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

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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).

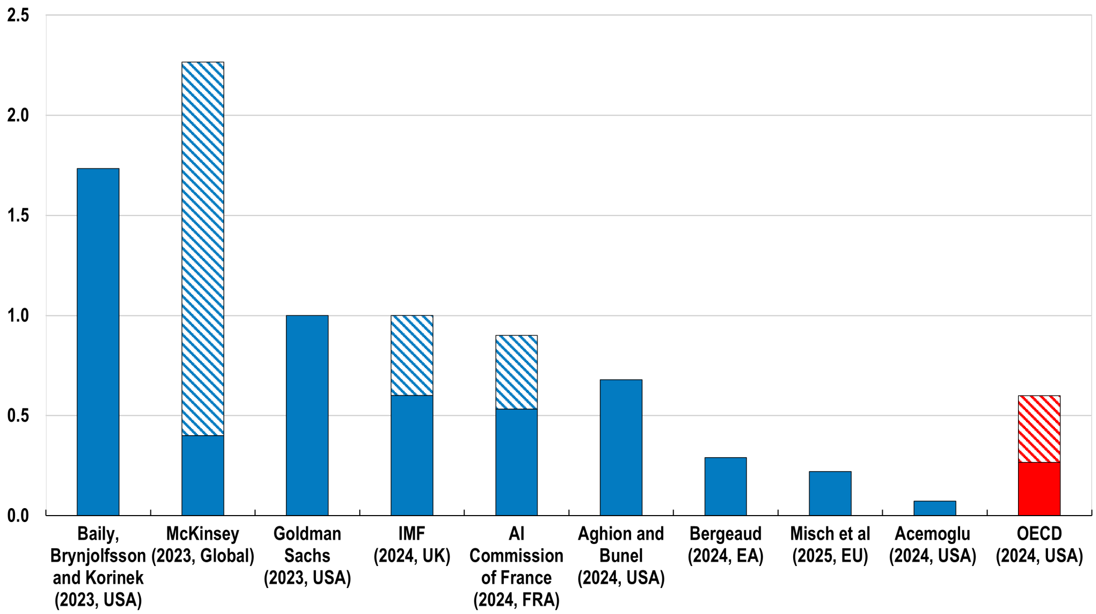
These growth projections are larger than those provided by Acemoglu (2024) but also significantly smaller than some of the more bullish predictions of other authors that have been widely discussed (see Chart 1). For instance, Briggs and Kodnani (2023) give an optimistic view based on their large aggregate 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]

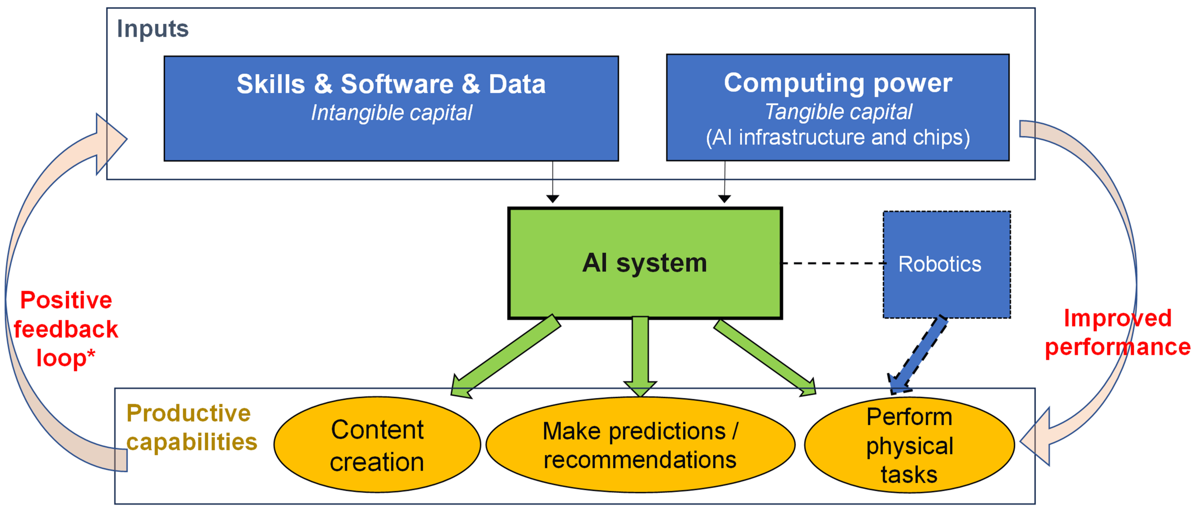
Building on this definition, and given this article's focus on productivity implications of AI, we propose conceptualizing AI systems as a form of production technology, combining various inputs to generate productive capabilities (Figure 1). These capabilities then allow AI-using firms to increase their 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

