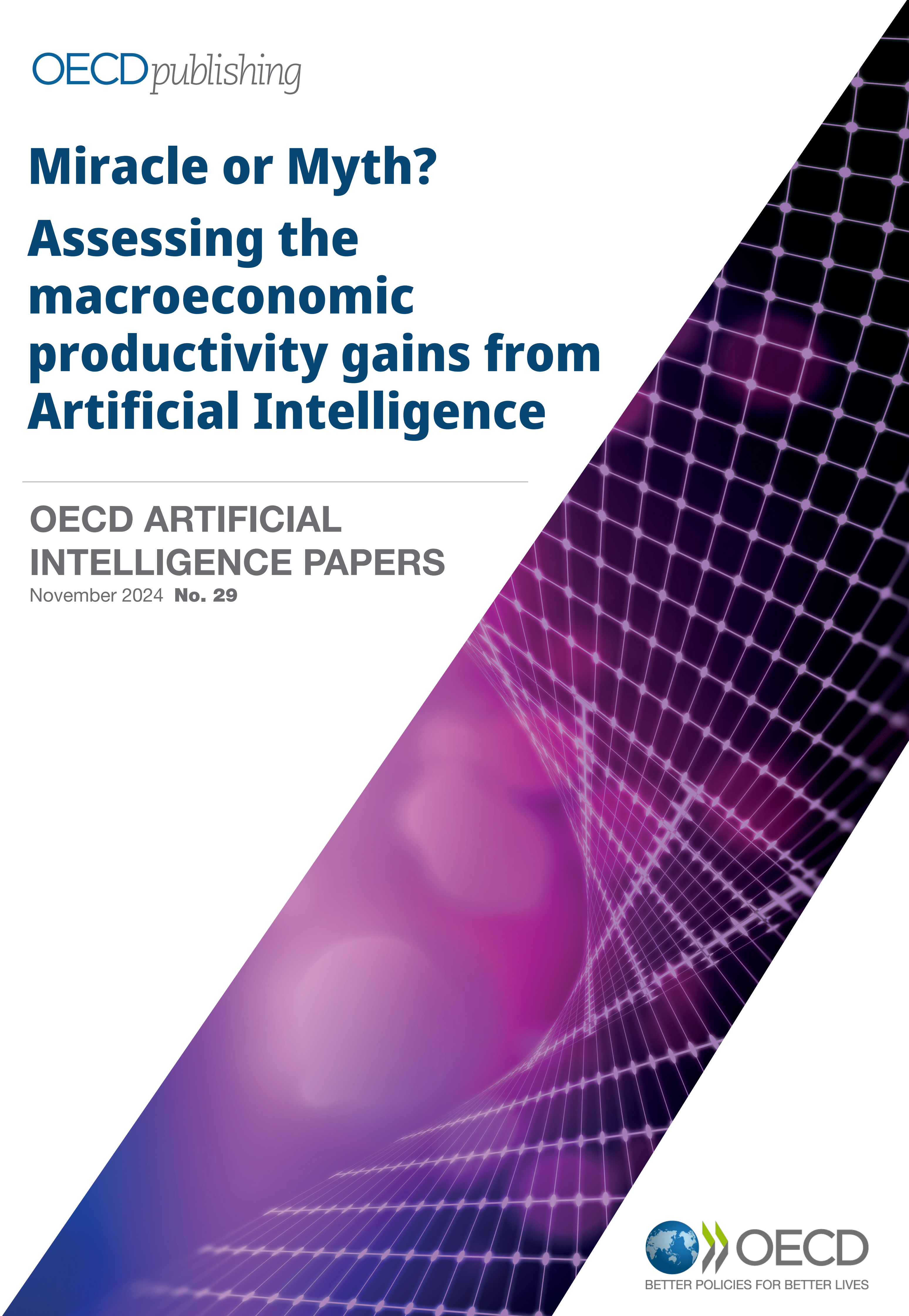
OECD publishing

Miracle or Myth? Assessing the macroeconomic productivity gains from Artificial Intelligence



OECD ARTIFICIAL INTELLIGENCE PAPERS

November 2024 **No. 29**

OECD
BETTER POLICIES FOR BETTER LIVES

OECD Artificial Intelligence Papers

Miracle or Myth? Assessing the macroeconomic productivity gains from Artificial Intelligence

ABSTRACT/RÉSUMÉ

Miracle or Myth?
Assessing the macroeconomic productivity gains from Artificial Intelligence

The paper studies the expected macroeconomic productivity gains from Artificial Intelligence (AI) over a 10-year horizon. It builds a novel micro-to-macro framework by combining existing estimates of micro-level performance gains with evidence on the exposure of activities to AI and likely future adoption rates, relying on a multi-sector general equilibrium model with input-output linkages to aggregate the effects. Its main estimates for annual aggregate total-factor productivity growth due to AI range between 0.25-0.6 percentage points (0.4-0.9 pp. for labour productivity). The paper discusses the role of various channels in shaping these macro-level gains and highlights several policy levers to support AI's growth-enhancing effects.

Keywords: Artificial Intelligence, Productivity, Technology adoption.

JEL Codes: C6, E1, O3, O4, O5.

******

Miracle ou Mythe?
Évaluer les gains de productivité macroéconomiques de l'intelligence artificielle

L'article étudie les gains espérés de productivité macroéconomique liés à la diffusion des technologies d'Intelligence Artificielle (IA) sur un horizon de dix ans. Il propose un modèle d'équilibre général multisectoriel qui intègre les interdépendances sectorielles entre entreprises et rend possible une agrégation au niveau macroéconomique des gains de productivité microéconomiques, compte tenu des différentes hypothèses d'exposition et d'adoption de l'IA dans chaque secteur. Le principal résultat du modèle est une estimation de la croissance annuelle de la productivité totale des facteurs attribuable à la diffusion de l'IA, dans une fourchette de 0,25 à 0,6 points de pourcentage (p.p), soit l'équivalent d'une augmentation de 0,4 à 0,9 p.p de la productivité du travail à un horizon de dix ans. L'article quantifie l'importance relative des différents mécanismes de ces gains de productivité agrégés et met en évidence plusieurs leviers de politique publique pour maximiser les gains potentiels de l'IA sur la croissance à long terme.

