the activities of industries O, P, and Q (henceforth "OPQ") to government activities, and refer to a measure that excludes OPQ as the market sector. This is a reasonable approximation but an imprecise one. An alternative (used primarily in this paper) is measures of the market sector, based on National Accounts data by institutional sector—non-market sectors, namely government and the non-profit institutions serving households (NPISH) sector, are omitted, leaving the "market sectors" comprising the non-financial and financial corporations and households sectors. One drawback of the market sector measures (when defined by institutional sector) is that it includes imputed rental since it is output of the households sector.

Real Estate. Output of the real estate industry includes imputed rent—the imputed income that households who own their own homes pay to themselves instead of paying a landlord for a rental property. This is rightly included in estimates of GDP for the purposes of cross-country comparability. However, for productivity analysis, imputed rent is unhelpful—it is income (and thus output and GVA) without corresponding labour input, since there is no equivalent imputation of owner-occupier hours worked. As such, many studies prefer to exclude imputed rent or, indeed, for convenience exclude the real estate industry entirely. ONS publishes series of labour productivity for the whole economy excluding imputed rent.

Imputed rent causes further challenges in industry-level analysis, including of reallocation effects. Given the additional imputed GVA without associated labour, labour productivity in the real estate indus-

17 The UK public sector also operates in other industries, including waste disposal (part of section E), libraries and other cultural activities (part of section R), and financial services (section K) given the operation of the central bank and the effective nationalization of some financial institutions after the GFC.

try appears to be very high. As such, it has an outsized effect on within-between decompositions of productivity growth across industries. The real estate industry has relatively little employment, and as a result, the estimates of hours worked can be noisy, since they rely on small samples of workers. Small (often erratic) moves in hours worked of the real estate industry can dominate reallocation effects. Using measures for the real estate industry excluding imputed rent is preferable (this is the approach used in Chart 1). Even this residual part of the real estate industry can cause issues—much of the income of the real estate industry is generated by capital (dwellings and other buildings), so the industry has a very low labour share and a high level of labour productivity. It can therefore be preferable to calculate within-between decompositions excluding the real estate industry entirely.

Agriculture. Another often-excluded industry is agriculture—notably in the United States, where "non-farm" measures are standard. The reason for the exclusion in the United States relates to the seasonality of agricultural labour and the potential for weather-induced volatility in output measures, which could cause challenges in interpreting the data (though in other countries, the seasonality may be different). Most data on the UK agriculture industry comes from the relevant central government department rather than ONS-run business surveys, but the data are thought to be robust. Agriculture is a small part of the UK economy in recent decades, so its exclusion will have little effect on aggregate productivity estimates.

Mining and Quarrying. In the UK context, the mining and quarrying industry (notably oil and gas extraction) might also be excluded. United Kingdom North Sea oil production peaked in the mid-1980s and again in the late-1990s-to-early-2000s and has been in fairly continuous decline ever since. Measured labour productivity in the mining and quarrying industry was in near continuous decline between 1997 and 2013, before recovering somewhat up to 2016 and then leveling off. This pattern is in contrast to the United States, which has seen sharp increases in mining productivity due to fracking (Gordon and Sayed, 2019), and also in contrast to major European countries, which mostly have little mining activity. The secular decline of UK mining and quarrying since around the turn of the century is a good argument to exclude it from aggregate measures.

Utilities. The utilities industries of energy generation and distribution and water supply are an interesting case. Similar to the mining industry, though to a lesser extent, these industries have also seen a decline in (measured) labour productivity since the early 2000s. The output of both industries is in large part measured directly by the volume of energy and water, respectively, transmitted to households. Over recent decades, there has been considerable effort in many countries to reduce consumption of energy and water for environmental reasons, leading to weak growth in (measured) output and a decline in (measured) productivity. We might therefore prefer to exclude these industries too.

Finance and Insurance. As discussed earlier, measured productivity of the finance and insurance industry may have been growing at unsustainable rates pre-

GFC and so might not be appropriate to include in the pre-slowdown "trend" rate. This is a similar argument as for the exclusion of the mining industry, but in reverse—while the mining industry is in secular decline, which is not representative of the economy as a whole, the finance industry was in a temporary boom, which is also not representative. There are also well-known challenges with the measurement of financial services output.

If one were to exclude, for one reason or another, all of the industries discussed in this section, what would that leave? Roughly 55 per cent of the economy by nominal GVA and roughly 70 per cent by hours worked, consisting of manufacturing, construction, retail and wholesale, transportation, accommodation and food services, ICT services, professional services, admin and support services, arts and recreation, and other services. We might call this remainder the "core market sector." (One could easily make an argument to exclude any of these remaining industries as well, but in order to retain a reasonably-sized aggregate, we will proceed with this group.)

Table 4 summarizes average annual growth of output per hour worked for a selection of aggregates that exclude one or more of the industries discussed in this section, with more alternatives in Table A5 in the Appendix. The slowdown is not much altered by excluding agriculture, mining, utilities, or finance. Excluding real estate makes the slowdown larger, since it notably increases average annual growth before 2006. Excluding government services makes the slowdown even larger. The full set of exclusions discussed here inflates pre-slowdown average annual growth to 3.6 per cent per year, and while it increases post-slowdown growth to 0.8 per cent per year, that still constitutes a very significant slowdown (2.8 percentage points).

What then to conclude on the size of the slowdown in the United Kingdom? The preferred "before" and "after" periods suggest slowdowns of around 1.5–1.6 percentage points for the whole economy and around 2.0 percentage points (1.9–2.3 percentage points) for the market sector. The range of industry groupings explored in Table 4 do not materially affect the results, though note these do not use the preferred pre-slowdown period. While any of these estimates clearly represent a very significant slowdown, that for the market sector are modestly smaller than the reported slowdowns in most of the articles in Table A3.

Drivers of the Slowdown

As described in Section 1, the literature on the UK productivity slowdown suggests that there are structural rather than cyclical drivers. Despite a wide range of suggested explanations and extensive research, none have been found to fully explain the slowdown. The recent literature, using the latest official data, typically finds the productivity slowdown in the United Kingdom slightly larger than in other developed economies, though with similar attributes: largely a slowdown in TFP, with some slowdown also in capital accumulation, and fairly widespread across industries with a particularly large role for a slowdown in manufacturing.

This section briefly reviews the drivers of

Table 4: Average Annual Growth in Output per Hour Worked, Different Industry Groupings and Restrictions, Before and After Slowdown and Difference

Industry Group	1997–2006	2010–2019	Difference
Whole economy	2.2	0.5	-1.7
x Agriculture (A)	2.1	0.4	-1.7
x Mining and quarrying (B)	2.3	0.6	-1.8
x Utilities (DE)	2.2	0.5	-1.7
x Finance and insurance (K)	2.1	0.7	-1.5
x Real estate (L)	2.5	0.4	-2.1
x Imputed rental (part of L)	2.4	0.5	-1.9
x Government services (OPQ)	2.9	0.4	-2.4
"Core market sector"	3.6	0.8	-2.8
Market sector (by institutional sector)	2.6	0.3	-2.2

Source: ONS, author's calculations.
Notes: The pre-slowdown period uses data for 1997–2006 since data on hours worked for detailed industries are not available prior to 1997. Industry sections from SIC 2007 given in brackets. "Core market sector" excludes all other listed industries, as defined in text. Period averages calculated as simple averages of annual natural log changes.

the UK productivity slowdown, both in an empirical and economic sense. First, updated growth accounting decompositions for the United Kingdom using the latest ONS and international data are presented. Second, UK-specific measurement issues that might "explain" (or give caution to) the UK productivity slowdown are considered. Third, some economic arguments to explain the UK slowdown are discussed.

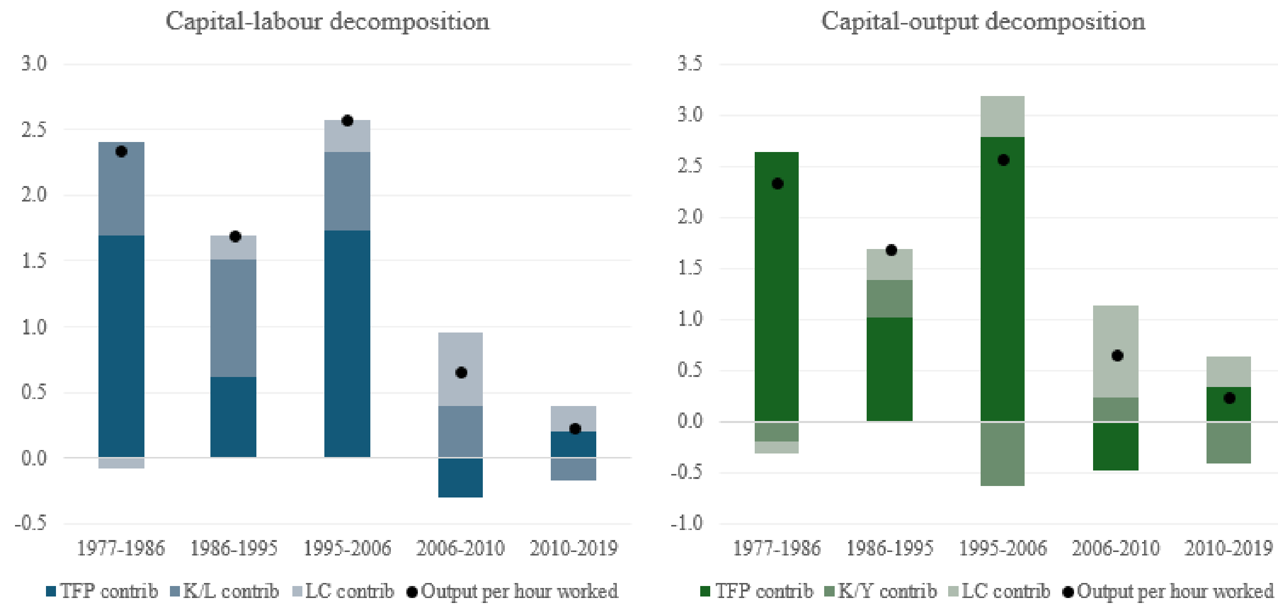
Growth Accounting Decompositions

Chart 3 shows two decompositions of growth in output per hour worked in the UK market sector, in various time periods over the past half century, using the latest ONS growth accounting estimates. The left panel contains the typical growth accounting decomposition, with the contribution of capital expressed relative to hours worked. On this basis, the slowdown in labour productivity growth in 2010–2019 relative to 1995–2006 is driven roughly two-thirds by TFP and one-third by capital deepening.

The right panel contains the decomposition proposed by Fernald and Inklaar (2022), which shows capital relative to output, with the contributions of TFP and labour composition rescaled (see Section 2). On this basis, the slowdown is due almost entirely to a TFP slowdown. The change in the capital-output ratio drags on labour productivity somewhat, but by much the same degree as before the slowdown.

Chart 4 shows the typical capital-labour decomposition of labour productivity growth for the non-agriculture market sector across 12 countries (those for which complete data are available), for two time periods, from the 2025-vintage of EUKLEMS-INTANProd. The bars in both the pre-slowdown (1995–2006) and slowdown (2010–2019) periods are sorted by the level of average annual labour productivity growth in the second period. In the second period, the United Kingdom has the lowest average growth rate of labour productivity growth and the largest estimated decline in TFP. In the pre-slowdown period, the United Kingdom has among the highest labour productivity and TFP growth. These data therefore suggest an unusually

Chart 3: Decompositions of Growth in Output Per Hour Worked, UK Market Sector



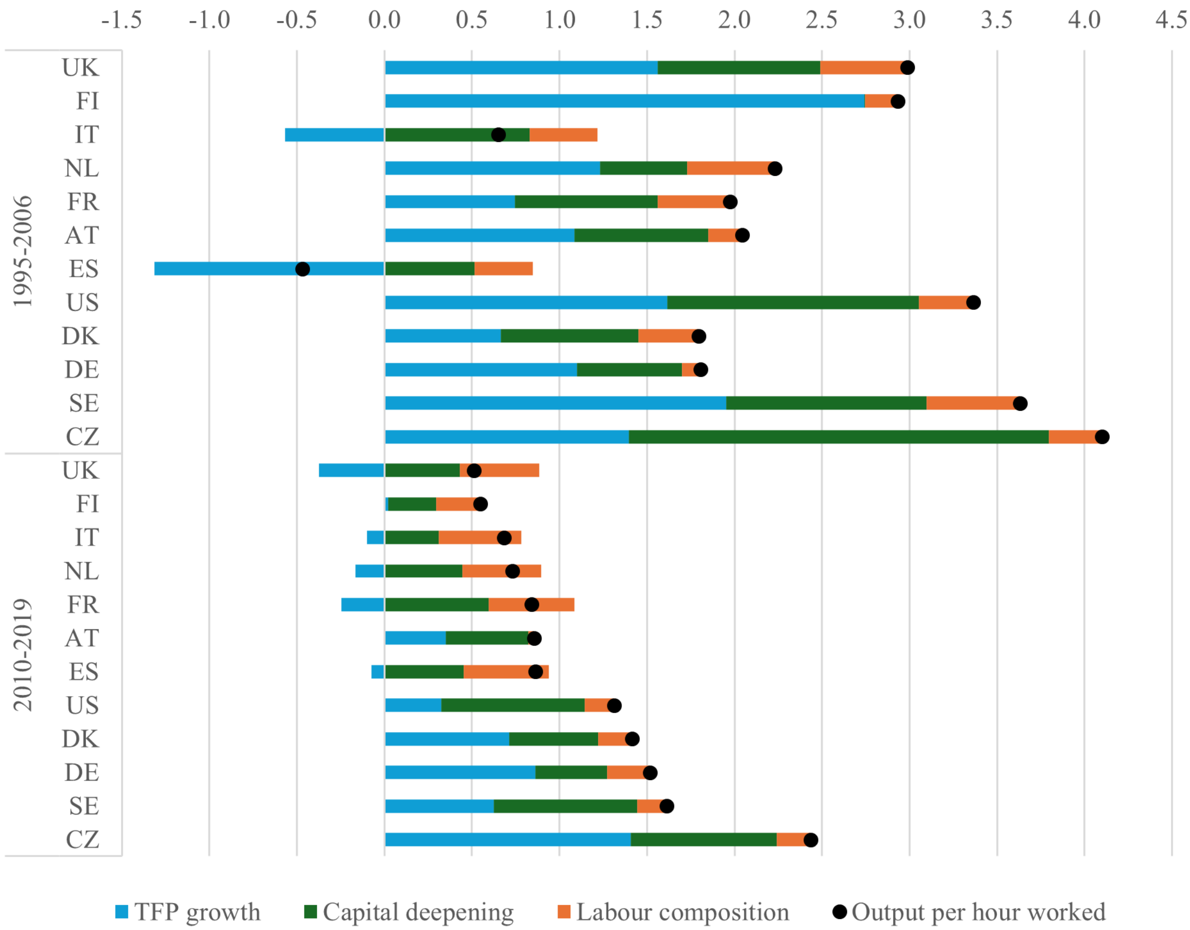
Source: ONS (2025), author's calculations.
Notes: Left panel uses "traditional" growth accounting decomposition, with capital per hour worked (K/L) weighted by the capital share of income (α), and labour composition (LC) weighted by the labour share of income ($1-\alpha$). Right panel uses decomposition proposed by Fernald and Inklaar (2022), using the capital-output ratio (K/Y) weighted by $\alpha/(1-\alpha)$, TFP weighted by $1/(1-\alpha)$, and labour composition (LC). Scales differ. Both decompositions derived from ONS growth accounting estimates published May 2025. Year ranges are from the level of productivity in the first year, e.g., 1977–1986 is the growth from 1977 to 1986, with the first growth rate being between 1977 and 1978 (the growth between 1976 and 1977 is not included). Periods based on discussion in Section 3.

large slowdown in productivity growth in the United Kingdom.

However, these data for the United Kingdom should be interpreted cautiously. First, the estimates of labour composition (LC) growth for the United Kingdom are consistently larger than estimates produced by ONS. Higher LC growth implies lower TFP growth in the EUKLEMS dataset. The ONS LC estimates make use of more detailed and comprehensive UK-specific data sources, while the EUKLEMS estimates rely on cross-European data sources, so the ONS estimates (which show slower growth) are to be preferred. Second, the capital estimates are also different from ONS estimates, especially in the "extended" module which includes additional intangibles and alters the deflator for ICT equipment, and results in substantially faster capital growth. With stronger labour composition and capital services growth in EUKLEMS than in ONS estimates, the TFP residual is mechanically much weaker. Third, the market sector definition is by the exclusion of industries, rather than by institutional sector, making it inconsistent with ONS growth accounting estimates in Chart 3.

That said, the pattern of the slowdown is similar in the United Kingdom as in other countries. In most of the countries in Chart 4 experiencing a slowdown in labour productivity growth, the slowdown is explained roughly three-quarters by TFP and one-quarter by capital shallowing. This confirms findings in the recent literature.

Chart 4: Decomposition of Growth in Output Per Hour Worked Across Countries, Non-Agriculture Market Sector



Source: EUKLEMS-INTANProd (2025-vintage), author's calculations.
Notes: Dots show average annual growth rates of output per hour worked, and bars show average annual contributions to OpH growth in percentage points. Bars in both time periods sorted low-high by OpH growth in the second period. See Appendix for country codes.

UK Measurement Issues

Much has been written on the potential impact of measurement issues on productivity statistics (Syverson, 2017; Goldin *et al.*, 2024; see also Martin and Riley, 2025, on advances in productivity measurement). In this section, some UK-specific measurement issues are considered. More pervasive measurement issues, including free digital goods and services, the challenges of quality-adjusting deflators, measuring public sector output (especially in healthcare), and the role of intangible assets, are largely not discussed here, except where they relate specifically to UK measurement practice.

Research and Development. In the 2025 annual national accounts update, the ONS will substantially increase estimates of investment in research and development (ONS, 2025), which will likely increase the level of GDP. This follows major changes to the business R&D survey in recent years (ONS, 2023), after it was identified that the previous sample design substantially underestimated the number of firms (especially small firms) conducting R&D, and thus the total value of R&D expenditure. These revisions will increase the level of R&D Gross fixed capital formation (GFCF) across the entire time series, though the precise revisions are unknown at the time of writing. This will make the R&D share of GDP in the United Kingdom more in line with other advanced economies and increase the level of UK GDP (and investment) relative to other countries slightly. This change is unlikely to materially alter the growth of GDP; rather this is likely to be a fairly uniform increase in the level of GDP over time. However, a concurrent change to the deflator for R&D investment (ONS, 2025) may have effects on real GDP growth.

Profit Shifting. Multi-national enterprises are increasingly able to shift the reporting of their profits across subsidiaries in different countries, which may be for tax or accounting purposes. Many MNEs have a presence in the United Kingdom, meaning that UK GDP could be under- or over-stated due to profit shifting relative to the value associated with production activities in the United Kingdom. Mion and Tong (2022) find that in 2017 more profit is recorded in the United Kingdom than would have been expected relative to a counterfactual activity-based measure. In 2007, less profit had been recorded in the United Kingdom than the counterfactual. This suggests that "true" GDP should be higher than measured in 2007 and lower than measured in 2017, which would accentuate the productivity slowdown slightly relative to current measurement.

Output Deflators. The deflation of services output is challenging, and is especially important in a services-dominated economy such as the United Kingdom. The preferred services output deflators in the United Kingdom are Services Producer Price Indices (SPPIs). O'Mahony and Samek (2021) found that UK SPPIs were not materially different to those for other countries; however, some UK SPPIs were only created around 2010 (especially those for professional services industries), with deflators for earlier years based on an alternative series which may not be consistent. In cases where no SPPI exists, ONS often use a wage-based deflator which likely does not account for quality change and may therefore overstate price growth and understate real output growth.

In addition, ONS use a "productivity adjustment" in the calculation of real GVA estimates for approximately 8.7 per cent of nominal GVA across a range of services industries.[18] This is usually the case when the industry output volume measure is based on the number of workers (rather than deflated turnover), or where the deflator is wage-based. It is unclear what measure of productivity ONS uses for these productivity adjustments. If it is based on

18 Author's calculation based on ONS methods information, see Appendix for details. The use of productivity adjustments is not recommended by Eurostat in their Price and Volume Handbook, because any adjustment in the absence of appropriate evidence is arbitrary. Of course, making no adjustment is also an assumption of no productivity growth, which is just as arbitrary. The preferred solution then must be to identify or construct suitable independent price indices that can be used as deflators, or direct volume estimates that are not based on production inputs (e.g. labour).

a measure of productivity that has seen a slowdown (and most have), then this adjustment may be reinforcing this slowdown by spreading it into other industries. For instance, if ONS is using whole economy output per hour worked as the productivity adjustment measure, then the slowdown in manufacturing productivity will be "spread" to other industries.

Hours Worked. Official UK productivity statistics published by the ONS use estimates of hours worked from the Labour Force Survey (LFS), using the so-called "direct method." That is, hours worked for the whole economy are based solely on the aggregation of reported hours actually worked by individuals on the LFS. Many other countries use a so-called "component method" to estimate hours worked, which instead uses a series of components derived from different sources.[19] Ward *et al.* (2018) found that estimates of hours worked in OECD countries that used a direct method were systematically higher than those using a component method, suggesting that the direct method was biased upward. Ward *et al.* (2018) construct a "simplified component method" for countries that use the direct method in their productivity statistics, which in the case of the United Kingdom is around 10 per cent lower.

A lower estimate of hours worked would, other things equal, increase estimates of output per hour worked by an equivalent amount. It is likely that the primary effect of this measurement issue is to alter the level of UK labour productivity, and particularly the level relative to other countries (the United States and major European economies use the component method in their official productivity statistics). Indeed, the OECD simplified component method estimate is a roughly constant 8 per cent below the ONS direct estimate. However, it is plausible that the bias from the LFS has been changing over time. Response rates to the UK LFS declined almost continuously from around 70 per cent in the late 1990s, to around 50 per cent in 2019, falling as low as 14 per cent in mid-2023. Declining response rates reduce the achieved sample, but also increase the scope for non-response bias. Any bias onto the growth of hours worked is unclear. Impacts by industry are also unclear and may not be uniform.

Capital Stocks. Measuring capital stocks consistently across countries is well-known to be challenging, but some issues may impact UK estimates more than other countries. First, major changes to ONS capital stocks methods in 2019 (ONS, 2019) included reducing assumed asset service lives and so increasing depreciation rates. Thus, ONS estimates of capital stocks are considerably lower than previously, which naturally means that the capital-to-output ratio is lower than previously. However, ONS did not adjust historical service life assumptions uniformly through time, instead maintaining previous assumptions from the 1960s and transitioning to the new assumptions between 1970 and 1997. As

19 Typically, one would start with an estimate of paid, usual or contractual hours worked from a high-quality source, perhaps administrative data, and then adjust it for deviations such as sickness, holiday, overtime, strikes, and so forth.

such, for a given volume of investment, estimated capital stocks will be larger historically than over recent decades. This has contributed to a falling measured capital-to-output ratio in the United Kingdom, which challenges the assumptions in some growth accounting decompositions. To the extent that these practices vary across countries, it could lead UK capital stocks to appear to be growing slower than other countries. The EUKLEMS-INTANProd database provides "harmonized" estimates of capital stocks and capital services which use the same depreciation assumptions across countries. While there are good reasons to think that economic depreciation rates do vary across countries (due to compositional, behavioral, or environmental reasons), harmonized assumptions may improve comparability.

Second, alongside normal depreciation, some capital assets are scrapped/retired before the end of their useful service life. This might be especially common during economic downturns. If this is not adequately adjusted in capital stock measures, it could lead countries with larger downturns to have their capital stock relatively over-stated, which would lead TFP to be relatively understated, following downturns in those economies. The United Kingdom experienced a relatively large economic downturn in 2008–09, so may be relatively more affected by this mismeasurement since then.

Intangibles. Following international guidance, only some intangibles are treated as produced assets in the UK National Accounts. The broader set of intangibles described in Corrado *et al.* (2005) and Bontadini *et al.* (2024), among others, may be more important in the United Kingdom than in some other countries given the importance of services to the UK economy. Indeed, Corrado *et al.* (2018) find that the United Kingdom and United States invest relatively more in these uncapitalized intangibles than many major European economies, so their exclusion from GDP may be more consequential to the United Kingdom than to many other countries. Similarly, data will be treated as a produced asset under SNA 2025, which will increase the level of GDP by roughly the value of the newly capitalized investment. Corrado *et al.* (2022) find that the United Kingdom invests relatively more in data assets than some other advanced European economies, so the revision to United Kingdom GDP and capital input may be larger in the United Kingdom than elsewhere. This suggests the importance of considering measures that account for additional intangibles to ensure fairer comparisons between the United Kingdom and other countries.

The United Kingdom In A Global Slowdown

It is beyond the scope of this UK-focused article to review explanations for the global productivity slowdown, which are well reviewed elsewhere. Instead, the United Kingdom is considered in the context of two of those proposed global drivers.

Environmental Factors. Many countries have attempted to reduce environmental damage over recent decades by reducing emissions of greenhouse gases, transitioning toward renewable energy sources, reducing use of materials, increasing recycling, and so forth. The United Kingdom has been making more progress than most countries: greenhouse gas emissions have fallen faster in the United Kingdom than in the United States and most major European economies, especially since about 2005. A similar pattern exists for water use.[20]

There are at least two potential impacts on aggregate productivity. First, growth of "traditional" (measured) output and productivity will be constrained in some industries, most notably the energy and water industries, but potentially also the transportation, mining, manufacturing, and construction industries. For energy and water industries, where output is measured (and defined, in a National Accounts sense) by the volume of energy and water transmitted, efforts to reduce usage directly constrain industry output and so productivity. Using data from the 2025-vintage of EUKLEMS-INTANProd (see Table A7 in the Appendix for details), the United Kingdom has the fourth slowest labour productivity growth of 19 countries in the period 1995–2019 for the energy industry (section D), and third slowest for the water (section E) industry. Thus, these industries appear to be dragging on aggregate UK productivity more than in other countries.

The second potential mechanism is a slowing in innovation more broadly. A country likely has a relatively fixed and limited supply of scientists, innovators, and researchers, and a limited supply of funding to support those people. A country that prioritizes environmental goals may have to do so at the expense of innovations in other fields. Similarly, businesses might have capacity to invest either to increase the efficiency of their operations (e.g. through business process improvements) or to reduce their environmental impact (and meet associated regulation). The latter may be socially desirable, but goes unmeasured in traditional economic statistics. Activity to reduce environmental damage can also be seen as an intertemporal trade-off—it may reduce productivity or profitability in the present but may be profit-maximizing in the long run.

Agarwala and Martin (2023) propose to add "unmeasured environmental protection output" to GDP, with an estimate that it could account for around 5 per cent of United Kingdom GDP—that may be larger than in other countries. De Ridder and Rachel (2025) construct emissions-adjusted TFP measures for a range of countries and find a significant increase in the adjusted measure of TFP (TFPE) growth for the United Kingdom. Indeed, they suggest that the United Kingdom did not experience a TFP slowdown once the decline in carbon dioxide emissions is accounted for.[21]

To the extent that the United Kingdom is a world leader in reducing its environmental footprint, this could have implications for the level and growth of measured productivity. If the United Kingdom

20 Based on data as presented by Our World in Data and AQUASTAT. See Appendix for details.

21 Agarwala and Martin (2022) make a similar adjustment for UK industries, but account for a wider range of emissions and pollutants than just carbon dioxide. They find substantially higher labour productivity growth with this adjustment, but still a slowdown from around 2007 onwards.

has a lower level of environmental damage per unit of "traditional" output than other countries, then its level of "true" (environmentally adjusted) productivity would be most mismeasured. Thus, accounting for environmental damage would raise the level of UK productivity relative to other countries. Similarly, if the United Kingdom has reduced its emissions and environmental damage faster than other countries, the bias on measured productivity would also be greatest. Indeed, Cárdenas Rodríguez *et al.* (2023) find that the United Kingdom has the second largest positive adjustment to TFP growth when accounting for pollution abatement (behind Belgium), at nearly 0.4 percentage points per year, compared to less than 0.2 percentage points per year for the United States and OECD average.

Services and Intangibles. Another global trend, at least among advanced economies, is a shift from manufacturing to services. It is argued that this will inevitably lead to a slowing in productivity growth, since the potential for productivity gains in labour-intensive services industries is lower than in capital-intensive production industries (Baumol's cost disease). If so, that might apply to the United Kingdom more so than in many other advanced economies. The manufacturing share of total value added in the United Kingdom is around 10 per cent—well below the average of other advanced economies. By contrast, the share of predominantly public services industries (public administration, education, health and social care) is around 20 per cent of total value added in the United Kingdom—a little above the average of other advanced economies. Given the aging and demographic change that has already been experienced and is expected to continue over coming decades, this trend is only likely to continue, both in the United Kingdom and other advanced economies. This has consequences both for measurement of productivity, since measuring the output and productivity of services is clearly challenging, but also for actual productivity growth.

As well as a services-oriented economy, the United Kingdom is also an economy for which intangible assets are especially important. The intangible share of investment is higher in the United Kingdom than in most other advanced economies, based on estimates that include a broader definition of intangible investment (Corrado *et al.*, 2022). Again, there is a measurement effect and a real effect. Measuring intangible assets remains difficult despite considerable efforts by the research community. National Accounts measures which include only a subset of intangibles as produced assets may understate UK GDP and labour productivity to a greater extent than in many other economies. International databases which account for additional intangible assets, such as the EUKLEMS-INTANProd, may therefore be especially important for the United Kingdom.

There are also important implications of an intangible-intensive economy for "true" productivity. Haskel and Westlake (2022) argue that the properties of intangible assets are not necessarily positive for aggregate productivity, at least not without the right institutions. Through their synergies and sunk costs, intangibles favour winner-takes-all dynamics which can hinder competition and the spread of ideas. Intangible-intensive firms may also struggle to obtain debt capital to expand, since intangibles can rarely be used as collateral. Studies have observed a decline in business dynamism and an increase in productivity dispersion, which are found to be associated with intangible-intensive firms and industries.

These issues may be more pervasive in the United Kingdom, as an intangible-intensive economy, than in many others. The obvious counterargument to this line of thinking is the United States, which is clearly also an intangible-intensive economy but has seen a better productivity performance than the United Kingdom over recent decades, despite a slowdown in productivity growth of broadly similar shape. However, the United States is a unique case in many respects (market size, dominant currency, venture capital, Silicon Valley), and so may not be a good comparator here. Alternatively, the United States may have more appropriate institutions (as per Haskel and Westlake) to enable an intangible-intensive economy to succeed.

Conclusion: Evidence Gaps For UK Productivity

I conclude by suggesting three avenues for measurement to enhance our understanding of UK productivity and its growth slowdown.

First, measures of labour input in the United Kingdom should be improved. labour is arguably the most important input in the production process and should be the easiest to measure. But UK measures of hours worked are well behind the international methodological frontier. As described in Section 4, official UK productivity statistics use a “direct method” to estimate hours worked, rather than the international best-practice “component method.” The implications for the level of UK productivity, especially relative to other countries, are clearly set out in Ward *et al.* (2018). Declining response rates for the UK Labour Force Survey, to as low as 14 per cent in 2023, have increased the scope for non-response bias—if the large non-responding cohort has different employment rates or hours worked than the responding cohort, this could be biasing the estimates. If that bias is changing over time, this could matter for the growth of hours worked, as well as the level. The size of any effect is unclear, but it has the potential to materially affect the recent history of measured UK productivity.

Labour composition estimates, which typically account for changes in the age and education composition of the workforce, may not capture other important worker characteristics. For instance, the role of on-the-job training, work experience (general, industry-specific, and firm-specific), and age mixes within firms are all understudied in the United Kingdom due to lack of suitable data.

Second, more research is needed on the role of worker-firm interactions. The United Kingdom lacks a linked employee-employer dataset (LEED), which is a powerful dataset of workers and firms, enabling rich analysis of the drivers of firm-level productivity. Development has been hampered by restrictions on accessing individual-level income tax data, though progress is (at the time of writing) beginning. Among many other things, this would allow research into the importance for productivity of movements of workers across firms (spreading ideas, improving matches) and within firms (building firm-specific human capital).

Third, the United Kingdom does not have current estimates of TFP constructed in a KLEMS framework.[22] Unlike GVA-based growth accounting, KLEMS-type accounting decomposes total output into the contributions of labour, capital, and intermediate inputs. This is only possible with separate estimates of the volumes of output and intermediate inputs, which is now available following the introduction of double deflation in official data in 2021. KLEMS measures relax some of the assumptions imposed by GVA-based productivity measures and better attribute productivity gains along supply chains. In an era of changing trade relationships and supply chain disruption (e.g. Brexit, deglobalization), a blurring of the boundary between capital and intermediate inputs (e.g. cloud computing), and digital advances enabling rapid changes in production functions (e.g. homeworking, food deliveries), KLEMS is the ideal framework.

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Appendix

Table A1 – UK output per worker estimates, by data vintages

			Compound average annual growth rates (%)			
Vintage	**Release**	**Last year of post-GFC period**	**Pre-GFC (1997-2007)**	**Post-GFC (2010-latest/2019)**	**Slowdown (post-GFC minus pre-GFC)**	***Memo: Latest estimate of post-GFC period***
BB12	Jul-12	2011	2.2	0.5	1.7	*0.7*
BB13	Jul-13	2012	2.2	-0.1	2.3	*0.6*
BB14	Oct-14	2013	2.0	0.4	1.6	*0.6*
BB15	Oct-15	2014	1.9	0.7	1.2	*0.6*
BB16	Jul-16	2015	1.9	0.5	1.4	*0.6*
BB17	Oct-17	2016	1.8	0.6	1.2	*0.6*
BB18	Jul-18	2017	1.8	0.6	1.2	*0.7*
BB19	Oct-19	2018	2.0	0.6	1.4	*0.7*
BB20	Oct-20	2019	1.9	0.5	1.4	*0.6*
BB21	Oct-21	2019	1.6	0.8	0.9	*0.6*
BB22	Oct-22	2019	1.7	0.7	1.0	*0.6*
BB23	Oct-23	2019	1.8	0.7	1.2	*0.6*
BB24	Oct-24	2019	1.8	0.7	1.2	*0.6*

Source: ONS (various vintages), author's calculations.
Notes: Update and modification of Table 1 from Martin and Mackenzie (2021), which was based on output per hour worked and went to BB21. In this version I have adjusted the post-GFC period to be growth from 2010 (i.e. first year of growth is 2011) to the latest year available or 2019. Parallel to Table 1 in the main text which was the equivalent for output per hour worked.

Table A2 – Descriptive statistics on the breadth of labour productivity growth across industries, 1998-2007

	1998	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Mean annual OpH growth across 78 industries (%)										
Unweighted	1.9	4.1	5.1	2.2	3.9	4.1	4.3	2.6	3.3	1.2
Weighted by hours	3.0	2.1	4.3	1.9	2.2	2.3	1.5	1.4	2.3	0.6
Weighted by nominal GVA	2.7	2.5	4.8	1.7	2.5	3.2	2.3	1.9	1.8	2.2
Median annual OpH growth across 78 industries (%)										
Unweighted	1.9	1.9	3.7	1.4	2.8	3.7	1.6	1.8	1.8	0.1
Weighted by hours	2.0	-1.8	1.3	-0.3	-1.1	1.5	0.8	0.1	1.5	-0.5
Weighted by nominal GVA	1.9	-1.8	2.3	-0.5	1.9	2.0	0.8	1.7	1.9	0.0
Proportion of 78 industries with positive annual OpH growth (%)										
Unweighted	59	58	65	54	60	65	65	58	58	51
Weighted by hours	67	44	62	47	50	53	60	56	63	38
Weighted by nominal GVA	62	45	64	46	52	57	60	58	61	43
Share of whole economy OpH growth due to top contributing industry (%)	33	42	28	28	35	26	44	50	39	57

Source: ONS (May 2025), author's calculations.
Notes: Hours weights and nominal GVA weights use the preceding year (e.g. 1997 weights for the 1998 growth rates). Industry breakdown is 78 mostly industry divisions (two-digit industries) of SIC 2007, with some aggregations.

Table A3 – Summary of output per hour worked growth rates before and after slowdown, UK growth accounting studies

Paper	Coverage	Source	Vintage	Pre-period	Pre growth	Post-period	Post period	Comments
Goodridge et al. (2014)	MS	ONS*	BB13	1990-2000 2000-2007	2.94 2.54	2007-2011	-0.47	Adjusted for R&D
Rincon-Aznar et al. (2015)	WE	TED	2014	2002-2007	2.7	2008-2013	-0.45	Adjusted for training
Goodridge et al. (2018)	MS	ONS*	BB13	1980-1990 1990-2000	2.70 2.94			Adjusted for R&D
Goodridge et al. (2018)	MS; bottom-up	ONS*	BB13	2000-2007	2.64	2007-2011	-0.46	Adjusted for R&D
Riley et al. (2018)	WE	ONS	BB17	1999-2007	2.1	2008-2016	0.2	
Riley et al. (2018)	MS	ONS	BB17	1999-2007	2.8	2008-2015	0.0	
Tenreyro (2018)	WE	ONS	BB17	2000-2007	2.0	2009-2015	0.4	
Oulton (2019)	WE	EUKLEMS	Sept 2017	2000-2007	1.91	2007-2015	0.08	
Fernald & Inklaar (2022)	WE	PWT	10.0	1985-1995 1995-2007	2.2 2.17	2007-2019	0.13	
Fernald & Inklaar (2022)	MS	ONS	BB20/21	1985-1995 1995-2007	3.8 2.82	2007-2019	-0.17	
Coyle & Mei (2023)	WE	ONS	BB21	1998-2008	1.63	2008-2019	0.35	
Coyle & Mei (2023)	WExL	ONS	BB21	1998-2008	1.50	2008-2019	0.05	
Coyle & Mei (2023)	WExOPQ	ONS	BB21	1998-2008	1.72	2008-2019	0.18	
Chadha & Samiri (2023)	MS	ONS	BB21	1997-2007	2.43	2009-2019	0.4	
Goodridge & Haskel 2023	MSxA	ONS*	BB22	2000-2007	2.46 2.32	2007-2019	0.12 0.10	National accounts Adjusted for additional intangibles
Goodridge & Haskel 2023	MSxA; bottom-up	ONS*	BB22	2000-2007	2.69 2.55	2007-2019	0.14 0.14	National accounts Adjusted for additional intangibles
Bontadini et al (2024)	MSxA	EUKLEMS	2023	1998-2007	2.91	2008-2019 2014-2019	0.49 0.93	Adjusted for additional intangibles
Bontadini et al (2024)	MSxA; bottom-up	EUKLEMS	2023	1998-2007	3.02	2008-2019 2014-2019	0.5 1.22	Adjusted for additional intangibles
van Reenen & Yang (2024)	WE	ONS	BB22	1997-2007	1.5	2007-2019	0.6	
van Reenen & Yang (2024)	WE	EUKLEMS	2023	1997-2007	1.94	2007-2019	0.51	
van Reenen & Yang (2024)	MS	EUKLEMS	Various	1979-1997 1997-2007	2.2 2.72	2007-2019	0.48	
van Reenen & Yang (2024)	MS	EUKLEMS	2023	1995-2007	2.54 2.65	2007-2019	0.48 0.71	National accounts Adjusted for additional intangibles
Goldin et al. (2024)	WE	EUKLEMS	2019	1996-2005	2.21 2.25	2006-2017	0.45 0.52	National accounts Adjusted for additional intangibles
Goldin et al. (2024)	WE	OECD	2019	1995-2005	2.22	2006-2017	0.47	

Notes: WE is whole economy; BU is bottom-up aggregation of industries; MS is market sector (MSxA is market sector excluding agriculture). ONS* is ONS data adjusted for additional intangibles.