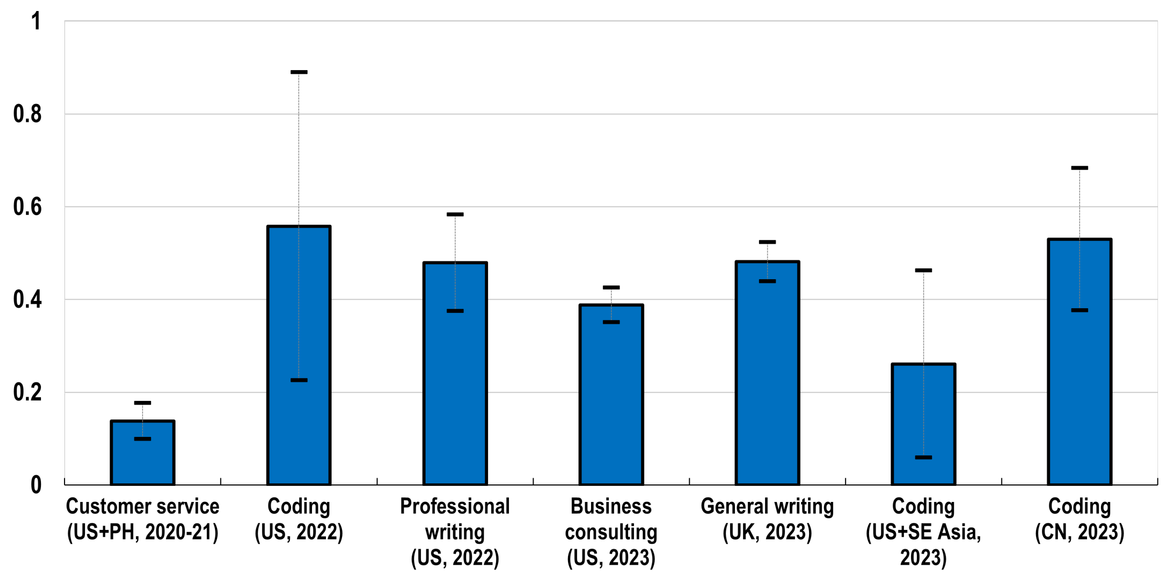
We follow the approach in Acemoglu (2024) to arrive at aggregate productivity impacts from AI. This approach allows relating aggregate gains from AI to three drivers that have an empirical underpinning and thus can be used for quantifying the gains: understanding and measuring the potential gains from 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

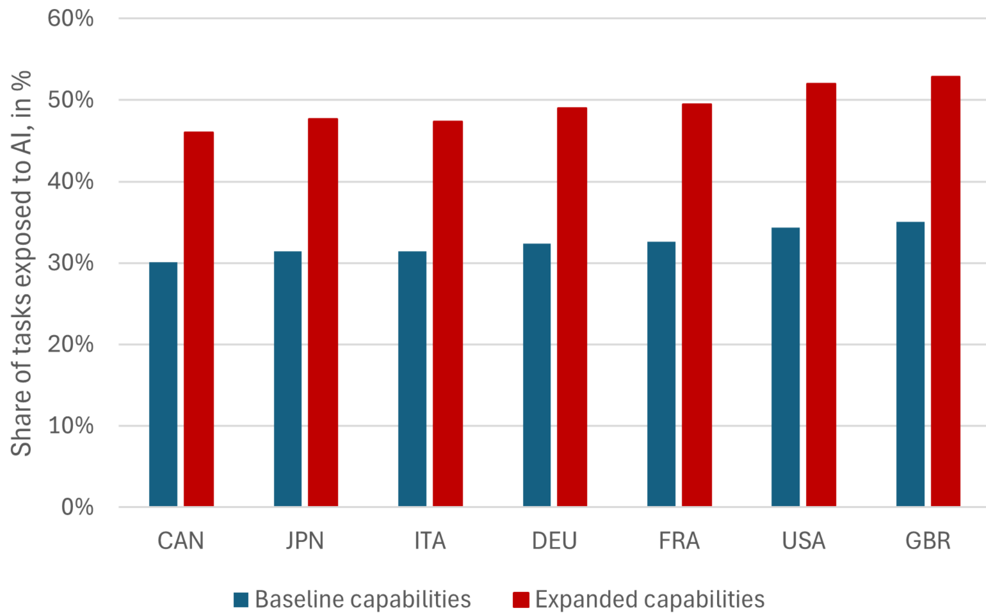
11 Firm-level evidence on pre-generative AI suggest gains that appear to be of a smaller magnitude, similar to the gains from other ICT technologies, although causal identification is more challenging than in the experimental settings at the task level – see Figure A.1 in the Appendix.