Mots clés : Intelligence Artificielle, Productivité, Adoption des technologies.

Codes JEL : C6, E1, O3, O4, O5.

Table of contents

Tables

Figures

Boxes

Miracle or Myth? Assessing the macroeconomic productivity gains from Artificial Intelligence

By Francesco Filippucci, Peter Gal, and Matthias Schief[1]

1. Introduction

Raising productivity growth is a priority for most OECD countries, which have experienced long-standing weak productivity performance, weighing on incomes and well-being.[2] Artificial Intelligence (AI) with its rapidly expanding capabilities is emerging as a new General Purpose Technology (GPT), comparable to earlier digital technologies such as the internet and personal computers, or previous breakthrough innovations like the steam engine and electricity (Varian, 2019; Agrawal, Gans and Goldfarb, 2019; Lipsey, Carlaw and Bekar, 2005). Generally, past inventions eventually led to periods of accelerated economic growth. Can AI play a similar role now and revive productivity growth? To study this question, the paper provides a range of estimates on AI's aggregate productivity effects over a 10-year horizon, using a novel framework to illustrate the role of various channels and conditions in helping achieve substantial macroeconomic gains.[3]

New advances in AI, in particular Generative AI (GenAI) based on Large Language Models, improve the performance of users in various tasks, previously thought unaffected by automation technology due to their

[1] Corresponding authors: Francesco Filippucci (Francesco.Filippucci@oecd.org), Peter Gal (Peter.Gal@oecd.org), and Matthias Schief (Matthias.Schief@oecd.org), all from the OECD Economics Department. The authors would like to thank Åsa Johansson, Tomasz Kozluk, Alvaro Pereira, Alain de Serres, and Filiz Unsal (all from the OECD Economics Department) for their valuable guidance and Christophe André, Manuel Betin, Sean Dougherty, Max Glanville, David Haugh, Sebastien Turban, David Turner (all from the OECD Economics Department), Stijn Broecke (OECD Directorate for Employment, Labour and Social Affairs), Flavio Calvino, Charles-Édouard Van De Put, the AI and Emerging Digital Technologies Division (OECD Directorate for Science, Technology and Innovation), as well as delegates to the Working Party 1 (WP1) of the OECD Economic Policy Committee (EPC) for useful comments and suggestions. The authors would also like to thank Sarah Michelson-Sarfati for excellent editorial support.

[2] See Fernald, Inklaar and Ruzic (2024); Goldin et al (2024); André and Gal (2024); OECD (2015) among others.

[3] A 10-year horizon allows us to capture a relatively long-term effect and remain comparable to most existing studies, while avoiding considering more speculative scenarios for the very long term, including the possibility of faster innovation and explosive growth (*singularity;* Nordhaus, 2021; Aghion, Jones and Jones, 2019; Trammell and Korinek, 2023). On the other hand, it is sufficiently long that the initial adjustment costs related to the adoption and integration of AI may be disregarded. The baseline results are obtained for the United States, given the availability of estimates needed to derive sector-level productivity gains. Under further assumptions, the calculations are then extended to other G7 countries (see more details below).

strong cognitive content and high knowledge intensity. In particular, micro-level empirical studies show large gains in the performance of workers when using AI in several business contexts: among customer service agents, by 14%, among business consultants, by nearly 40%, and among software programmers, by more than 50%.[4] In light of AI's impressive capabilities to boost productivity at the individual level, it is sometimes taken for granted that aggregate gains from AI will also be very large.

However, it is not guaranteed that micro gains in a few tasks translate to comparable gains at the macro level. First, many tasks cannot currently be carried out or supported by AI since it primarily impacts cognitive, knowledge intensive activities (ICT, finance, professional services), while tasks that have a strong physical component (e.g. construction, large parts of manufacturing and personal services) are much less affected. Second, not all firms and workers find it yet worthwhile or feasible to adopt the technology; adoption rates measured in official statistics are still low and their future evolution is a key uncertainty.[5] Third, general equilibrium mechanisms and production networks imply that aggregate gains from AI may differ from the simple sum of sectoral gains. For example, unresponsive demand to price declines for the type of activities where AI improves productivity (due to a rapid saturation in demand, e.g. in the case of legal services) may induce strong sectoral reallocation to sectors with lower gains from AI and reduce aggregate growth.

Recent work that quantifies the macroeconomic effects of Generative AI provides very different assessments regarding its capacity to revive sluggish productivity growth (Figure 1). For instance, Briggs and Kodnani (2023) suggests an optimistic view based on their large aggregate productivity growth estimates, amounting to 1.5 percentage point (p.p.) labour productivity boost per year, comparable to the size of *total* productivity growth observed over the past decades.[6] In contrast, Acemoglu's (2024) assessment is much more cautious, based on the small growth effects (on the order of 0.1 p.p. labour productivity gains per year)[7] he projects using a task-based aggregation framework and Hulten's (1978) theorem.[8] Aghion and Bunel (2024) use the framework in Acemoglu (2024) but rely on different

[4] Previous non-Generative AI already showed important advances such as reaching human level image recognition, and sophisticated predictive analytics. See Filippucci et al. (2024) and Lorenz, Perset and Berryhill (2023) for more on AI and Gen AI capabilities in particular. Researchers also report high expectations about AI's potential to improve their own productivity and ultimately speed up innovation, with interesting advances already in protein folding, genetics or mathematics. This channel is outside the scope of this paper, however, given the lack of quantifiable evidence on this mechanism and given that its impact would likely materialise over a longer horizon than our 10-year window.

[5] McElharan et al (2023); US Census Business Trends and Outlook Survey (reporting around 5% adoption rate among US firms in 2024) and Eurostat statistics on "Use of artificial intelligence in enterprises" (reporting 8% adoption among firms in the EU in 2023).