Table A4 - Summary of TFP growth rates before and after slowdown, UK growth accounting studies

Paper	Type	Coverage	Source	Vintage	Pre-period	Pre growth	Post-period	Post period	Comments
Goodridge et al. (2014)	K-L	MS	ONS*	BB13	2000-2007	1.21 1.19	2007-2011	-2.1 -2.09	Baseline Adjusted for R&D
Rincon-Aznar et al. (2015)	K-L	WE	TED	2014	2002-2007	0.98	2008-2013	-1.71	Adjusted for training
Goodridge et al. (2018)	K-L	MS; bottom-up	ONS*	BB13	2000-2007	0.97 0.94	2007-2011	-2.17 -2.17	Baseline Adjusted for R&D
Riley et al. (2018)	K-L	MS; bottom-up	ONS	BB17	1999-2007	2.0	2011-2015	0.0	
Tenreyro (2018)	K-L	WE	ONS	BB17	2000-2007	0.6	2009-2015	-0.2	
Oulton (2019)	K-L	WE	EUKLEMS	2017	2000-2007	1.01	2007-2015	-0.3	
Fernald & Inklaar (2022)	K-Y	WE	PWT	10.0	1985-1995 1995-2007	0.92 1.86	2007-2019	-0.44	Contributions of TFP are dTFP/(1-a)
Fernald & Inklaar (2022)	K-Y	MS	ONS	BB20/21	1985-1995 1995-2007	1.21 2.51	2007-2019	-0.31	Contributions of TFP are dTFP/(1-a)
Fernald & Inklaar (2022)	K-L	WE	PWT	10.0	1985-1995 1995-2007	0.50 1.08	2007-2019	-0.26	
Fernald & Inklaar (2022)	K-L	MS	ONS	BB20/21	1985-1995 1995-2007	0.74 1.61	2007-2019	-0.21	
Chadha & Samiri (2023)	K-L	MS	ONS	BB21	1997-2007	1.52	2009-2019	0.2	
Chadha & Samiri (2023)	K-Y	MS	ONS	BB21	1997-2007	2.41	2009-2019	0.33	Contributions of TFP are dTFP/(1-a)
Goodridge & Haskel (2023)	K-L	MSxA	ONS	BB22	2000-2007	1.64 1.44	2007-2019	-0.31 -0.28	National accounts Adjusted for additional intangibles
Bontadini et al (2024)	K-L	MSxA	EUKLEMS	2023	1998-2007	1.21	2008-2019 2014-2019	-0.22 0.34	Adjusted for additional intangibles (both periods)
Bontadini et al (2024)	K-L	MSxA	EUKLEMS, ONS	2023, BB23	1970-2007	0.74	2008-2019 2014-2019	0.03 0.59	Adjusted for additional intangibles and consumer digital services mismeasurement (both periods)
van Reenen & Yang (2024)	K-L	MS	EUKLEMS	Various	1979-1997 1997-2007	0.64 1.43	2007-2019	0.06	
van Reenen & Yang (2024)	K-L	MS	EUKLEMS	2023	1995-2007	1.22 1.14	2007-2019	0.06 -0.07	National accounts Adjusted for additional intangibles
Goldin et al. (2024)	K-L	WE	EUKLEMS	2019	1996-2005	1.14 1.23	2006-2017	0.3 0.31	National accounts Adjusted for additional intangibles
Goldin et al. (2024)	K-L	WE	OECD		1995-2005	1.73	2006-2017	0.09	TFP includes labour composition

Notes: K-L is capital-labour; K-Y is capital-output; BU is bottom-up aggregation of industries; MS is market sector (MSxA is market sector excluding agriculture); WE is whole economy

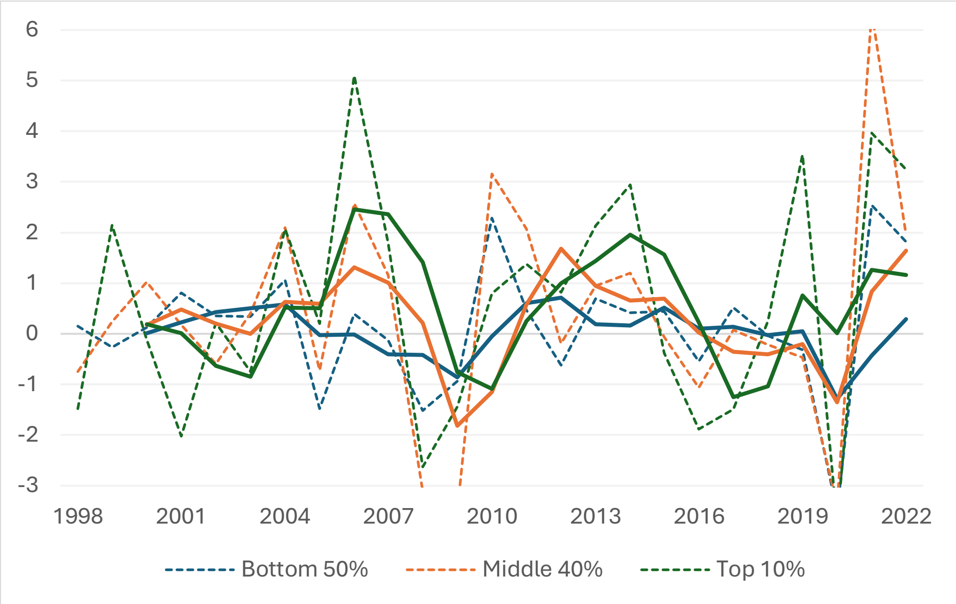
Table A5 - Average annual growth in output per hour worked, additional industry groupings and restrictions, before and after slowdown and difference

Industry group	1997-2006	2010-2019	Difference
Whole economy	2.2	0.5	-1.7
x Agriculture (A)	2.1	0.4	-1.7
x Mining and quarrying (B)	2.3	0.6	-1.8
x Manufacturing (C)	1.2	0.4	-0.9
x Utilities (DE)	2.2	0.5	-1.7
x Construction (F)	2.4	0.5	-1.9
x Wholesale and retail; transportation; accommodation and food services (GHI)	2.4	0.6	-1.8
x ICT services (J)	1.4	0.1	-1.3
x Finance and insurance (K)	2.1	0.7	-1.5
x Real estate (L)	2.5	0.4	-2.1
x Imputed rental (part of L)	2.4	0.5	-1.9
x Professional, scientific services; admin and support services (MN)	2.4	0.6	-1.8
x Government services (OPQ)	2.9	0.4	-2.4
x Arts, entertainment; other services (RST)	2.3	0.5	-1.8
x KOPQ	2.9	0.7	-2.2
x LOPQ	3.3	0.3	-3.0
x KLOPQ	3.3	0.7	-2.7
x ALOPQ	3.2	0.3	-2.9
x AKLOPQ	3.2	0.6	-2.6
x ABDELKOPQ ("Core market sector")	3.6	0.8	-2.8
Market sector (by institutional sector)	2.6	0.3	-2.2
ABCDEH (excluding "Hard to measure")	5.2	0.4	-4.8
ABC (excluding "Hard to measure" modern)	6.9	1.0	-5.8

Source: ONS, author's calculations.

Notes: The pre-slowdown period uses data for 1997-2006 since data on hours worked for detailed industries are not available prior to 1997. Industry sections from SIC 2007 given in brackets. "Core market sector" as defined in text. Period averages calculated as simple averages of annual natural log changes. "Hard to measure" definitions following Coyle (2025).

Chart A1 – Contributions of parts of the firm-level productivity distribution to aggregate labour productivity growth



Source: ONS (2024), author's calculations.
Notes: Trailing three-year averages in solid lines, annual data (as published) in dashed lines.

Productivity adjustment in GDP(O) industry output deflators

ONS use "productivity adjustment" in the calculation of real GVA estimates for approximately 8.7% of nominal GVA across a range of services industries. This is calculated based on the ONS "GDP(o) data sources catalogue", version published 11 October 2024 consistent with Blue Book 2024, available at:
https://www.ons.gov.uk/economy/grossdomesticproductgdp/datasets/gdpodatasourcescatalogue

Table "BB24 - CURRENT PRICE & VOLUME" provides details about the sources and methods for nominal (current price) and real (volume) estimates of industry output. Column O, titled "Use of Prod Adj", shows whether an industry estimate uses a productivity adjustment. On the "Cover" tab, this is described as "used to take account of efficiency gains in the production process when using input series such as jobs and wages".

The table below summarises the instances of the use of the productivity adjustment. This is usually the case when the industry output volume measure is based on the number of workers (from Workforce jobs = WFJ), or where the deflator is wage-based (using Average Weekly Earnings = AWE). The sum of the weights of associated industry output (based on column H of the table) is 8.7% (87 parts per 1000).

The use of productivity adjustments is not recommended by Eurostat in their Price and Volume Handbook, because any adjustment in the absence of appropriate evidence is arbitrary. Of course, making no adjustment is also an assumption of no productivity growth, which is just as arbitrary. The preferred solution then must be to identify or construct suitable independent price indices that can be used as deflators, or direct volume estimates that are not based on production inputs (e.g. labour).

It is unclear what measure of productivity ONS uses for these productivity adjustments. If it is based on a measure of productivity that has seen a slowdown (and most have) then this adjustment may be reinforcing this slowdown by spreading it into other industries. For instance, if ONS are using whole economy output per hour worked as the productivity adjustment measure, then the slowdown in manufacturing productivity will be ‘spread’ to other industries.

Table A6 – Summary of use of productivity adjustment in industry output deflators

Industry	Weight of relevant part in total industry GVA (parts per 1000)	Way in which the productivity adjustment is used
Mining support service activities (division 9)	0.8	Output volume is number of workers with prod adj
Motion picture, video and television programme production, sound recording and music publishing activities (division 59, market and non-market elements)	6.3	Deflator is wage-based with prod adj
Programming and broadcasting activities (division 60, part of market sector element)	0.5	Output volume is number of workers with prod adj
Computer programming, consultancy and related activities (division 62)	27.2	Deflator is SPPI with prod adj
Information service activities (division 63)	4.4	Deflator is SPPI with prod adj
Financial service activities, except insurance and pension funding (division 64, parts)	11.7	Deflator is wage-based with prod adj
Activities auxiliary to financial services and insurance activities (division 66, parts)	5.4	Deflator is wage-based with prod adj
Activities of head offices; management consultancy activities (division 70, part associated with head offices)	1.4	Output volume is number of workers with prod adj
Scientific research and development (division 72, both market and non-market elements)	9.0	Deflator is wage-based with prod adj
Education (division 85, part of private sector element)	0.8	Deflator is wage-based with prod adj
Residential care activities (division 87, market sector element)	7.9	Deflator is wage-based with prod adj
Social work activities without accommodation (division 88, market sector element)	8.2	Deflator is wage-based with prod adj
Activities of membership organisations (division 94, market sector element)	3.1	Deflator is wage-based with prod adj

Source: Author’s elaboration of ONS GDP(o) data sources catalogue.

Table A7 – Summary of output per hour worked growth in selected industries, across countries

	Average annual growth (%)		Rankings	
	UK	Median of other countries	UK rank	Countries with slower growth than UK
Energy (section D)				
1995-2006	5.0	4.2	6/19	JP, AT, FR, CZ, FI, SI, LU, BE, DK, IT, LV, DE, SE
2010-2019	0.1	0.5	12/19	IT, JP, BE, EL, DE, LV, CZ
2005-2019	-2.8	-1.1	18/19	CZ
1995-2019	0.5	1.7	16/19	SE, LV, CZ
Water and waste (section E)				
1995-2006	-1.8	-0.5	15/19	DE, LV, DK, IT
2010-2019	-2.6	-0.5	17/19	IT, SI
2005-2019	-3.4	-0.7	18/19	IT
1995-2019	-2.4	-0.8	17/19	SI, IT
Utilities (sections D and E combined)				
1995-2006	1.8	1.9	10/19	CZ, BE, LV, ES, DK, DE, US, SE, IT
2010-2019	-1.2	-0.2	16/19	IT, LV, CZ
2005-2019	-3.0	-0.5	18/19	CZ
1995-2019	-0.8	0.4	17/19	CZ, IT
Mining and quarrying (section B)				
1995-2006	-5.4	2.7	18/18	
2010-2019	-3.1	0.8	16/18	NL, DK
2005-2019	-6.3	1.2	16/18	NL, DK
1995-2019	-5.6	2.0	18/18	

Source: EUKLEMS-INTANProd (2025 vintage), author's calculations.
Notes: Data for Estonia, Slovenia and Slovakia start in 2000. US not available for energy and water separately, but available for combined utilities industry. Estimates use 'basic' module, which does not include adjustment for capitalisation of additional intangible assets. Figures quoted in text based on period 1995-2019.

Country codes

Presented in order as in Chart 4 in the main text. Selection based on countries with complete data in EUKLEMS-INTANProd 2025-vintage.

Country code	Country name
UK	United Kingdom
FI	Finland
IT	Italy
NL	Netherlands
FR	France
AT	Austria
ES	Spain
US	United States
DK	Denmark
DE	Germany
SE	Sweden
CZ	Czechia

Changes in carbon dioxide emissions and water use per capita

The UK has seen one of the largest falls in carbon dioxide per capita emissions over recent decades among advanced economies, which may be associated with weaker measured productivity growth.

Table A8 shows carbon dioxide emission per capita for selected advanced economies and selected years, using data gathered by Our World in Data, available from: https://ourworldindata.org/grapher/co-emissions-per-capita

The UK saw modest falls between 1990 and 2005, and substantial falls between 2005 and 2019. Between 1990 and 2019 or between 2005 and 2019, the UK has the second largest fall in per capita carbon dioxide emissions (behind Denmark in both cases) of the advanced economies included in the table.

Table A8 – Summary of trends in carbon dioxide emissions per capital across selected advanced economies

	Carbon dioxide emissions per capita (tonnes per person)							Cumulative change (%)	
Country	**1990**	**1995**	**2000**	**2005**	**2010**	**2015**	**2019**	**1990 to 2019**	**2005 to 2019**
UK	10.5	9.7	9.6	9.4	8.1	6.5	5.4	-48.2	-42.3
USA	20.2	20.2	21.4	20.7	18.3	16.5	15.6	-22.9	-24.9
Canada	16.5	16.7	18.3	17.7	16.2	15.7	15.4	-6.5	-12.8
France	6.9	6.6	6.8	6.7	5.9	5.1	4.8	-30.6	-29.0
Germany	13.2	11.5	11.0	10.6	10.2	9.8	8.5	-35.8	-19.7
Italy	7.7	7.8	8.2	8.6	7.2	6.0	5.6	-26.5	-34.1
Japan	9.4	9.9	10.0	10.1	9.5	9.6	8.7	-7.0	-13.5
Austria	8.1	8.1	8.3	9.6	8.6	7.7	7.7	-5.5	-20.4
Belgium	12.1	12.4	12.4	12.0	10.5	9.0	8.7	-28.2	-27.6
Czechia	15.9	12.8	12.4	12.2	11.2	10.0	9.6	-40.0	-21.7
Denmark	10.4	11.8	10.2	9.5	8.9	6.2	5.3	-48.8	-44.0
Finland	11.4	11.4	11.0	10.9	12.0	8.1	7.7	-32.7	-29.3
Netherlands	10.8	11.1	10.7	10.8	10.9	9.6	8.7	-19.8	-19.6
Spain	5.9	6.6	7.6	8.4	6.0	5.8	5.3	-10.3	-37.0
Sweden	6.7	6.7	6.2	6.0	5.7	4.4	4.0	-40.9	-33.4
EU27	9.2	8.5	8.4	8.6	7.8	7.0	6.5	-29.5	-24.5
World	4.3	4.1	4.1	4.5	4.8	4.7	4.8	11.3	5.7

Source: Our World in Data, author's calculations.

A similar pattern exists for water use. Data on water use from Our World in Data is sourced from UN Food and Agricultural Organization (FAO) AQUASTAT database, which has more years of data and more up to date data available, so I extract data on "Total water withdrawal per capita" directly from AQUSTAT., available here: https://data.apps.fao.org/aquastat/?lang=en

The data on water withdrawals is lumpy for several countries, including for the UK. It is unclear if this reflected genuine year-to-year changes or measurement inconsistencies over time. The UK sees a sharp increase in water withdrawals per capital in 2000, having been roughly flat from 1990 to 1999 – this may reflect a measurement change. It then declines sharply between 2000 and 2007, with the exception of a spike in 2006 which is likely a genuine change associated with a hot summer that year. Per capital water withdrawals then decline modestly from 2007 onwards.

Given the lumpiness of the data, the UK's position relative to other countries depends markedly on the time periods chosen. Between 2000 and 2019, the UK has the largest relative fall of economies in the table. However, relative to 1990 or 2005 (shown in Table A9) the fall is only slightly larger than average.

Table A9 – Summary of trends in water use per capita across selected advanced economies

	Total water withdrawal per capita (cubic meters per person)							Cumulative change (%)	
Country	**1990**	**1995**	**2000**	**2005**	**2010**	**2015**	**2019**	**1990 to 2019**	**2005 to 2019**
UK	210	208	276	170	127	125	125	-40.3	-26.1
USA	2207	2085	1987	1902	1561	1362	1315	-40.4	-30.8
Canada	1602	1453	1312	1267	1186	978	954	-40.4	-24.7
France	661	582	550	550	451	433	399	-39.7	-27.4
Germany		595	549	492	485	363	309		-37.2
Italy	723	762	792	630	563	564	564	-22.0	-10.4
Japan	737	707	712	653	633	628	619	-16.1	-5.3
Austria	496	434	454	423	407	377	354	-28.7	-16.5
Belgium	856	814	735	610	518	354	365	-57.4	-40.2
Czechia		266	227	200	174	152	143		-28.6
Denmark	245	185	139	119	129	143	163	-33.7	36.9
Finland	471	506	453	429	430	432	634	34.7	47.6
Netherlands	546	440	526	702	651	492	479	-12.3	-31.7
Spain	990	883	891	865	752	675	616	-37.8	-28.8
Sweden	347	318	303	291	287	242	207	-40.3	-28.9

Source: AQUASTAT, author's calculations.
Notes: Total water withdrawal is defined as "Annual quantity of water withdrawn for agricultural, industrial and municipal purposes. It can include water from primary renewable and secondary freshwater resources, as well as water from over-abstraction of renewable groundwater or withdrawal from fossil groundwater, direct use of agricultural drainage water, direct use of (treated) wastewater, and desalinated water. It does not include in-stream uses, which are characterized by a very low net consumption rate, such as recreation, navigation, hydropower, inland capture fisheries, etc." (UN FAO).

Are UK Regional Productivity Disparities Really Narrowing? An Investigation into Recent Productivity Data Revisions

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Abstract

Recent UK data revaluations by the UK Office for National Statistics (ONS) on regional productivity data suggest that, after decades of interregional productivity divergence, the UK may finally once again be returning to something of an interregional productivity convergence framework. The aim of this article is to examine these data carefully, and to identify precisely what the recent ONS data really do tell us about UK regional productivity growth. We argue that the published data produce results from which it is difficult to infer anything about regional productivity convergence or divergence.

Nowadays it is generally well understood that UK interregional differences in productivity are amongst the highest in the industrialized world (McCann, 2020), and that over the last four decades, London and its close hinterland regions have steadily pulled away and decoupled from the rest of the United Kingdom on almost every economic and socio-economic dimension (McCann 2016, 2024). Indeed,

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the United Kingdom was the first OECD country to shift from a pattern of national economic growth being accompanied by interregional productivity convergence to one in which national economic growth is associated with interregional productivity divergence. This four decade-long divergence process has been documented extensively.[2] Today, the fact that the United Kingdom exhibits amongst the highest interregional productivity disparities of any OECD country (McCann, 2020) means that half of the UK population are living in regions which are poorer than the Czech Republic or the US state of Mississippi, and whose multi-dimensional quality of life is similar to Alabama or Tennessee (Veneri and Murtin, 2019). Indeed, these enormous regional productivity and prosperity disparities are argued to have been a major contributor to the Brexit vote and the levelling up debates (McCann and Ortega-Argilés, 2021). This raises profound questions regarding economic policy and governance, especially in a highly centralized unitary state such as the United Kingdom (McCann, 2023).

Recently, the UK Office for National Statistics (ONS, 2024a) has published results which suggest that the tide may be turning, and that the productivity growth of the London economy is underperforming relative to the rest of the United Kingdom. In particular, the period spanning the Covid-19 lockdowns saw profound shocks on the UK national and regional economies. The new ONS data suggest that these shocks adversely impacted on the London economy and favoured other regions.

In other words, after decades of interregional productivity divergence, these findings suggest that the United Kingdom may finally once again be returning to something of an interregional productivity convergence framework, akin to the earlier post-war decades (McCann, 2016; Carrascal-Incera *et al.*, 2020). These findings have garnered significant high-level coverage in the media (Romei, 2024a and 2024b), and form the basis of recent high-level political and policy debates. In particular, the apparent switch from interregional divergence to convergence appears to lend powerful support to the recent efforts of the government to 'level up' the UK economy (HM Government, 2022), while at the same time concerns regarding the performance of the London economy as a global economic powerhouse have increased.

The aim of this article is to examine these claims carefully, and to identify precisely what the recent ONS estimations really do tell us about UK regional productivity growth. The ONS regional data revisions to GVA per hour worked show that London's GVA per hour worked fell substantially over 2019-2022, while GVA per hour worked rose on average in the rest of the country, and in every other region except Wales. London's decrease in GVA per hour worked was a result of a small fall in GVA and a large increase in hours worked,

2 See McCann, 2016, 2020, 2024; Carrascal-Incera *et al.*, 2020; McCann and Yuan, 2022; Martin and Sunley, 2023; Allen, 2024; Bhattacharjee *et al.*, 2024a and 2024; and Farquharson *et al.*, 2024)

while many other regions displayed increasing GVA along with falling hours worked.

These results seem somewhat surprising for two reasons. First, the total number of labour hours worked at the regional level in London appears to move in the opposite direction to the rise of the population in the London. Second, the labour productivity results - which combine changes in GVA and hours worked - imply a negative or inverse production function operating at a region-wide scale, something which prima facie would appear to be difficult to understand. The years spanning the Covid-19 lockdown represent a profoundly atypical period so our conclusion is that we cannot infer any behavioural or structural changes from the data of this period.

In order to demonstrate these issues, the rest of the article is organized as follows. The first section will set out the UK economic geography of productivity, and will explain the key patterns and features of UK regional growth over the last four decades, right up to the eve of the Covid-19 lockdown period. This provides us with the wider context against which any Covid-19 era regional productivity shocks can be assessed and interpreted. In the second section, we discuss in detail the recent evidence produced by the ONS (ONS, 2024a) on the productivity performance of UK regions during the period of 2019-2022 which points to a UK shift from interregional productivity divergence to one of convergence. The third section reports on other contemporaneous evidence also produced by the ONS which, as with evidence reported in the second section here from other sources, appears to tell a somewhat different story from that which the revised ONS estimates suggest. In the fourth section, we examine in detail the recent evidence produced by the ONS in order to identify the precise sources of these new results, which appear to differ from much of the other available evidence. What we uncover is that the results depend almost entirely on revised data and the changes in the number of London's 'productivity hours' worked and 'productivity jobs'. These changes are very noticeable in the London area, and differ markedly from anywhere else in the United Kingdom. Our analysis also shows that London's 'productivity hours' worked and 'productivity jobs' produce regional productivity results which are difficult to understand from the perspective of production function analyses, as are those of seven other UK regions. We discuss in the fifth section with what we consider to be the likely reasons for these unusual productivity results and what we can infer from them. The sixth section concludes.

Regional Productivity Growth

In this section we provide a concise explanation of the major features of UK regional growth patterns over the last four decades, right up to the eve of the Covid-19 lockdown period, so as to provide a context against which any Covid-19 era regional productivity shocks can be assessed and interpreted.

In the postwar decades up until the 1980s, UK regional productivity disparities were comparatively low by the standards of advanced economies (Carrascal-Incera *et al.*, 2020), with the London economy typically displaying a GDP per capita premium of the order of 25 per cent-28 per cent over the UK regional average (McCann, 2016), and with the city-size distribution conforming most closely to Zipf's Law in the late 1970s (McCann, 2020). During this period, while the national economy grew the UK interregional economic system displayed productivity convergence processes (Carrascal-Incera *et al.*, 2020), as did almost every other industrialized economy (Blanchard and Katz 1992; Barro and Sala-i-Martin 1995; Barro 1997; Carrascal-Incera *et al.*, 2020). However, from the late 1980s onwards the UK shifted from a regime of interregional productivity convergence to interregional productivity divergence in which UK regional productivity growth and overall regional economic growth has been dominated by the London economy. The first observable shift in the data appears around 1988, with London's GDP per capita surging over the next two decades to something of the order of 170-175 per cent of the UK average (McCann, 2016) [3] and output per hour worked as 135 per cent of the UK average,[4], where it still remains.

In marked contrast, during this same period, the regions of the North and Midlands of England plus Wales and Northern Ireland all relatively declined in productivity such that today they display overall GDP per capita levels of between 40 per cent-50 per cent of those of the London economy. Meanwhile, during this four-decade period, as well as London, the other southern and eastern English regions plus Scotland steadily improved their productivity performance relative to the other weaker English and Celtic regions (McCann and Yuan, 2020). The decline and limited recovery of many cities in the former industrial regions means that once London is removed from the sample of UK cities, today there are no systematic urban scale-productivity relationships across the UK urban system (McCann and Yuan, 2020). The United Kingdom is unique in this regard amongst OECD countries.

There has been some recent evidence which tentatively suggests that the UK regional productivity divergence may be slowing down or even ameliorating. If we consider the pre-lockdown periods, using a slightly different measure of productivity, namely output per job at constant prices, Rodrigues and Bridgett (2023) argue that during the pre-crisis period 1998-2007, annual productivity growth in London outstripped the annual productivity growth in the rest of the UK by some 1.4 percentage points, at almost twice the rate of the rest of the United Kingdom, whereas during the period 2007-2019 London's annual productivity grew by 0.1 percentage points below that of the rest of the United Kingdom (Rodrigues and Bridgett 2023). This suggests that in the post-crisis period, London was relatively sluggish in its productivity growth performance in comparison to other regions, and the London downturn itself was a major explanation for the UK's post-crisis productivity growth down-

3 https://www.statista.com/statistics/1168072/uk-gdp-per-head-by-region/

4 https://www.productivity.ac.uk/the-productivity-lab/the-tpi-productivity-scorecards-for-english-regions-and-devolved-nations/

turn (Rodrigues and Bridgett, 2023).

This phenomenon of London's slowdown in output per hour worked has been documented extensively by the Data Lab[5] of The Productivity Institute. At the same time, however, during the period 2010-2021, London had the highest rate of job growth, and given its size, also a higher absolute increase in the number of jobs (ONS, 2023a) than any other part of the United Kingdom, alongside an average unemployment rate (Powell, 2021) and relatively low long-term sickness rates (ONS, 2023c). Declining output per hour worked was associated with strong job growth and high participation and activity rates in London, with a result that GDP per capita increased consistently. As such it is unclear on the basis of these data whether the sluggish growth in output per job (Rodrigues and Bridgett, 2023) or output per hour worked of the London economy is due to genuine shifts in the underlying regional convergence-divergence growth regimes, or rather due to a diminishing marginal productivity associated with greater employment and output expansion in the London economy.

On this point, other evidence is also useful. Recent evidence on the wage and employment trajectories of university educated graduates (Stansbury *et al.*, 2023) suggests that constant returns to scale to higher education are evident in the London economy, whereas other UK cities display diminishing returns to higher education. Indeed, these findings concur with the observation of a lack of any systematic scale-productivity relationships in UK cities (McCann and Yuan, 2022), an observation which is also in marked contrast to US cities which all display increasing returns to higher education (Burn-Murdoch, 2023).

While London's post-crisis productivity growth performance was clearly far weaker than its pre-crisis performance, it is also the case that these types of analyses and the conclusions derived by Rodrigues and Bridgett (2023), are sensitive both to the particular productivity index used and also the starting year chosen for a time-series comparison. The reason is that London experienced a productivity surge during 2006-2008 which was noticeably above the 1998-2005 trend, and which resulted in a marked London productivity spike in the immediate pre-crisis years. As such, using 2007 or 2008 as a starting year for a time-series gives a rather different picture from using starting years such as 1998, 2005 or 2010 (Martin and Sunley, 2023).

On this specific point, using ONS data on regional Gross Value Added (GVA) at 2019 prices applied to ITL1 regions in which all UK regions are indexed to a value of 100 in 1998, Martin and Sunley (2023) show that the growth in overall scale of the ITL1 London economy has continued to outpace all other parts of the United

5 https://www.productivity.ac.uk/the-productivity-lab/the-tpi-productivity-scorecards-for-english-regions-and-devolved-nations/

6 ITL1 stands for International Territorial Level 1, and these represent the 12 large UK statistical regions with an average population of over 5.5 million people. ITL2 represent 41 smaller definitions of regions, and ITL3 represent the 182 smallest definitions of internationally comparable regions. In order to ensure comparability

Kingdom, and that this was true both during the pre-crisis period 1998-2008 as well as during the post-crisis period 2009-2020.[6] These findings also concur with research by National Institute (NIESR) which finds that that London's real GVA (Bhattacharjee *et al.*, 2024a and 2024b) and real household income (Bhattacharjee *et al.*, 2024a) increased between 2019 and 2024 relative to the rest of the United Kingdom, a finding which is also broadly consistent with the IFS's judgement that any progress towards 'Levelling Up' during the period 2019-2024 has been 'glacial' (Farquharson *et al.*, 2024) at best, and in some respects is moving in the opposite and wrong direction.

The online supplementary material to this article also discusses other ONS evidence produced at broadly the same time, which, as with the evidence from other sources reported here, appears to tell a somewhat different story from that which the revised ONS (2024a) estimates suggest.[7] In particular, these other pieces of evidence suggest that London's GDP and GVA did not decrease notably during this period and was recovering rapidly from a sharp decline during the Covid-19 lockdown period.

On the basis of all of these pieces of evidence, the overall outcome of these four decade-long diverging regional growth patterns is that the more geographically peripheral regions of the United Kingdom which were also previously heavily industrialized, have declined the most relative to London and its hinterland, resulting today in a marked core-periphery economic structure of the United Kingdom. In the post-crisis period London's productivity growth has slowed markedly, even slightly below other regions, but allied with faster employment growth and the prevailing productivity gaps, the overall interregional gaps in GDP per capita appear not to have narrowed, except for the results of the recent ONS data revaluations as discussed below.

ONS Data on UK Regional Growth Contractions and Expansions 2019-2022

In this section we discuss in detail the new evidence recently produced by the ONS (ONS, 2024a) on the productivity performance of UK regions during the years 2019-2022 spanning the Covid-19 lockdowns, evidence which points to an apparent UK shift from interregional productivity divergence to one of convergence.

Recent data revaluations on UK regional productivity published by the UK Office for National Statistics (ONS) on 17 June 2024 (ONS, 2024a) show that between 2019 and 2022, output per hour worked in the London economy fell annually by 0.9 per cent and cumulatively by 2.7 per cent (Romei, 2024a), whereas across the UK during the same period output per hour worked increased annually by 0.8 per cent (ONS, 2024a) and cumulatively by 2.5 per cent

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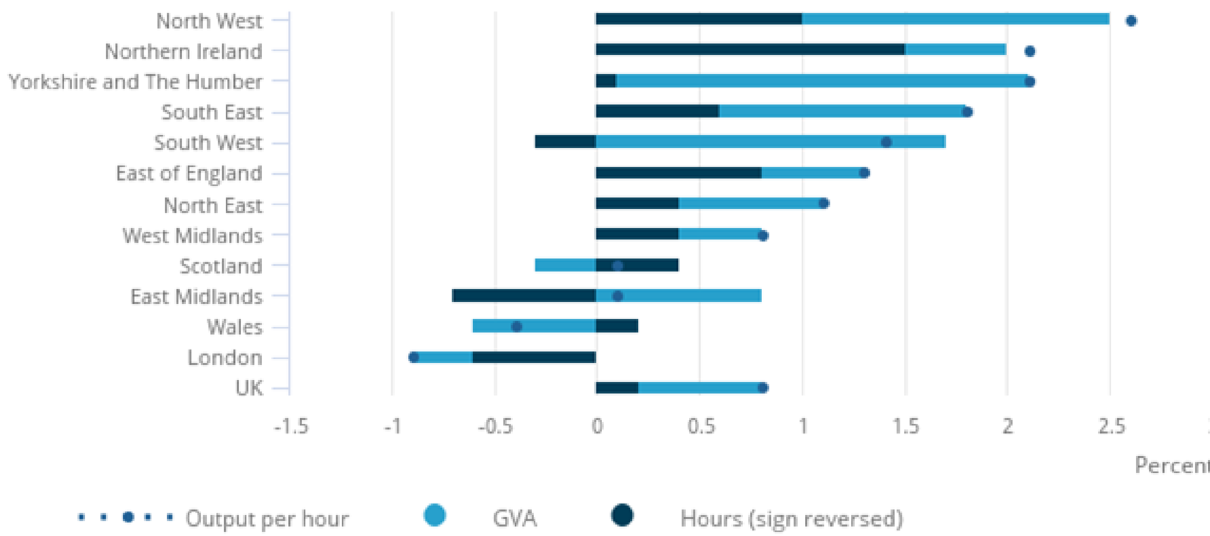
post-Brexit, the UK ITL1 regions are the same as the UK's OECD-TL2 definition of regions, the UK's ITL2 regions are consistent with the Eurostat NUTS2 regions, and the UK's ITL3 regions are the same as the OECD-TL3 regions. See: https://www.ons.gov.uk/methodology/geography/ukgeographies/eurostat

7 The online appendix can be found here: https://csls.ca/ipm/48/IPM_Supplementary_Material.pdf.

Chart 1: Cumulative Average Annual Growth Rates for Output per Hour Worked, Gross Value Added, and Total Hours Worked for UK ITL1 Regions and the United Kingdom, 2019-2022



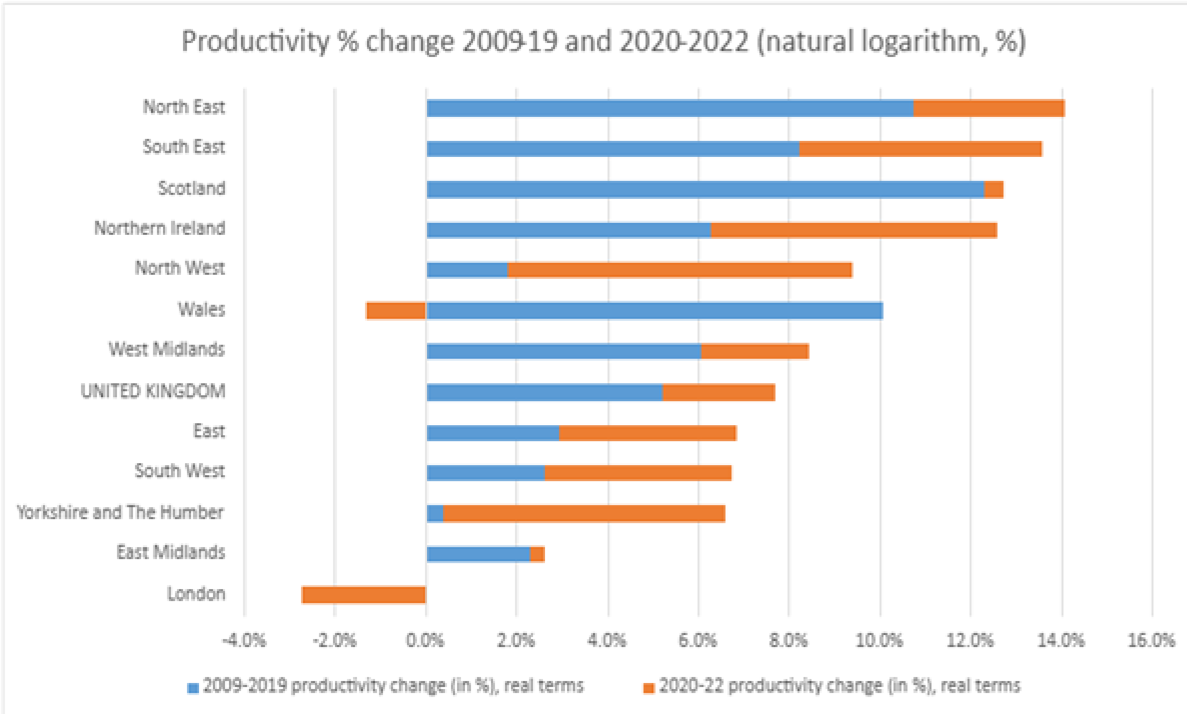
Source Table 3 in ONS, 2024a.