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]

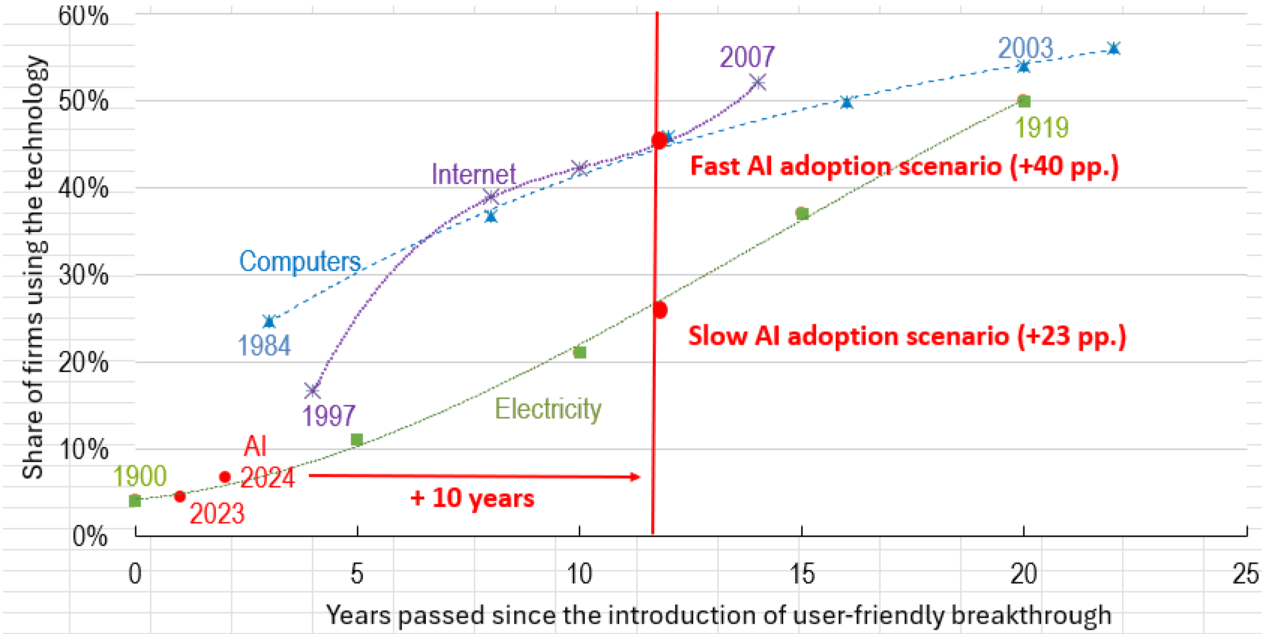
Starting from task-level estimates, we calculate the average AI exposure of detailed occupations based on the O*NET dataset. For each G7 country, we then aggregate occupations into industries and compute aggregate exposure, weighting each industry by its value-added share in the national economy. Chart 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



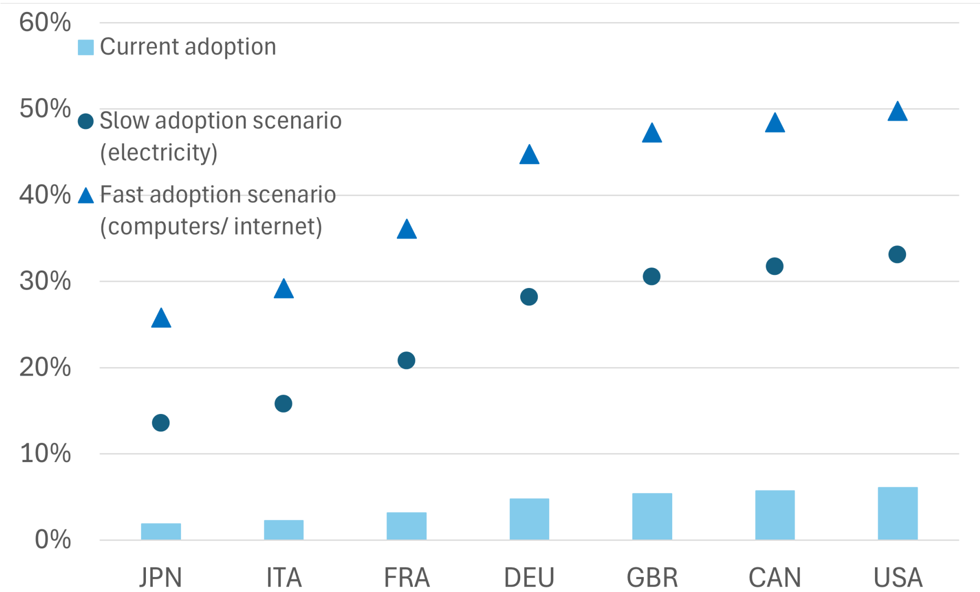
Source: adapted from Filippucci, Gal and Schief (2024), building on United States Census (internet and computers) and Woolf (1987) for electricity adoption of businesses and United States Census Bureau, Business Trends and Outlook Survey (BTOS) for AI adoption.