[6] A more recent work by authors in Goldman Sachs (2024) expresses more cautious views about the economic benefits of AI, especially in the context of high but volatile stock market valuations and their justifiability. Further estimates include Bergeaud (2024), Rockall, Pizzinelli and Tavares (2024), McKinsey (2023) and JP Morgan (2024). Theoretical approaches scan an even broader range of possibilities for Ai's growth potential: Aghion, Jones and Jones (2019) and Trammell and Korinek (2023) and explore scenarios that could lead to explosive growth, and limiting factors through factor and demand reallocation, such as Baumol's growth disease.

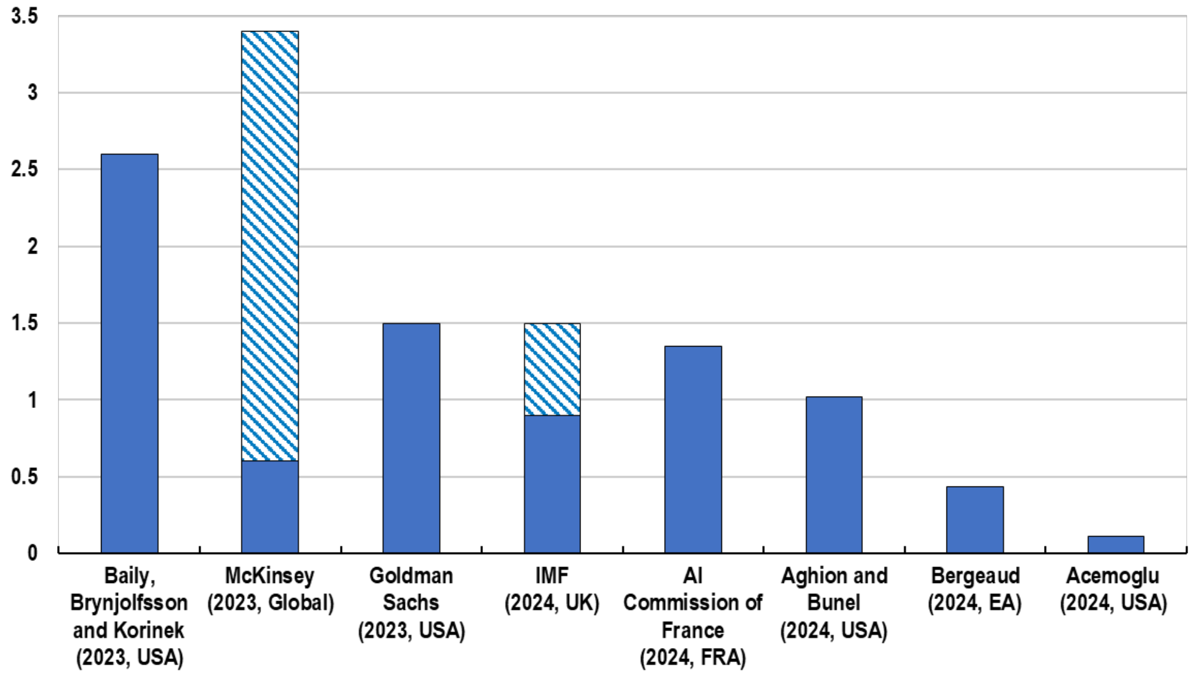
[7] More specifically, Acemoglu (2024) calculates overall TFP gains of 0.66 percent over 10 years, and also suggests GDP gains of 1.16 percent (which translate into labour productivity gains, given that total labour is fixed in has framework). Annualising this figure and interpreting it as percentage point increase in growth yields 0.12pp per year labour productivity boost.

[8] Hulten's (1978) theorem states that in a competitive economy with constant returns to scale the impact of micro-level (e.g., sectoral or firm-level) productivity gains on aggregate productivity growth can be approximated to a first order as the weighted sum of the micro-level productivity gains, where the weight of a given sector or firm is given by the ratio of its gross sales to GDP (i.e., its Domar weight). See further explanation and discussion in Section 2.3 and in Annex 1.

assumptions from the literature to arrive at numbers that are in between but closer to the optimistic end of the spectrum (around 1 p.p. point boost).

Figure 1. AI's predicted macro-level productivity gains vary substantially across studies

Predicted increase in annual labour productivity growth over a 10-year horizon due to AI (in percentage points)



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

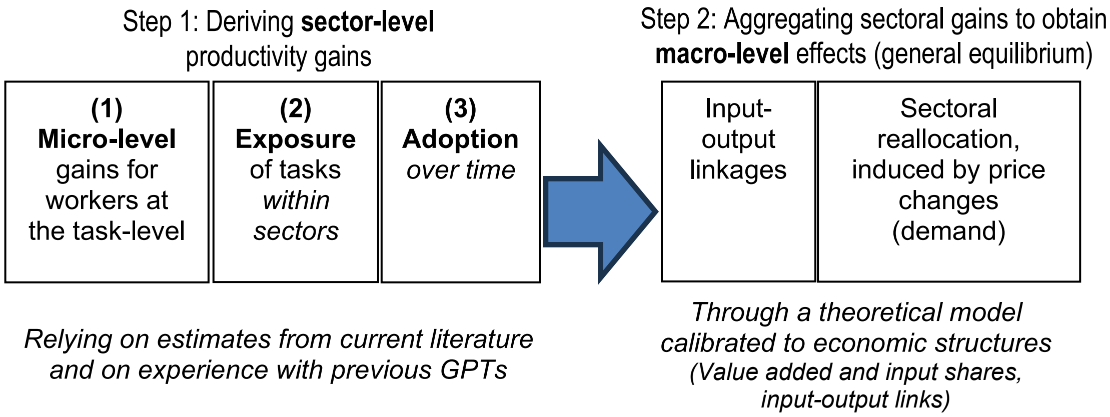
Our key contributions to the debate are twofold. First, we systematically document the role of various channels that determine macro-level gains by providing scenarios derived from different assumptions. These scenarios include expanded AI capabilities, either within cognitive activities augmented by additional, complementary digital tools (software) or extended to physical tasks through further integration with robotics technologies (e.g. autonomous vehicles). Second, we explicitly study the role of general equilibrium mechanisms – in particular reallocation across sectors following demand responses to the AI-driven supply shock and changing input-output linkages – that can shape the size of aggregate gains and which go beyond the first-order approximation provided by Hulten's theorem (Baqaee and Farhi, 2019). Sectoral reallocation over the long run can play a moderating role to aggregate growth through Baumol's growth disease, as argued by Aghion, Jones and Jones (2019) and demonstrated in historical episodes (Nordhaus, 2008) as well as by new calculations presented in this paper.[9] In the context of reallocation, considering input-output links is important as AI gains emanating from the most affected sectors – currently,