(Romei, 2024a). These new data revisions led to excited headlines in the *Financial Times* concerning how the capital's losses have 'upended' London's post-pandemic growth story (Romei, 2024b), and indeed apparently, London's whole growth trajectory since the 2008 global financial crisis (Romei, 2024a). However, whether in fact these data revaluations do imply an underlying shift from interregional divergence to convergence requires some careful consideration.

In Chart 1 we reproduce exactly Figure 3 from ONS (2024a) which reports these results in detail. The logic of the construction of Chart 1 is as follows. For each ITL1 UK region, as for the United Kingdom as a whole, the chart superimposes the contribution to regional productivity growth (in terms of output per hour worked) of annual GVA growth 2019-2022, calculated cumulatively across these three years, along with the growth in hours worked (sign reversed for ease of exposition). The annual GVA growth 2019-2022 is coloured in light blue/turquoise, while the growth in the number of hours worked is coloured in black . Note that the sign-reversal means that a black bar to the left implies an increase (positive growth) in the total number of hours worked while a black bar to the right implies a decline (negative growth) in the total number of hours worked. The dark blue dot represents the annual growth in output per hour, calculated across 2019-2022.

In terms of the first group, namely the regions experiencing a combination of output growth and falling hours worked, we see in Chart 1 that the North West comes out as the region whose annual productivity growth spanning the pandemic years was

Chart 2: Cumulative Regional Productivity Growth Rates (GVA per Hour Worked) Between 2009-2019 and 2020-2022



Source: Van Ark 2025 based on ONS, 2024a

the strongest. At 2.6 per cent, the region's annual growth in output per hour was comprised of annual output (GVA) growth was 1.5 per cent, while the labour hours worked fell by 1 per cent.[8] This is followed by Northern Ireland, whose annual growth in output per hour of 2.1 per cent was comprised of a 0.5 per cent annual growth in GVA plus an annual decline of 1.5 per cent in hours worked. This type of pattern, namely a growth in output per hour comprised of a combination of a growth in GVA and falling hours worked is also repeated in descending order in the cases of Yorkshire and Humber, South East, East of England, North East and West Midlands.

In terms of the second group, namely those regions which exhibit output growth and increasing in hours worked, the two regions in this category are the South West and the East Midlands, with the annual growth output per hour of the former (1.4 per cent) being much higher than the latter (0.1 per cent). The third category are the regions displaying output falls and declining hours worked, and in this category there are only Scotland and Wales. The fourth category are the regions displaying both falling output and also increasing hours worked. This is only the case for London, with London's output (GVA) falling annually by 0.3 per cent and the number of hours worked increasing by 0.6 per cent.

The decade-long slowdown and recent re-

8 The numbers may not sum exactly in that they are based on the additions of raw percentage figures rather than additions of logarithmic transformations.

versal in the London productivity performance is shown in Chart 2. London flatlined for a decade, followed by a dip during the Covid-19 crisis period. The ONS data (ONS, 2024a) show that, in terms of real output per hour (2019=100), productivity in London barely changed between 2010 (99.45) and 2019 (100), with a decline since 2019, leaving London's real output per hour in 2022 (97.34), some 3.7 per cent below its 2007 peak of 101.04 and 2.66 per cent below its 2019 level (ONS, 2024a; Romei, 2024a). As of 2022, London was 26.2 per cent more productive in terms of output per hour worked than the UK average, a lower hourly productivity premium than at any stage since 1998, and well below the 2007 peak of close to 40 per cent (Romei, 2024a).

At a more detailed geographical scale, the recent data revaluations suggest that the 2019-2022 productivity decline in London was associated with declines in output in all three Outer London ITL2 areas and also zero growth in Inner London East, accompanied by increases in the total hours worked in Inner London East and in two other Outer London areas for the 2019-2022 period (ONS, 2024a). Meanwhile, during this same period of 2019-2022, hourly productivity in the United Kingdom as a whole grew annually by 0.8 per cent, comprised of a 0.6 per cent annual increase in overall GVA and a 0.2 per cent fall in the number of hours worked (ONS, 2024a). This was a period during which the South East and North West regions contributed the most to national growth, with the North West enjoying the highest annual productivity growth rate of 2.6 per cent (ONS, 2024a).

Overall at the national level, labour productivity in terms of output per hour worked increased in 30 out of the 41 ITL2 subregions of the UK between 2019 and 2022, and in 7 out of the 12 ITL1 regions this productivity growth was achieved primarily by the number of hours worked falling while overall GVA increased (ONS, 2024a), while in 2 ITL1 regions (East Midlands and South West) rising GVA was also accompanied by to a lesser extent by a rising number of hours worked. In Scotland falling GVA was accompanied by even greater falls in hours worked, thereby increasing hourly productivity (ONS, 2024a). In contrast, London experienced a falling GVA output of 0.3 per cent per annum alongside increasing hours worked of 0.6 per cent per annum, leading to annual falls in hourly labour productivity of 0.9 per cent (ONS, 2024a).

For the period 2019-2022 the recent data revaluations point to possible changes in UK regional growth trajectories associated with the Covid-19 lockdown shocks. The data suggest that the lockdown period was associated with major changes in both the annual and cumulative regional GVA growth rates alongside the changes in hours worked. The ONS evidence as discussed in the previous sections implies that London faced the second highest fall in output 2019-22 (after Wales) and the second highest increase in hours worked (after East Midlands), the combination of which led to the highest overall regional fall in output per hour worked. In other words, while London's productivity and overall economic growth performance deteriorated markedly during the years traversing the Covid-19 lockdowns relative to the rest of the United Kingdom, other regions

Table 1. London Productivity Jobs and Productivity Hours, 2019–2022 (ITL2 and ITL3)

	Jobs % Change				Hours % Change			
	% Change 2019-2022	Annual % Change 2019-2022	Annual % Change 2020	Annual % Change 2021	% Change 2019-2022	Annual % Change 2019 -2022	Annual % Change 2020	Annual % Change 2021
LONDON	3.49	1.16	-1.33	0.75	1.80	0.61	-11.07	7.97
Inner London West	3.56	1.19	-2.76	3.48	1.22	0.41	-10.89	9.42
Inner London East	6.31	2.10	-0.56	0.37	4.77	1.58	-10.04	6.96
Outer London East & North East	2.34	0.78	-1.99	-0.67	2.95	0.98	-8.65	4.02
Outer London South	4.22	1.41	0.57	-1.82	0.04	0.02	-12.51	6.22
Outer London West & North West	-0.42	-0.14	0.16	-2.35	-0.14	-0.05	-13.85	8.40

Source: ONS (2024b)

of the United Kingdom appeared to have improved both their productivity growth and overall economic growth performance in relative terms during this same period.

Yet, at the same time, other evidence discussed above and also in the online supplementary material suggests that London's Covid-19 fall in output was only temporary and its ongoing recovery was relatively fast (ONS, 2025a,b,c). As such, the trends are still somewhat unclear. These recent data revaluations therefore raise the question as to whether the different regional growth changes observed during the years 2019-2022 are transient or represent more fundamental and permanent post-Covid shifts in regional growth trajectories from the pre-Covid period of interregional divergence to a post-Covid interregional convergence trajectory.

Productivity Jobs, Productivity Hours Worked, and Population Changes

A key issue concerns the revised number of 'productivity hours worked' and 'productivity jobs' used to calculate the revised output per hour estimates. The specific data which the ONS (2024a) used in their recently revised 'productivity hours per week' worked and 'productivity jobs per year' calculations are given in Table A1 and Table A2 of the online supplementary material, respectively, and which themselves are derived from Tables 12 and 13, respectively, of ONS (2024b). Here in Table 1 we report simply the growth rates in the productivity jobs and the productivity hours and in Table 2 we also report the population changes for London.

As we see in Table 1, between 2019 and 2022, London increased its number of productivity hours by 0.6 per cent per annum, while the number of productivity jobs increased by 1.16 per cent per annum

Table 2: London Population Changes 2019-2022 (ITL2 and ITL3)

	Pop Change 2019-22	% Change 2019-22	Annual % Change 2019-22	Annual % Change 2020-21
LONDON	-95,809	-1.07	-0.36	-2.29
Inner London West	-111,328	-9.19	-3.06	-12.25
Inner London East	-65,332	-2.69	-0.89	-4.21
Outer London East & North East	12,946	0.67	0.22	0.24
Outer London South	5,416	0.41	0.14	-0.12
Outer London West & North West	62,489	2.98	0.99	2.11

Note: The change 2019-2020 is from mid-2019 to mid-2020, and this continues for the following years. The detailed mid-year population estimates are discussed in the online supplementary material.
Source: ONS (2024e)

during the same period 2019-2022. This was comprised of a 2020 fall of 11.7 per cent in productivity hours and a fall of 1.3 per cent in the productivity jobs, followed immediately by rapid increases in the number of both productivity hours and jobs in 2021, representing a greater recovery than any other region except the East Midlands. However, these revised 'productivity hours' and 'productivity jobs' figures (ONS, 2024b) which are used in the revised regional productivity estimates (ONS, 2024a), appear to be inconsistent with estimates for the total population over the same period.

London's population fell at precisely the same time that both its 'productivity jobs' and 'productivity hours' increased. Table A3 in the online supplementary material reports the various detailed mid-year population estimates for ITL1, ITL2 and ITL3 London (ONS, 2024c) while Table 2 here provides the population growth rates for the ITL1 London region and its ITL2 component sub-regions. As we see in Table 2 for London as a whole, the ITL1 London population contracted annually by 0.36 per cent per annum between 2019 and 2022. This ITL1 London population contraction was accounted for entirely by population falls in the ITL2 Inner London areas of 3.1 per cent per annum for Inner London West and 0.9 per cent per annum for Inner London East, respectively. Meanwhile, during this period 2019-2022, all three Outer London ITL2 regions experienced very low population growth rates.

During the period 2019-2022, London's 'productivity hours' worked and 'productivity jobs' are therefore both apparently increasing (ONS, 2024b) at precisely the same time that London's population is contracting at its fastest rate for more than five decades (ONS, 2020), a contraction due to the Covid-19 lockdown (ONS, 2024c). In particular, as we see in Table 2, between 2020 and 2021, when London's population fell by 2.29 per cent in one year (ONS, 2024c), we see in Table 1 that the number of 'productivity hours' worked in London apparently increased by 7.97 per cent and the number of 'productivity jobs' increased by 0.75 per cent (ONS, 2024b), respectively. From Table 2 we also see that for the Inner London areas between 2020 and 2021, the population of Inner London West fell by 12.25 per cent, while that of Inner London East fell by 4.21 per cent. At the same time, apparently, the number of 'productivity hours' worked in Inner London West increased by 9.42 per cent and in Inner London East by 6.96 per cent. In other words, the overall London pattern is that the productivity jobs and productivity hours were increasing at the same time that London's population was falling.

Meanwhile, 'productivity hours' worked fell in the North West, North East, Yorkshire and Humber, West Midlands, East, South East, Scotland, Wales and Northern Ireland; in other words in 9 out of the 11 other ITL1 regions, at precisely the same time that these same regions experienced population growth (ONS, 2024d and 2024e). Of course, one might argue that changes in total residential population and the total number of productivity hours worked might a priori not need to be highly correlated. Indeed, employment, participation, unemployment and activity rates vary by location, income group, household types, employment tenures and demographic structures.

However, these differences tend to be observed at small neighbourhood or small-town scales. In larger territories, such as regions, these differences tend to disappear, except for the case of regions with high in-migration of retired people, primarily for lifestyle and natural amenity reasons. Other than these cases, once we consider ITL1 region-wide populations sizes of between 2 million and 9 million, these differences tend to largely disappear, such that we would expect that population growth and the growth in the total number of productivity hours worked move in a similar direction for ITL1 regions. It therefore seems very difficult to reconcile the population figures for London with the revised data for the number of 'productivity hours' worked or the number of 'productivity jobs'. This requires us to consider these population and labour input data in more detail.

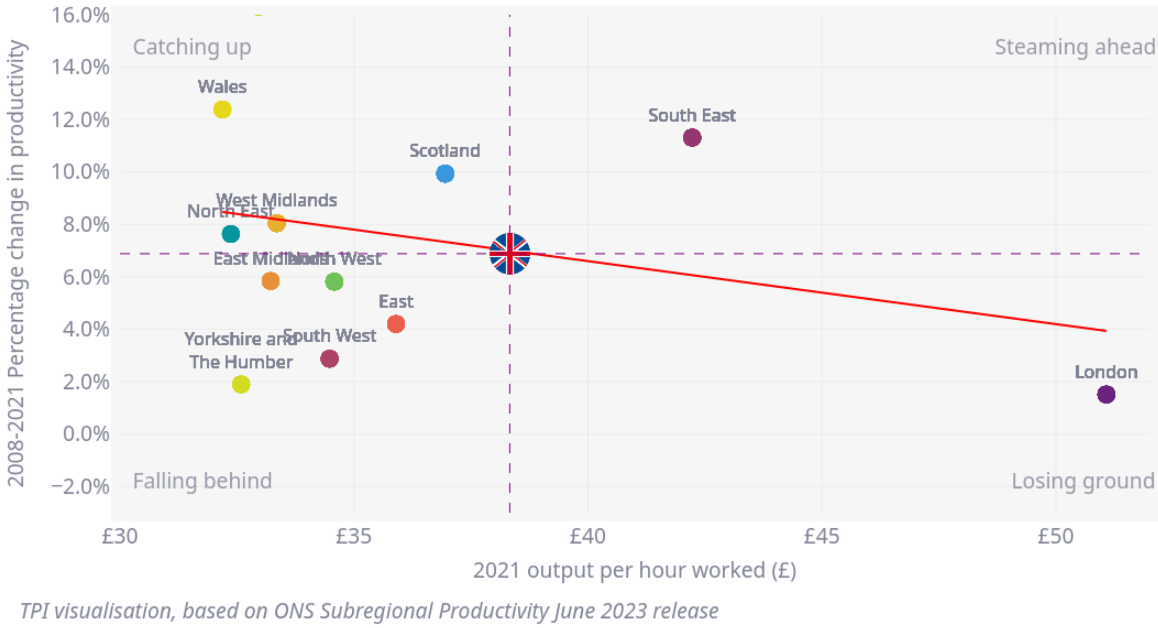
Data Checks

In order to try to reconcile the GDP, GVA, labour inputs and population data for London reported in section 3 and in the online supplementary material with the revised ONS (2024a) data reported in section 2, we need to delve even deeper into the data revisions to seek further clues as to how these changes may have arisen.

In order to better understand the nature, scale and pattern of the changes in regional productivity drivers and outcomes which are associated with the 2024 revised estimates, we can plot the relationships between the estimates published in 2023 and 2024 from a broad range of perspectives.

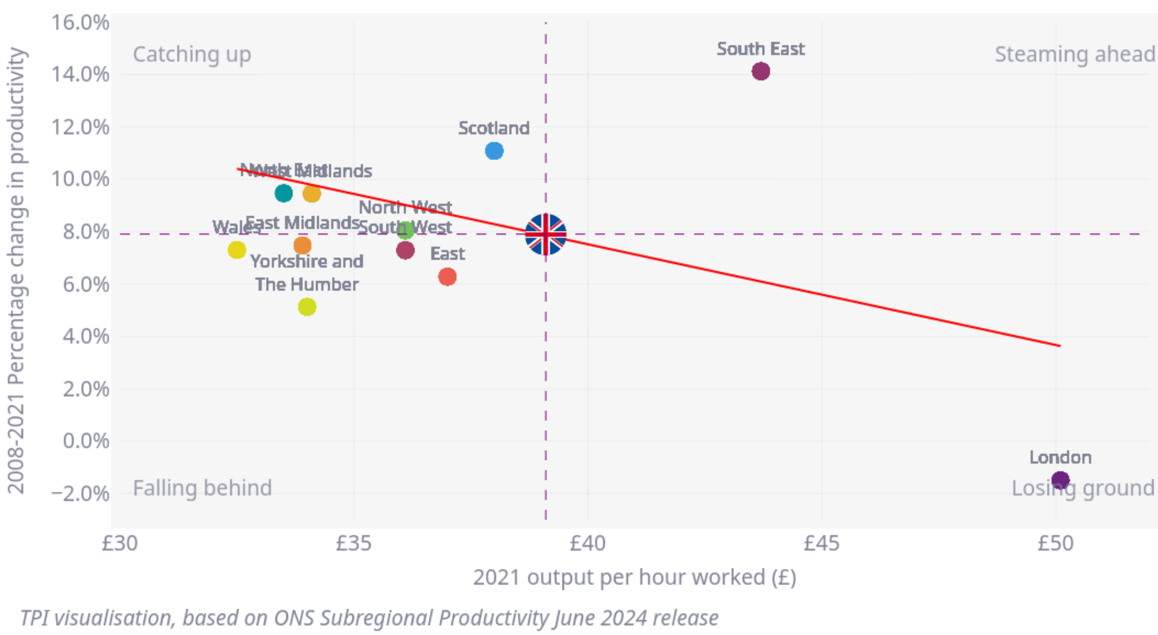
Charts 3 and 4 compare the relationships between the regional nominal smoothed GVA per hour with the productivity changes 2008-2021 for both the 2023 and 2024 data releases, respectively. As we see, the 2024 data release noticeably downgrades the productivity growth performance of London and Wales with respect to the rest of the UK regions.

Chart 3: UK ITL 1 Regions 2021 Nominal Smoothed GVA per hour, versus 2008-2021 Productivity Change (2023 Data Release)



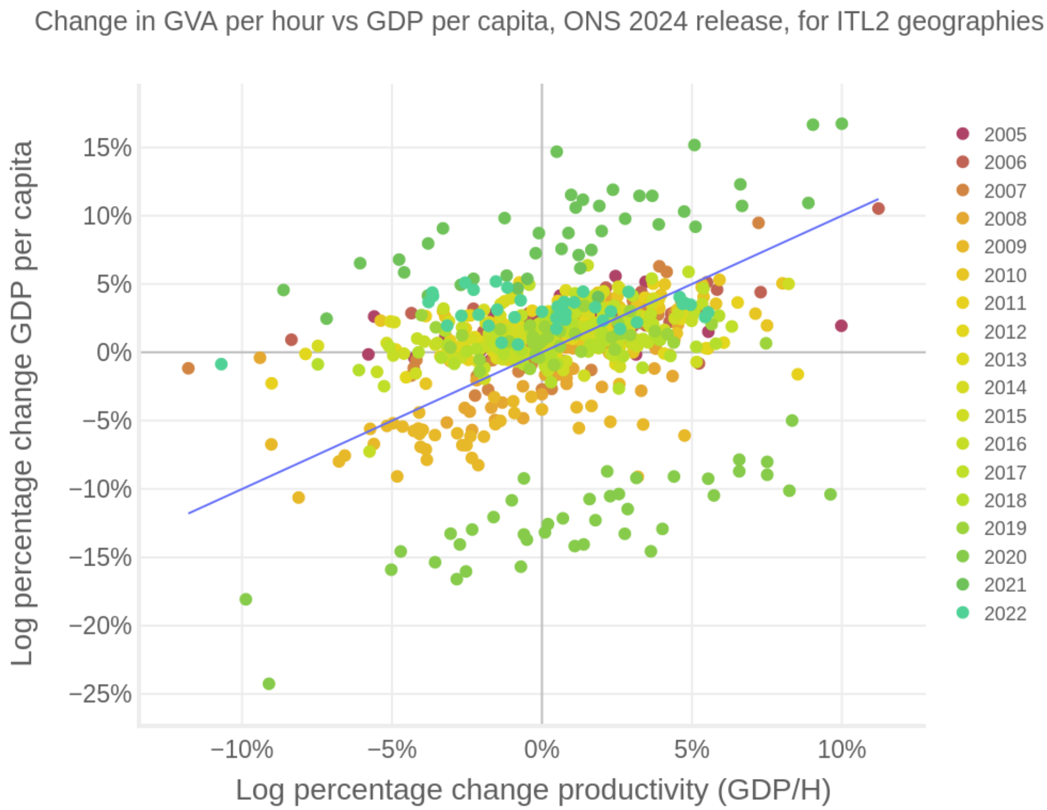
Source: 2023 ONS data release

Chart 4: UK ITL 1 Regions 2021 Nominal Smoothed GVA per hour versus 2008-2021 Productivity Change (2024 Data Release)



Source: 2024 ONS data release

Chart 5: The Relationship Between GVA per Hour Worked and GDP Per Capita with Respect to the Year



Source: 2024 ONS data release

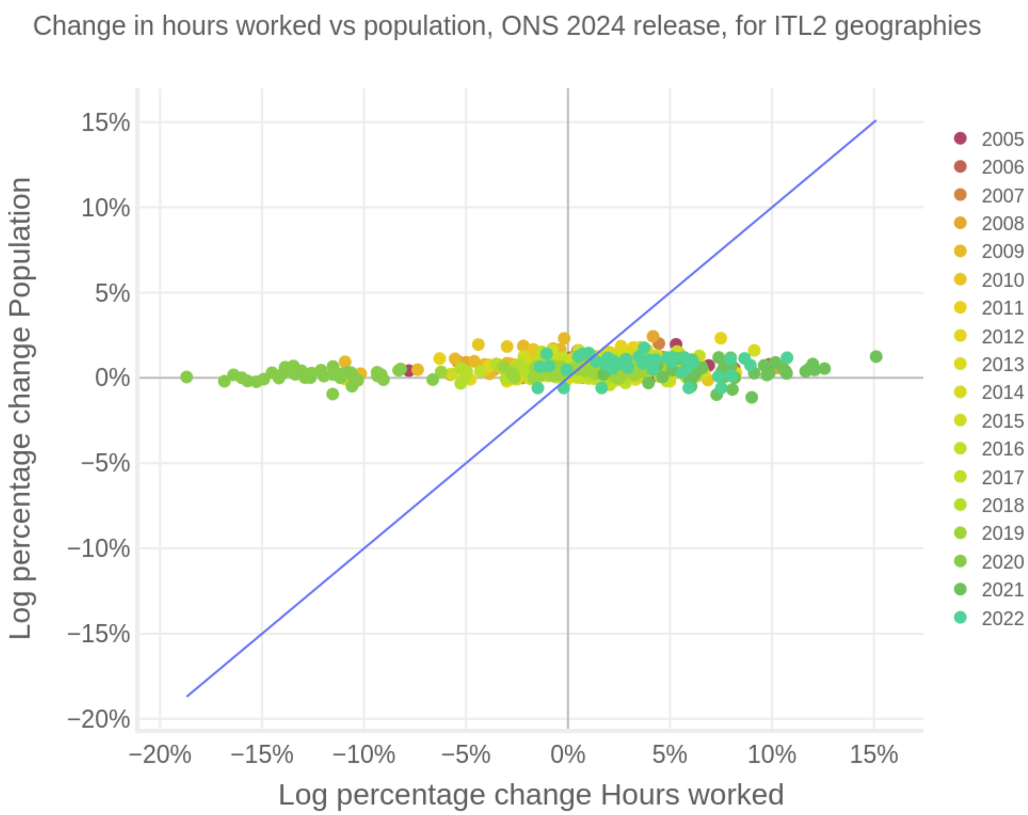
Charts 3 and 4 suggest that the 2024 data revaluations of the 2023 data release are not marginal in terms of their impacts on our perceived understanding of the long-run convergence or divergence relationships of the UK interregional economic system.

The 2024 data revisions, however, have not impacted evenly across all time period or places. Chart 5 shows the scatterplot of the relationship between GVA per hour worked and GDP per capita for ITL2 regions with respect to the year. As we see, for the 2020 and 2021 data there is far less correspondence with each other than might have been expected from numerous economic studies, with the data for the years of 2020 and 2021 appearing to behave markedly different to other years.

Meanwhile, there is almost no discernible UK-wide difference in the reported hours worked between the 2023 and 2024 releases, except that in the 2024 data release there has been a large correction from the 2023 release for 2021. However, as we see in Chart 6, if we consider the total hours worked and the population data with respect to the year, the relationships bear little or no resemblance to each other, with rather unusual separated clusters of regions, again for the years 2020 and 2021.

If we also consider the total hours worked and the population data with respect to the ITL2 region, again these relationships bear little or no resemblance to each other,

Chart 6: The Relationship Between the Change in 'Productivity Hours' Worked and the Change in Population with Respect to the Year

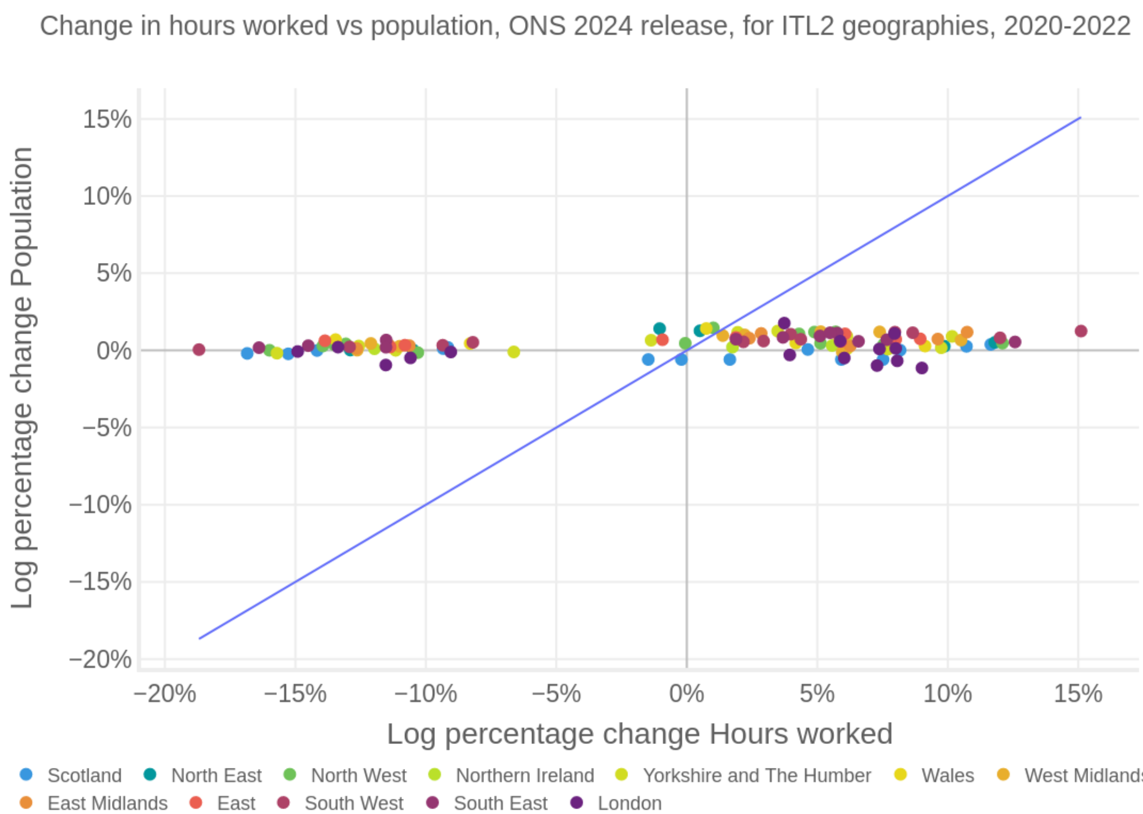


Source: 2024 ONS data release

with very unusual separated clusters of regions, as depicted in Chart 7. In particular, the largest differences occur in the links between population data and the numbers of hours worked for the ITL1 London region and its ITL2 sub-regions of London, where in the 2023 release the reported rate of population decline in 2021 was 13 per cent for Inner London West, whereas this has been revised to a decline of just 1.1 per cent in the 2024 release. Meanwhile, according to the 2024 release the growth in the number of hours worked in 2021 for London stays roughly the same at around 9 per cent, whereas the growth in hours worked for 2022 is again high for both the London and Scotland ITL1 regions, but generally more modest for the North West. The addition of 2022 does create large differences in productivity growth for a few regions, most notably (and negatively) for London. This can be seen from the comparison of the volume of GVA with GDP which are reasonably well aligned and where the London ITL2 areas seem to do reasonably well in both measures. Therefore, the drop in productivity is due to the large reported increase in hours worked in London.

As we see in the online supplementary material, combining all of these data suggests that for most regions the GVA data and the GDP data are broadly consistent between the 2023 and 2024 data revaluations. There are no dramatic differences

Chart 7: The Relationship Between the Change in 'Productivity Hours' Worked and the Change in Population with Respect to the ITL2 Region



between GDP volumes and GVA volumes in either the 2023 or 2024 data releases, and also that GVA is internally consistent between the regional GDP and productivity data. Where there are differences, these are from 2019 onward, most notably during the Covid-19 crisis for the years 2020 and 2021. Nominal GVA measures are the most heavily revised figures, and especially downward revisions for London and Wales, and it appears that the 2024 data revaluations are 'correcting' some of the extreme values from the 2023 release. For example, according to the 2023 release Inner London West's GVA per capita was growing by 20.1 per cent in 2021, whereas in the 2024 release this has dropped to 11.5 per cent.

In general, the combination of the lack of correspondence between the GVA per hour and the GDP per capita ITL2 data for 2020 and 2021, alongside the rather unusual, separated clusters of regional data for the years 2020 and 2021, suggests that there are likely to be problems with the revised data regarding the number of hours worked and the implied price deflators. The data on the numbers of hours worked in each region is likely to be a reason for the lack of expected correspondence between the 2023 and revised 2024 figures on productivity, and this also arises from a reconsideration of Chart 1 above.

Explaining the Unusual Productivity Results

Lack of Economic Rationale

Returning to our initial observations, Chart 1 implies that seven UK ITL1 regions (North West, Northern Ireland, Yorkshire & Humber, South East, East of England, North East and West Midlands) experience a combination of total output growth and falling total hours worked during the years spanning the Covid-19 era. All of these regions exhibited population growth during this period (ONS, 2024f and 2024g), even though they also exhibited falling hours worked. In contrast, London which is by far the UK's most productive and technologically advanced ITL1 region, displays falling total output while increasing the total hours worked during this same period 2019-2022. Moreover, London is the only ITL1 region facing a falling population between 2020 and 2021 and between 2019 and 2022 (ONS, 2024f,g). Again, the hours worked and the population change appear to be at odds with each other. In other words, during the period spanning the Covid-19 lockdowns, the UK regions, each of which involves millions of people and many hundreds of thousands of firms, displayed aggregate features which appear to be the opposite of those typically understood in the economics of regional productivity.

Following a very standard production–function logic, Q_{rt}-regional output at time t-is assumed to depend on the technological level ϕ, the regional capital stock K_r, and the regional labour stock L_r:

$$Q_{rt} = A\,e^{\phi t} K_r^{\alpha} L_r^{1-\alpha} \qquad (1)$$

Expressed in labour-productivity growth rates, this becomes

$$\dot{Q}_{rt} - \dot{L}_{rt} \;=\; \phi + \alpha(\dot{K}_{rt} - \dot{L}_{rt}) \qquad (2)$$

In other words, labour productivity growth in terms of output per hour, is positively related to the level of technology plus the (weighted) growth in the capital-labour ratio. Assuming that in the short-term the rate of growth of capital is very small, and especially during the Covid-19 lockdown, then increasing labour hours worked would be expected to be associated with a diminishing rate of labour productivity growth, but increasing total output growth. Similarly, falling labour hours worked imply increasing labour marginal productivity growth but falling total output.

Regarding the results reported in Chart 1 (Chart 3 in ONS, 2024a), only four out of the twelve UK regions correspond to these relationships defined by equations (1)-(2) in which the growth of regional output Qrt is positively related to the number of hours worked. These are the South West, East Midlands Scotland and Wales. Both the South West and the East Midlands are expanding both in terms of output growth and the hours worked, while Scotland and Wales are both declining both in terms of output growth and the hours worked.

In contrast, there are eight regions whose productivity relationships are in fact the complete opposite of the relationships sketched out in equations (1)-(2). These regions are North West, Northern Ireland, Yorkshire & Humber, South East, East of England, North East, West Midlands and London. Indeed, during the 2019-2022 period spanning the Covid-19 pandemic, these eight regions, which together account for two-thirds of the overall UK population, appear to correspond to a production function which looks like it is written as:

$$Q_{rt} = -Ae^{\phi t} K_r^{\alpha} L_r^{1-\alpha}, \tag{3}$$

This apparently *negative* or *inverse* production function is difficult to understand in economic terms of the relationship between the regional labour hours worked L_r, and the output Q_r produced.

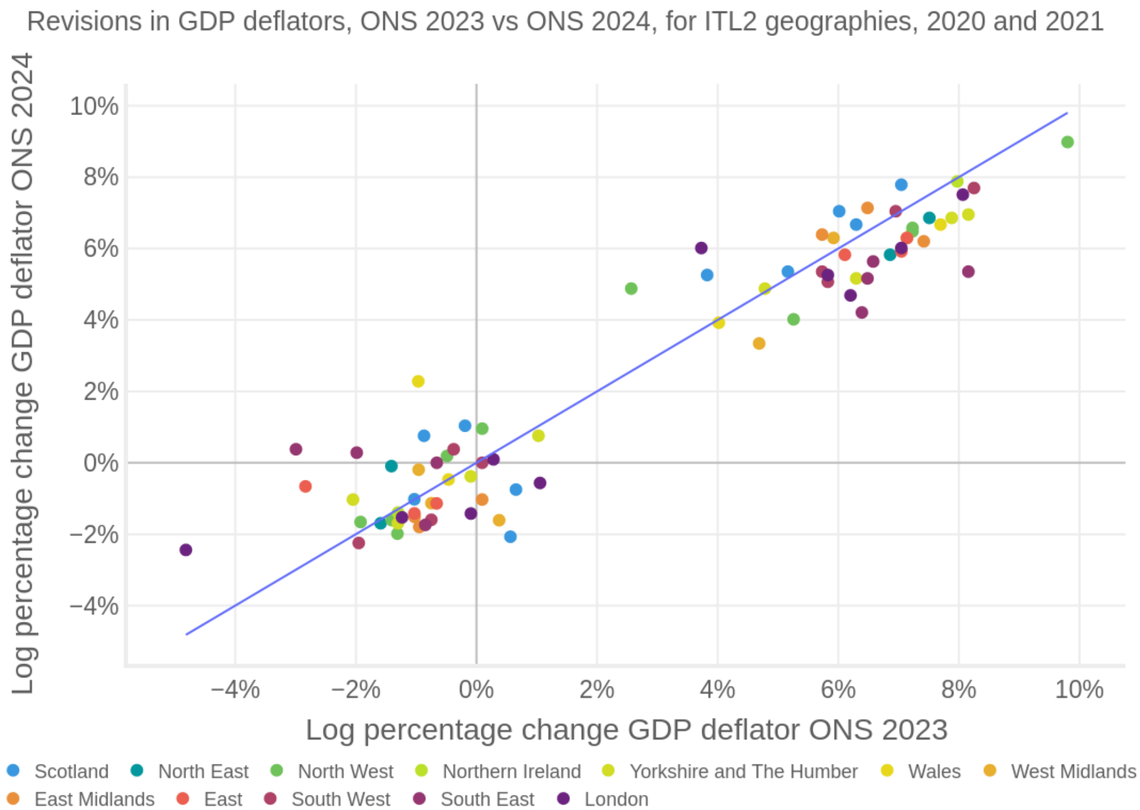
Possible Regional Productivity Effects of the Covid-19 Lockdowns

At a stretch, it might be argued that for some unexplained reason the Covid-19 pandemic lockdown might somehow have provided a large negative 'technology' ϕ shock to the London region, and a simultaneous positive 'technology' ϕ shock to seven other regions (North West, Northern Ireland, Yorkshire & Humber, South East, East of England, North East, West Midlands) while leaving Scotland, South West, East Midlands and Wales, largely unaffected in terms of how 'technology' interacts with the rest of the regional production function elements.

In this regard, for the London region, one of the features of the pandemic era was the so-called 'donut effect', whereby across OECD countries many people relocated away from large city centres to suburbs, smaller towns or rural areas (Bond-Smith and McCann, 2024), and the population data suggests that indeed London was alone amongst ITL1 regions in experiencing population decline during 2019-2022, after which it recovered beyond its pre-2019 population levels. Given that GVA is calculated at the workplace, this 'donut' effect may have had an adverse shock effect on London's productivity (McCann and Vorley, 2021) if out-migrants re-registered their work locations outside of London. However, during the pandemic, most workers who shifted to hybrid online work were still working for firms with the same registered workplaces in London. Moreover, large cities with higher shares of tertiary-educated white-collar workers who were better able to adapt to new technologies such as Zoom, Teams, Google-Meet, typically passed through the pandemic relatively unscathed in comparison to smaller places with relatively more blue-collar workers (Bond-Smith and McCann, 2024). London has much higher shares of tertiary educated workers employed in activities more amenable to new communications technologies than other large UK cities and regions, casting doubt on the argument that London faced an adverse technological shock in comparison to all other UK regions. Conversely, it is very difficult to identify why Covid-19 lockdowns would systematically provide a positive technology shock to so many other regions whose industrial, labour market and employment profiles were much less amenable to the hybrid work-from-home online technologies.

Similarly, as we see in Chart 8, it is difficult to identify any systematic Covid-19

Chart 8: The Relationship Between the ITL2 Regional Price Deflators for the ONS, 2023 and 2024 Releases



lockdown-related effects on regional price deflators which would account for the revised ONS (2024a) results, with the implied regional price deflators splitting into two separated clusters for no immediately obvious reason. In addition, we also have other information on regional deflators in the years leading to the onset of the Covid-19 pandemic in the form of regional capital deflators at both the ITL1 and ITL2 levels (Becker and Martin, 2023a). What we observe is that during these years immediately prior to the pandemic lockdown, there was very little change in regional deflators and almost no change whatsoever in the deflators relating to regional ICT investments (Becker and Martin, 2023b), the very technology most associated with the work-from-home revolution (Bond-Smith and McCann, 2024) driven by the pandemic lockdown itself. Similarly, if we consider regional real estate cost deflators, the pandemic shocked city centre business district office markets, most notably London (Strauss, 2024a). However, the evidence suggests that this process has recently been reversed (Byers, 2023; Oliver, 2024), with real estate demand in London now outpacing other regions (Romei, 2024c and 2024d;, 2025a; Oliver, 2025). In other words, price deflators for central London would be expected to be lower than for other areas adjacent to London 2019-2022, but increasing markedly by 2023-2024. As such, the patterns of regional capital deflators and regional real estate price deflators that we observe also do not appear to account for the (ONS, 2024a) revised figures.