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.

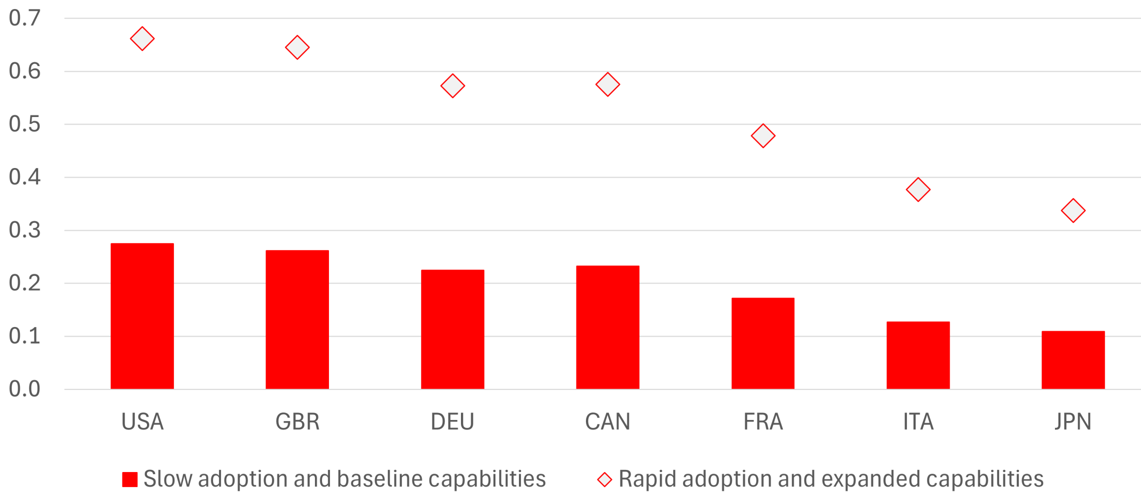
AI's Impacts on Innovation and Research

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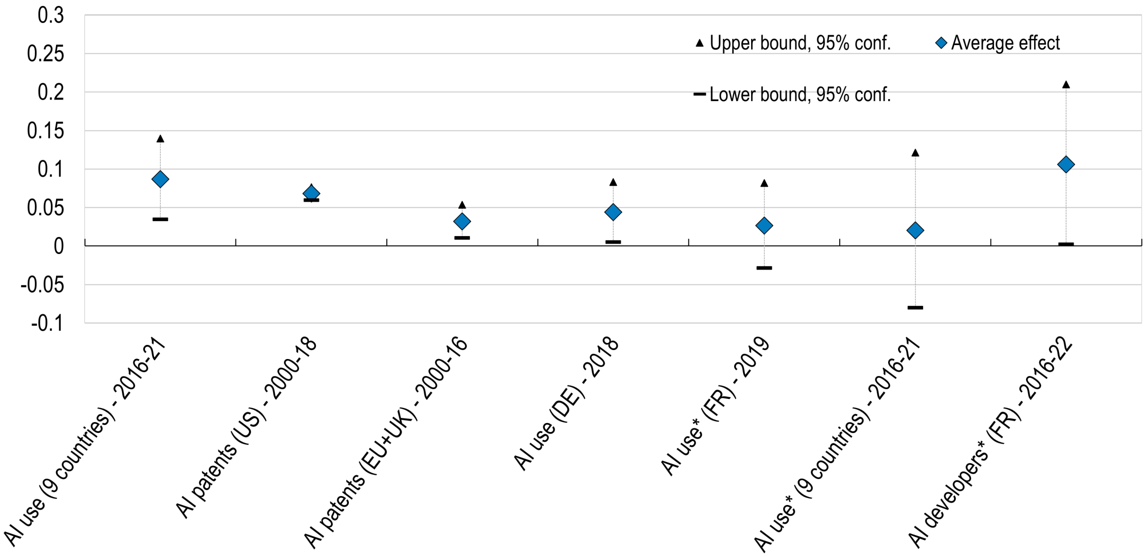
Figure A.1: The Relationship Between AI and Productivity at the Worker Level: Selected Estimates from the Literature



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).