[9] This role of long-term cross-sectoral reallocation is distinct from that of short- to medium term adjustment to shocks especially within sectors. Within sector reallocation contributes significantly to sector level productivity growth as firms with increased productivity attract more resources in subsequent years (Decker et al., 2020; Calligaris et al., 2023).

knowledge intensive services such as ICT services, finance and professional services – can also expand production in downstream sectors – such as manufacturing industries.

We assess the macroeconomic productivity gains from AI by proceeding in two broad steps (Figure 2). First, we calculate expected *sector-level* productivity growth from AI by combining estimates from the growing literature on (1) micro (worker) level performance gains from AI, (2) the share of production tasks that can be improved by AI (*exposure;* Eloundou et al., 2024)[10], and (3) the extent of AI adoption across firms (*adoption;* Filippucci et al., 2024). This step builds on Acemoglu (2024) and adapts it to our sector-level setting.[11] Second, we aggregate these sector-level gains using a multi-sector general equilibrium model that is calibrated to the observed structure of the economy and accounts for sectoral input-output linkages, the role of demand in driving price adjustments, and factor reallocation across sectors (Baqaee and Farhi, 2019).

Figure 2. The framework for aggregating AI's productivity gains from micro-to-macro



Note: Step 1. is inspired by Acemoglu (2024), adapted to our sector-level framework. Step 2. builds on the multi-sector model in Baqaee and Farhi (2019).
Source: Authors' elaboration.

The model's predictions are calculated under different sets of assumptions (scenarios). Some assumptions concern AI development and use, such as capabilities – determining micro level gains and exposure – and future adoption and diffusion. Other assumptions are more related to structural features of the economy that can influence the potential macroeconomic gains. Such structural features include: (1) frictions that inhibit factor (e.g. labour) reallocation across sectors, such as adjustment costs related to workers changing jobs across different sectors; and (2) low elasticity of demand to the relative price changes resulting from AI-driven differences in productivity growth across sectors – broadly speaking, another source of adjustment friction to the AI driven shock.[12]

[10] Upcoming OECD work by Calvino, Dernis and Samek (2024) provides a sectoral taxonomy of AI which could provide an alternative source of assessing cross-sectoral differences in exposure.

[11] This step is also adopted by Aghion and Bunel (2024) and Bergeaud (2024). See more in Section 2.

[12] This friction emphasises the possibility that even though AI leads to varying productivity gains across different sectors, resulting in changes in relative prices, the demand for goods and services may not significantly adjust in response to these price changes, possibly due to a rapid saturation of demand. A similar phenomenon happened with industries impacted by previous waves of productivity improvements, although over very long periods (e.g. textiles and the automation of their production; see Bessen, 2018). The responsiveness of demand is also related to the social acceptability of AI (e.g. in the legal system: will people accept AI judges?), explored in Cazzaniga et al. (2024).

The main scenarios in this paper suggest that AI will significantly contribute to annual Total Factor Productivity (TFP) growth in the US by around 0.25-0.6 p.p. This implies around 0.4-0.9 p.p. contribution to annual labour productivity growth, when assuming a standard capital multiplier of 1.5. To put these figures into perspective, US annual TFP growth was around 1 percent and labour productivity growth around 1.5 percent in the US, and even lower for the OECD, over the past two decades. Our estimates thus indicate that Generative AI will likely be an important source of aggregate productivity growth over the next 10 years, even though current AI technology alone is unlikely to bring productivity growth back to the levels seen in the 1960s.[13] 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 US TFP growth during the 1995-2004 period (Byrne et al, 2013; Bunel et al, 2024)[14]. This is higher than the range for AI-driven gains in our main scenarios – however, if AI capabilities become applicable in a wider range of activities, notably thanks to further integration with robotics technologies, we find comparable effects.

Our scenarios yield the following broad lessons about the importance of various factors influencing the size of the expected gains:

- First, high and widespread adoption across many sectors of the economy, along with expanded AI capabilities – notably via the development of complementary digital tools or further integration with robotics technologies – is a key driver of achieving higher aggregate TFP gains.
- Second, if AI's sector-level productivity gains remain concentrated in a few sectors, inelastic demand and adjustment frictions related to factor reallocation can lower the aggregate productivity gains due to "Baumol's growth disease" (Baumol, 1967; Nordhaus, 2008).[15] The size of this drag is not large in our main scenarios, on the order of 0.1 percentage point lower annual TFP growth, which is a sixth of the total growth benefits. However, a stronger concentration and larger disparity across sectors – which are more consistent with historically observed dispersion in sectoral productivity performance – can lead to a reduction of the aggregate gains by nearly a third by increasing the effect of "Baumol's growth disease".
- Third, if physical or manual tasks are also exposed to AI, notably thanks to further integration with robotics technologies, the productivity benefits will also be more widespread across sectors, with no negative drag from reallocation frictions. This leads to a very substantial aggregate growth impact of around 1pp per year.

These results are obtained from calibrating the model and the determinants of sectoral productivity gains – micro-level gains, the likely adoption paths and the exposure of activities to AI – to the United States. In addition, we also illustrate cross-country differences among G7 economies regarding AI's productivity impact by relying on variation in country-specific sectoral structures (observed through national I-O tables and the occupational compositions of sectors), and by assuming different adoption rates of AI (building on

[13] The expected productivity gains from AI should not necessarily be seen as an extra boost over existing rates, since AI's impact may already be appearing in recent productivity figures. Additionally, past forecasts of productivity growth often assumed ongoing technological advancements, potentially encompassing AI developments. AI represents a continuation of digital technologies that have been contributing to productivity growth.