More fundamentally, however, is the fact that even a pandemic lockdown-induced 'donut' effect on large cities would not in any way account for London's combination of falling total output and increasing total hours worked. Nor would it account for the combinations apparently enjoyed by seven other regions (ranging in population from 1.9m to 9.2m) of rising total output and falling total hours worked. Indeed, much of the country during 2020 and 2021 was being supported by the government-funded 'Coronavirus Job Retention Scheme', commonly known as the 'furlough scheme' (Clark, 2021), and this was especially important in economically weaker regions. Given that so many businesses and commercial transactions were frozen during the 2020-2021 lockdown period, it is difficult to understand how these other regions could have experienced a combination of increasing total output allied with falling total hours worked.

Conclusions

In this article we have examined whether the recent UK regional productivity revisions point to an underlying shift from regional divergence to one of regional convergence. In order to do this, we have surveyed the range of different data sources produced from different arenas, including official statistics, and examined these in detail, in order to identify the likely drivers of the observed regional productivity shifts.

Our analysis points to major data revisions for the years 2020 and 2021 which heavily impact on the reported productivity performance of UK regions for the period 2019-2022 spanning the Covid-19 lockdown. We highlight that some of these revisions lead to results and distributions which are very difficult to understand in terms of economics, even in the light of the Covid-19 lockdown shock. Instead, rather than any underlying Covid-19-related technological, structural or behavioural changes inducing a shift from interregional divergence to convergence, the most likely explanation for the data pointing towards a shift from regional divergence to regional convergence is to be found in terms of the quality and reliability of the official statistics in development for the period 2019-2022.

The Covid-19 lockdown period posed serious challenges to data-gathering and data-building. As such, in order to really understand whether the ongoing trajectory of UK regional productivity growth is one of divergence or convergence, it will be necessary to observe several more years of data as they emerge.

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Online Supplementary Material to Accompany the Paper

"Are UK Regional Productivity Disparities Really Narrowing? An Investigation into Recent Productivity Data Revisions"

Fokke Reitze Gouma, Philip McCann and Raquel Ortega-Argilés

Appendix A: Additional Material and Evidence on Regional Growth

In terms of other ONS economic and productivity data which appears somewhat inconsistent with the ONS (2024a) data discussed in section 3, the *Regional Economic Activity by Gross Domestic Product* recently reported that of all the ITL1 regions, London experienced the largest increase in both overall real GDP (4.9%) as well as in real (4.2%) GDP per capita in 2022 (ONS 2024b)[1]. This is largely a result of the fact that while during the lockdown periods of 2020 and 2021 London experienced the largest contraction amongst all UK ITL1 regions, this contraction was followed immediately by the strongest GDP and GDP per capita recovery of all UK regions in 2021 and 2022 (ONS 2024b)[2] and also for 2023 (ONS 2025a)[3]. Indeed, in general, regions which faced greater contractions in 2020 and 2021 responded with greater 'bounceback' growth rates after that (ONS 2025a,b,c). The scale of London's GDP per capita contraction was not noticeably different from many other UK city-regions and urban areas (ONS 2024d). According to the Regional Economic Activity data, the regional GDP per capita rankings remained unchanged from those during the immediate pre-Covid period, while the London region's 2022 GDP per capita levels were almost exactly at 2019 levels (ONS 2024d)[4].

Similarly, in terms of Gross Value Added (GVA), London increased its overall GVA strongly at current prices between 2019 and 2022. ONS (2024c) reports London's GVA at current basic prices increasing between 2019 and 2022 by 12.18% from £472.3bn to £529.8bn while ONS (2024d) reports London's GVA at current basic prices increasing between 2019 and 2022 by 9.61% from £473.7bn to £519.2bn. London exhibited a strong post-lockdown recovery which is till continuing. In other words, these various real GDP and nominal GVA figures move in a similar direction and imply that between 2019 and 2022 the London region economy did not noticeably decrease its output, unless regional price deflators more than offset nominal GVA rises.

Appendix B: London Productivity Hours, Productivity Jobs and Population

The detailed levels and changes in 'productivity hours', 'productivity jobs' and population in the London economy at both the ITL1 large region and ITL2 sub-regional areas are reported below in Tables A1, A2 and A3, respectively, and derived from Tables 12 and 13 of ONS (2024e)

[1] Table 1 (ONS 2024b)
[2] Figure 1 (ONS 2024b)
[3] Table 1 and Figure 1 (ONS 2025a)
[4] In Table 11 of ONS 2024d, Greater London's GDP per capita at 2019 prices changes from £57,519 in 2019 to £57,417, a fall of 0.18%.

Table A1: London Productivity Hours 2019-2022 (ITL2 and ITL3)

	Mid-2019	Mid-2020	Mid-2021	Mid-2022	Hours Change 2019-2022	% Change 2019-2022	Annual % Change 2019-2022	Annual % Change 2021	Annual % Change 2020
LONDON	189,483,361	168,500,284	181,940,978	192,950,598	3,467,237	1.802	0.61	7.97	-11.07
Inner London West	76,437,852	68,110,209	74,530,838	77,366,584	928,732	1.215	0.41	9.42	-10.89
Inner London East	47,693,375	42,901,313	46,144,750	49,968,055	2,274,680	4.77	1.58	6.96	-10.04
Outer London East & North East	18,829,250	17,201,034	17,893,062	19,384,423	555,173	2.95	0.98	4.02	-8.65
Outer London South	15,645,356	13,687,765	14,539,120	15,652,790	7,434	0.04	0.016	6.22	-12.51
Outer London West & North West	30,877,528	26,599,965	28,833,209	30,578,747	-44,319	-0.14	-0.048	8.40	-13.85

Table A2: London Productivity Jobs 2019-2022 (ITL2 and ITL3)

	Mid-2019	Mid-2020	Mid-2021	Mid-2022	Jobs Change 2019-2022	% Change 2019-2022	Annual % Change 2019-2020	Annual % Change 2020-2021	Annual % Change 2019-2022
LONDON	5,748,843	5,672,525	5,715,107	5,949,919	201,076	3.49	-1.33	0.75	1.16
Inner London West	2,173,947	2,113,909	2,187,683	2,251,265	77,318	3.56	-2.76	3.48	1.19
Inner London East	1,450,175	1,441,988	1,447,381	1,541,669	91,494	6.31	-0.56	0.37	2.10
Outer London East & North East	632,578	619,963	615,813	647,405	14,827	2.34	-1.99	-0.67	0.78
Outer London South	510,553	513,457	504,080	532,091	21,538	4.22	+0.57	-1.82	1.41
Outer London West & North West	981,591	983,209	960,150	977,489	-4,102	-0.42	+0.16	-2.35	-0.14

Table A3. London Population Estimates Mid-Year 2019-2022 (ITL2 and ITL3)

	Mid-2019	Mid-2020	Mid-2021	Mid-2022	Pop Change 2019-22	% Change 2019-22	Annual % Change 2019-22	Annual % Change 2020-21
LONDON	**8,961,989**	**9,002,488**	**8,796,628**	**8,866,180**	**-95,809**	**-1.07**	**-0.36**	**-2.29**
Inner London West	**1,212,016**	**1,230,445**	**1,079,697**	**1,100,688**	**-111,328**	**-9.19**	**-3.06**	**-12.25**
Camden	270,029	279,516	210,390	218,049				
City of London	9,721	10,938	8,618	10,847				
Hammersmith & Fulham	185,143	183,544	183,295	185,238				
Kensington & Chelsea	156,129	156,864	143,940	146,154				
Wandsworth	329,677	329,735	328,367	329,035				
Westminster	261,317	269,848	205,087	211,365				
Inner London East	**2,420,819**	**2,429,787**	**2,327,434**	**2,355,487**	**-65,332**	**-2.69**	**-0.89**	**-4.21**
Hackney	281,120	280,941	259,956	261,491				
Haringey	268,647	266,357	264,130	261,811				
Islington	242,467	248,115	216,767	220,373				
Lambeth	326,034	321,813	317,498	316,812				
Lewisham	305,842	305,309	299,810	298,653				
Newham	353,134	355,266	350,626	358,645				
Southwark	318,830	320,017	306,374	311,913				
Tower Hamlets	324,745	331,969	312,273	325,789				
Outer London East & North East	**1,924,686**	**1,929,278**	**1,933,840**	**1,937,632**	**+12,946**	**+0.67**	**+0.22**	**0.24**
Barking & Dagenham	212,906	214,107	218,534	219,992				
Bexley	248,287	249,301	246,543	247,835				
Enfield	333,794	333,587	329,601	327,224				
Greenwich	287,942	289,034	289,254	291,080				
Havering	259,552	260,651	262,022	264,703				
Redbridge	305,222	305,658	309,836	310,911				
Waltham Forest	276,983	276,940	278,050	275,887				
Outer London South	**1,309,450**	**1,314,617**	**1,313,022**	**1,314,866**	**+5,416**	**+0.41**	**+0.14**	**-0.12**
Bromley	332,336	332,752	329,830	329,578				
Croydon	386,710	388,563	390,506	392,224				
Kingston Upon Thames	177,507	179,142	167,845	168,302				
Merton	206,548	206,453	215,324	214,709				
Sutton	206,349	207,707	209,517	210,053				
Outer London West & North West	**2,095,018**	**2,098,361**	**2,142,635**	**2,157,507**	**+62,489**	**+2.98**	**+0.99**	**2.11**
Barnet	395,869	399,007	388,639	389,101				
Brent	329,771	327,753	338,918	341,221				
Ealing	341,806	340,341	366,127	369,937				
Harrow	251,160	252,338	260,987	261,185				
Hillingdon	306,870	309,014	304,792	310,681				
Hounslow	271,523	271,767	287,940	290,488				
Richmond Upon Thames	198,019	198,141	195,232	194,894				

If instead we use the revised population estimates (ONS 2024g), this gives the London 2019 population as 8,889,743, the 2020 population as 8,867,008, the 2021 population as 8,804,769, the 2022 population as 8,869,043, and the 2023 population as 8,945,309. These figures imply that the fall in London's population in 2021 is 62,239, or -0.7% relative to 2020 (ONS 2024g). London is the only ITL1 which exhibits a population fall between 2020 and 2021.

In terms of demographic data, for each of the years between 2012 and 2020, the regional population data are based on mid-year population estimates. These are based on the 2011 Census and then adjusted annually using other information and surveys of local and regional population growth (ONS 2023b, 2024g). Following the 2021 Census rebased population estimations are also constructed (ONS 2023b, 2024g). As we see, there were very big swings in UK population trends between 2020 and 2022. In terms of changes to the UK mid-year populations, net in-migration fell dramatically from 224,000 to 111,000 between the year ending June 2019 to June 2020 and then rose (following the post-Census 2021 revised estimates) to 254,000 for the year ending in June 2021 to 634,000 in June 2022, and then to 906,000 for the year ending June 2023 (ONS 2024i), representing the largest annual population surge in 75 years (ONS 2024h). Many in-migrants first move to London, and although London's population fell between 2019 and 2022 it recovered quickly from 2023 onwards.

Appendix C: Scatterplots Comparing ONS 2023 Regional Productivity Data and the Revised 2024 Regional Productivity Data

In the following figures, we depict different checks in order to help us to better understand the sources of the differences between the previous regional output per hour data reported by the ONS in their publications up to and including 2023 and those arising from the revised 2024 published data.

The analysis is carried for ITL2 regions spanning the years 2006 to 2002 inclusive and we compare different aspects of the old and revalued data in order to identify areas of agreement and areas of difference.

In terms of the nomenclature that we use in the following figures:

GVA/H = Gross Value Added per Hour Worked
GVA/H_v = Gross Value Added per Hour Worked Volumes (i.e. corrected for price deflators)
GVA_p_calc = Calculation of deflators = log % change in GVA – log % change in GVA-v
GDP_v = Gross Domestic Product Volumes
GDP/C_v = Gross Domestic Product per Capita Volumes

When comparing the revalued data from 2024 to previous 2023 data, what we observe in the following figures, is that in Figures A1, A2, A3 and A5, where data points diverge significantly from a simple linear relationship, these data points are almost entirely related to the years 2020-2022 (green dots).

In Figures A4, A7 and A8, there is a high level of correspondence in the relationships between the published data of 2023 and 2024, although again, even in these cases, it is the revalued data for the years 2019-2022 which are slight outliers.

In Figure A6 we observe a rather unusual pattern of regional price deflators, with two separate clusters emerging more than 5 percentage points apart from each other on both axes' dimensions, and with an average clustering distance of some 8 percentage points from each other on both axes. Both clusters are populated by ITL2 regions from all parts of the UK.

In Figures A9 and A10, the growth in GVA per hour (volume measure) bears little relationship with the growth in GDP per capita (volume measure), and this is true for both the 2023 and 2024 data releases. Again, the outliers are almost entirely related to the years 2019 to 2022.

In Figures A11 and A12 se wee that the change in hours worked at the regional level bears no relationship with population change at the regional level, and this is true for both the 2023 and 2024 data releases. Again, it is the years 2019-2022 which show the greatest (upper and lower) dispersion from the regional averages.

In Figures A13 and A14 we also see no relationship between total regional hours worked and regional population change, but we do see, in manner reminiscent of Figure 6, that the regions are grouped into two very distinct clusters, separated by more than 5 percentage points, with an average cluster distance of some 20 percentage points apart. These clusters are populated by ITL2 regions from across the country.

As with the price deflators in Figure A6, given that the UK regional economic system has such a clear core-periphery structure we might have expected clearer pattern to be observed in terms of the economic geography of price deflators, but this appears not to be the case.

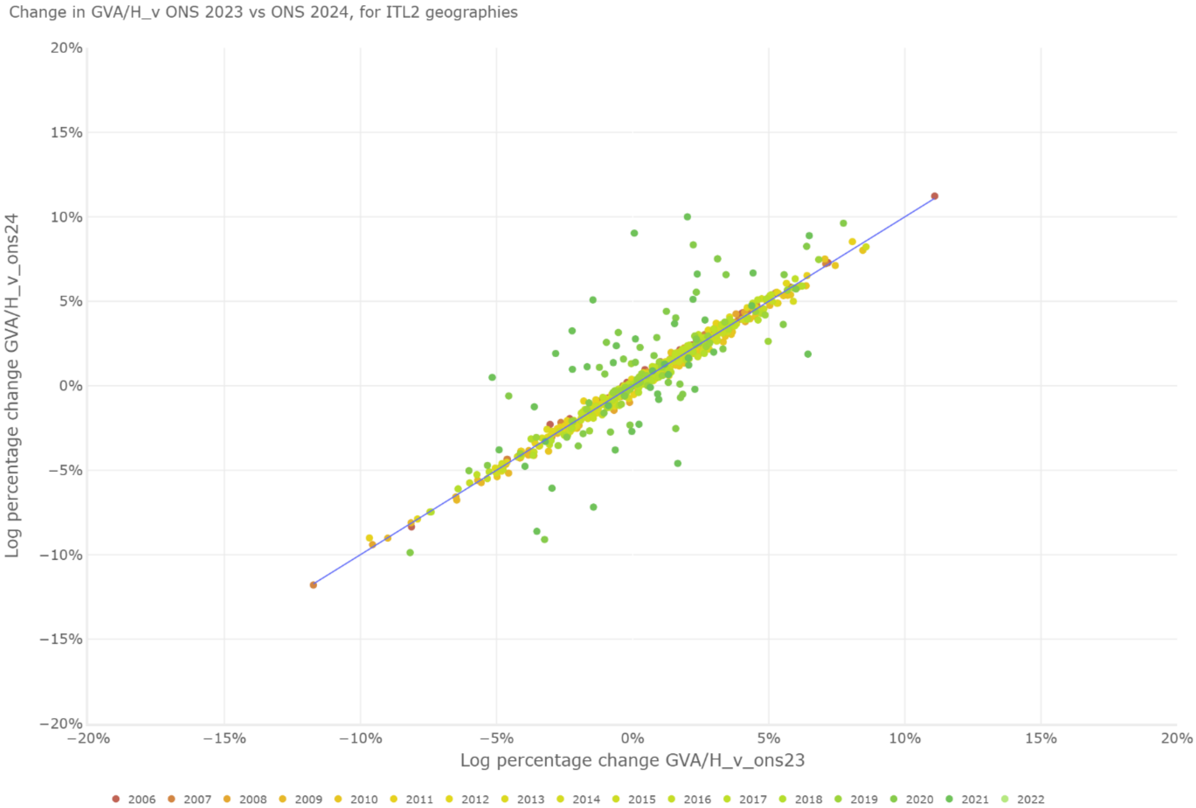
Finally, as we see in Figure A15 for the ITL2 regional population growth data, there is a high degree of correspondence between the 2023 and 2024 ONS releases for approximately half of the ITL2 regions, while for half of the ITL2 regions the population change is more than 2 percentage points. By far the largest deviations are for London regions with population growth differences of between 3 and 12 percentage points.

Combining all of these data points suggests that the GVA data and the GDP data are broadly consistent between the 2023 and 2024 data revaluations. However, the GVA per hour and the GDP per capita bear little or no correspondence with each other, as might have been expected from numerous economic studies. Moreover, given the fact that the total hours worked and the population data also bear little or no resemblance to each other, with unusual separated clusters of regions and price deflators, suggests that there are likely to be problems with the data regarding the number of hours worked. In particular, the major differences occur in the links between population data and the numbers of hours worked for the ITL1 London region and its ITL2 sub-regions.

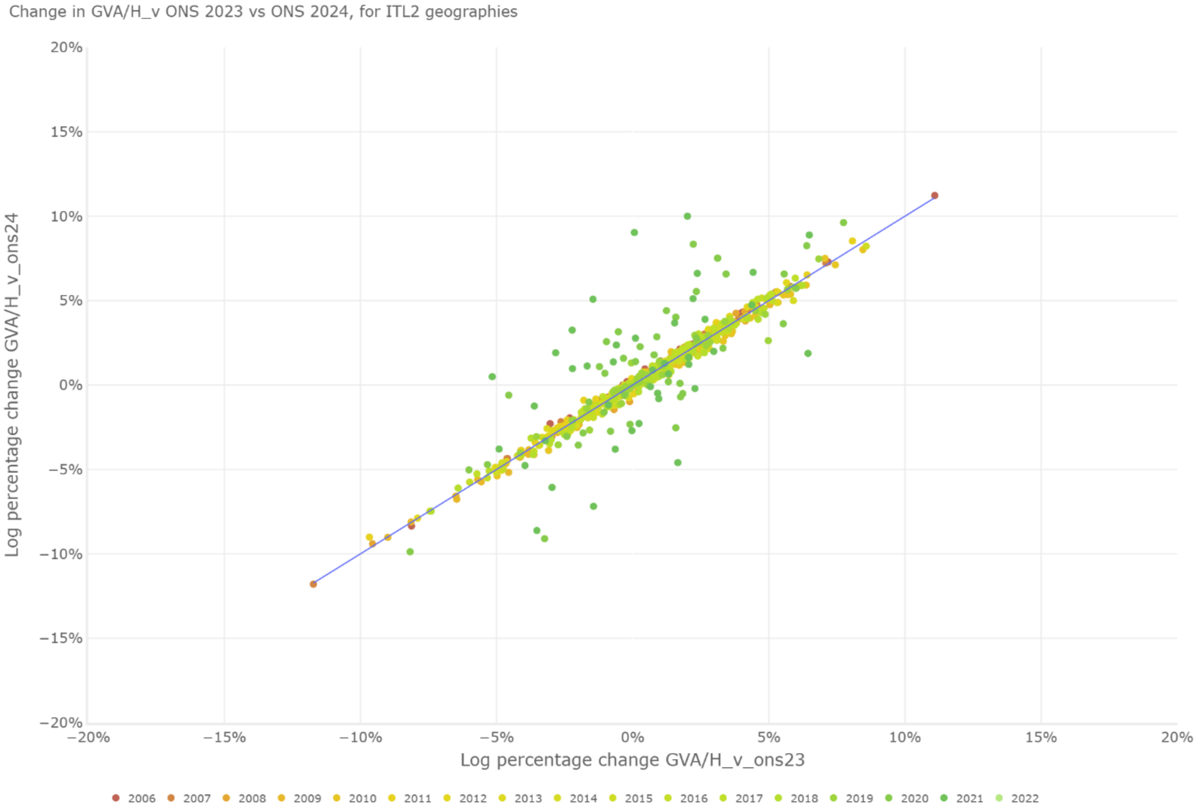
Finally, Figures A16-A19 depict the smoothed productivity (output per hour) growth rates since 2008 according to the 2023 and 2024 data releases by the Office for National Statistics.

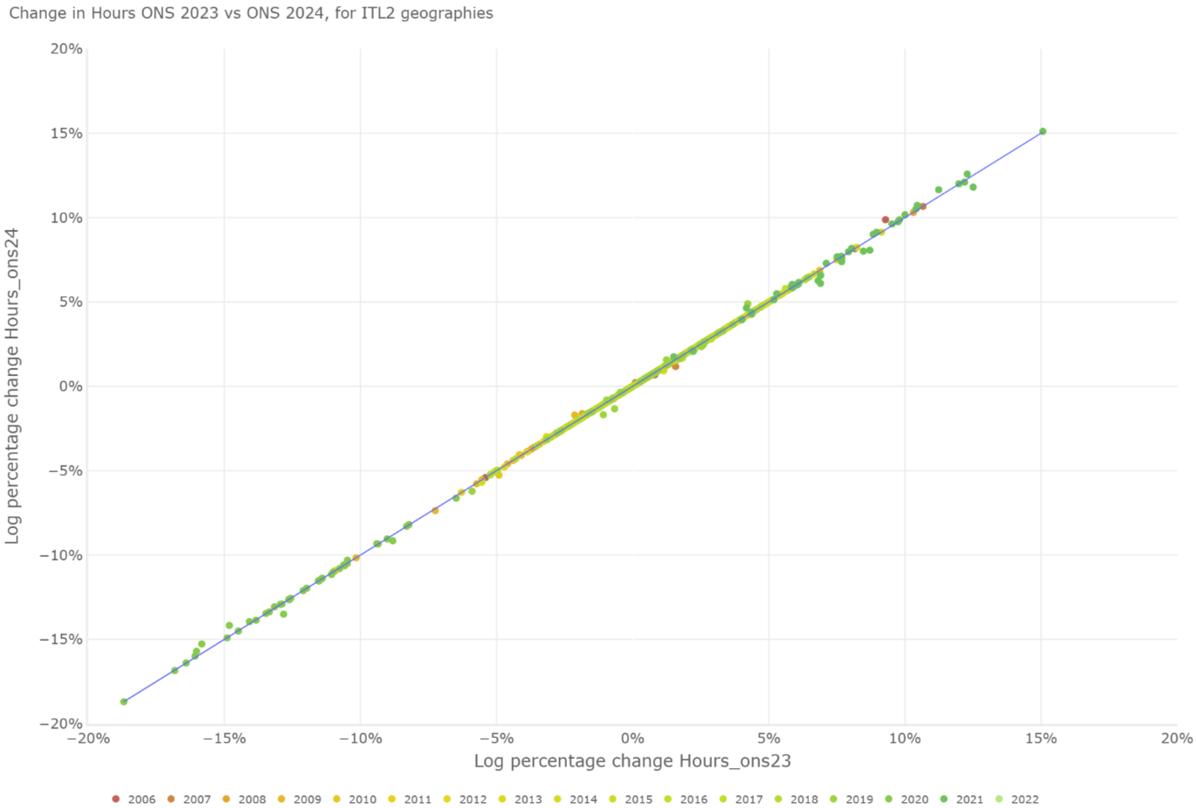
Figures A16 and A17 we compare the output per hour growth rates 2008-2019 from the 2023 and 2024 data releases, respectively. As we see, the overall adjustments appear to be rather small. In contrast, Figures A18 and A19 compare the output per hour growth rates 2008-2021 from the 2023 and 2024 data releases, respectively. As is clear from a comparison of these two figures, the differences are very significant indeed, with the overall slope reflecting these relationships becoming much steeper and the positioning of London and Wales decline markedly while that of the South East improves markedly.

Figures A1 (above) and A2 (below)

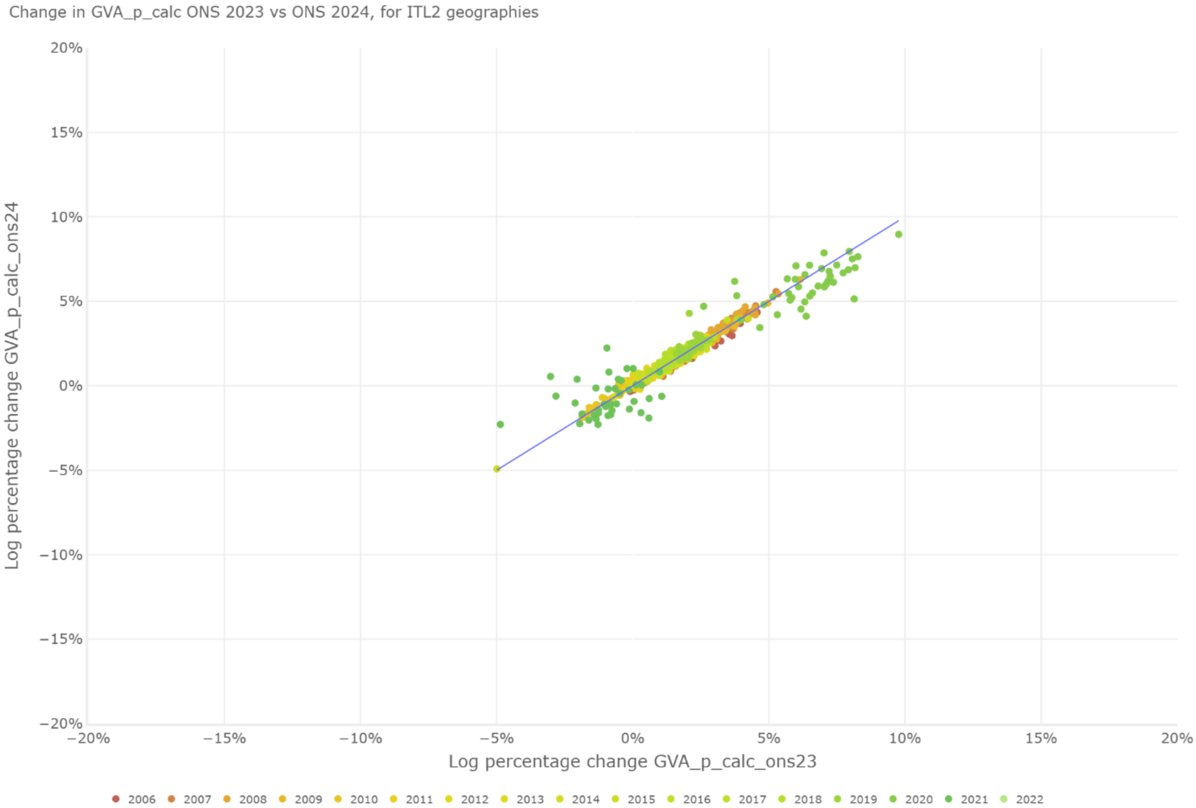


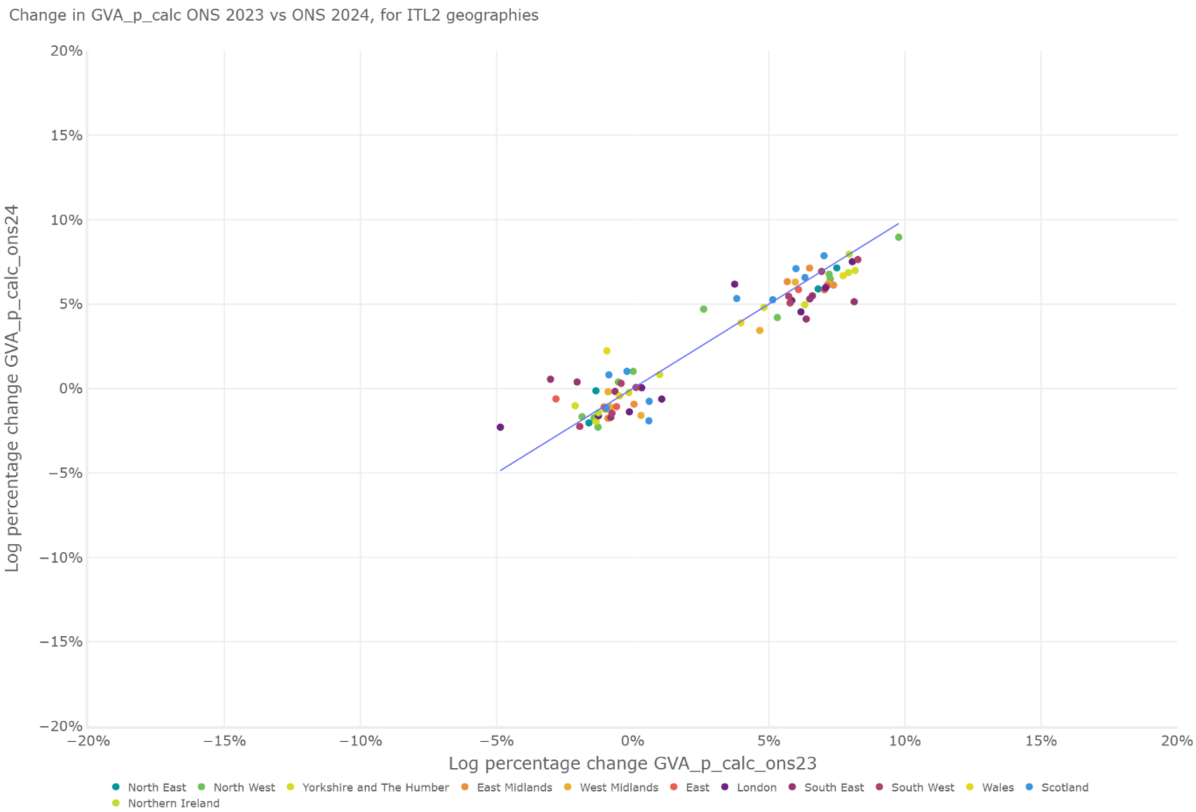
Figures A3 (above) and A4 (below)



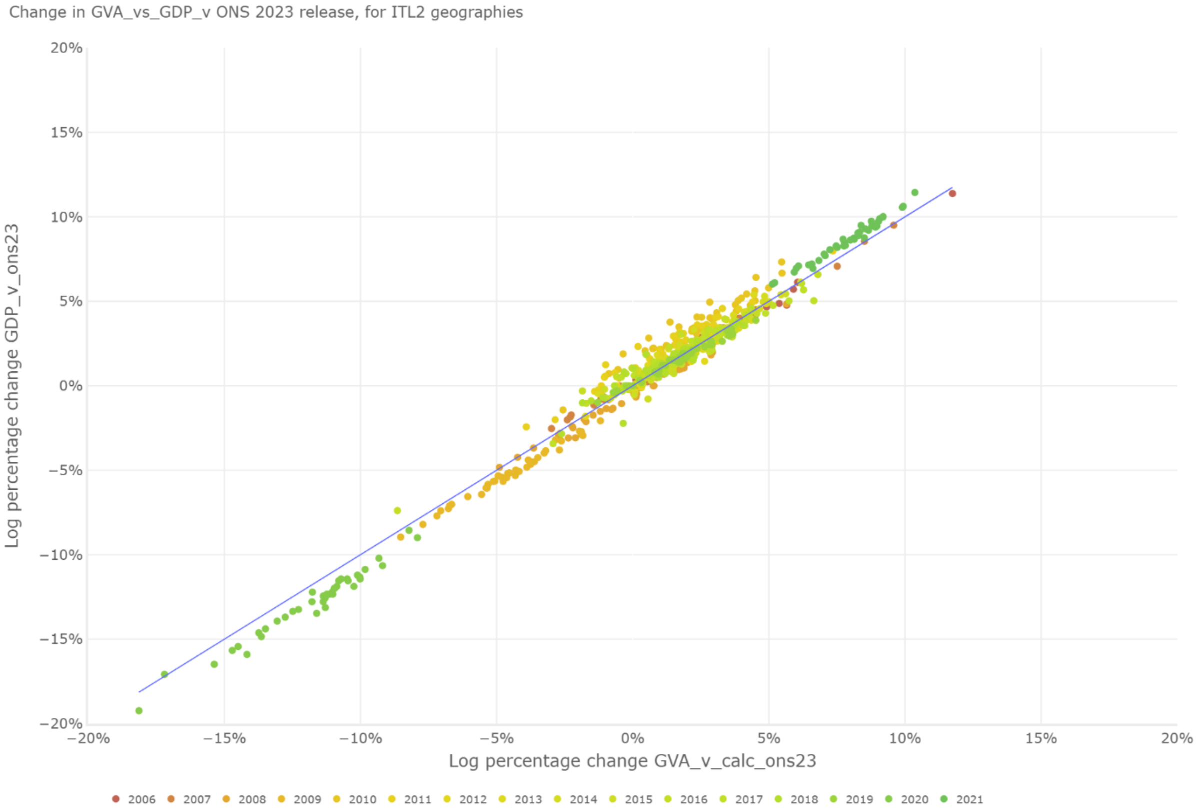


Figures A5 (above) and A6 (below)

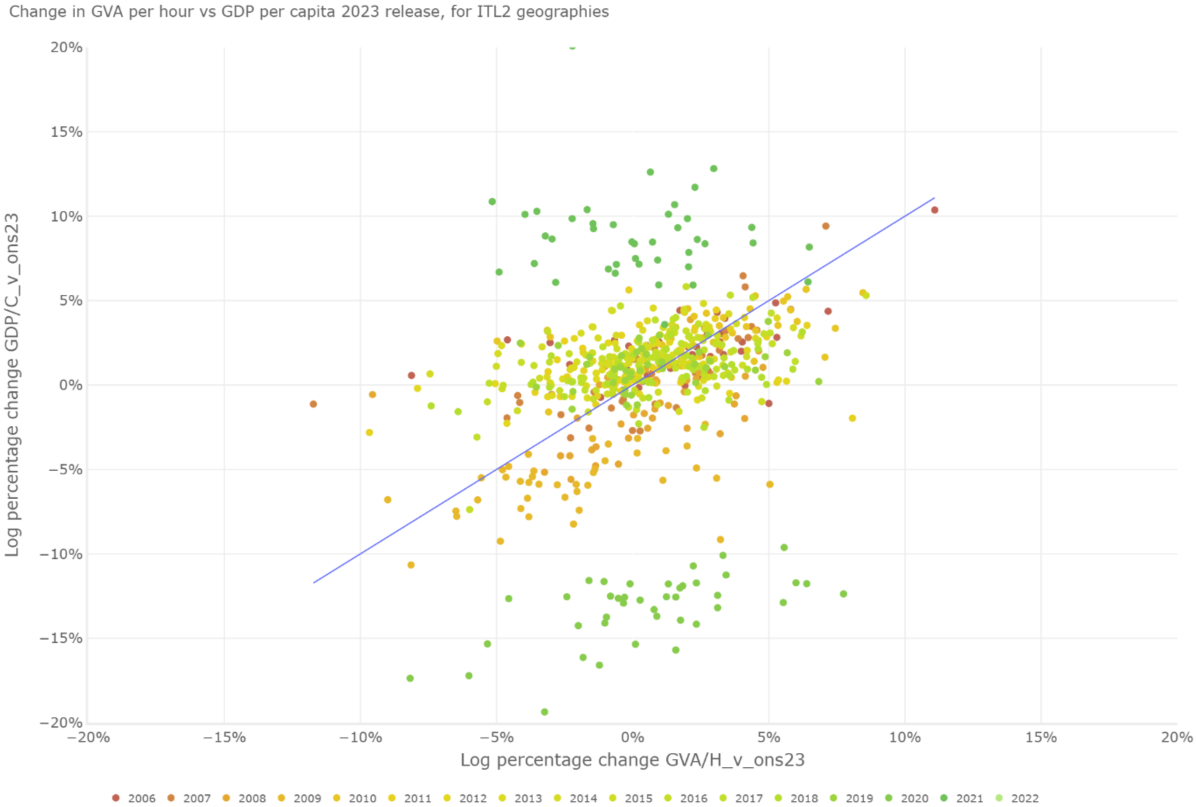


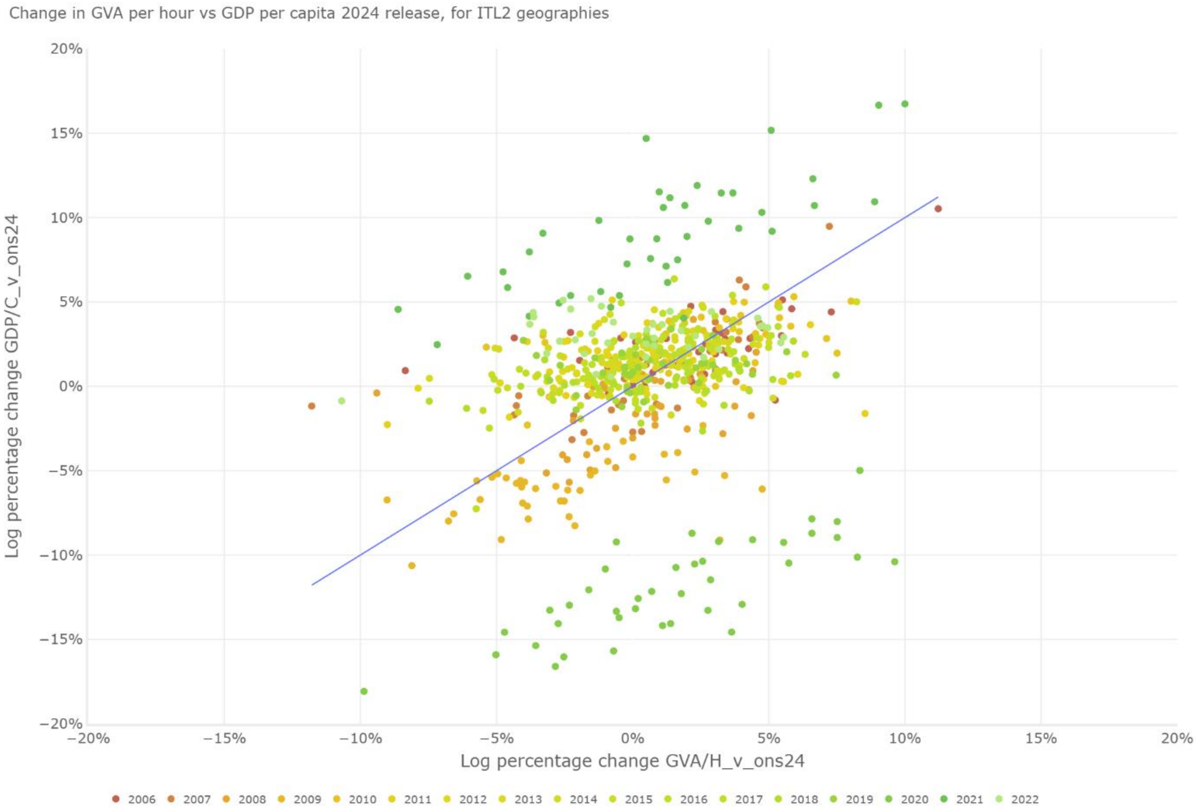


Figures A7 (above) and A8 (below)