[14] EU countries mostly missed out on these gains, however, which points to the importance of cross-country differences and the potential role of policy settings in reaping the economic benefits of technological waves (Van Ark, O'Mahoney and Timmer, 2008).

[15] The differential performance across sectors can lead to a drag on aggregate through other mechanisms which we do not incorporate, such as the sectoral bottlenecks channel (Acemoglu, Autor and Patterson, 2024). This captures the idea that when the productivity of input producers improves at a highly different pace, then the productivity of downstream producers – who combine those inputs – will suffer.

the currently observed large cross-country variation).[16] We find that the combined effect of these differences leads to substantial variation in the size of the expected productivity impacts from AI across countries, driven primarily by adoption patterns as well as by sectoral exposure to AI. In particular, in most scenarios, gains of comparable size to the ones obtained for the US arise in Germany and Canada; while in France and Italy, the expected gains would be about half of that. In scenarios where frictions are assumed to be more important, differences in the sectoral linkages of the economy also play a role, resulting, for example, in lower predicted aggregate gains for Germany and Japan likely related to the details of the input-output structure (e.g. stronger reliance on specific upstream sectors).

Our findings imply that the macro-level productivity gains from AI depend on several conditions and should not be taken for granted by extrapolating from the important micro-level benefits in specific tasks. As also stressed by the OECD Principles on Artificial Intelligence[17], governments have a key role to play in ensuring trustworthy AI development, deployment and use which in turn benefit the economy and society. In particular, the broader, macroeconomic productivity impacts from AI can be influenced through several policy areas:

1. AI diffusion and adoption: Governments can support the *capabilities* of firms to adopt AI in a wide range of sectors through educational and skills development policies (OECD, 2023c) and via improving access to digital technologies, including through liberalised digital trade (OECD, 2023d). Governments can also support *incentives* to adopt AI by ensuring that markets remain competitive and incumbency advantage does not translate into persistent gains which discourages technology adoption by lagging firms or potential new entrants (Aghion and Bunel, 2024; Calligaris et al, 2024; Berlingieri et al, 2020). Ensuring that open-source solutions remain a viable alternative to closed ones would also facilitate diffusion (Andre et al, 2024).
2. Demand for AI powered goods and services: Trustworthiness is key to ensure demand for AI powered goods and services will meet supply and thus enable broad-based macroeconomic productivity gains. Governments need to strike a balance between ensuring safety and reliability of AI for the user while at the same time not discouraging experimentation and further development of AI technologies. An important focus should be on improving transparency about the capabilities of the technology, and by resolving legal uncertainties about accountability (OECD, 2019a).
3. Reallocation of factors: Governments should support workers in transitioning between jobs and across sectors through re-training and other labour market policies (Causa et al., 2022). The productive allocation of capital should also be facilitated through well-developed financial systems, in particular with measures that recognise the growing importance of intangibles (Demmou and Franco, 2021).

The next section presents the conceptual framework, discussing the assumptions, the modelling choices, as well as caveats and potential enrichments. Section 3 describes the results along several scenarios and illustrations, including extensions to other countries than the US. Section 4 concludes with a brief discussion and potential future extensions.

[16] We plan to extend the set of countries to OECD and potentially beyond.

[17] OECD (2024c) and https://oecd.ai/en/ai-principles. See also Acemoglu, Autor and Johnson (2023) and Baily, Brynjolfsson and Korinek (2023) for a discussion of how the development and use of AI could be shaped to ensure broader societal benefits that go beyond the more specific question of productivity growth which is our focus here.

2. Conceptual framework, assumptions, and modelling choices

2.1. Quantifying AI's aggregate productivity effects: from micro to macro

A fast-growing body of research provides estimates of the expected performance gains from AI at the individual worker or firm level.[18] But how do these microeconomic gains translate into aggregate productivity growth? Answering this question requires a suitable macroeconomic framework, and there are several approaches taken in the recent literature (Table 1):

- Briggs and Kodnani (2023) derive aggregate productivity effects starting from gains observed in firms using AI. They introduce a set of assumptions about labour substitution and reallocation to arrive at aggregate effects, without relying explicitly on a formal theoretical model.
- Acemoglu (2024), and, building on him, Aghion and Bunel (2024) and Bergeaud (2024), derive aggregate gains in a task-based theoretical framework (Acemoglu and Restrepo, 2018) by aggregating *worker*-level performance gains from AI in specific tasks - identified in the literature - to macroeconomic gains. The advantage of this approach is that it builds on micro-level evidence on AI capabilities and offers a consistent way to translate them to aggregate effects. In addition, it also allows to study the implications for wage disparities and economic inequality. For instance, Acemoglu (2024) uses the task-based framework to study not only aggregate growth but also distributional implications, namely the extent to which the wages of different demographic and skill groups are impacted by AI.[19]
- Another group of studies rely on the properties of aggregate production functions to explore the potential macroeconomic implications of AI (not shown in Table 1 due to their focus on the qualitative, theoretical mechanisms rather than on quantifying aggregate effects). For instance, Aghion, Jones and Jones (2019) focus on the limiting factors to explosive growth through factor and demand reallocation, such as Baumol's growth disease. Trammell and Korinek (2023) explore how AI might affect the various parameters and inputs in an aggregate production function, including scenarios that could precipitate substantial, even accelerating, economic growth.

In this paper, we take an intermediate approach between the micro and the more macro based studies and make *sectors* the key component of our modelling framework. In particular, we study the question of the aggregate productivity gains of AI in two broad steps (see Figure 2 in the Introduction): first, by calculating sector-level productivity gains building on the approach by Acemoglu (2024) (Section 2.2 below), then by aggregating these sectoral gains through a multisector general equilibrium model (Section 2.3), building on Baqaee and Farhi (2019).[20]

---

[18] For recent overviews, see for instance Besson et al. (2024); Council of Economic Advisers (2024); Ben-Ishai et al (2024). Specifically, firm level studies which focus mostly on pre-Generative AI technologies, often in combination with other digital tools, include Calvino and Fontanelli (2023); Czarnitzki, Fernández and Rammer (2023); Alderucci et al. (2020); Damioli, Van Roy and Vertesy (2021). Worker level studies which focus on specific tasks carried out with the help of more recent language based Generative AI (LLM) tools include Brynjolfsson, Li and Raymond, (2023); Peng et al (2023); Noy and Zhang (2023); Dell'Acqua et al (2023); Haslberger, Gingrich and Bhatia (2023).