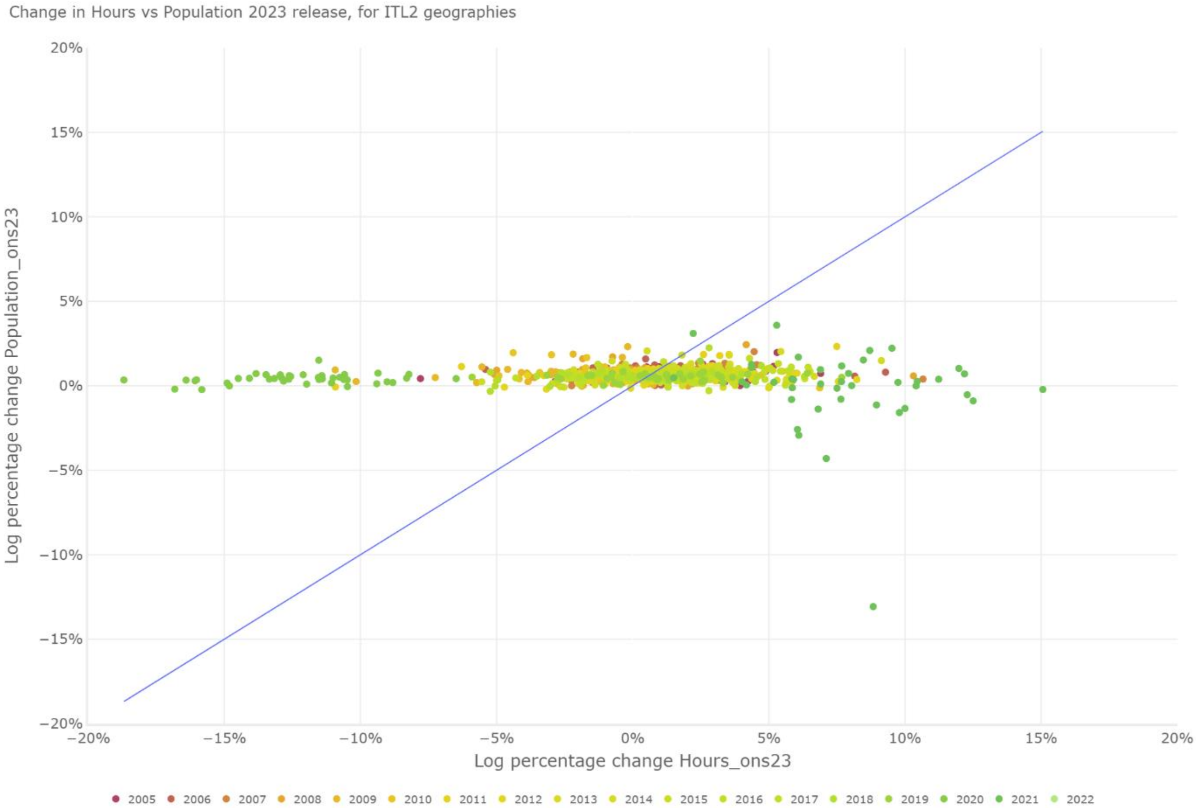


Figures A9 (above) and A10 (below)





Figures A11 (above) and A12 (below)



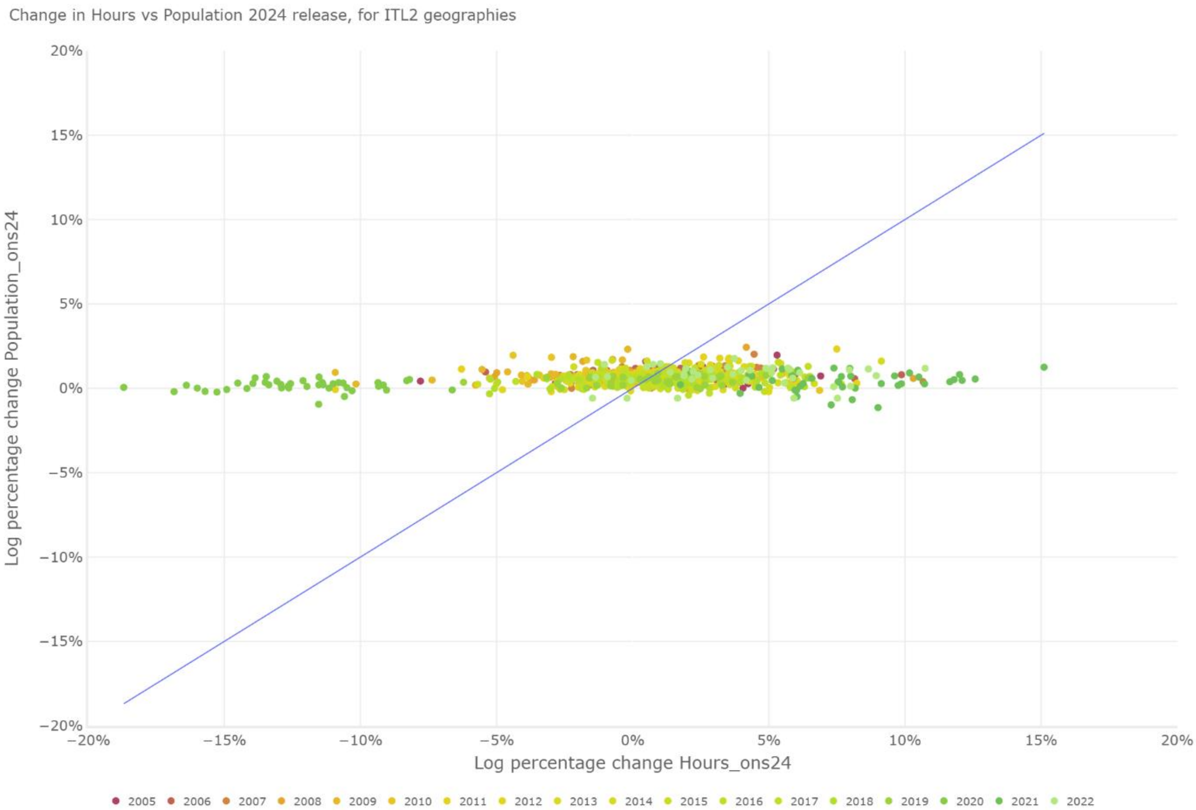
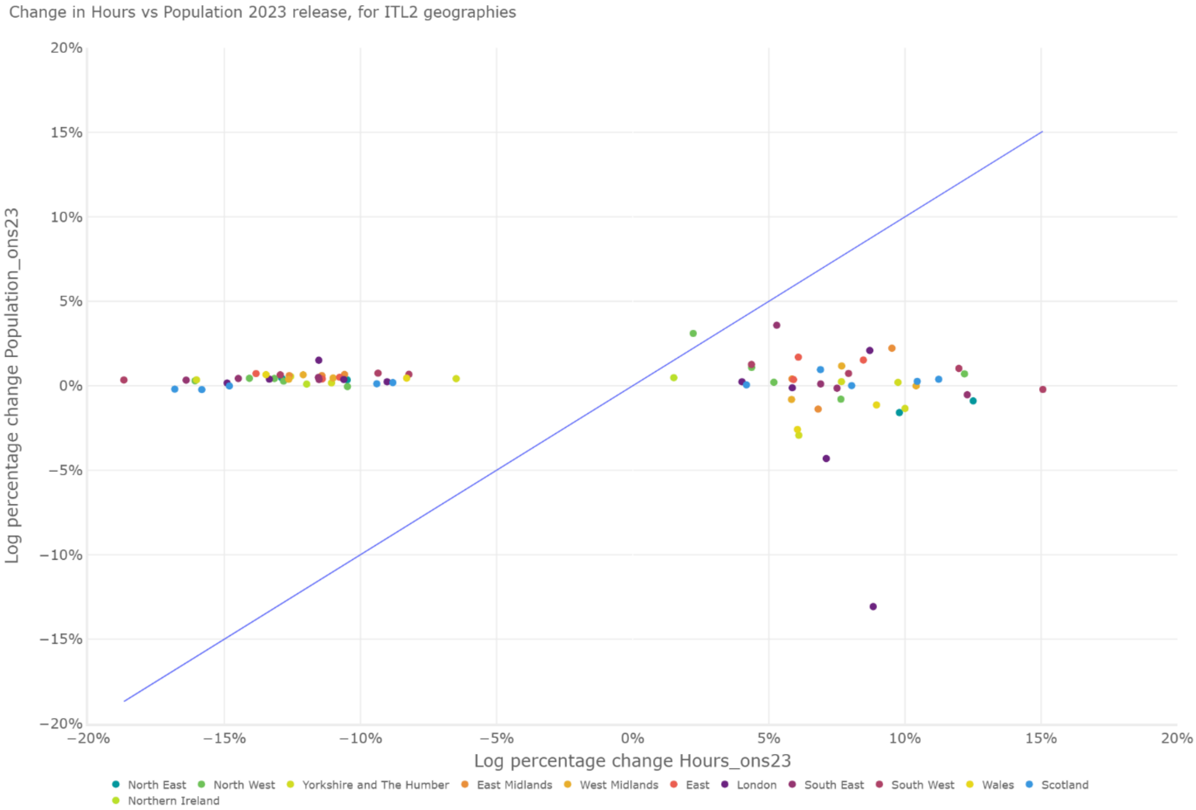


Figure A13 (above) and A14 (below)



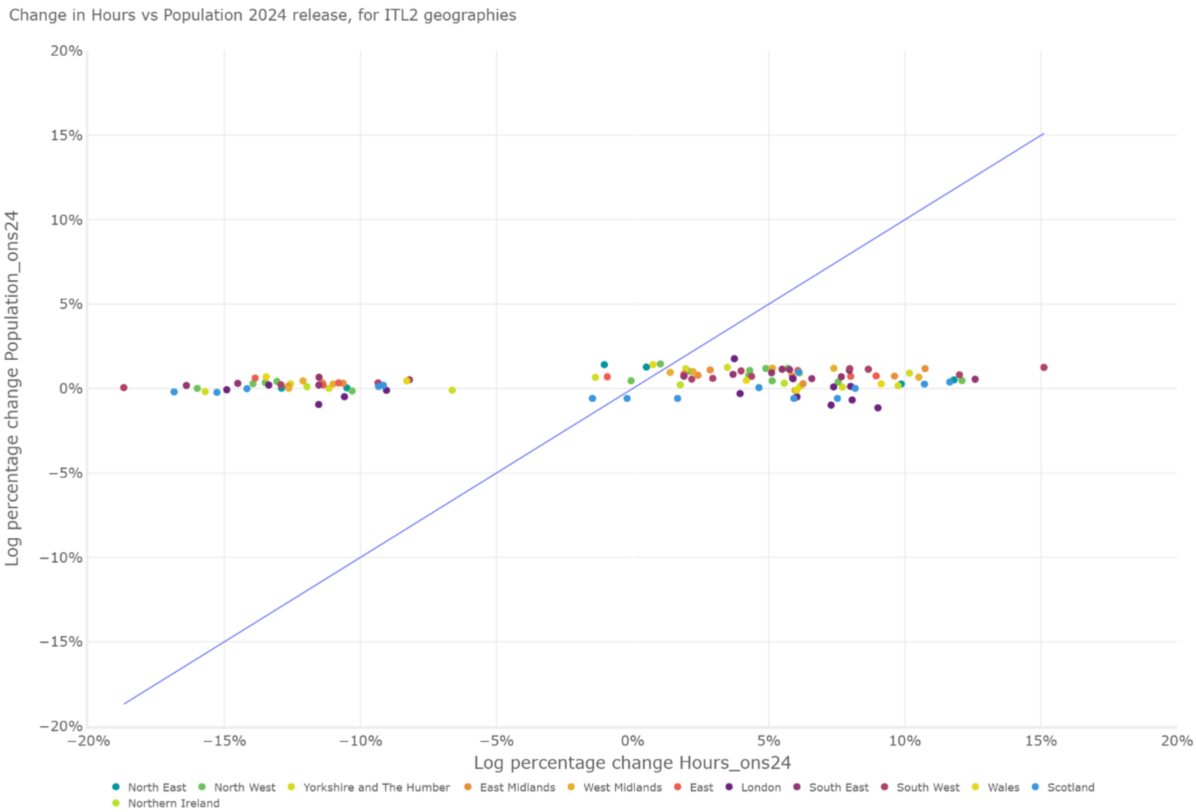
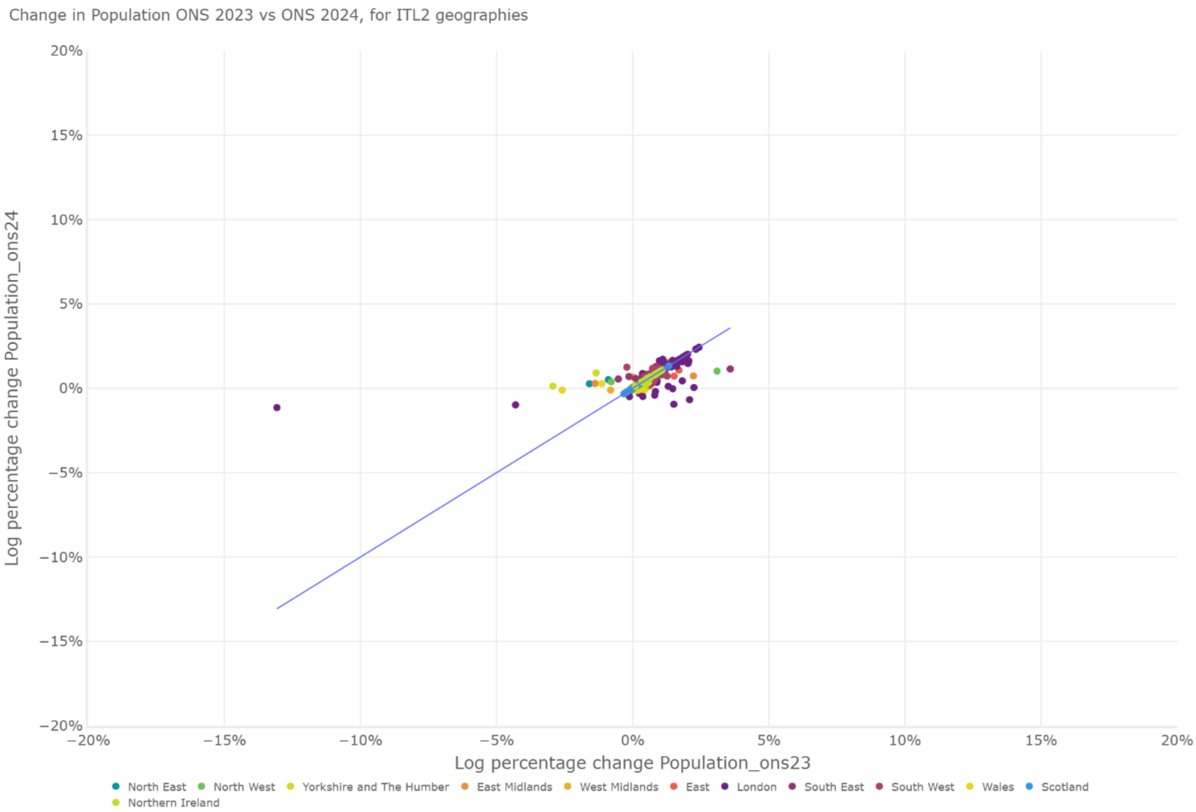


Figure A15



Change in Population ONS 2023 vs ONS 2024, for ITL2 geographies
20%
15%
10%
5%
0%
−5%
−10%
−15%
−20%
Log percentage change Population_ons24
−20%
−15%
−10%
−5%
0%
5%
10%
15%
20%
Log percentage change Population_ons23
North East
North West
Yorkshire and The Humber
East Midlands
West Midlands
East
London
South East
South West
Wales
Scotland
Northern Ireland

Figure A16

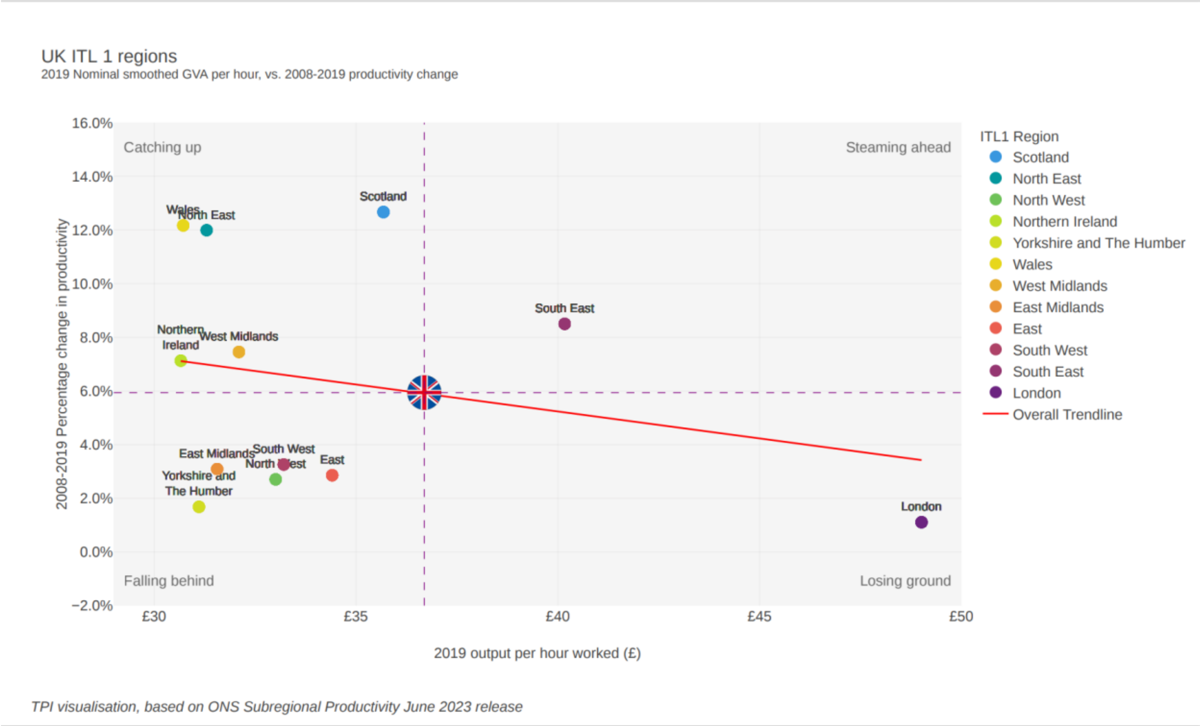


Figure A17

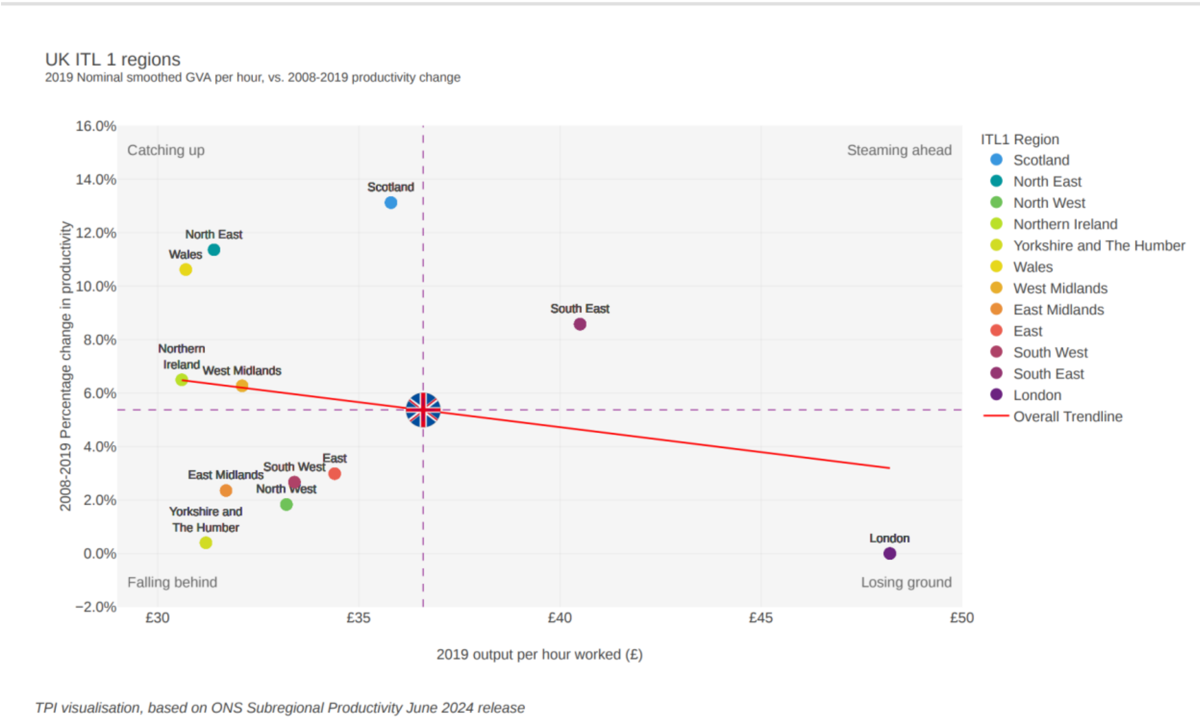


Figure A18

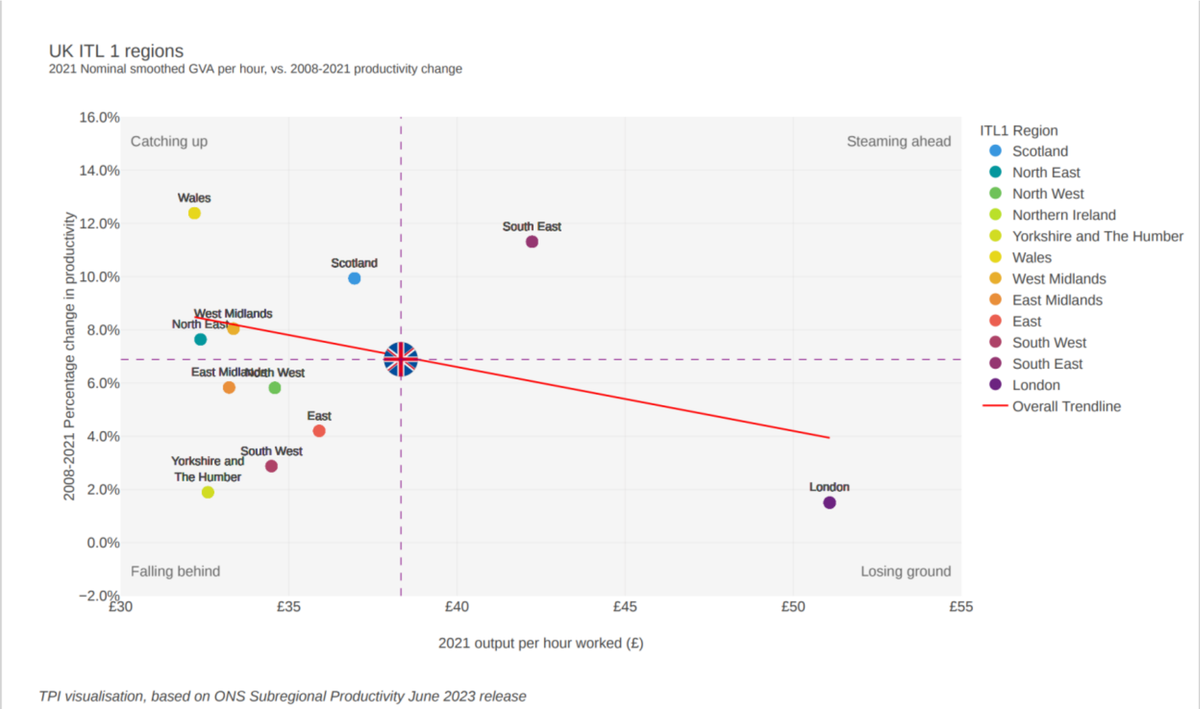
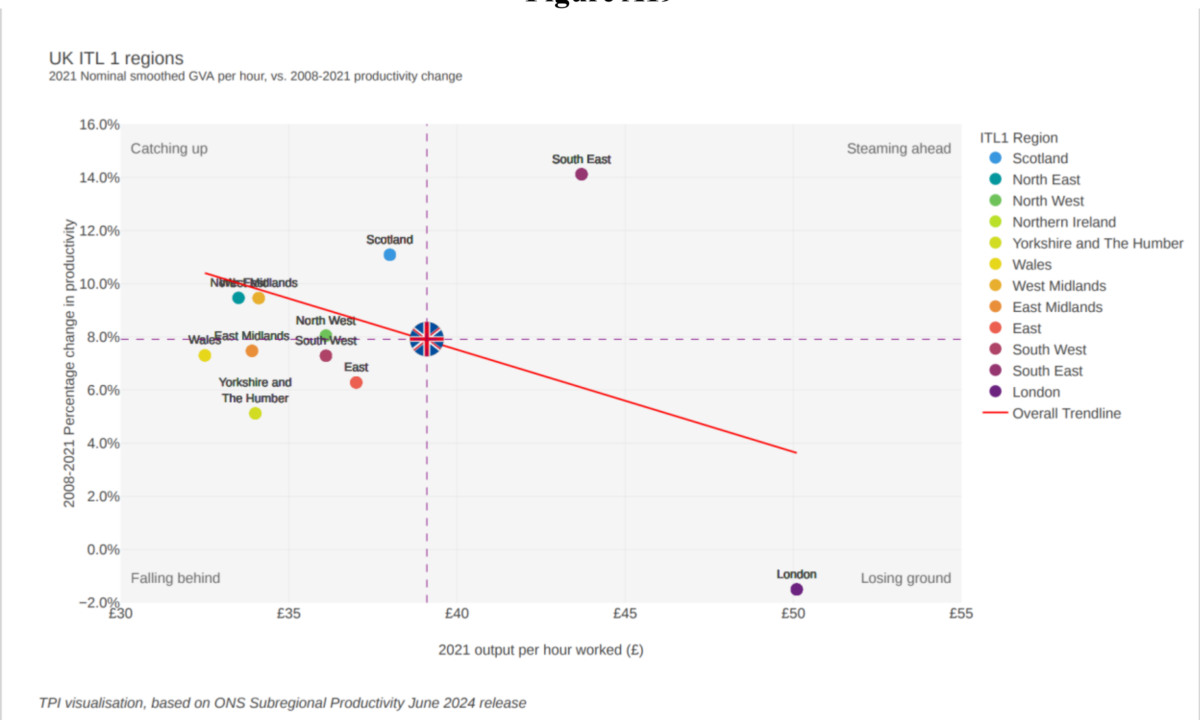


Figure A19



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ONS Response to "Are UK Regional Productivity Disparities Really Narrowing? An Investigation into Recent Productivity Data Revisions"

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Abstract

Understanding the relative convergence or divergence pathways of regional productivity in the United Kingdom is an important topic for regional economic policy. As such, ONS welcomes that the authors have examined this topic based on our published regional and sub-regional productivity data and appreciate the opportunity to comment on the article.

The article notes the apparent shift away from divergence in productivity between UK ITL1 regions towards convergence within the most recent data (particularly for the period 2019-2022). The authors are clearly sceptical of this result and present a number of arguments concerning the data that they see as potentially giving rise for caution on this result. They then conclude that it will be necessary to observe a few more years of data before we are able to draw strong conclusions on the issue.

It is worth noting that the methods used by ONS to produce regional and sub-regional productivity data are based on a top-down approach from national accounts data down to regions. As such, revisions to the currently published data for 2019-2022 remain a possibility when the data is updated in future annual Regional and Sub-regional Productivity publications. Perhaps most importantly, those updates will include data for more recent years that will be less impacted by the economic effects of the covid period. As such, we agree with the author's overall conclusion that it would be wise to wait until we have some further years of data available before reaching a definitive viewpoint on the issue of UK regional productivity convergence and

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divergence. However, whilst we note the arguments presented in the paper about the 2019-2022 productivity data, our response below discusses these in light of aspects of the data that we think are helpful to users and that may help explain the trends seen in the published data.

Revisions in 2023

One aspect of the article we feel is important to review is the emphasis the paper places on the revisions made in the Regional and Sub-regional productivity output, 2022 (published in April 2024) versus the previous Sub-regional Productivity output published in June 2023 (with data up to 2021). Our rationale for this is that in June 2023 statistical systems were still recovering from the impacts and delays to statistics caused by the pandemic. By contrast, in April 2024, the availability of input data was much improved. So, we expect our more recent output to be of higher quality and as such, do not view the June 2023 version of the data as necessarily the best basis for comparison.

We would argue a better way to consider the data is by comparison of the latest data to a pre-covid period. The authors also use this approach frequently when they focus on comparisons between 2019 and 2022. The rest of our response will follow this approach and focus on discussing the issues raised when it compares the 2019 and 2022 data.

Note that in summer 2025, ONS plan to publish a Quality and Methodology Information (QMI) report to accompany the "Regional and Subregional Productivity" annual publication. This QMI will include further detail on how and why revisions are made to the data, alongside a discussion of the data sources and the methodology behind the final data. We hope this will prove to be a useful resource.

Growth in London's Hours Worked, but a Decline in London's GVA

One result drawn out in the article is that the data shows some ITL1 regions having growth in GVA but a decline in hours worked over the 2019-2022 period, while London shows the opposite (a decline in GVA but an increase in hours worked). The authors note that this would infer a negative production function for London and are doubtful of the economic sense of this.

To examine the data in more detail we have looked at the data for the 2019 to 2022 period by ITL2 region. (This can be seen in Fig 4 in the ONS Regional and Subregional Productivity, April 2024 release). Comparing the 5 London ITL 2 regions to other UK ITL2 regions, the data highlights that it is the GVA data in a couple of the London ITL2 regions that is more atypical when compared with other regions rather than the labour input data. In particular 'Outer London West and North West' ITL 2 region had seen large GVA declines while hours worked stayed broadly constant.

Examining London's GVA performance over this period highlights the impact of the transport sector on the recent data. GVA in 'transport and storage' was one of the few industrial sectors still significantly underperforming pre-covid levels in 2022. GVA in the sector remained 35 per cent below 2019 levels in real terms in London (compared with a 9 per cent decrease for the United Kingdom excluding London), with the biggest impact in 'air transport' (down 67 per cent in London).

Employment in both air transport and the wider transport and storage sector would have been similar to pre-pandemic levels by 2022. This means there was a large drop in productivity in this sector in London in 2022 relative to 2019. This supports the observed ITL2 productivity data, where 'Outer London West and North West', home of Heathrow airport, has the largest productivity decline over the 2019 to 2022 period.

In contrast to this sector, as the authors note, many other industrial sectors in London were probably doing well during the 2019 to 2022 period.

> "[L]arge cities with higher shares of tertiary-educated white-collar workers who were better able to adapt to new technologies such as Zoom, Teams, GoogleMeet, typically passed through the pandemic relatively unscathed in comparison to smaller places with relatively more blue-collar workers"

Therefore, the overall productivity growth rate for London is the combination of these different sectors with different performances: some continuing to expand with both increases in GVA and hours worked, whilst a few industries, most notably air transport and the wider transport sector, had a notable decline in GVA. Overall, in such circumstances, it is perfectly reasonable that the overall impact might be for hours worked in London to have risen over the period but GVA declined, particularly given the share of Outer London which falls within these industries.

It is also reasonable to expect that there are other regions where the opposite happened with some industrial sectors having very strong productivity growth enabling the region overall to have had rising GVA despite declining hours worked. For example, the ITL 2 regions with the strongest productivity growth over the period were East Yorkshire and Northern Lincolnshire, and Lancashire. These areas had particularly strong GVA growth in the manufacture of food products, and/or the manufacture of transport equipment.

A key point to note here is that the productivity calculations are calculated using gross value added as the numerator, and not total output. GVA can be impacted by intermediate costs as well as by changes in output. For example, when comparing 2022 with 2019, the UK air transport industry was also having to deal with significantly higher energy prices. While demand for air travel had largely recovered from the pandemic period by 2022, it would not have been sufficiently high to allow the industry to pass these higher costs onto consumers via higher air fares; therefore the ratio of total output to GVA would have changed.

For the period 2019-2022, therefore, the data (as published in the April 2024 version of Regional and Subregional Productivity) shows the transport sector as having been a significant drag on London's overall productivity growth levels. Looking ahead, as we obtain further years of data, changes to the GVA and productivity performance of different UK industrial sectors will continue to have an impact on the regional productivity data. For example, if the GVA and productivity of the UK air transport sector were to substantially improve from 2022 levels, then this would likely help raise London's overall productivity level relative to other regions. This is one of the reasons why we agree it is worth waiting for further data before reaching a strong conclusion on the divergence/convergence issue.

Population Change

A secondary criticism made in the article concerns the growth data for productivity jobs and hours and how this compares to population change data across ITL regions. The inference being that there should be a correlation between changes in population and changes in productivity jobs and productivity hours.

Views on how strong such a correlation should be will vary. However, we will note that these are very different measures and there are a number of reasons why we should not expect them to directly correlate. Firstly, population includes everyone including children, retirees and working age people not in employment. By contrast, measures of productivity jobs and hours are only including the subset of the population who are in employment.

A second important factor is that population is a 'residence' based measure while 'productivity jobs and hours' are 'workplace' based measures. The missing link between the two is commuting. So, a change in the amount of commuting between regions can directly lead to differences between the growth rate of 'population' and the growth rate of 'productivity jobs or hours'. In London, between 2019 to 2022, the authors themselves note the key development that occurred to population over this period. In section 4 of their article they note that

> "[O]ne of the features of the pandemic era was the so-called 'donut effect', whereby across OECD countries many people relocated away from large city centres to suburbs, smaller towns or rural areas (Bond-Smith and McCann, 2024), and the population data suggests that indeed London was alone amongst ITL1 regions in experiencing population decline during 2019-2022, after which it recovered beyond its pre-2019 population levels."

While many people relocated away (reducing London population) during the 2019 to 2022 period, a large number of those movers will have nevertheless retained their London based employment. As such, we would have expected that London's reduction in population over the period might have been greater than the reduction in hours or jobs within London (including people working at home with London located jobs) and indeed that is what the data shows.

More generally, while some people do respond to changes in regional labour demand by moving, it is much more common for hours to be adjusted instead. Changes in hours worked, either in the intensive margin (individuals working more or fewer hours) or the extensive margin (firing and hiring of people) are typically short term responses to changes in labour demand, while relocating tends to be a much more long term response. Therefore, to the extent that one might expect a relationship between the two, it would be a long term relationship rather than seeing a relation hold in each individual year. And even that long-term relationship might be impacted by some of the factors mentioned above such as changes to commuting flows, or the share of working age residents.

Overall, the factors mentioned here underscore why we strongly recommend analysts examining productivity data via GVA per hour worked, or GVA per job filled metrics, rather than focusing on GVA per head which can often be a misleading metric of regional productivity due to the influence of commuting flows and changes to population demographics.

New Measures of Public Service Productivity: Lessons and Results from the United Kingdom

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Abstract

Since the early 2000s, governments, including that of the United Kingdom, have increasingly focused on measuring and improving public sector productivity. In response, the Office for National Statistics (ONS) has been tasked with developing and refining statistical methods to reflect ongoing reforms in public service delivery. In 2025, a new review concluded, which addressed the evolving landscape of public services, with particular reference to the impact of the Covid-19 pandemic. Building on the Atkinson principles, the review introduced innovative methodologies which will be of international interest. These methods provide stronger evidence that public services can achieve both productivity gains and losses, depending on capital investment and funding stability. Applying the latest methods developed under the review suggests that UK GDP growth could have been 0.1 percentage points higher annually since 1997, driven by higher public sector output growth of around 0.5 percentage points per annum. This challenges the long-standing assumption, rooted in Baumol's Cost Disease theory, that public services are inherently non-progressive. The Review's findings are particularly timely given the 2025 revision of the System of National Accounts (SNA), which allows for quality adjustments in measuring public service output. This article highlights the importance of adopting these improved methodologies internationally, as part of the upcoming SNA implementation cycle, to better capture the true value and performance of public services.

Since at least the early 2000s, governments around the world, and particularly in the United Kingdom have been focused on the productivity performance of the public sector. In the United Kingdom, around 20 per cent of Gross Domestic

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Product (GDP) is accounted for by the outputs of public services, comparable to most other western economies. How best to measure this substantial part of the economy, particularly in real terms, has been a long-term question for national accountants. The government's desire to find innovative ways to improve UK public services without increasing spending or taxes as well as the recent experience of Covid-19, have brought this back into focus.

In 2023, the then Chancellor of the Exchequer commissioned the National Statistician to undertake a general refresh of methods taking into account the impact of the Covid-19 pandemic on the design and delivery of the public services. In March 2025, the UK Statistics Authority published the outcomes of its work in the Independent Review of the Measurement of Public Services Productivity (UK Statistics Authority, 2025), also referred to as the *Public Sector Productivity Review* (hereafter call the Review).

This article will begin by reviewing the existing literature and key debates surrounding public service productivity. It will then outline the core Atkinson methodology, which underpins much of the current analytical framework. The discussion will move on to the key outcomes of the ONS Review, including outstanding methodological questions. It will then present the main results, and conclude with a summary of findings and implications for future research and policy.