[19] These models are also useful for modelling pure automation (i.e. technological change that *reduces* overall labour demand with a depressing effect on wages). They contrast the automation effect, which is causing labour displacement, with countervailing forces such as (1) new task creation, which can cause a labour reinstatement effect; (2) complementary labour demand to rising capital demand – as the productivity of machines improves – and (3) the positive general equilibrium effects of higher productivity on aggregate demand and hence labour demand.

[20] Aldasoro et al (2024) also takes a sectoral approach but they focus on output and inflation while taking aggregate productivity benefits given.

Table 1. A comparison of a few recent empirical studies and our paper

Key assumptions and modelling choices		Papers			
		Briggs and Kodnani (2023) (*Goldman Sachs*)	**Acemoglu (2024)**	**Aghion and Bunel (2024)**	**This paper**
I. Assumptions 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 GPTs' 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?*	No	Yes	No	No
	Innovation	Not considered	Not considered	Not considered	Not considered

Notes:
* Based on micro-level studies that identify task-level gains from using LLMs.
**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.
For a more detailed discussion, see the text in Section 2.
Source: Authors' comparison of the cited studies.

The sectoral general equilibrium approach is useful for our purposes for several reasons. First, it allows to incorporate the empirical finding that AI benefits a larger share of the tasks performed in some sectors than in others (what the literature calls *exposure* to AI). For instance, knowledge intensive services that rely strongly on cognitive tasks are found to be highly exposed to Generative AI (Eloundou et al, 2024; Felten et al, 2021; see more in the next subsection). Second, sectoral productivity gains imply higher sectoral output and, generally, lower prices, which in turn enables expanded production in downstream sectors through cheaper and more abundant inputs (input-output links). Our multi-sector model allows to capture the importance of such linkages, which matter for how the economy adjusts to uneven sectoral productivity gains. Third, aggregate productivity gains depend not only on sectoral productivity gains but also on how demand responds to output price changes in different sectors and how it fosters reallocation of labour and capital across sectors, which our sectoral focus and emphasis on general equilibrium allows to study. Finally, the sectoral focus also lends itself to account for differences across countries in their sectoral composition. Going beyond the choice of the quantification and modelling framework, the papers listed in Table 1 and our approach also vary with regards to assumptions about AI's micro level gains, the exposure of economic activities to AI and the adoption rate of AI, which we discuss in Section 2.2. Specific modelling choices regarding the impact of AI-driven productivity gains on structural change, in particular labour reallocation, cross-sectoral links in production, and capital deepening also matter and will be discussed alongside the model in Section 2.3.

While the framework developed in this paper provides a useful lens to gauge aggregate productivity gains from AI over a relatively long-run horizon (over 10 years), it relies on several modelling assumptions. First, within-sector developments, such as permanent or rising productivity differences across firms (shown empirically by Andrews, Criscuolo and Gal, 2016 and modelled theoretically in Akcigit and Ates, 2021)[21], differences in AI adoption across firms (Calvino and Fontanelli, 2023) or changes in the misallocation of resources (Restuccia and Rogerson, 2017) due to AI are not modelled. Current evidence is inconclusive about the role of AI through these mechanisms, some of which pertain to competition issues, explored in ongoing parallel work (Andre et al., 2024; OECD, 2024a).[22] Second, we do not model the implications of an AI-driven acceleration of innovation, research or technological progress (Aghion, Jones and Jones, 2019; Trammell and Korinek, 2023). This could have large consequences for economic gains in the very long term. However, given our focus on a 10-year horizon and the lack of quantifiable evidence on this mechanism, we do not incorporate this potential effect.[23] Third, we do not explicitly model the production or the provision of AI, the required investment and its contribution to aggregate growth or the potential negative effects of factoring in the costs involved when using AI.

We make several additional simplifying assumptions in our modelling approach. First, we model sectoral output via a stylised production function in which a single factor, representing labour and capital, is combined with intermediate inputs to produce sectoral (gross) output, and where the productivity improvements from AI are modelled as an increase in sectoral multi-factor productivity. Hence, we do not take a stance on whether AI disproportionally raises the productivity of capital or labour, which are both plausible[24]; neither do we explicitly model capital accumulation and the dynamic adjustment through investments (which also relates to the J-curve hypothesis by Brynjolfsson, Rock and Syverson, 2021). Instead, we use a simple capital multiplier of 1.5 at the aggregate level to turn TFP growth to labour productivity growth. Additionally, labour market issues are tackled in a very limited way (restricting mobility across sectors) but we do not study aggregate employment or distributional consequences, which would

[21] AI may exacerbate performance differences across firms, if already more capable incumbents can better exploit its potential, creating competition issues; or it leads to a disproportionately positive effect on lagging performers. Also, AI development may be hampered by a lack of competition.

[22] Within sector reallocations under AI may be large, given reorganisation and reskilling needs; on the other hand, AI itself could ease reallocations (through improving labour market matching or capital allocation, for instance).

[23] Promising contributions to innovations from AI have emerged in fields such as molecular biology and pharmaceuticals (protein folding), the design of advanced materials, and solving certain math problems, to name a few areas. Survey evidence among researchers shows optimism that AI can raise their productivity. See more in previous OECD work by Filippucci et al. (2024).

[24] A consensus on the specific nature of AI-driven technological change has yet to emerge: AI may increase the productivity of capital, for instance, by making it easier to re-program machines for different tasks. At the same time, AI promises to raise the productivity of labour, for example, by providing quick access to relevant information or by automating routine tasks, allowing workers to concentrate on their main activities (see Acemoglu, 2024, for arguments along this line).

deserve a separate modelling approach (Acemoglu and Restrepo, 2018).[25] Allowing for imperfect competition and accounting for AI's potential impact on competition could limit the aggregate gains from AI due to lower input-output multipliers, lower supply and higher prices as well as lower adoption. Finally, this paper does not explore the broader societal risks associated with AI, which may undermine its economic benefits or hold back the development and adoption of AI in the first place (as touched upon in Filippucci et al., 2024).