The Existing Literature and Key Debates

Productivity is a long-standing topic of interest to economists and policy makers as productivity is ultimately a driving determinant of standards of living and economic progress. When reflecting on service provision, the classic consideration which has underpinned much academic debate is Baumol's Cost Disease (Baumol, 1967). This remains a seminal theorem in economics: it argues that the real costs of labour-intensive industries (predominantly services) tend to rise faster than those in industries driven by innovation and technological advancements. This is because labour costs in these industries must keep pace with other sectors, without the equivalent increases in productivity as observed in predominantly manufacturing industries. This story is inherently pessimistic in terms of its underlying expectations for productivity gains in the public services, and other similar services; it essentially argues that productivity growth in these sectors will always lag that of other sectors of the economy.

Other studies have started from the more optimistic perspective that there is productivity growth possible in these sectors and observed weakness are, at least partially, driven by measurement techniques, particularly when the sum of real costs is used as a proxy for the volume of output. Under this model, widely used by almost all countries, and frequently still used in national accounts estimation around the world, the common movement in output and inputs necessarily deliver productivity growth of zero, by assumption.

Many governments and academics have found this approach deeply unsatisfactory, either as a reflection of reality or as a metric, which can be sold to the general public.

The defining study which resulted from this need for better measures was the in-depth investigation from 2003 to 2005 by Sir Tony Atkinson in his independent review of the measurement of government output in the National Accounts, (Atkinson, 2005). He makes the case for direct measurement of output, augmented by adjustment of the volume to reflect changes in quality. This seminal text informed the development of the System of National Accounts (SNA) 2008 in how to conceptualize and then empirically measure the outputs of the public services contained in GDP and established a set of key principles which informed future work.

However, the European System of Accounts (ESA) (2010) which generally follows the SNA as its guiding principles took a flatly opposite view and banned quality adjustment within its 2010 iteration on the basis that more methodological work was required to deliver consistent methods which could be applied across Europe.

The exclusion of these elements from ESA 2010, primarily for reasons of practical consistency, was often misinterpreted, leading to the mistaken belief that the Atkinson Review diverged from core national accounts measurement principles, such as those outlined in the SNA or ESA. In fact, the opposite is true: the Atkinson Review applied core valuation methodologies used in the market sector and considered their application to the non-market sector, specifically public services.

The United Kingdom, along with countries such as Canada and the United States (see below), moved forward with further investigating or implementing these methods, particularly in the areas of health and education, despite the position taken in ESA 2010. Operating under the banner of 'public service productivity', the ONS developed a dataset parallel to the national accounts. Whilst this dataset drew on national accounts data, it also incorporated quality adjustments. As a result, this extended dataset, delivered outside the national accounts, offered valuable insights for policymakers, especially in cases where public service reforms affected the quality rather than the quantity of outputs. This work in the years immediately post-Atkinson's report managed to address the largest parts of the public services, but gaps remained. Dawson *et al.* (2005) further developed these methods for application.

The end-result was a difficult statistic to translate into policy application, being (using cost weights, which can change year-by-year dependent on public spending plans) just under 40 per cent of the public services being quality-adjusted and just over 60 per cent not quality adjusted. By 2016, the Bean Review (Bean, 2016) concluded that the evolution of government data sources and the depth of experience in running the health and education methods gained over the previous decade meant that a new investment in this area could be justified. This led to new quality adjustments being delivered in three policy areas:

- The Criminal Justice System (excluding Policing) was introduced in 2018.
- Adult Social Care was introduced in 2018.
- Children's Social Care was introduced in 2019.

Together these three form around 10 per

cent by weight of all public services and moved the overall balance to just under 50 per cent quality adjusted versus just over 50 per cent not quality adjusted, with a substantive share of the latter representing collective services which are generally perceived as more difficult to measure.

Work on this topic was not restricted to the United Kingdom. There is equally a parallel stream of research in the United States,starting with Fisk *et al.*, (1997), which takes account of the different models of provision utilized in that country. Hall (2017) reviews the literature on adjusting medical sector output for quality in the United States and Cutler *et al.* (2022) provides a US health account. Gu and Wong (2015) equally undertake similar work on Canada's education sector.

Of most significance to the development of this agenda are Schreyer (2010) which broadly mirrored the Atkinson approach in health and education, considering these across OECD countries, and Schreyer (2012) which proposed alternative models, with less reliance on quality adjustment. Following these developments, Diewert (2018) analysed the development of imputed output prices, effectively solving the challenge through quality adjusting prices rather than directly adjusting quantities, as per Atkinson. Meanwhile Foxton *et al.* (2019) and Martin and Riley (2024) undertook reviews of the key lessons learnt through the application of the Atkinson model. Martin and Riley (2024) provides a general review of recent work, particularly in relation to the health sector, including Bojke *et al.* (2018) who suggests current practice could be strengthened by adding further characteristics of the quality of healthcare, including additional National Health Service (NHS) Outcomes Framework indicators. Davies (2020) considers a range of indicators that might be used to draw international comparisons.

Foxton *et al.* (2019) in particular highlighted a set of outstanding questions which merited further investigation around how different aspects of quality, as well as different quality adjusted services, should be weighed against one another in estimating public service output and hence productivity measures. These can be summarized as seven substantive issues:

- How should various aspects of quality change be valued and weighted?
- How should different quality-adjusted services be weighted together?
- How to keep pace with the rate of technological change?
- Is it preferable to follow individuals or use aggregate data?
- What to do when a change in policy affects our measure?
- Where to source objective weights?
- How to trade-off consistency of estimates with different needs for data in relation to devolved matters?

While Atkinson's approach remains the main guide for practical applications, several key imperatives drive the need for further work. These resulted in the 2023-2025 Review led by Sir Ian Diamond as the then-UK National Statistician (UK Statistics Authority, 2025). These included methodological questions, such as those raised above, the ongoing changes observed in public services, the potential for Artificial Intelligence and other innovations to transform public service delivery, as well as Atkinson's call for periodic reviews in his report. All of these, however, were dwarfed by the impact of Covid-19 from 2020 onwards, and the necessary policy responses which transformed public service delivery.

Whilst this article will summarize in the main the latest methodological advances delivered by the Diamond Review, a key question remains outstanding. How do the best efforts of statistical offices to apply Atkinson prove or disprove Baumol's contention that productivity growth in such sectors is inherently lower than observed in other sectors of the economy? The concluding section returns to this question in the light of the latest UK estimates to evaluate whether we should be inherently pessimistic or optimistic around the potential for productivity growth in the public services.

The Core Atkinson Methodology

The essence of Atkinson's argument was that in a competitive market, the value society places on a good, service, input or asset is reflected by the market price. This market price should reflect and equilibrate supply and demand. On the supply side, it should reflect the costs of production, including an appropriate margin. On the demand side, it should represent the discounted sum of benefits the consumers believes they will accrue from the product at the time of purchase. The essential logic is that, under the presence of meaningful competitive forces, if there is a rival producer who can deliver the product at a lower cost, or by accepting a lower margin, this will mean they can bid the price lower. Equally, and again in a competitive model, a consumer who believes they will secure more value from the product will be willing to bid up the price. Where the price balances it must be the case that:

Sum of Costs plus margin = Market Price = Discounted sum of Expected Benefits

As such, under conditions where a market (or exchange equivalent) price cannot be observed directly, such as in public services which are often provided free-at-the-point of consumption, this offers two proxy methods which can be used to understand the value of the final output of such public services:

- A sum of costs methodology (referred to as 'inputs = outputs') where the value of the output is set equal to the value of the inputs which go into its production, and given the government does not make profits, no margins applied , or

- A methodology which looks to proxy the discounted sum of expected benefits by splitting the analysis into two computable components: a direct measure of the volume of the relevant output (e.g. the number of hospital operations) and a direct measure of the quality of the final output (e.g. an operation that results in greater average improvements in patients' quality of life is valued more highly than one with lesser improvements.).

In both cases, comparing the aggregate volume growth of all inputs with the volume growth of outputs would deliver an estimate consistent with the concept of Gross Value Added (GVA) growth as applied in the private sector. Dividing the volume of output by the volume of inputs would present a productivity measure. For the 'inputs = outputs' approach to measuring output, this always gives an implicit result that productivity is assumed to be constant. Hence this method is considered inferior as without being able to apply an appropriate proxy for the margin discussed above, this method is a weak proxy for the exchange equivalent price.

The second method requires a direct measure of quality improvements and rests on two assumptions, which are worth making explicit:

- The quality adjustments act in a way synonymous with a market price, so the better the quality of the product, the higher the quality adjustment factor, in the same way that this would normally be reflected in a higher market price.

- The Government is able to act as a rational 'social planner', making optimum decisions relating to the quantities of each public service to deliver, such that costs are spent up until the quantity where consumers would no longer desire additional units of output.

The first of these assumptions have two corollaries:

- As a quality improvement is implicitly equivalent to an output improvement in volume terms a 1 per cent increase in quality is equivalent to a 1 per cent increase in output.
- This is clearly equivalent to market transactions – if a factory makes one good brick in one time period and then makes in the next time period two broken bricks which cannot be sold for a positive price and can only be given away (price = £0), simply because there are two bricks quantity has not doubled, instead it has fallen one hundred percent.

It is this recognition, that one needs to adjust measures of output to deliver a closer analogy of the methods used in the market sector, which marks Atkinson's Review as the landmark which it is. Regarding the social planner assumption above, this is clearly impacted by budget constraints: whilst with an unlimited budget the social planner may be able to achieve the desired outcome, it may well be that within a fixed budget it is not feasible to take all optimal decisions and achieve:

Sum of Costs = Discount sum of Expected Benefits

As such, assuming the budget available to government is insufficient to deliver this equality, one can still assume the government would choose those interventions where the downstream benefits on average exceed the sum of costs. As such, the sum of costs would inherently be expected to under-estimate the value produced. One would expect governments to draw from the top of the distribution of projects in terms of benefit-to-cost ratios. Indeed, UK fiscal policy, governed by the HMT Green Book (HM Treasury, 2022) is explicit this is the case. For this reason, capturing a direct measure of output and applying a quality adjustment is clearly essential to accurately reflect the value created by the public sector in a form comparable to those observed within the market.

These principles of applying quality adjustment to estimate output were accepted as part of a wider trend of economists becoming increasingly comfortable in addressing social welfare function issues.

Questions Raised by the Public Sector Productivity Review

The Public Sector Productivity Review was, to a significant extent, motivated by the Covid 19 pandemic and its aftermath. The pandemic highlighted two key challenges. First, measures of public services productivity can be subject to significant changes in times of crisis which traditional measurement systems often struggle to accommodate. Second, differences in national accounting methodologies across countries can undermine international comparability. Joint research by the ONS and OECD (Mitchell *et al.*, 2022) demonstrated that, in addition to genuine differences in the timing and impact of the pandemic and in policy responses, part of the variation in reported GDP figures stemmed from inconsistent methods used to measure public services. These methodological discrepancies contributed to the observed cross-country differences in economic performance.

In addition to COVID-19, there were other issues which required renewed attention from the perspective of measurement, reinforcing the Atkinson principle that methods require routine updating to continue to meet need. The passage of time delivered two distinct challenges:

- **Changes experienced within public services areas** – in some areas a service may have been re-designed in a fundamental fashion such that the measures no longer reflect the landscape. For example:

o During the Covid pandemic, the Health sector created new Test and Trace capabilities which was outside the existing measurement framework, requiring the creation of new metrics.

o In 2018, a significant change in UK welfare payment policies was made as the introduction of Universal Credit replaced a number of benefits which formed the core of the ONS measurement model until that time. As reacting to Covid-19 was prioritized the ONS reverted to 'inputs = outputs' for the measurement of productivity in social security administration. A new method was therefore a priority for the Review as with other areas affected by changes, which impacted measures including Education.

- **Changes within the measurement of the service areas** – in some areas the service may have remained consistent through time, but the measurement system may have deteriorated. This may have been for a number of reasons:

o Data sources may have ceased to be published by various agencies. For example, during the pandemic, various educational examinations were replaced by teacher-grading as students were unable to attend school and moved to home-teaching. Similarly measures of re-offending which are captured through re-conviction data had to be paused whilst courts were closed during the pandemic, and hence re-conviction patterns exhibited unusual trends.

o Data quality may have deteriorated due to falling sample sizes or other statistical reasons.

o In some areas data is forecast to cover more recent time periods, but the model may need updating and bringing up-to-date. Below we first discuss the changes related to Covid-19 and then other changes which formed part of the Review.

The Direct Impact of Covid-19

The Covid-19 pandemic delivered a fundamental challenge to almost all area of public services, which broadly fell into four categories:

- Doing the same activities in a new way, in ways one could measure.
- Doing the same activities in a new way, in ways one could no longer measure.
- Doing new activities:
- Changing the relative weights between different activities

Both health and education services, alongside numerous others saw the operating model for their services fundamentally transformed by Covid-19. In health services, even setting aside Test and Trace, there were dramatic movements from high-cost in-patient routine operations to medium-cost critical care. Whilst this new task was more labour-intensive and staff in the NHS worked harder than ever before, in cost-weighted volume terms, activity fell during this period, due to the lower value cost-weighting attributed to this provision.

In education, where output is measured via exit qualifications (e.g. GCSEs in England), it is not just the current year's teaching and learning which shape this year's results: the previous ten years of formal education, and pre-primary early years' provision, need to be taken into account. As such the existing methodology pro-rated qualification results back through the cohort's education, using a method called cubic splining. So, for example, a significant fraction of a student's success in Year 11 has been attributed to previous years.

Covid-19 fundamentally disrupted this pattern and caused attainment to behave in fundamentally different ways. However, it would be inappropriate to model that a student sitting their exams in 2021, and whose results suffered due to disruption in 2020, should see their 2017 attribution downgraded: pre-Covid, the student would likely have performed as well as the preceding cohort in that year.

Preventative Services and Latent Capability

At the heart of the conceptual challenges raised by Covid-19 was the role of preventative services. Following on the discussion above which demonstrated the need to quality-adjust output data to reflect the true value created by a service, the impact of prevention had already been recognized as one of the most challenging issues as such services are generally designed to cost significantly less than the downstream benefits they may unlock. Consider a low-cost tobacco cessation program designed to reduce future demand for costly cancer treatments. In such a case, a cost-based approach, even if quality-adjusted, may undervalue the program's long-term benefits. This is especially true when using a cost-weighted activity index to aggregate services, as high-cost treatments like cancer operations would disproportionately influence the overall valuation. Weale (2024) describes exploratory work in this area on diabetes prevention.

In a similar fashion, excess capacity which is laid down to help a system cope with periods of peak/surge demand, would generally appear to depress productivity in the years where inputs spent but not used to produce output, even if these investments may be essential in allowing the system to work at peak times. How to account for this latent capacity was another key issue for consideration.

Opportunities Presented by New Data

Moving on to issues beyond Covid-19, there was an opportunity for the Review to benefit from significantly more data across government than in 2005. This allowed consideration of situations where services can now be reliably measured and where data can be disaggregated to better match inputs and outputs at the detailed level. The importance of disaggregation is particularly important when estimating volumes because this process also allows more detailed deflators to be used.

The Challenge of Collective Services

Atkinson, as other authors, divided services into those which were 'individual' and those which were 'collective'. That is those where the service would affect one individual – such as an operation on person x means the same operating theatre and medical staff cannot simultaneously be used for person y – and those which affect us all – for example, no-one can 'opt-out' of the UK-wide nuclear deterrence. How to value this deterrence, and how it changes (would citizens today feel better defended if the UK government had purchased an additional nuclear submarine earlier?) are significant questions, which have not been resolved globally (Smith, 2024).

This challenge remains as fundamentally difficult today as faced by Atkinson and those who have worked on this topic in the interim. Importantly, the Review did not draw a distinction between individual and collective services, a distinction with a long heritage in national accounts, finding this to be an increasingly unhelpful and outdated concept in a period of increasingly personalized services and better data allowing the link between individuals and services to be better understood.

The Challenge of Services with Multiple Outcomes

Measuring the output and the outcomes delivered by a service can be complex even when there is a simple one-to-one relationships (e.g. health services), but some services are characterized by delivering multiple outcomes. Policing is a clear example, with responsibilities to both prevent and solve crime, deliver crowd-control, undertake missing persons investigations, work to reduce re-offending with key partners, attend road-traffic accidents, undertake community policing, and tackle anti-social behaviour, alongside counter-terrorism activity and addressing organised crime. This raises a number of distinct challenges:

- Mapping inputs to each activity.
- Accessing good quality and consistent activity data, with no double-counting.
- Calculating the relative weights of these activities in the aggregation process based on accurate and timely data.
- Attributing outputs and outcomes to the participating bodies. For example, if police work with local probation staff to manage dangerous offenders upon release, how should this activity be split between police and probation agencies?

This complexity made policing an area which Atkinson was unable to resolve, and so at the start of the Review it was still the second largest individual service (after defence) to be treated as 'inputs = outputs'. Resolving this was therefore a priority. Similarly, in social security administration and taxation the question of how to weight different taxes and benefits directly relate to this. The Review implemented alternative weighting methodologies which may better reflect the value users receive (for example, do citizens place more weight on a benefit which delivers a larger share of benefits disbursed or which costs more to administrate?)

The Outcome of the ONS Review

The Review, developed over two years contains 120 recommendations, divided into all areas of the public services. Healthcare, social security administration, criminal justice and fire, and policing form the bulk of these recommendations by number, even though several of those may be referred to as future developmental work. In general, the Review has refreshed input and output data sources, but in addition the key issues by area considered were:

- Environmental services and local services – Scope and definition of service areas
- Tax administration – What is the output?
- Public order and safety – Data and implementation
- Social security administration – Fundamental change of service design (Universal Credit)
- Healthcare services – Preventative services and equivalization
- Education services – The impact of Covid
- Defence services – Conceptual challenges

Finally, the Review explored accelerating the pace of statistical production to enable more timely measures using nowcasting techniques. A longstanding limitation of using quality adjustments for outcome measures is the publication delay as many of these measures can take a long time to be produced. For example, the rate of reoffending, which is used as a quality adjustment for the criminal justice services, is based on re-convictions by a court or other legal process. As it can take up to two years before a case is labelled as a re-conviction, the statistics becomes less useful for policy

2 More information on this aspect of the Review can be found in ONS (2023) and ONS (2024d).

purposes.[2]

Environmental and Local Services

Before one can begin to produce estimates for different activities, one must define their scope to ensure completeness and prevent duplication. However, such definitions also need to reflect public and technical understanding of the scope of different activities, and to be internationally agreed, so comparisons can be undertaken.

The definitions used in the United Kingdom align to the UN Classification of Functions of Government (COFOG), which were last updated in the 2010s (The last revision was 2019). It is recognized internationally that these need to be refreshed. For example, while decommissioning nuclear reactors—currently a major component—is undoubtedly important as an environmental protection service, there is significant scope to broaden the definition to better reflect the full range of government activities relevant to the environment.

In this instance, the Review identified the challenge that around 50 per cent of those activities (by cost-weight) which today an informed citizen may expect to be considered as being concerned with the environment are classified under different sections of the classification system. For example, forestry is listed under 'economic affairs' because its primary function was previously perceived to be the production of timber, an economic asset. Today carbon sequestration and cultural services from forestry are, at least in the United Kingdom, given greater weight, so one could argue it should be moved to environmental services.

Redefining environmental and local services would have two benefits. First, it would better show what share of public services are actually targeted at protecting the environment; conceivably 5 per cent of public services on a broad reading could be classified this way. Second, it would compel us to address whether various locally managed services should be within this envelope, for example local planning functions or waste collection and management.

As such the Review submitted a recommendation to the current global consultation that a wider Environmental Services section should be created, split into three parts: Environmental Protection (broadly equivalent to the current 'Environmental Protection' COFOG category), Natural Resource Management to cover areas such as forestry, planning and waste management, and Climate Change and Net Zero to cover adaptation and other similar activities.

Tax Administration

Tax administration is a service area which traditionally had not benefited from a direct measure of output. As such, this service was calculated on an 'inputs = outputs' basis. The first course of action therefore is to ask: what is the output that is being delivered, accompanied by a subtler question of what output do citizens benefit from? In areas like education where the citizen is directly receiving the service this is relatively simple to map. Similarly, if the health service delivers more health interventions this is broadly understood as additional output which is of value (one imagines no one will agree to an unnecessary surgical intervention – so there is a natural limit on volume of activity).

In an area like tax this is less clear. If the tax collecting agency collects more tax than is mandated by law, or collects it from the wrong people, this is clearly not a socially positive output: citizens would not place a positive value on this output. Akin to the 'broken bricks' argument, there would not be a positive price amongst citizens for over-taxation.

One could therefore simply count the number of taxpayers validly caught under each tax regime (Income Tax, National Insurance, etc.), and cost-weight these together. However, this again misses the point of where the value is created. The value is created for citizens by the tax agency (HM Revenue and Customs or HMRC) collecting the quantity of tax specified in law so that the government can spend funds on the delivery of public services. Collecting too little tax or collecting more than legally specified are both of less value to citizens.

This means that not all tax schemes are of equal value. Some taxes are relatively expensive to administer and raise smaller levels of tax, while others are relatively cheap to administer and raise large quantities of tax (e.g. PAYE Income Tax). Just eleven specific taxes schemes in the United Kingdom have harvested around 88-89 per cent of all tax revenues in recent years It feels appropriate to assume the public and ministers are more concerned about the efficiency and productivity of those schemes rather than the smaller ones.

The Review resolved this by 'revenue-adjusting' the various tax schemes, so their value in aggregation better reflects the tax-revenue collected rather than the costs of delivery. This adjustment reflects an intermediate step whilst the ONS and HMRC explore methods to adjust for fraud and error as a quality adjustment. The ONS is also exploring how to take account of taxes raised outside HMRC, primarily via local government, and customs and excise duties raised by HMRC.

Public Order and Safety

Another problem caused by the outdated COFOG structure is the grouping together of services which are now perceived to perform a diverse range of functions. Public order and safety is a prime example, being an amalgam of policing, immigration, fire services, civil and criminal courts, probation, prisons and other criminal justice activities. This covers a mixture of civil (some immigration activities, civil and county courts, some police activity, fire) alongside criminal detection, prevention and punishment services. There is therefore a variety of inputs and funding models. For example, some services use fee regimes, such as some courts and tribunals, whereas others are funded from taxes.

For this reason in 2018, the ONS split criminal justice services and fire services from policing and immigration. These services all benefit from input and output metrics alongside outcome measures. Whilst most of these have been subject to extensive revision and updating under the Review, primarily focused on ensuring up to date data sources are used, the more extensive changes relate to policing and immigration.

Historically, policing and immigration

services relied on an 'inputs = outputs' approach. However, these two areas differ significantly in terms of input growth, particularly in recent years as immigration has gained greater political salience. They also differ on data availability to develop comprehensive direct output measures, although both appear now to be feasible.

A key issue that remains is determining the appropriate weighting of different outputs within individual services, particularly policing where the Review has identified a number of discrete data sources across different types of activity. While a successful investigation leading to a conviction is clearly a positive output, more ambiguous cases raise important questions. For instance, if an investigation identifies a suspect but fails to proceed due to an unwilling witness, should this outcome be considered equivalent to a conviction? Or should it be down-weighted, perhaps through a quality adjustment on the grounds that, while it may not yield immediate results, it could still contribute positively in the future by generating intelligence or evidence that supports later cases? In addition, sourcing appropriate data to weight together criminal and 'non-criminal' outputs is difficult when inputs are not always clearly delineated between the two. Overall, the ONS identified sufficient data to progress developing metrics which are likely to be delivered in 2026 and 2027.

Social Security Administration

Social Security Administration historically benefited from a direct measure of output, but only for benefits administered by the UK Department for Works and Pensions (DWP). Tax credits and child benefit are both administered by HMRC, which is the tax and customs authority, and were omitted alongside housing benefits administered by local government.

Immediately pre-Covid, the implementation of a new benefit system, Universal Credit (UC), replaced seven benefits with a single consolidated benefit. Since, as with Tax Administration, the activity measure used was the number of case-files, this change had three implications. First, it consolidated seven case files into one case file, which would show up as an 85 per cent drop in output even though this likely came with significant input savings. Secondly, as implementation was phased, with easier cases being ported into UC first, the remaining activity within the legacy benefits appeared to increase in average costs, as only the more complex cases remained, whilst UC appeared artificially cheap on the same basis. Finally, Tax Credits were one of the schemes being replaced but were not included in the existing output measure. Their inclusion would appear to replace no output with a positive output biasing productivity upwards.

To prevent these impacts, ONS reverted to 'inputs = outputs' in 2018 with the aim of rapidly developing a new model to cope with these effects. The new method, which has now been introduced, adjusts UC outputs for complexity and for the number of component benefits received. This gives a cleaner output metric, which could be combined with the legacy benefits to better reflect overall output.

However, this measurement change left a final challenge. Consider a simplified example: two separate benefits, each providing a citizen with £50 in year 1, are replaced by a single benefit of £100 in year 2. All three benefits (the original two benefits in year 1 and the combined benefit in year 2) cost £1 each to administer. From the citizen's perspective, the value received remains unchanged—£100 in total. Under the traditional model, which weights outputs by the number of case files and their associated costs, productivity also remains unchanged. In year 1, two case files (each with a cost-weight of £1) yield an output of £2, divided by £2 of input, resulting in a productivity score of £1. In year 2, one case file (cost-weighted at £1) divided by £1 of input also gives a productivity score of £1, despite the fact that the same outcome was achieved with half the administrative effort.[3]

The Review found this approach increasingly difficult to defend, because cost-weights do not necessarily have a strong alignment with the concept of value.[4] To correct for this distortion, a benefits-weighting approach was used. The single case file in year 2 is assigned double the weight of each case file in year 1, reflecting the consolidation of two benefits into one. This adjustment results in an output of £2 divided by £1 of input, yielding a productivity score of £2. While this is a highly stylized example, it illustrates the core principle which builds on the foundational work of Atkinson (2005), which flagged that cost-weighting, whilst it had the attractive qualities of being readily available and in consistent market prices, crucially can deviate from value significantly enough to be the worst of all viable alternatives. There is a strong argument that cost weights, whilst probably unavoidable, are the weakest component of the core methodology and effort should be taken to find alternatives.

Healthcare

Healthcare is a well-established sector, which has benefited from substantial efforts to improve measurement of inputs and outputs since 2005. As part of the Review numerous smaller remaining issues were addressed. However, two issues were noted as key at the start of the process, with one further issue arising as the work developed.

Preventative Activities

Better reflecting preventative services involved firstly ensuring those services are captured as distinct units of output, and then exploiting new methods to measure their impact on outcomes. Preventative activity of NHS providers is already accounted for elsewhere in healthcare output,

3 Schreyer (2010:p 11) makes a particular effort to defend cost-weighted activity indices: "For non-market producers, unit costs can replace prices to value different kinds of services. However, unlike market prices that combine consumer and producer valuations of products, unit cost weights reflect in the first instance the producer or supply side (or government's willingness to pay). This implies that it is the production value and not necessarily the societal value that is attributed to education or health care. However, the purpose of output measurement is not to provide estimates of the societal value, so the use of cost weights does not constitute a major drawback in the context of the national accounts."

4 Indeed, if it did, there would be no need to move beyond 'inputs = outputs' methods as one can read 'costs' for inputs.

taking into account the following considerations:

- Pharmacological treatments were already captured meaning only behavioural support were added
- Drug and alcohol misuse output were estimated using the total number of psychosocial interventions; although this did not distinguish between the intervention setting, as there are not enough data to disaggregate unit costs by setting.
- For smoking cessation, the number of quit attempts was used as the activity measure.

In 2023, ONS reviewed the coverage of preventive healthcare leading to the introduction of new activity measures to capture the growth in the volume of activities provided by local authorities:

- Local authority commissioned treatments for drug or alcohol misuse excluding NHS providers
- Local authority commissioned smoking cessation services

Equivalization of Services Delivered in Different Providers

The granular data available for healthcare activity and costs enables a high degree of differentiation in weights between different services. However, where process improvements lead to lower-cost service delivery methods, which are recorded as separate activity types, they are assigned a lower weight in output, meaning efficiency gains from moving to lower cost treatment are not represented in the productivity measure. This is particularly notable in the case of elective surgery, where procedures may be carried out either as an inpatient procedure, a day case procedure or as an outpatient procedure. Historically, separate unit costs have been used for each procedure type. Therefore, if procedures transition from overnight hospital stays to same-day treatments and costs fall, this results in the measurement system in more lower-weighted activity and so appears as a reduction in output, even though in reality the same care is being provided more efficiently

The ONS has developed equivalized unit costs for equivalent treatments across different modes of provision. These are applied by combining activity and expenditure across different services categories within each Healthcare Resource Group (HRG). HRGs are clinically meaningful groupings of patient activity derived from NHS patient records, primarily using procedure and diagnosis codes. They provide a means of determining fair and equitable reimbursement for healthcare services by providing consistent 'units of currency', based on expected resource use.

This approach generates a new unit cost, calculated as a weighted average of the previously separate unit costs, reflecting both higher and lower-cost modes of care. For inpatient and day case procedures, there is no restriction on inclusion in the equivalization. If a HRG exists in more than one of those components, an equivalized weight will be applied. For outpatient procedures, unit costs are only equivalized where the HRGs tariff (the price paid by commissioners under the NHS Payment Scheme) is equal to that of elective inpatient and day cases.

Disaggregation of Healthcare as a Domain

Since 1997, healthcare has accounted for an increasing share of public services, reaching just under 40 per cent in the latest year of data (2022). It is delivered by the NHS in each of the four UK nations, alongside the UK Health Security Agency (UKHSA), and various Public Health bodies which often form a collaboration or partnership between the NHS and local government. The NHS itself can be divided into primary (GPs, opticians, dental, etc.), community (services such as district nursing, wheelchair provision, palliative care, alongside some Covid-facing services such as Test and Trace and Vaccination) and secondary (hospitals) services. As each of these healthcare services has expanded, they have individually grown larger than any other public service category reported in the Public Service Productivity statistics. The publication of quarterly healthcare productivity data during the Review led to increased public and policy interest, particularly when compared to NHS England data which only covered the hospital sector. As such, the need to disaggregate overall 'healthcare' into components which better enable policy analysis is a clear priority for future work.

Education

Education, like healthcare, benefited at the start of the Review from a mature set of productivity measurements, taking account of examination results at age 16, as a general proxy for educational attainment, as well as a measure of bullying to proxy for student well-being outcomes. During the Review, alongside the common work of improving datasources, work focused on ensuring COVID-19 did not impact estimates of previous years. Improved output metrics covering primary and further education were also incorporated, alongside GCSEs which reflect secondary achievement. Finally, the bullying measure, which acted as a proxy for a range of well-being issues was replaced with a wider 'well-being' measure drawn from the Understanding Society survey funded by the ESRC.[5]

The most substantive intervention related to the distribution of achievements in GCSEs back through previous years of schooling. This used a cubic splining approach to pro-rate fractions of overall attainment back through the student's career, with the greatest weights put on the most recent years. However, as explained above, this model of 'casting back' had the flaw that a one-off event such as Covid-19 in 2019-20 and 2020-21 acted to reduce schools outputs for earlier years.

To address this, the average attainment of earlier cohorts who had recently sat the same school year was utilized as a proxy. The rationale was that, for example, the attainment of those who sat Year 7 in 2015 was better measured by the outcomes of students who had sat Year 7 immediately prior to this cohort and who completed their final qualifications in the years preceding Covid-19. This was considered more robust than trying to retain the ex-

5 https://www.understandingsociety.ac.uk/.

isting methodology and strip out a common 'Covid' effect'.

The common 'Covid effect' for 2019/20 was calculated as a residual: once the attainment of the previous year's schooling was fixed for the cohort who sat GCSEs in that year, the difference between actual attainment and the fixed contribution from previous years was attributed to the pandemic. This residual effect was applied as a common factor to the attainment of every cohort in school during the pandemic. As these cohorts reach their final examinations, their in-year contributions are calculated using the traditional method, given the impact of the fixed elements during and pre the Covid years. This method will be utilized until all students who were in school during Covid-19 have worked their way through the system and the full 'original' method can be applied without adjustment.

Before this change could be implemented, the Review first had to address the underlying raw qualifications data. The COVID-19 pandemic caused widespread disruptions, including school closures and the cancellation of examinations. In response, teacher-assessed grades (TAGs) were provided for GCSE results in place of typical attainment grades. This approach resulted in grades becoming inflated, making the data unsuitable for use in the quality- adjusted output measure, as this could overestimate both output and productivity.

Initially, ONS used a "learning loss" metric based on Renaissance Learning data (2022), commissioned by the Department for Education, to estimate the impact on reading and maths. However, this metric only covered 2019–2020 and risked double-counting output. Experts recommended the National Reference Test (NRT) as a better alternative. Introduced in 2017, the NRT assesses Year 11 students in English and maths without the pressures of formal exams. Results are benchmarked against 2017 GCSE outcomes to track trends. Though not a final attainment measure, the NRT was adopted by ONS to provide more consistent qualifications data during the pandemic years.

Finally, the Review applied changes to reflect the changing governance models in England's schools, predominantly the shift from local authority control to academy providers to better account for variations in the funding (inputs) received by different providers. By 2022/23, over 40 per cent of primary, 80 per cent of secondary, and nearly 45 per cent of special schools were academies. To better capture this change, the number of categories of institutions increased from five to ten, distinguishing between academy and local authority schools across phases, including alternative provision. Updated expenditure weights now allow for more accurate cost-weighting and assessment of each phase's contribution to productivity. This will support evaluation of whether academization has improved educational efficiency.

Defence

Defence is one of the largest activities, reflecting around 10 per cent of total public services, and is currently measured on the 'inputs = outputs' basis due to the conceptual challenges in deriving a measure of output. These challenge have been long-standing, and were neither resolved in the Atkinson Review (2005) nor in subsequent research, including Prtak (2019) and RAND Europe, (2021). Whilst the Ministry of Defence has considered the issues of measuring defence output in the intervening years, it has also been unable to definitively deliver an appropriate approach. Defence, therefore, remains the largest single service which is treated in this fashion.

In essence the challenge is that a direct measurement of defence output would not be appropriate because defence has a primary function of deterrence, in which active deployment of the armed forces is to be avoided if possible. For example, while defence capital assets, such as aircraft and ship are designed to perform their function in rare combat situations, they primarily act as a deterrence to prevent conflicts from arising and/or escalating.

However, estimating outcomes such as wars being avoided is highly speculative, as is measuring threats such as terror attacks. Deriving a suitable 'unit' of deterrence, or the capability of the military to deliver against its five priority outcomes, is challenging, as the capabilities of the armed forces vary over time, depending on the type of threat, technological advances, and military strategy.[6] Additionally, there is a considerable degree of confidentiality with regard to the activities of the military for reasons of national security thus limiting data availability.

Finally, there is a pertinent question of ethics and political sensitivity when considering the frameworks for defence output. For example, it would not be appropriate to have defence output fall in the absence of active deployment, nor would it be appropriate to measure the number of adversaries neutralized in operations.

The Review commissioned Smith (2024) to consider the measurement of defence productivity further, who concluded:

> "For defence, there is a problem of comparability because the nature of the activities, capabilities and objectives of defence change over time, and for good reasons, as threats, technology and strategy evolve... When these activities or capabilities are discontinued to reorient to the new context, measured output will have fallen while the military are fully occupied doing different activities. For defence, performance measures include elements such as success in operations, maintaining readiness, and stopping equipment being delivered late, over budget and not meeting technical requirements. These are difficult to convert into indicators that would match national income accounting criteria."

Although progress in measuring output remained limited, the Review made significant improvements in the treatment of inputs by replacing indirect estimates, which are typically based on deflated finan-

6 https://www.gov.uk/government/publications/ministry-of-defence-outcome-delivery-plan/ministry-of-defence-outcome-delivery-plan-2021-to-2022

cial data, with more direct volume measures. Where indirect methods continued to be used, the Review incorporated higher-quality source data and deflators. Additionally, it proposed new methods for developing a direct output measure that distinguishes between active deployment and deterrence as separate components.[7]

Results of the Review

Whilst only 25 of the 120 recommendations of the Review have been implemented at the time of drafting this article (June 2025), comparing the 2025 vintage of data to the 2022 vintage, published prior to the commencement of the Review, growth was slower than originally estimated in the pre-2010 period, and faster in the following period. As shown in Chart 1 the total public services productivity compound annual growth rate (CAGR) between 2010 and 2019 was estimated to be 0.9 per cent, up from 0.8 per cent.

As Chart 1 also shows, while recovery from the Covid-19 pandemic has occurred, productivity levels across all public services together have not recovered to the peak seen in 2019. The key question is: to what extent is the 2019 peak a fair comparator? This depends on how far citizen behaviour and needs have adjusted through Covid-19. For example, the cancellation of cancer and other diagnosis activity during the pandemic has resulted in more instances of complex cases being overrepresented in the post-pandemic period (see, for example, Barclay *et al.* 2024). While this effect may erode over time, the data suggest it continues to drag which may imply that previous achievements should be perceived as an aspirational goal.

Chart 2 also showcases the large and growing importance of healthcare in understanding public services in the United Kingdom. Table 1 presents the change in the relative shares of public sector expenditure by sector between 1997 and 2025.

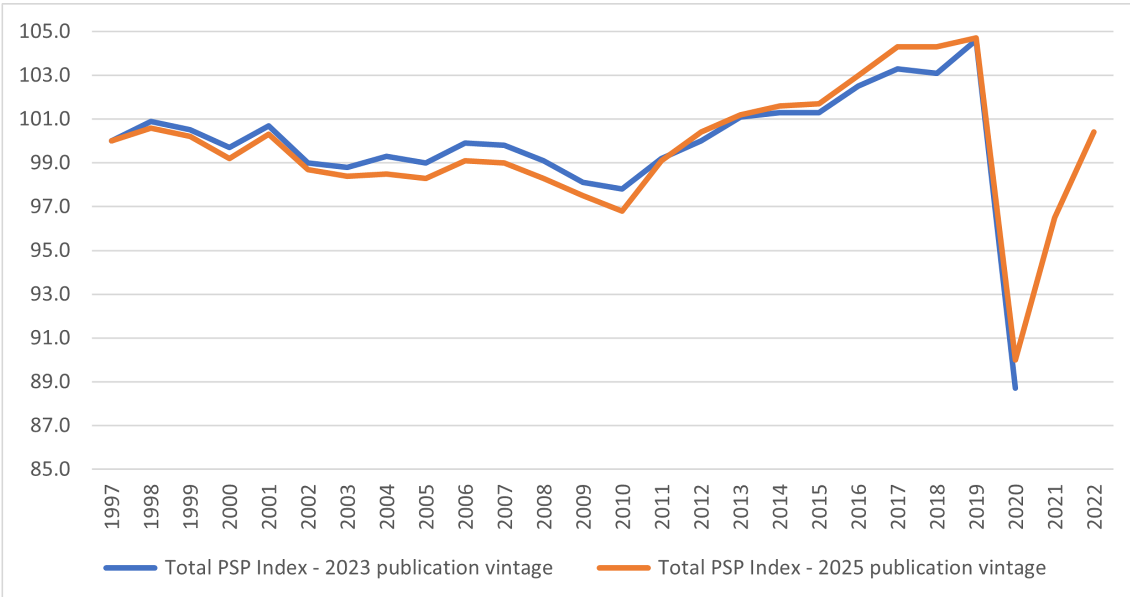
Health spending, as a fraction of all public spending has grown by 11.8 percentage points, whilst education has fallen by 2 percentage points and, despite the aging demographic adult social care has grown by only 0.1 percentage points. Defence has shrunk by 5.3 percentage points, while public order and safety, combined with policing and immigration has fallen 1.5 percentage points. Health's relative strong productivity performance appears correlated with sustained funding and investment, whereas other sectors appear to have faced greater struggles without that investment, as shown in Chart 3. While productivity in education has increased it shows a decline in total expenditure on public services.

One of the key challenges in assessing the share of total public services that are quality-adjusted following the Review, is that this proportion has shifted for two main reasons:

1. Following its rapid growth between 2020 and 2021, the expenditure share for

7 The Review considered this issue further and developed some research methodologies which will be written up in greater depth as a standalone article to follow. These are summarised in Annex E of the Review. https://uksa.statisticsauthority.gov.uk/publication/national-statisticians-independent-review-of-the-measurement-of-public-services-productivity/pages/26/.

Chart 1: Updated Whole Public Service Productivity – 2025 Vintage Compared to 2022 Estimates (1997=100)



Source: Authors calculations based on data contained in ONS (2023) and ONS (2025)

Table 1: Expenditure Weights in Per cent and Percentage-point Change – 1997 and 2025

	Health	Education	Adult Social Care	Public Order & Safety	Children's Social Care	Defence	Police & Immi gration	Other
1997	28.0%	18.0%	5.3%	4.2%	1.9%	14.4%	5.5%	22.7%
2025	39.8	16.0	5.4	3.1	2.7	9.1	5.1	18.8
Change (pp)	11.8	-2.0	0.1	-1.1	0.8	-5.3	-0.4	-3.9

Source: Table 8 ONS (2025)

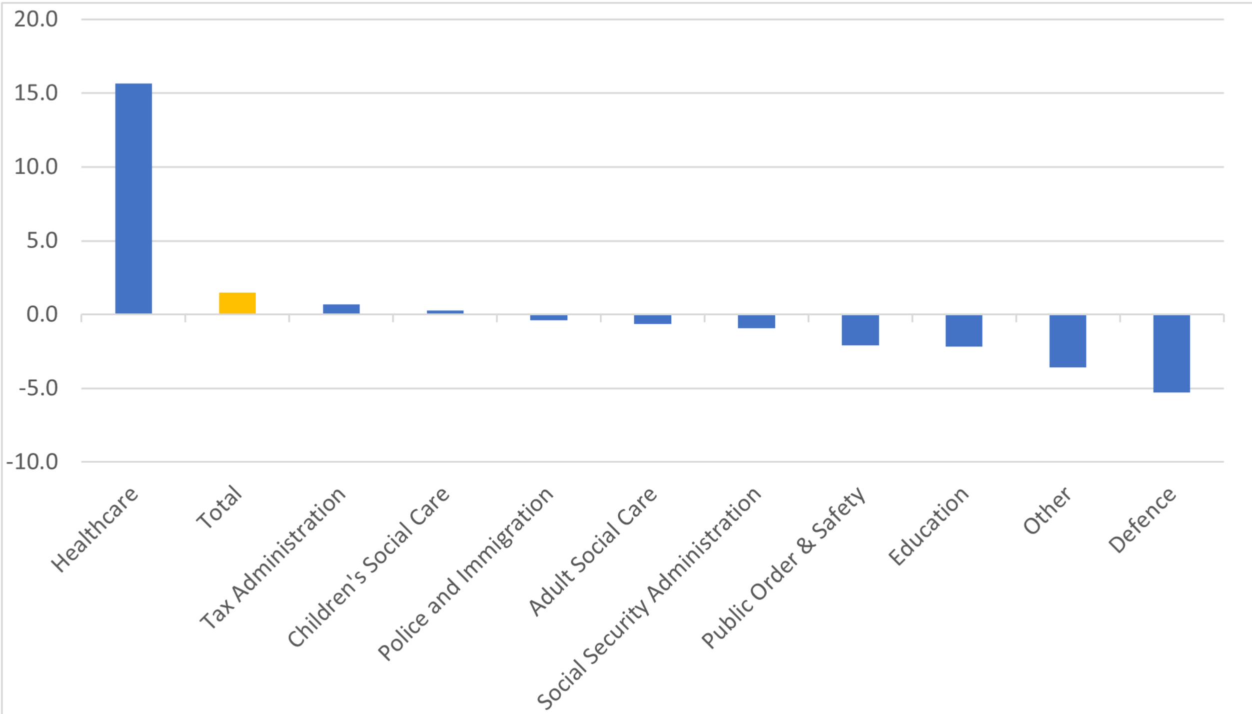
test, trace and vaccinations activities decreased between 2021 and 2022. Because test, trace and vaccinations are not adjusted by quality and the contribution to growth is calculated based on the previous year's expenditure share (which is 2021 for growth in 2022), this results in a lower share for quality-adjusted output in 2022.

2. Service areas where expenditure is not quality-adjusted, such as "Other" government services and Police and Immigration also increased their shares of expenditure in 2022. Therefore Table 2 presents the resulting data in two ways: the full up-to-date data and a version of the data, holding the 2021 weights constant into 2022, to show a like-for-like counter-factual reflecting the impact of the methods changes. In the latter case the share of quality-adjusted estimates increased by about 3 percentage points.

Conclusions

This article presents an update on nearly 20 years of methodological development by the ONS for the measurement of public services productivity, following finalization of a Review commissioned by the UK government. Improving the headline statistics is not sufficient though. Understanding the differences between sectors is vital. Work

Chart 2: Contribution to Whole Public Service Productivity Growth by Type of Service – 1997-2022 (percentage points)



Note: Weighted contribution reflects the change in productivity between 1997 and 2022 times the change in the relative weights amongst total public services. For example, whilst Defence remains 'inputs = outputs', the change reflects its diminishing share of total public services.
Source: Authors calculations based on data contained in https://www.ons.gov.uk/economy/economicoutputandproductivity/publicservicesproductivity/datasets/publicserviceproductivityestimatestotalpublicservice(ONS2025)

also needs to be done to deliver explanatory supporting information, including disaggregations. Hence the ONS has also invested in surveying new management practices and use of time for the public sector and focused effort on producing more detailed data, particularly relating to healthcare.

Nevertheless, this article has focused on a strategic set of headline conclusions:

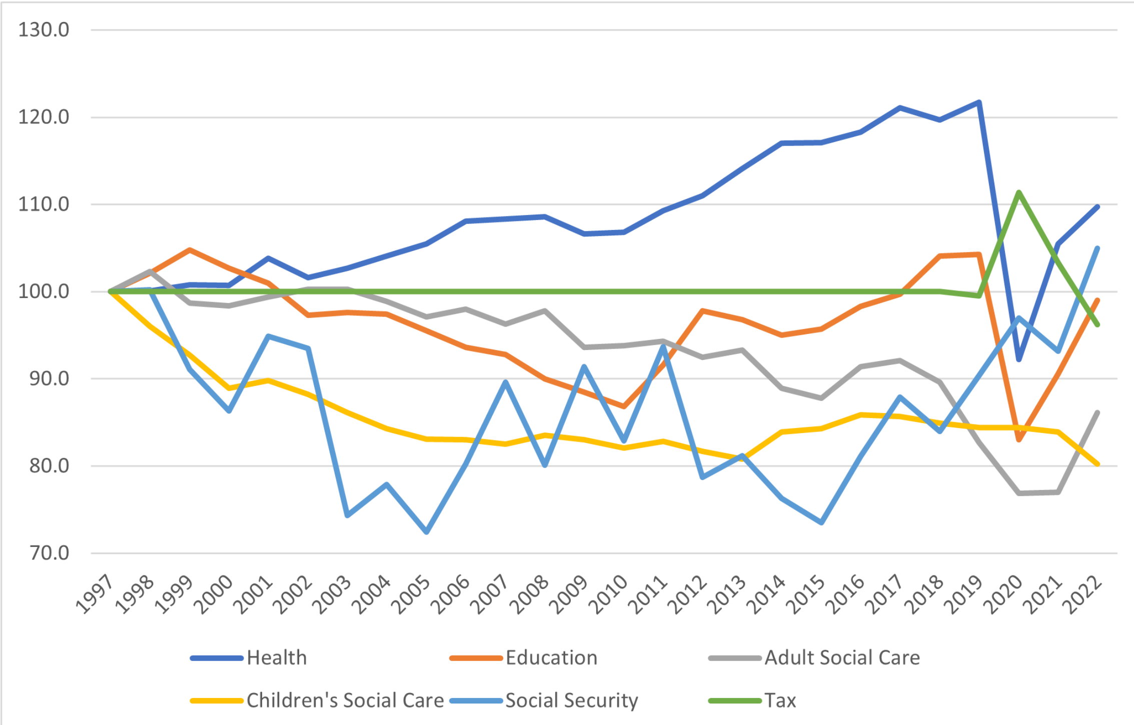
First, the principles underpinning the Atkinson Review appear to still hold true and implementation is becoming increasingly feasible as different areas of government have invested in their data. Assuming the same is true in other countries, the potential to apply these methods elsewhere to achieve a generalized improvement in

Table 2: Shifts in the Shares of Quality Adjusted and Non-quality Adjusted Estimates

Publication Vintage	Quality adjusted direct output	Quality adjusted indirect output	Non-quality adjusted direct output	Non-quality adjusted indirect	Total quality adjusted
2021	48.68%	3.75%	11.79%	35.78%	52.43%
2022	48.63	3.57	11.49	36.32	52.20
2022, holding 2021 weights constant	51.62	3.75	9.40	35.24	55.37

Source: Authors calculations from ONS (2025)

Chart 3: Public Sector Productivity Growth by Service, 1997-2022 (1997=100)



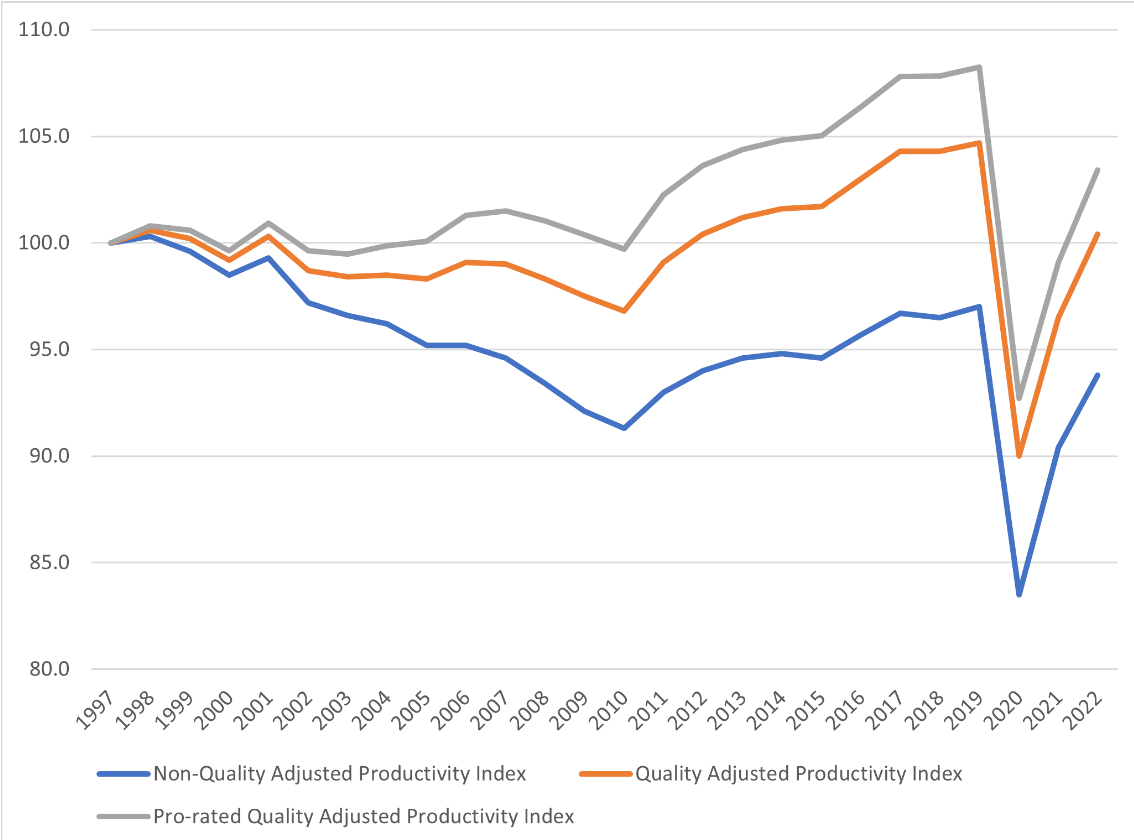
Authors calculations based on data contained in ONS (2025)

volume output and productivity is within reach.

Second, Charts 2 and 3 demonstrate that whilst it may appear that the quantitative impact of these revisions is modest, this disguises large variations by service area. This shows that even at high levels of aggregation the use of 'inputs = outputs' or 'sum-of-costs' methods are deeply flawed approaches to estimating public sector output. While the new 2025 System of National Accounts supports the inclusion of quality adjustments in measuring public services, it also stresses the practical and methodological challenges of such adjustments thereby permitting the continued use of the 'inputs = outputs' convention in national accounts.

Third, even when applied to just 60 per cent of public services, quality adjustment has a significant effect by transforming flat or negative productivity growth into positive trends, as illustrated in Chart 4. Using an index where 1997=100, productivity without quality adjustment declined to 97.0 by the pre-COVID peak, while quality-adjusted productivity rose to 104.7. This shift changes the narrative from one of stagnation to one of modest improvement before the pandemic, followed by a recovery right after the collapse in 2020 due to the pandemic. Similarly, as of the latest data, the quality-adjusted index has rebounded to above 100, whereas the non-quality-adjusted index remains at 93.8 (ONS 2024c). A simple simulation further illustrates the potential impact: if all currently unadjusted services experienced quality improvements at the average rate of those already adjusted, the resulting trajectory—shown as the highest line in Chart 4—would imply a substantial uplift. If this

Chart 4: The Impact (Actual and Imputed) of Quality Adjustment (1997=100)



Note: Pro-rated quality adjustment is calculated by subtracting the non-quality index from the quality-adjusted index, dividing by the share in each year of expenditure which is quality adjusted, and multiplying by 100.
Source: Authors calculations based on data contained in
https://www.ons.gov.uk/economy/economicoutputandproductivity/publicservicesproductivity/datasets/publi cserviceproductivityestimatestotalpublicservice(ONS2025)

estimate reflects the true value of quality improvements, incorporating them into national accounts could add an average of 0.1 percentage points to annual GDP growth over the period 1997–2025.

The increased availability of data for quality adjustments, when accurately measured, demonstrate the clear capability of public services to demonstrate productivity growth. This requires us to reconsider the validity of Baumol's Cost Disease as a useful way of conceptualizing services of this type, as the new estimates show reasonable public service productivity growth in the United Kingdom.

Understanding public service productivity should not be a niche activity. Anyone who wants to understand, or set policy relating to, public services should review what these data communicate. Quality of outcomes matter and if universally applied, could increase have a positive impact on measured average per annum GDP growth. Finally, with government debt approaching 100 per cent of GDP in the United Kingdom, the need to ensure government services are being delivered in such a way that it maximizes the delivery of outcomes and outputs per input is as important as it has ever been.

All of this is of particular importance as the world's National Statistical Institutes prepare to implement the new revision of the System of National Accounts, which expects countries to apply quality adjustments to the volume measure of the public services within the national accounts. The methods discussed above to improve public service productivity should therefore not be viewed in isolation from the wider economic statistics system. The Review includes a roadmap for implementation into UK national accounts and this will likely form one of the most substantive changes in the SNA 2025 revision, in terms of impact on the level of GDP. To ensure continued international comparability, and meaningfulness of GDP data, other countries should look to prioritize similar improvements also.

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De-industrialization and the Great Productivity Slowdown: What Comes Next?

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Abstract

Productivity growth in advanced economies has been slowing internationally for many years. Despite much academic research, there is no consensus on why. Many researchers assume a break in productivity growth around 2007-09. This article argues that there was no such break. Rather, the slowdown is a much longer-term phenomenon and is largely an inevitable consequence of de-industrialization. Unfortunately data measurement – especially of productivity - remains biased towards a now small manufacturing sector, rather than the dominant services and digital sectors. Whatever policies are pursued, manufacturing will continue to shrink as a share of value-added and the measured productivity growth trend will continue to slow. Policy needs to look forwards, not backwards. That means a focus on welfare improvements, not GDP growth and investment in the new technologies and growing sectors, not a doomed fight to restore the manufacturing glories of the past. Investment policies should support critical digital networks, especially to support services such as health and education which are key to productivity in the services sector. Investment is also needed in the transition to net zero to address the climate crisis. These developments would be growth positive and may stem the measured productivity slowdown for a time.

The trend in productivity growth has been slowing in most advanced economies for many years, leading to slower than expected output growth. The slowdown has been especially noted in the United Kingdom where it has been a research focus for at least 15 years. In 2022, the United Kingdom established an academic-led Produc-

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tivity Commission, echoing initiatives in at least 10 other countries (Pilat, 2023).

Despite an extensive academic literature, there is no agreed understanding of why productivity growth has slowed internationally, nor why the United Kingdom has underperformed (Goldin *et al.*, 2022), nor even when the productivity slowdown started. The United Kingdom has been investing less than other countries on a national accounts basis but there is no consensus on why that has happened either. The problem is nicely summarized by this BBC news report (Islam, 2023):

> "The future of the economy and prosperity depends on investment spending. The United Kingdom has an underinvestment crisis, and it affects both the private and the public sector."

The United Kingdom was in second place in the G7 for private investment, as a share of the economy in the mid-1990s, but has now fallen behind the rest. The long-term impact of this is low productivity - we take more time to produce less than our rivals - which results in low growth, low real wages, and then problems raising money for public services.

This article takes a fresh look at some of the underlying issues. It argues that the long-term slowdown in productivity growth results naturally from the inevitable de-industrialization of advanced economies, as they become dominated by their services sectors. The slowdown can therefore be expected to continue for the foreseeable future. The arguments can be viewed as drawing on the classic "Balassa-Samuelson effect" (Balassa, 1964 and Samuelson, 1964) and the "Baumol disease" (Baumol, 1967) but go somewhat further.

This article contains seven sections. The first section considers when the productivity slowdown started. Many analyses start by assuming a break point during the Great Financial Crisis (GFC) of 2007-09. This article draws on a publicly available historical database to suggest that the slowdown in advanced economies has been more gradual, stretching back perhaps 50 years for the United States and at least 25 years for the United Kingdom. The assumption that there was a break point around the GFC, rather than a longer-run structural change, may have hindered previous analysis.

Section 2 addresses the causes of the productivity slowdown. Most of the existing literature does not attempt a root-cause explanation, rather it documents and accounts for the slowdown in differing dimensions, without 'solving the puzzle'. In contrast, a simple explanation based on naturally evolving economic structure following de-industrialization, appears to account for much, if not all, of the relevant patterns in the data. The proposition that the developed economy productivity slowdown is a natural consequence of the economic maturity of industrialization has been made by others (e.g. Vollrath, 2020), but in the United Kingdom the long-term process may have been obscured by events: the demand boom of 2002-2007, the GFC from 2007-2009, exit from the EU from 2016 onwards, and the Covid-19 pandemic from 2020 and its inflationary aftermath.

Section 3 contrasts the slowdown with what has been happening to broader living standards. The slowdown in productivity and GDP growth seems inconsistent with the IT revolution that has dramatically changed the way we all live. GDP is likely becoming a less good proxy for changes in living standards. In part that is because the national accounts do not capture well the productivity improvements of many service sector industries. Given the clear benefits to living standards from the growth of IT, investment policy should prioritize the digital economy through the rapid improvement of digital networks. That would enable the service sector to thrive.

Section 4 considers some public policy issues. If nothing else, slower output growth as a result of slowing productivity growth, creates problems for the fiscal position: Governments rely on economic growth to finance growing stocks of sovereign debt. Many countries are now faced with rising sovereign debt: GDP ratios which may cause future funding crises. Can growth be restored to its former rate? What sort of investment does policy need to promote and support? How can growth in living standards be maximized?

Section 5 looks at selected sectors where higher investment in services could produce improvements in living standards, with a focus on education and health. Investment in people is the key to support many service sector businesses, even if not counted as such in the national accounts. That investment should draw heavily on the opportunities provided by the digital transformation.

Section 6 considers the one further policy area in which investment might stimulate at least a temporary return to higher growth: The transition to net zero carbon emissions. To deliver and utilize new supplies of secure, plentiful renewable energy, will require huge investment in infrastructure and changes to industrial and commercial processes that could boost productivity and output growth. Section 7 concludes.

This article is not anti-growth, nor is it intended as a counsel of despair. The constructive recommendations are that policy needs to focus on the maximum sustainable rate of growth going forwards, given the evolving economic structure, not trying to recreate or even compare with past performance. To do that, policy needs to support investment that supports the services sector, especially the growing digital environment, with the aim of more sustainable, healthy economic growth, and to focus on improving living standards rather than the production of 'things'.

When Did the Productivity Slowdown Start?

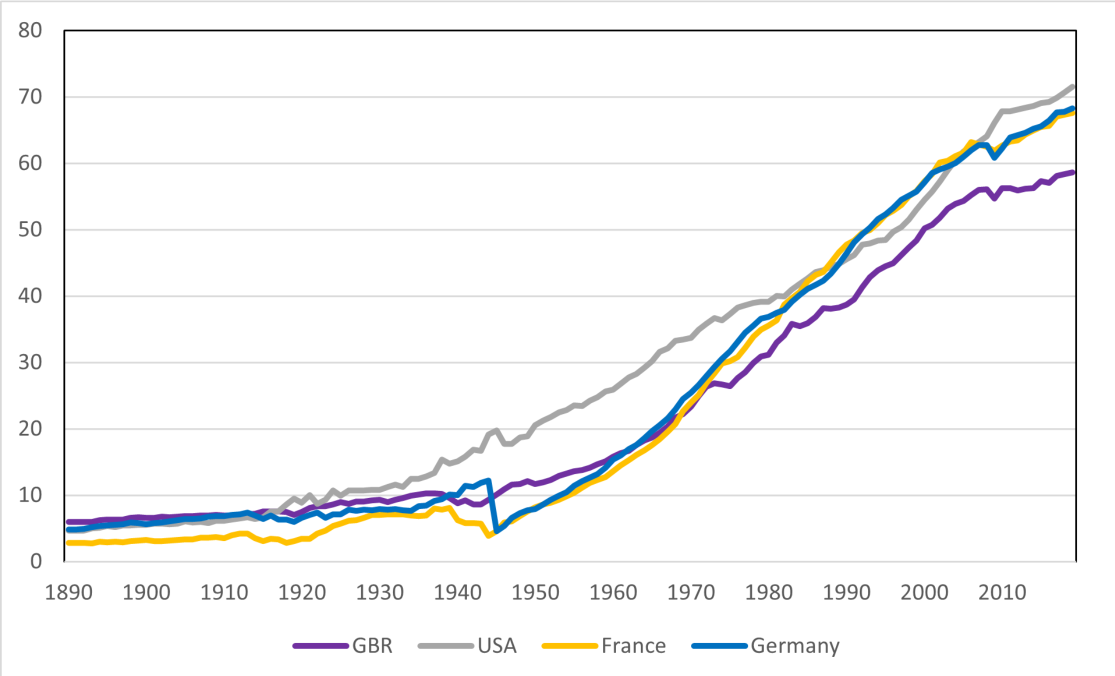
There has been a slowdown in productivity growth amongst the world's most advanced countries, since at least the GFC of 2007-09. This is shown in Chart 1, which replicates a chart from the UK Productivity Commission's first evidence review (Productivity Commission, 2022).[2]

Panel A of Chart 1 is potentially misleading. When comparing productivity levels over the long term these are two consid-

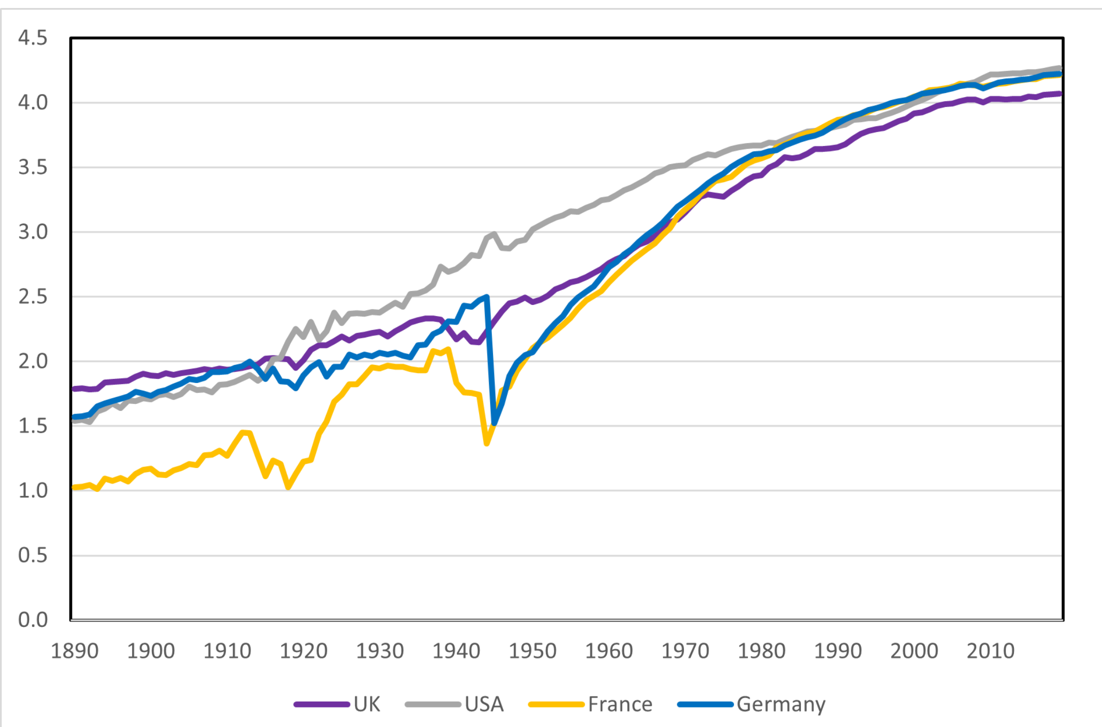
2 Chart recreated here uses data from version 2.6 of the database published online by Bergeaud *et al.* (2016) which was updated after the PC 2022 report.

Chart 1: Productivity Growth Slowdown in Advanced Economies, 1890-2019

Panel A: Output per hour (expressed in $US 2010 ppp)



Panel B: Output per hour (expressed in logs)



Source: Calculations based on the public database underlying Bergeaud *et al.* (2016).

erations. First, the challenges of data measurement are severe, within each country over time and especially across countries. These data have been meticulously calculated and are probably the best available, but such data - like most macroeconomic data - are always only estimates. Confidence intervals are not available, and we have little idea how accurate the numbers really are. For example, the data are constructed using estimated purchasing power parity exchange rates to enable international comparisons.

Second, the data is non-stationary, and this distorts one's visual interpretation. Charts of absolute (index) levels for over a century mean that proportionately larger differences in the distant past look small relative to more recent data. The conventional solution is to use a log transformation, as shown in Panel B of Chart 1, so that a given percentage change or difference is seen to be the same magnitude at every time point.

The difference in visual interpretation between the two panels of Chart 1 is striking. The peak in US productivity growth for example, is shown in Panel B of Chart 1 to be around the late 1960s, not immediately prior to the GFC as in Panel A. There is no clear break point in Panel B, with the GFC appearing as a small blip. Panel B of Chart 1 thus suggests that the slowdown in productivity growth has been more common across countries, and much longer lasting than generally appreciated. Recent differences between countries are important but not as historically unusual as often assumed, even before allowing for the uncertainty in comparative estimates.

As an example of other evidence, Tenreyo (2018: Chart 3 and 6) demonstrates very clearly, that the peak in UK productivity growth was around 1970 and that it has been declining since then, albeit not smoothly. But unfortunately, the analysis of why (including sectoral compositions), as in many other papers, focuses only on much shorter periods where events at a cyclical frequency dominate. The United Kingdom does appear to have slowed more than the United States, Germany or France. The thesis advanced in this article is that the slowdown is a consequence of economic maturity in general and de-industrialization in particular. The United Kingdom was the home of the Industrial Revolution and may be at a more mature stage of post-industrial economic development than others. Rather than being an outlier, the United Kingdom may indicate the shape of things to come elsewhere.

The dating of the slowdown in the United Kingdom and the United States, is complicated by the fact that, prior to the GFC, both countries had long-lasting aggregate demand booms. That was not evident in inflationary pressures over the period, but it can be seen in growing current account deficits (as a share of GDP).[3] Those deficits were matched by capital inflows, which likely helped to fuel the expansion of the banking systems in both coun-

3 The US current account deficit as a share of GDP reached 6 per cent in 2006, its biggest ever. The UK deficit had been on a long-term (but cyclical) worsening trend since the 1960s and reached 3.9 per cent by 2008. It subsequently reached 5.4 per cent by 2016 before finally recovering to 2.4 per cent in 2024.

tries and hence contributed to the eventual financial crisis.

When looking at productivity or output trends, one should not extrapolate economic performance forward from a single peak of a boom (or bottom of a trough), especially when the booms are long and the peaks are high. But this is commonly done. A frequent approach is to look for a structural break around the GFC of 2007-09. Examples include Riley *et al.* (2018) and Barnett *et al.*, (2014). The latter calculate the pre-crisis trend growth in labour productivity between 1997 Q1 and 2008 Q1, and project that forward from 2008 Q1. This extrapolates a trend which is too strong, starting from a peak, and thus creates a much bigger 'productivity puzzle' than there really is. Fisher (2024) shows that alternative trend assumptions can almost eliminate the existence of a UK-specific puzzle, at least up to the start of the Covid-19 pandemic in 2020. The pandemic has clearly affected comparisons of growth since 2020, and the United Kingdom's exit from the European Union will also have had an ongoing impact on both productivity and output. These near-term events may well obscure the underlying trends for some years to come.

What Caused the Productivity Slowdown?

Much of the productivity literature does not attempt a root cause explanation of why advanced economies are slowing down, nor why the United Kingdom would be underperforming. Rather, research tends to describe or account for it by identifying patterns in the data.

Coyle (2023) offers a summary of research on the apparent weaknesses in the United Kingdom's performance relative to peers, including: [4]

- weak Total Factor Productivity (TFP) growth, from under-investment and lack of capital deepening (Carella *et al.*, 2023);
- a low-level of Research and Development spending (Jones, 2022);
- under-investment in intangibles (Corrado *et al.*, 2022, Goodridge and Haskel, 2022);
- extreme United Kingdom differences in regional/spatial productivity (Tilley *et al.*, 2023);
- wage flexibility leading to less automation (Pessoa and Van Reenen, 2014);
- lack of inward investment (Driffield *et al.*, 2021);
- over-centralization of institutions (Westwood *et al.*, 2021);
- a lack of public investment in education (Nelles *et al.*, 2022);
- a shortage of technically qualified graduates (Stansbury *et al.*, 2023);
- insufficient infrastructure investment (Coelho *et al.*, 2014); and
- welfare spending (Driffield *et al.*, 2022).

This selection is not exhaustive of the explanations on offer. For example, over-regulation and high taxes are often cited by business and popular media.

This article does not take a view on the relative merits of these propositions, many

4 This is a selection of references: apologies to those not included who wrote about the same topics.

of which are well-researched, important observations and all of which have strong supporting evidence. They contribute significantly to our understanding of many aspects of productivity, but even collectively, they do not appear to have reached any consensus on the root causes of its slowdown.

In this article we draw two working conclusions from the existing literature: First, despite the slowdown being an international phenomenon, and the measured United Kingdom under-performance persistent, there is no single cause that has been identified to convincingly explain either. At best, there is a long list of candidate explanations. Second, the explanations offered seldom amount to root-cause explanations. Rather they account for or document the slowdown and locate it in a particular dimension – which is useful - but they do not provide causality. For example, to explain that low productivity has been caused by low TFP, or weak investment, or reflects weak regional performance simply relocates the underlying question. To claim causality, one would need to identify the original shock and/or the fundamental economic and social forces at work.

Economic policy is much more likely to be effective if one is sure of the root cause(s) of the problem. Otherwise, the risk is of addressing the symptoms only. Alleviating symptoms may be worthwhile, and this article does not take issue with many of the policy recommendations that have been made, which can be justified on grounds other than productivity growth. But policy is failing to address the fundamental productivity objective.

Structural Explanations for the Global Slowdown

One hypothesis for the slowdown is that there is a lack of ideas that can be translated into investment opportunities (Bloom *et al.*, 2017). That hypothesis appears to be quite widely cited but does not sit easily with the internet-based revolution over the past quarter century which has visibly transformed the way most people work and live. Nor is it a root cause explanation unless one can explain why the lack of ideas has occurred. Nevertheless, it is worth bearing in mind as it could be consistent with the explanation advanced here.

This article argues that there is a very straightforward but uncomfortable explanation for why productivity is slowing down. As economies industrialize and then de-industrialize, their structure changes. First away from agriculture and to manufacturing (supported by services as an intermediate input). Then from manufacturing towards services as a final-expenditure item. Additionally, we now see many services becoming digitalized.

As an economy moves from manufacturing to services to digital, it follows that measured productivity growth will naturally slow and so will gross fixed capital formation (GFCF) measured by the national accounts as investment. There are good reasons related to economic dynamics for why this compositional shift occurs. One can think of this as a simple 'S-curve' model of economic development.

Essentially, whether production of a good or service has high labour productivity growth depends on the extent to which labour can be substituted by machines and that is less easy to achieve – and hence a slower process - in many service sector industries, especially where the actions of an individual person is the essence of the service provided (much of entertainment, hospitality, beauty, etc). This is the essence of the 'Baumol disease', although that has been interpreted rather narrowly by many: It is certainly not a disease, as interpreted here it is simply part of economic maturity.

As an economy industrializes, investment in more complex plant and machinery made possible by previous advances drives manufacturing productivity up and relative prices down. Simultaneously, the growth of employment in manufacturing (away from agriculture) increases the real incomes of workers. As relative prices of manufacturing goods fall, and income rises, demand for manufactures increases. Thus, the market for goods expands, facilitated further by international trade. Through the Balassa-Samuelson effect, an increase in wages in the tradable goods sector will also lead to higher wages in the non-tradable (service) sector even if productivity growth is not replicated, adding further to demand. The process of productivity improvement in manufacturing is self-reinforcing. New processes create the technology to support more efficient production techniques, 'standing on the shoulders of giants'. Total manufacturing production and employment can rise alongside strong manufacturing productivity growth.

Eventually there are both demand and supply limits. The market for goods will start to become saturated. Even if total demand continues to rise alongside real incomes, it will no longer keep up with the rate of technical progress in production. At that point the manufacturing sector maintains its productivity growth by first slowing workforce growth and then by shedding workers. New generations of workers are absorbed by the growing services sector. Over time the service sector displaces the manufacturing sector as the dominant source of value added - whether measured as output, income, expenditure or via employment. This has happened in all developed countries.

In 1970, UK manufacturing was over 30 per cent of total output. By 2024 it was just 8.6 per cent. It was 10.0 per cent in the United States (2024), 9.7 per cent in France (2023), 18.5 per cent in Germany (2023) and 19.2 per cent in Japan (2022).[5] In all these countries, the sector shares have been declining on trend for some considerable time, with expenditure on goods being outgrown by services and with the remaining domestic manufacturing often being displaced partly by imports. There have also been upward trends in public sector output which is predominantly services.

In 2024 UK manufacturing investment was around 15 per cent of business investment, but the latter is just over half of total investment meaning that manufacturing investment was only around 8 ½ per cent of GFCF. And manufacturing employment was only around 8 per cent of total UK employment. Productivity in the service sector does improve over time. But service sector output is conceptually more

5 Sources: FRED database St Louis Federal Reserve, OECD data and national statistical offices.

difficult to define, harder to measure and can be harder to value. As an example, the contribution of financial services to the national accounts is known to be extremely difficult to estimate. Financial income and expenditure can depend on the price fluctuations of financial assets and the units of output are not well-defined.

Output (and hence productivity) measurement can be particularly problematic for public services where the price is not set by market forces and/or there may be no measured price at all (e.g., most UK education up to age 18 and many public health services).

In the United Kingdom, the Office for National Statistics is engaged in extensive work to improve public sector productivity statistics to incorporate quality-adjusted measures of output (Heys, 2025). These are much more difficult to estimate, less timely and do not have a long history. As well as services increasing in final expenditure, one of the accompanying trends to deindustrialization has been that value-added in manufactured goods is increasingly being provided from inputs classified as services.