2.2. Deriving sector-level productivity impacts of AI

To determine sector-level productivity gains over the next 10 years ($Sectoral\ Productivity\ Growth_{j,[t,t+10]}$), we adapt the framework in Acemoglu (2024) to the sectoral context and consider three key estimates: micro-level performance gains at the worker and task level; the share of tasks in each sector that is potentially affected by AI (exposure to AI); and the degree of adoption of AI in the sector. Formally, estimates of the increase in sectoral productivity from AI in a given sector j are obtained by multiplying average micro-level gains found by studies focusing on specific tasks ($Micro\ Level\ Gains$) with the share of tasks in industry *j* that can be performed faster or better with the help of AI ($Exposure_j$) and the projected adoption rate ten years from now*,* which may be sector specific ($Adoption\ Rate_{(j)t+10}$):

$$Sectoral\ Productivity\ Growth_{j,[t,t+10]} = Micro\ Level\ Gains * \ Exposure_j * \ Adoption\ Rate_{(j)t+10} \quad (1)$$

The assumptions and sources about all these components are discussed in the subsections below.

2.2.1. Micro-level performance gains from AI

To estimate aggregate gains from AI, most existing studies use as a starting point the available evidence on micro level performance gains among workers and firms that use AI. Among the papers shown in Table 1, Briggs and Kodnani (2023) rely on firm-level studies which estimate an average gain of about 2.6% additional annual growth in workers' productivity, leading to about a 30% productivity boost over 10 years. Acemoglu (2024) uses a different approach and start from worker-level performance gains in specific tasks, restricted to recent Generative AI applications.[26] Nevertheless, these imply a similar magnitude, roughly 30% increase in performance, which they assume to materialise over the span of 10 years. However, they interpret these gains as pertaining only to reducing labour costs, hence when computing aggregate productivity gains, they downscale the micro gains by the labour share.[27] In contrast, we take the micro studies as measuring increases in total factor productivity since we interpret their documented time savings to apply to the combined use of labour and capital. For example, we argue that studies showing that coders complete coding tasks faster with the help of AI are more easily interpretable as an increase in the joint productivity of labour and capital (computers, office space, etc.) rather than as cost savings achieved only through the replacement of labour.

[25] Regarding distributional consequences, Acemoglu (2024) argues that, unlike previous automation technologies, AI is unlikely to exacerbate inequality given its applicability in both high- and low-wage occupations. For a discussion of how the task-based framework is relevant for understanding the various channels of new technologies, such as AI, on productivity and labour demand, see Acemoglu and Restrepo (2019).

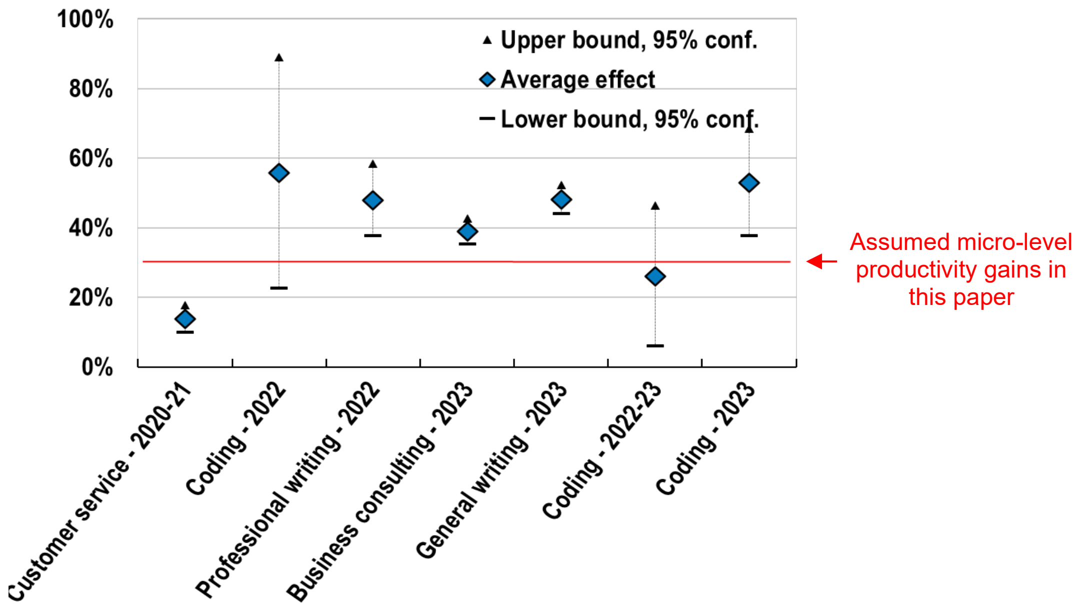
[26] Aghion and Bunel (2024) and Bergeaud (2024) take a similar approach.

[27] Acemoglu (2024) and Aghion and Bunel (2024) downscale worker-level gains by an "AI exposure"-adjusted labour share of 0.57, resulting in 14.4% total cost savings, while Bergeaud (2024) downscales worker-level gains by labour share of 0.48, resulting in 16.8% total cost savings.

To obtain micro-level gains for workers performing specific tasks with the help of AI, this paper relies on the literature review conducted by Filippucci et al. (2024) (Figure 3). The studies are based on randomised controlled trials and cover estimates of the performance improvement observed after the adoption of AI in a range of activities: AI support for customer services (Brynjolfsson, Li and Raymond, 2023) (1st estimate on Figure 3), the effect of AI coding assistants on software developers (Peng et al., 2023; Cui et al, 2024; Gambacorta et al, 2024) (2nd, 6th and 7th estimates, respectively), and the gains from using Large Language Models such as ChatGPT in speed and quality of professional writing tasks (Noy and Zhang, 2023) or in business consulting performances (Dell'Acqua et al., 2023)(3rd and 4th estimates, respectively) and the performance improvement with Large Language Models assisting with general writing (Haslberger, Gingrich and Bhatia, 2023) (5th estimate). The point estimates indicate that the effect of AI tools on worker performance in specific tasks range from 14% (in customer service assistance) to 56% (in coding), estimated with varying degrees of precision (captured by different sizes of confidence intervals). We will assume a baseline effect of 30%, which is around the average level of gains in tasks where estimates have high precision (low confidence bands; for the 1st, 4th and 5th estimates).