There have been many stories over the years comparing the retail price of a fashionable pair of training shoes with the manufactured cost (e.g. Solereview, 2022). A reasonable estimate seems to be that an Asian producer receives only about 20-25 per cent of the western retail price. Most of the cost goes to a variety of input services from elsewhere such as design, transport, marketing and sales (plus taxes and profits). Even within a producer's share of cost, factories will have bought-in or in-house services which make the true 'manufacturing' share of value added less than recorded. An extreme case would be where the actual shoe production was person-less but there could be a growing number of high-value people involved in providing the input services to the final retail item.

As manufacturing processes continue to become ever more automated, that is likely to result in ever-diminishing value added. This process is not new or unique. It is broadly what happened to agriculture after the industrial revolution. Agriculture in the United Kingdom was once very labour intensive – in 1600 it accounted for about two thirds of the male workforce (Wallis *et al.*, 2018). It has now become highly mechanized and counts for just 1 per cent of total UK employment – and only around 0.7 per cent of GDP, even though the United Kingdom clearly produces vastly more food now than it did 400 years ago. Manufacturing value-added will continue shrinking as a share of value-added in advanced economies, under the force of its own relative productivity growth.

It is worth noting that the structural changes described here as the source of the productivity slowdown are fundamentally driven by changes in supply, embodying improved production processes to automate. Of course, demand patterns also change, but the process of manufacturing becoming ever more efficient until its value-added share declines does not require any exogenous changes to demand preferences.

Summary of the Model

Given that any theory or model is only as useful as its explanations of the world, we can ask what this simple S curve model of development would help explain. It would suggest the following:

- The productivity slowdown would not be consistent across sub-sectors which are at different stages of maturity.
- The slowdown would not start at an identifiable fixed point in time – it would happen slowly unless accelerated by a shock. There need be no break point.
- The slowdown would not occur at the same time in all countries - which differ in economic structure and work cultures. But it would become observable in all advanced economies as they matured.
- Manufacturing as a share of value added will continue to decline and hence the measured productivity slowdown will continue.
- It could explain the United Kingdom as an early case. The United Kingdom was the first to have an Industrial Revolution and was one of the first to experience widespread de-industrialization.
- Studies looking for some other exogenous factor(s) to explain a 'sudden' slowdown would not find one, but their results should all be consistent with the de-industrialization narrative.

The history of the past quarter century, and most of the current research literature, would appear to be consistent with these predictions of an S curve development model, but more work would be needed to investigate it thoroughly, ideally through testable propositions not considered here.

Productivity and Living Standards

Over 35 years ago, Robert Solow astutely observed that 'you can see the computer age everywhere but in the productivity statistics' – itself evidence that the productivity slowdown started a long way back. The period since then has seen one of the most astonishing transformations in human existence. The creation and expansion of the internet, personal computing and finally smart mobile devices, means that there has been a massive change in the way people live. It is still changing. Transportation, communications, entertainment, education, how and where people work, how they socialize and even meet life-long partners. And this is pretty much available to everyone.

In the United Kingdom, as of 2024, some 94 per cent of the adult population are estimated to have owned a smart phone. In 2023, smart phone ownership ranged from 80 per cent of the over-65s to 98 per cent of the 16-24s. Going back to 2008, those numbers were 4 per cent for over-55s and 29 per cent for 16-24s. Of course, the 6 per cent or so of adults who do not have a smart mobile device is a considerable number – 2.5 million individuals in the United Kingdom – although many of those might have access to the internet through other channels.

With the prevalence of mobile computing devices, so much has changed – home shopping deliveries, ticket purchases for travel or entertainment, car parking, banking and other finance, television, life-long learning, the list is long. The 'productivity' of individual human activity has changed in dramatic fashion. And many more improvements are still possible as other services become digitized. Yet the data suggest that this transformation has happened at the same time as the unprecedented slowdown in productivity growth (Van Ark *et al.*, 2023).

How can one reconcile these two observations? The answer may be partly in mismeasurement. As noted previously, there is an inherent difficulty in quantifying the quality of services and hence their true price (Coyle and Mei, 2022). Another possibility is network effects: It is not the smart phone alone which delivers benefits to consumers, but the services that the device gives access to. Mobile computing devices are frequently used for accessing social media. The average social media user is reported as spending over 15 hours a week doing so (Kemp, 2024). This activity does not involve much marginal cost: some electricity and the cost of data allowances if not connected to wi-fi. There are some fixed costs for access to hardware and software.

GDP was never designed to measure living standards and the past 15 years may be evidence of a greater disconnection between the two, as consumers place less value on owning 'things' and more on experiences. This topic has been explored by McAfee and Brynjolfsson (2017), amongst others. Given this conundrum, what can one say constructively for policy? People's digital access should be prioritized if that is where societal benefits can most readily be achieved i.e. in virtual networks rather than physical networks. The government's job should be to make sure that the national digital infrastructure is close to the frontier, reliable, comprehensive regionally, that the systems are safe to use, that consumers are well served (e.g. preventing monopoly pricing) and that government itself takes advantage of the opportunities to improve its own productivity.

There is a tax issue. A huge amount of personal utility is being generated by social media with very little monetization and hence little tax revenue, and not just because of the large corporations which manage their tax liabilities internationally. The main form of revenue generation for social media platforms appears to be advertising. There is also a monetizable gain by tech firms in the value of consumer data which allows targeted behavioural research to underpin advertising, product design, and sales.

To make sure governments can pay for public services, they need to consider their tax policies in relation to digital services. As an example, it would be worth considering whether some digital services need to be taxed regardless of whether they are commercially monetized. A tax of 1p/1¢ for every individual digital event (posts, mails etc), would probably solve any government's tax revenue challenges. To avoid voter distress, such a tax should be imposed on social media owners and related platforms directly, rather than on their individual users. This can be justified in part by the costs of policing social media to investigate and prevent abuse. Taxation of service providers based on usage would likely force more explicit charging for consumers, which could have some benefits such as reducing anti-social usage.

Public Policy Issues

Given that slow productivity growth is creating public policy problems in all advanced economies, we have seen surprisingly few attempts to directly improve supply-side performance of the economy.

In contrast, there have been persistent attempts since the GFC to stimulate growth through unconventional monetary policy alongside growing fiscal deficits – the latter sometimes as an unplanned consequence of low growth outcomes.

Given that the productivity slowdown is fundamentally a supply-side issue, demand expansion would never be an effective or sustainable policy response. One should not look to monetary policy or the fiscal stance as a cause or a solution. There are certain structural aspects - the size of the public sector, its investment content, how efficiently it is organized, and the level and incidence of taxation - which are all relevant. We do not address those detailed fiscal issues here, as they are relatively well-researched. We focus instead on the extent to which public policy can interact with the structural issues created by a service-sector economy.

Is Exponential Growth Sustainable?

It is quite common in economic studies to assume that the average growth rate of output over the past can be extrapolated into the future as a benchmark (e.g. NIESR, 2025, Figure 1.1). But there is no economic rationale for why output growth should be a constant parameter. The most basic theories of growth break down the driving forces into growth of the labour supply and technical progress. These elements change slowly, and for short-term analysis can be assumed to be exogenous to the problem, but neither is necessarily constant. Fisher (2024) explores some of the limits to population and workforce growth. Here we ask whether output can keep growing exponentially.

Suppose an advanced economy grew at 2 per cent per year. At that rate, output doubles every 36 years and quadruples every 72 years. Clearly, that could not be reflected in the quantity of 'things' being produced. Many of the Earth's physical planetary boundaries are already either under stress and possibly broken and there are forecast shortages in key materials (rare earth metals for example). Manufacturing may come increasingly to depend on the circular economy: reuse, refurbish, repurpose, reclaim, and recycle.

Market forces will also ensure that patterns of demand and supply shift away from those materials which are in scarce supply: their relative prices will rise, making the circular economy more attractive. Overall, it seems optimistic to think that manufacturing growth can always remain positive. A continued expansion of services is much more likely than manufactures, with services being bounded more by labour supply and energy than raw materials. The widespread adoption of artificial intelligence (AI) could boost the productivity of services and lift labour constraints. A combination of renewable and nuclear energy, and new energy storage technologies, could lift what would otherwise become a hard constraint on energy supplies, without contributing to greenhouse gas pollution.

Could Policy 'Stop the Rot'?

If a natural process of deindustrialization leads inexorably to a measured productivity slowdown, would it be possible to adopt policies to preserve the status quo or even reverse that trend? Unfortunately not. Unless one could somehow prevent manufacturing becoming more productive, it will inevitably ‘eat’ its own value added. Responding with attempted demand expansion could make outcomes for output and incomes worse over the medium-term. Initially, excess demand growth creates inflationary pressures and/or trade deficits. Growing imbalances in the economy eventually need to correct. If not policy-induced then eventually such demand bubbles collapse under their own weight. Macroeconomic policy analysis long ago concluded that over the long-run, it is the supply-side of the economy that determines the sustainable rate and level of output (albeit subject to second-order hysteresis effects).

This should not be taken as the ‘politics of despair’, nor of an ‘anti-growth’ agenda. Rather it argues for focusing policy on what is beneficial looking forwards not backwards, and on improving living standards, not the quantity of things.

It might be possible to close gaps in productivity levels between countries, but not by following policies which worked for the historical economic structure. For example, promoting domestic manufacturing of steel, cars or electrical goods and agriculture might be beneficial on economic security grounds but would no longer employ many people. The shares of manufacturing or agriculture in an advanced economy will never return to what they once were. With that in mind, promoting investment remains a crucial economic policy, and governments need to take a more imaginative view of what is needed to support the evolving economic structure.

The Digital Infrastructure and Working from Home

As noted in Section 3, to facilitate structural change and maximize the benefits from new technology, governments need to encourage investment in the digital infrastructure, including cloud computing and AI. One benefit is the growing ability of people to work from home (wfh). In 2019, 4.7 per cent of UK employees worked from home. By end 2024, 13 per cent wfh all the time and another 27 per cent for part of the time.[6] And even at the office many business meetings now happen through video conference calls rather than require travel.

Wfh is popular amongst many staff as it reduces the costs and stress of commuting, can sometimes allow more focus on work without distractions by colleagues, and can facilitate flexible engagement with domestic duties such as child or healthcare. For employers, it can result in reduced need for office space and less time wasted in travel delays.

On the downside, wfh can miss out on many of the productivity benefits from working together with colleagues in an office, including training, knowledge sharing, and culture. And for some people it is important to detach work from domestic surroundings.

Productivity losses from wfh do not have

6 Source: Forbes: UK Remote and Hybrid Working Statistics, 2025 available at https://www.forbes.com/uk/advisor/business/remote-work-statistics/.

to be accepted. Some people work from home still have poor IT equipment and/or are using unfriendly software, badly. Investment and training could resolve that, whilst better software and hardware to support instant inter-staff communication could improve staff knowledge sharing and training relative to a crowded office.

New work processes designed for a domestic environment deserve more attention and investment. Workflow management techniques could be substantially improved: Monitoring staff working remotely could be made more efficient than patchy manual oversight in a large office.

As noted when discussing healthcare, improved efficiency comes from altering existing processes to adapt optimally to new technology, not the reverse. And even if wfh does not always work everywhere for everybody it can be made to work well for many.

There are indirect consequences of wfh which could greatly change the economy. More people working from flexible locations takes some of the pressure off the transport network. It would also shift demand from facilities based in cities (retail, catering, health) to those in suburbs, feeder towns or even remote locations. This may lead to a boost in regional investment – and not solely in regional cities.

The 'return to the office' policy in its extreme form is a 'return to the past' mentality, often driven by concerns about reduced worker commitment. But it could also reflect the fact that most executives and managers do not have career experience in wfh and have not been trained in how to optimize wfh or hybrid working and do not feel confident in doing so. It is the senior staff who may be the biggest obstacle to productivity gains.

What Sort of Investment Do We Need?

The BBC report cited earlier (Islam, 2023) noted the following:

> "This spring, Mr Hunt (The UK Chancellor of the Exchequer in early 2023) announced a new scheme to allow every pound invested by businesses in **IT equipment, plants or machinery** to be deducted in full from taxable profits" (this author's emphasis in bold).

The investment needed to support services can be quite different to that needed for manufacturing. In the national accounts 'investment' is largely fixed capital formation. Historically, economic analysis of the business cycle - such as the accelerator model of investment - had a physical production context in mind in which there is a large element of fixed capital.

Policy needs to reconsider the nature of the investment required in the face of structural change. An old-fashioned focus on plant and machinery is irrelevant to most of today's service sector businesses. The service sector is not homogenous, and investment patterns differ, but investment in people is common for professional work at least. Investment in communications, advertising, and commercial premises may also be more important than machines that produce things. Investing in networks such as cloud computing or AI use, are more important than simply buying IT equipment (Andrews *et al.*, 2020). And the nature of commercial premises is changing to include professional workers' own homes.

A lot of such investment spending by the service sector, including training, is not fixed capital and hence not recorded as investment. It is not surprising that GFCF is slowing down as a share of total final expenditure if it excludes concepts of investment spending which are especially important to the growing services sector.

Current measures of GFCF reflect 'produced capital' and so do include some intangibles including brand names, software and databases, research and development, mineral exploration and evaluation, and entertainment, literary and artistic originals and other forms of intellectual property. But they do not generally include investments in human capital, natural capital or social capital (Coyle, 2023). Such estimates can be made and are available from academic research but are not yet part of official statistics in most countries.

In the United Kingdom there has been a research focus on the importance of intangibles such as brands and patents, although this has not been a proactive focus of public policy to date. Haskel and Westlake (2022) investigate both the problems and potential solutions.

One facet of investment in people is that it is less able to play the traditional role of a fixed asset in securing finance. Firms such as technology start-ups, that are based on ideas and people but not physical assets, can find it difficult to obtain bank finance even though they need to pay wages up front, rent premises, and advertise before earning an income stream. Unsecured lending, including overdrafts or credit card debt, is usually very expensive and small business entrepreneurs may have to offer a claim on their own residential property as security for a loan, which significantly increases their personal risk.

Consideration of how to finance start-ups that have no tangible assets would be an area worth further consideration. Equity finance is often more appropriate than (bank) credit but the supply of equity investment for small businesses is less well orchestrated than the supply of bank lending. If the United Kingdom government wishes to address the productivity puzzle by stimulating investment, it needs to take a broad view of what type of investment is required in the light of the clear structural changes that have occurred and are ongoing in the United Kingdom economy.

Investment in Health and Education

There are huge opportunities to invest in public services in all advanced economies. Increasing the use of new technology which could substantially improve public sector productivity. To be clear from the outset, this does not mean attempting to recreate all existing public services on-line for everybody. The services will need to adapt to make best use of the technology.

In the United Kingdom, the focus is especially on health and education which are largely provided, for most people, by the state. Some of these services, for some people, will not always be amenable to change, but the following trends are already underway:

- People with health concerns may consult health professionals on-line or self-diagnose for simple ailments. This can be much more efficient, freeing up both patient time and clinical resources.

- A multi-media approach to education can be deployed, which uses teaching staff efficiently and delivers more effective learning outcomes. This approach is increasingly commonly used for post-graduate or part-time studies.

Each country faces a strategic choice to make in terms of health and education investment. As countries become richer, it is notable that individuals (and/or governments on their behalf) tend to spend a greater proportion of their total income on health and education for themselves and their families.

Given that revealed preference, one should expect to see spending on health and education rising slowly as a share of GDP over time. The UK data do show an increase, but not a smooth one. In 1980, total UK spending on healthcare was just over 5 per cent of GDP and had reached 10 per cent by 2019. Within that, public healthcare spending rose from around 4 per cent of GDP to a peak of over 7 1/2 per cent in 2009/10 [7] before falling back somewhat over the ensuing decade to be around 7 per cent by 2019.[8] The data since 2020 have been distorted by the effects of the Pandemic and so are not considered here.

It is often alleged that the United Kingdom has not seen the benefits of extra spending on health and education, but usually these statements are based on unmet demand (such as waiting lists), rather than achievements (number of patients treated). Prior to the recent pandemic, UK life expectancy had been steadily rising for at least 180 years if not longer – albeit the improvements have slowed over the past decade.

In 1980 around one in seven of UK youth went into higher education[9] and by 2019 over half were going to university.[10] One can of course argue about the quality of degrees, and the nature of what is taught, but UK health and education have clearly improved significantly over the long run, in large part because the state has spent more on them. The United Kingdom, like other countries, faces a choice whether to pursue private or public models for these services. If that choice is to be public provision, then the NHS needs sufficient investment to deliver efficiently. That would be consistent with NHS spending continuing to rise somewhat faster than GDP.

Investment is necessary to ensure efficiency. Yet allegations of inefficiency are often used as an argument against increased NHS spending.

7 The peak in these figures and those quoted below for education will have been distorted by the sudden fall in GDP during the GFC. But pre-GFC levels of UK GDP were recovered by 2013 Q2 and the trends since then have still been of general decline as a share of GDP.

8 Sources: Statista and Health Foundation, 2019.

9 The higher education system in 1980 was mixed between universities and 'polytechnics' which were set up to focus on technical subjects such as engineering. From 1992, all polytechnics have become designated as universities.

10 In 1950 the number was just 3 1/2 per cent. Source: Times Higher Education.

All firms and organizations are inefficient to some degree whether private or public. Good managers are constantly identifying and removing inefficiencies, at the same time as investing in and developing new processes, products and services. New inefficiencies arise to displace the old, and the process is never-ending. If one waited for all inefficiencies to be tackled before new investment was allowed, the long-run productivity outcome would be very poor in any context. Squeezing budgets or bureaucratic spending limits applied top-down to 'save money' nearly always lead to poor productivity outcomes. Managers struggling to maintain services in such circumstances often face cost increases they do not control, exceeding budgets they cannot influence. The outcome of such pressure is short-term decision making which reduces efficiency in the longer term. This includes cutting planned investment expenditure as the quickest way to meet a budget shortfall. Hiring cheaper, less experienced staff or leaving vacancies open for longer, also tend to lead to poor long-term outcomes.

If insufficient money is available to fund a service, ultimately someone must decide what is not going to be done. If that is not consciously decided at the top level, then managers or front-line staff will make those decisions instead. That is how quality and efficiency of both public and private services become reduced when budgets are squeezed top-down.

Similarly, measurement of performance is not a substitute for improving it. In some circumstances, what is measured miraculously improves to the detriment of what is not. In other circumstances, underperformance may be exaggerated as part of a 'cry for help'. Measurement and targets are essential but one needs a follow-up strategy of how to engage and respond constructively, otherwise such measures just become an extra cost burden.

Any net increase in public expenditure needs to be funded either by recourse to taxation or debt. If the United Kingdom decides that it wants continually improving health services, then a choice needs to be made as to how much of that is provided by the private sector and how much by the public sector. The consequences of greater private sector provision are worth spelling out. Ultimately it would mean that the NHS was no longer the main health provider for all the services it currently offers. In some areas this is already happening: in 2023 less than half of adults in England had an NHS dentist.[11]

Private health care provision would become increasingly funded by private health insurance. That could allow overall expenditure on health to rise in line with the revealed preference of UK citizens and would doubtless generate substantial new investment in private facilities. It would reduce financial pressure on the NHS. And it would probably help move the United Kingdom towards the productivity frontier, if it made the workforce healthier. That private-sector solution would be politically challenging. To support a voluntary shift by those who could afford to pay, the private system would likely have to provide a

11 Source: NHS Dental Statistics for England 2022-23

better quality of service than the NHS, creating a two-tier system. To enforce a shift by closing existing public services could mean that those on low incomes no longer had access.

In the United States, health expenditure is over 18 per cent of GDP but is dominated by large, vested interests charging high prices for drugs and medical services, with manifestly poor outcomes for many of those on lower incomes (Deaton, 2023).

Education in the United Kingdom faces similar choices. In 2010, government spending on education was over 5.6 per cent of GDP but by 2019 it had declined steadily to around 5.2 per cent of GDP.[12] There was no alternative policy to expand private sector education.

To be clear: this article is not advocating a party political or ideological position on whether investment in health and education should be public or private or with a particular mix. But it is making the case for an ambition, backed by policy, to increase total investment in health and education over time, rather than continuing with a budgetary squeeze or passive decline.

Investing in the Transition to Net Zero

The Climate Change Threat

Climate change is arguably the single most important challenge facing humanity today (Stern, 2006; WEF, 2024). The Earth has already warmed by over 1.5°C since the 'pre-industrial period' of 1850-1900 (used as the reference point in the 2015 Paris Agreement). Most of that warming has happened in the past 50 years or so and recent data indicate an acceleration (WMO, 2025). It is not just a long-term problem – the world economy has already witnessed major loss of life and huge financial losses as a result of climate change (EEA, 2024).

To achieve net zero greenhouse gas emissions and ultimately move to net extraction there needs to be some basic changes in the global economy. At its simplest, fossil fuels need to be replaced by energy sources that do not produce greenhouse gases such as renewables (wind, solar, hydro) or nuclear. To enable that, investment is also needed in industrial-capacity energy storage solutions: the wind does not always blow, and the sun does not always shine.

Price mechanisms and pollution taxes are also among the necessary mechanisms to address the externality of greenhouse gas emissions. But carbon pricing is not sufficient to address climate change, even if it were to be comprehensively and consistently applied – which it has not been. Carbon emissions need to be eliminated, not just discouraged or compensated for. The reasons why carbon pricing is necessary but not sufficient to achieve that are explored in Fisher *et al.*, (2023).

The Cost of the Transition

Transition to net zero is necessary to pre-

12 Source: World Bank.

serve the existence and effectiveness of a global economy. It should not be thought of as a net cost. The costliest path would be to allow global temperatures to rise to a catastrophic level, leading to a disintegration of the global social and economic system.[13] Investing in the transition to net zero is a pre-requisite for the survival of the global economy. It is also a huge business opportunity for the private sector and provides a channel for governments to stimulate renewed economic growth.

The transition will create demand for new goods and services – this could range from electric cars and local renewable energy generation through to an increased demand for efficient air conditioning. Those businesses which can provide appropriate new products and services will thrive, investing in new facilities and creating new jobs.

At the same time the transition will shift production methods to be more sustainable. Contrary to the 'cost' arguments, renewable energy is likely to be much cheaper as well as more secure in the long run. Offshore wind is now reckoned to be the cheapest form of energy supply in the United Kingdom (Carbon Brief, 2023).

The key question is how investing in the transition could help restore economic growth and productivity. The historical process of industrialization was able to continue for so long partly because it could rely on new power sources which became available. The economy moved from wood, to coal, oil, gas and nuclear with each contributing to electricity generation. The mass exploitation of renewable energy sources is a fundamental factor which might change the structure of the economy towards high productivity sectors, at least during the transition.

In employment terms, the benefit of moving to net zero is perhaps clearer: In the US coal industry in 1923 883,000 people were employed. By 2013 that had fallen to just under 85,000 and by 2023 to 55,000.[14] In contrast the US solar industry in 2022 employed 263,000.[15] New jobs will be generated in the new industries, not the old.

Although new energy forms could support renewed productivity growth, the focus of public investment in the transition should be on preserving and improving the quality of life. Clean air and a sustainable environment are an investment in natural capital (Dasgupta, 2021) even if that is not currently reflected in GDP.

Green Investment Strategy

The United States and EU have taken different approaches to stimulating green investment. The United States passed the Inflation Reduction Act (IRA) in August 2022. It contained some two dozen tax provisions and committed to $370 billion in federal funding for clean energy, with the goal of substantially lowering national carbon emissions by 2030. The effect of the IRA is a subject of political debate,

13 Dasgupta (2021) has a good discussion on these issues.

14 Source: IBIS World website.

15 Source: IREC website.

but it does seem to have galvanized relevant sectors of the US economy. It is widely thought to be one reason why the United States has grown faster than other advanced economies since it was implemented.

The EU announced a 'European Green Deal Investment Plan' in 2020. This was a set of policy initiatives by the European Commission with the overarching aim of making the EU climate neutral in 2050. It comprised two principal financing streams totalling €1 trillion. Critics have complained that most of this was not new funding, merely an exercise in greenwashing (Varafoukis and Adler, 2020). Much of the EU green agenda does seem to have been pursued through regulation and the economy did not respond as positively in growth terms as did the United States.

Whatever the claims and criticisms of the different approaches embedded in United States and EU policies, it seems clear that to achieve net zero will require a pro-active policy approach, and preferably one which directly boosts the real economy.

The transition to net zero will generate huge public benefits which the private sector cannot internalize on its own. In some areas public funding will be needed. In other areas incentives for the private sector will be needed to drive the economy forward quickly. That balance is subject to political debate, but drawing on the United States and EU plans, and UK experience to date (both positive and negative) the requirements might be tentatively proposed as follows:

- The amounts of new money invested (public or private) need to be credibly large and commensurate with the existential threat posed by climate change.
- A range of financing tools should be used by the public sector to alleviate financial constraints: tax credits, guarantees, public-private partnerships etc.
- The plans should be certain and must be honoured in delivery, to enable both public and private sectors to plan and implement. If subject to second thoughts, or de-funding on short-term financial or political grounds, credibility is lost.
- A full transition plan for net-zero should be published, to demonstrate how it is to be achieved and against which progress can be judged.
- Ideally the transition plan would have multi-party support. Although no government can constrain a future government entirely, swings in policy – even those caused by frequent changes in junior government ministers - can destroy long-term policy consistency.
- The plans should be judged on how they map into reductions in GHGs but can also be designed to maximize their impact on stimulating productivity and growth.

Conclusions

Despite the evidence and analysis submitted to the UK Productivity Commission, and an extensive academic literature elsewhere, there is no consensus on why there has been an international slowdown in productivity growth, nor why the United Kingdom has been underperforming (Goldin *et al.*, 2022). There is a lot of detailed evidence accounting for the slowdown, identifying absolute or relative weaknesses, but little root cause analysis. That makes it hard to construct effective policies to address that slowdown.

In reviewing the data, this article observes that the international slowdown has been under way since well before the Great Financial Crisis (GFC). It has been present at least since 2000 in a range of advanced economies, and for the past 50 years in the United States.

Many studies look at the specific productivity slowdown in the United Kingdom since the GFC in 2007-09. But the demand-driven expansion of United Kingdom (and United States) output in the years 2002-2007 means that such studies generate a bigger puzzle than is warranted.

Over the longer period, the pattern of slowdown seems consistent internationally. It most likely reflects the de-industrialization of mature economies, leading to slower measured productivity growth as a natural and inevitable outcome of a change in economic structure.

Exponential GDP growth at a constant rate, as currently measured, is unlikely to be feasible, given the constraints imposed by the limited physical resources of the planet.

The underlying slowdown is likely to continue but the conclusions of this article should not be taken as anti-growth, nor a counsel for despair. Policy should be aiming to support the maximum sustainable growth rate going forward. It should do that looking at how the economy is evolving, not by looking at or even comparing with the 'glories of the past'.

Macroeconomic data does not seem to be reflecting enormous changes in lifestyle following the internet-based IT revolution. It does not seem plausible that living standards have been growing as slowly as has GDP per capita. Society itself is focussing increasingly on aspects of welfare going much broader than material possessions. Existing economic indicators are not sufficient to measure the nature of well-being in a services-dominated society.

Any national investment strategy should focus on maximizing the benefits to society arising from deployment of new technology. Many of the services provided by mobile computing are not monetized and that does create an ongoing problem for the tax base which needs to be addressed.

Building on the Productivity Commission evidence with regards to intangibles, investment policy needs to go much wider than the traditional focus on supporting physical or even produced capital assets. That includes, especially, investing in the workforce themselves. As the structure of the economy changes, so does the nature of the investment required.

As part of a new approach to investment strategy, the article argues for a more activist policy on investment in services that are currently being provided by the public sector in the United Kingdom, especially health and education. The strategic choice is between maintaining these services as public provisions and investing in them appropriately, or to actively incentivize more private sector provision. Continuing to depress budgets below costs, with consequent insufficient investment would be damaging to UK productivity and hence growth going forward.

The global economy needs to raise its investment game on the transition to net zero. UK policy to date has been piecemeal, subject to myopic budget constraints, continual revision and under-delivery. The

United Kingdom is in danger of falling a long way behind the United States and EU in transforming its economy to a competitive net zero.

There is no trade-off between achieving net zero and long-run growth, environmental stability is a pre-requisite for raising living standards globally.

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The Challenges of Productivity Measurement — Review Article on *The Measure of Economies: Measuring Productivity in an Age of Technological Change*

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Abstract

This is an important book about an immensely important topic—productivity measurement. The editorial and author team, comprising some of our strongest experts on the subject, have compiled a collection of chapters that is both eclectic and timely. They marshal theoretical and empirical analyses to explore a wide range of issues now confronting researchers and practitioners. The chapters describe not just how measurement works at present, but also how things *might* be done better (often offering practical approaches for getting to that point). The book's target audience includes researchers, measurement practitioners, and specialized business- or government-sector analysts whose work involves productivity issues. It would serve as an excellent primer for those entering the productivity-analysis sphere, while at the same time offering something to the most seasoned experts. Overall, the volume can serve as a guide in the continued effort to improve productivity measurement.

Part of my job as a reviewer of *The Measure of Economies: Measuring Productivity in an Age of Technological Change* has been taken care of before I begin. I do not need to convince readers of the *International Productivity Monitor*, of all publications, about productivity's importance in determining the economic fortunes of people, businesses, and economies. The same could be said about the significance of accurate productivity measurement to economists, business people, and policymakers alike. All this would be preaching to the choir.

This is an important book about an immensely important topic. It should be

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read—and read closely—and can serve as a reference for years to come. Editors Marshall B. Reinsdorf and Louise Sheiner, along with their assembled team, embody an enormous amount of individual and collective talent. The volume harnesses their intellectual capabilities to explore and explain the many ways productivity measurement is being and should be done. ("Is being" and "should be" are not always the same, often for understandable reasons. One crucial function of the book is to explain where practice falls short of its conceptual ideal and why.) The result is a book filled with the accumulated knowledge and experience of some of our strongest experts in productivity measurement.

So, this book should be read. By whom is a bit more open for discussion. This is not an airport-bookstore tome. While perhaps not quite as technical as the median paper in an academic journal, much of the book's content operates near the level of a 400-level specialized undergraduate course, and some parts could easily fit into a PhD sequence. This not a critique (blessed is any popular-science writer who could make a book on productivity measurement an airplane page-turner), but rather guidance as to the intended audience.

For those equipped to handle this level of technical detail, the book conducts an excellent tour of many facets of productivity measurement. The target audience includes researchers, measurement practitioners, and specialized business or government analysts whose work involves productivity issues. The book would serve as an excellent primer for those entering the productivity-analysis sphere, while at the same time offering something to the most seasoned productivity experts. The breadth of the measurement issues covered within (perhaps not comprehensive, but moving in that direction) exceeds the knowledge of almost any individual. It certainly far exceeded mine.

A Summary

Reinsdorf and Sheiner have thoughtfully curated the covered topics. The areas aim at today's measurement and research needs while at the same time spanning some classic issues in productivity theory and empirics. (Perhaps their unfading relevance is why they are classics.) Indeed, if I were to ask myself what topics any course of study into measuring productivity these days should cover, the resulting list of desiderata looks awfully similar to a browse through the book's table of contents.

Chapter 1 Written by Karen Dynan (Harvard and the Peterson Institute for International Economics) and Louise Sheiner (Brookings), this logical leadoff uses economic theory to explain why growth in output per worker—labour productivity—is a good proxy for the change in average economic well-being in an economy. There is, of course, a long history of discussion inside and outside economics about the shortcomings of using GDP as a measure of welfare. These critiques apply to productivity as well, where output is the numerator—and arguably to the inputs in productivity's denominator, too. A common rejoinder is empirical: seemingly more inclusive welfare metrics end up highly correlated with GDP anyway. This chapter goes further, showing theoretically that real output and productivity growth actually capture better than one might think the more expansive concept of welfare (essentially, the collected area between the demand and supply curves of every produced and consumed unit of every product).

Chapter 2 Brent R. Moulton (formerly Bureau of Economic Analysis) offers a very useful update on how the BLS's price-measurement programmes have changed in the years since the Boskin Commission. The Commission argued that shortcomings in price-index measurement implied true economic growth was being understated by more than one percentage point per year—about one-third of average reported real GDP growth at the time. After sketching the basic structure of the BLS price-measurement apparatus, the chapter details changes undertaken in response to the Commission's report and estimates how much they affected reported price indexes. Ultimately, the chapter surmises that these changes have brought inflation overstatement (and hence output-growth understatement) down from the Commission's mean estimate of 1.1 percentage points per year to 0.8 percentage points. (Of course, this implies that productivity and real-income growth are also both 0.8 percentage points higher per year than measured.)

Chapter 3 Carol Corrado (Georgetown) reckons with the effects—on both the numerator and denominator of the productivity ratio—of failing to account for intangible capital in a way consistent with our treatment of physical capital. Recent efforts, including the *System of National Accounts 2025* as just adopted by the UN Statistical Commission (editor Marshall Reinsdorf was an important contributor on valuing data assets), have brought some once-intangibles such as R&D and software into national accounting. This has been hugely beneficial, and other expansions are being considered. At the same time, producers still apply many resources to building what are conceptually capital inputs but are not counted as such (e.g. organisational capital, brand, supply-chain relationships). At creation, these intangibles are output in concept but not recorded as such; later, when applied to production, their use as factor inputs is ignored and their product attributed instead to productivity. The chapter exposits this and sketches potential magnitudes across different intangibles, stressing that some forms (or former intangibles such as R&D) are expressly aimed at raising productivity.

Chapter 4 Using a combination of empirics and theory, Diane Coyle (Cambridge) discusses the ways specific products influence productivity and its measurement. Three threads run through the chapter: (i) product churn affects the mechanics of price-index measurement and yields systematic biases; (ii) quality changes within products affect welfare and require special treatment; and (iii) the span of products available is itself a direct determinant of welfare and productivity. The first two deal with how product-level changes must be handled to obtain accurate price deflators for aggregate output; the third explores constructing output metrics that capture the direct effects of product-variety changes.

Chapter 5 David M. Byrne (Federal Reserve Board) investigates the most salient aspects of productivity measurement in digital-goods industries. Rapid technological progress, high product churn, and wide price swings introduce numerous measurement challenges. After showing how fast these industries have grown—implying their increasing weight in productivity aggregates—the chapter lays out the many data and methodological hurdles and explains where current practice falls short. IT capital and digital services receive special attention.

Chapter 6 Authored by Louise Sheiner and David M. Cutler (Harvard), this chapter is another deep dive into an important but hard-to-measure sector—healthcare. The sector is enormous and still growing as a share of the economy, so its productivity matters greatly for aggregates. The authors argue that the sector's reputation as a productivity laggard is not justified. They grapple with measurement difficulties and explain how current approaches likely understate productivity growth, especially once quality changes in both inputs and outcomes are recognized. Other difficulties—such as the sometimes long lag between expenditures and health outcomes—are also considered, and the chapter closes with suggestions for improvement.

Chapter 7 Nicholas Z. Miller (Carnegie Mellon) steps outside traditional national accounting and considers how environmental goods might be treated alongside standard products in output and productivity measurement. The chapter lays out a growth-accounting model of environmentally-adjusted output that subtracts pollution "bads" from goods output. Quantifying the model with the empirical literature on air-pollution damages, the chapter calculates an environmentally adjusted total-output series for recent decades. The differences from reported GDP are profound. For example, while GDP growth averaged 2.3 per cent per year from 1957–1970, environmentally adjusted growth averaged only 1.1 per cent. By contrast, the pollution reductions following the Clean Air Act Amendments raised environmentally adjusted growth to 2.4 per cent per year over 1971–2016 versus 1.6 per cent for GDP. The chapter recommends ways to implement environmentally adjusted accounts.

Chapter 8 Erica L. Groshen (Cornell), Michael W. Horrigan (Upjohn Institute), and Christopher Kurz (Federal Reserve Board) close the book by confronting the practical realities of productivity measurement as traditional survey methods show fissures and outright breaches. After laying out conceptual issues in using alternative and non-traditional data sources, the chapter inventories approaches that statistical agencies have already adopted—e.g. a new car-price index from J. D. Power, detailed medical-records-based healthcare prices, and credit-card data to measure services. It then considers potential restructurings of the US federal statistical system.

Some Overarching Reactions

As different as the book's individual chapters are, certain thoughts arose repeatedly as I read.

One is—*not to put too fine a point on it*—that I have spent a considerable portion of my research career avoiding the various conceptual, theoretical, and practical measurement considerations exposited in the book. In many of my studies I chose market settings where tricky considerations are ameliorated by the market's attributes, focusing on products where quantity and price data exist for easily comparable units: cubic yards of ready-mixed concrete, square feet of hardwood plywood, yards of 100-count cotton yarn, and so on.

That is great work if you can get it. Most productivity practitioners do not have this luxury, particularly statistical agencies that must deliver productivity metrics for the entire economy and virtually every major industry. There are markets with outputs so heterogeneous that direct unit comparison is impossible (e.g. passenger aircraft), markets with no clear countable units (e.g. business consulting), and even sectors where defining the output is hard (e.g. insurance). Moreover, output is merely the numerator of productivity; input quantities must also be measured well. Without applying the approaches discussed in this book, we would never be able to measure progress in measuring progress.

A second observation is how much productivity measurement is actually about *price* measurement. Conceptually, the dual tells us that productivity growth can be measured either via quantities or via prices. Yet practitioners rarely have both quantity and price data in buckets ready for use; they usually observe expenditures. To use quantities they must first divide expenditures by prices. Thus, whichever side of the dual one chooses, price measurement is inescapable.

Third, product composition matters—a lot, even within industries. The old defence that idiosyncratic micro factors cancel out at the macro level has never held for productivity measurement. For instance, non-random product entry and exit can bias price indexes, and the scope of product variety itself is in the productivity metric, while rapid technological progress and product churn in IT raise a surfeit of measurement issues.

Fourth, given the manifold difficulties in translating concept to practice, it is remarkable that our statistical agencies deliver productivity-growth metrics that are even approximately right. Yet they cover a broad set of sectors, strive to implement best practices, and do so with what appear to be very limited resources.

Where to Now?

The book makes two points simultaneously through the breadth and depth of its coverage: first, we have a lot of work to do; second, we have made a lot of progress. Many places remain where measurement falls short of the theoretical ideal, but imperfect measures still capture much and are less imperfect than they used to be. Going forward, the solid—if yet unattained—conceptual foundations of ideal measurement mean we know where the holes are. That directs our efforts as we work to fill them. I have no doubt this book will serve as a guide in those endeavours.