Figure 3. Micro-level performance gains from AI for workers in specific tasks

Estimates of the impact of Generative AI from recent micro-level studies



Note: The figure collects estimates from studies that assess the impact of Generative AI (Large Language Models) in assisting with specific tasks of workers.
Source: Compilation by Filippucci et al. (2024) (first five estimates); more recent studies by Cui et al. (2024) and Gambacorta et al. (2024) (last two estimates).

A plausible downside risk to the magnitudes identified from these studies is that they evaluate the effects in experimental settings, typically among early adopter firms and in contexts that are likely to be most amenable to AI-assistance.[28] When extending to a broader range of tasks, later adopters, and into real life

[28] This possibility is only partially accounted for by our strategy of calibrating gains from AI in a specific sector proportionally to exposure of tasks in a given sector (see Section 2.2.2). Sector-level exposure simply corresponds to the share of tasks exposed to AI, where tasks are categorised as exposed vs. non exposed in a binary way, without accounting for possible lower or higher impact on different tasks.

settings, the effects may turn out to be smaller (Acemoglu, 2024). Moreover, these studies may not fully take into account that the use of AI entails costs which need to be factored in to arrive at the true productivity gains.

On the other hand, an upside risk that could arise over the longer run is the emergence of new types of economic activities that better integrate AI or the entry of new firms that bring novel business models and make the collection of data – a key ingredient of AI – fully embedded in their operations. This corresponds to what Agrawal, Gans and Goldfarb (2022) call system-wide adoption, which in the case of earlier GPTs took time to appear but brought stronger economic benefits, as opposed to "plug-and-play" or point-solution based adoption, which simply replaces a given task with the new technology.[29] In the task-based framework of Acemoglu and Restrepo (2018), this upside risk would be akin to the arrival of new tasks or occupations enabled by AI in which humans can be productively employed. This would also be in line with the historical experience of the appearance of new occupations over several decades building on previous technologies (Autor et al, 2024).

Finally, our strategy aims at studying the possible future impact of *current* AI capabilities, considering also a few additional capabilities that can be integrated into our framework by relying on existing estimates (AI integration with additional software based on Eloundou et al, 2024; integration with robotics technologies). In addition, it is clearly possible that new types of AI architectures will eliminate some of the current important shortcomings of Generative AI – inaccuracies or invented responses, "hallucinations" – or improve further on the capabilities, perhaps in combination with other existing or emerging technologies, enabling larger gains (or more spread-out gains outside these knowledge intensive services tasks; see next subsection). However, it is still too early to assess whether and to what extent these emerging real world applications can be expected.[30]

2.2.2. The exposure of different sectors to AI

The degree to which AI can potentially affect a specific occupation or sector is called *exposure* to AI in the literature (Felten et al, 2021; Eloundou et al, 2024). It is derived from the type of tasks that humans carry out and the extent to which AI is capable of doing those tasks or helping with them.[31] High exposure of a sector (or occupation) means that it consists of a large share of tasks that AI can assist with.[32] This concept allows to extend micro-level (task-level) performance gains to more aggregate, sector or macro-level productivity effects.

[29] One example from previous technologies relates to the optimal exploitation of electric power, which emerged with the reorganisation of factories. This reorganisation maximised the benefits of accessing energy over a broader area, in contrast to the concentrated energy sources used previously, such as steam engines.

[30] For instance, Google's DeepMind lab has published preliminary findings about combining machine learning based methods with logical or symbolic architectures to improve math problem solving performance (Google, 2024). Symbolic architectures rely on a set of internally consistent rules instead of learning from observed patterns as is done in machine learning and were the leading paradigm at the early days of AI in the 1950s, before machine learning took off (OECD, 2019b).

[31] The distinction of whether AI is a complement or substitute to humans in specific tasks is not directly modelled in our framework. In both cases, fewer workers are required to produce a given amount of output, hence productivity is increased. However, distributional consequences, which are outside of the scope of this paper, may differ. We also do not model quality improvements in goods or services, which may arise if human capacities are augmented by AI, as discussed by Trammel and Korinek (2023).

[32] Other sources include the World Economic Forum and Accenture which is similar in spirit to Felten et al (2021) but differentiates between lower exposure values which are considered as complements from higher values which are considered substitutes (WEF, 2023). Cazzaniga et al (2024) also differentiate exposure based on the complementary nature to humans, driven not only by technological factors but social acceptability.

Briggs and Kodnani (2023) from Goldman Sachs assume that around one third of total tasks (hence about one-third of jobs) will be exposed to AI. Acemoglu (2024) assumes 20% of US labour tasks are exposed to AI, based on aggregating task-level exposure measures from Eloundou et al. (2024).[33] Aghion and Bunel (2024) considers a broad range from several studies, including Gmyrek et al (2023), at 18.5% and substantially higher figures from Pizzinelli et al (2023), at 60%.[34]

We follow Acemoglu (2024) and rely on the recently published work by Eloundou et al. (2024), who evaluate which tasks can be performed faster with the help of AI, using both human evaluators and an AI tool (OpenAI's GPT) itself as an evaluator.[35] In line with the authors' assessment, we use the results obtained by human evaluators. We consider two measures from the study: first, the share of tasks for which the required time for completion substantially decreases using Generative AI (LLMs) (*baseline exposure)*; second, an alternative measure that includes tasks where gains are achievable if other software is developed on top of current LLMs (*expanded capabilities*). The inclusion of this more optimistic and forward-looking case among our scenarios is motivated by the fact that some of the capabilities of LLMs considered by Eloundou et al. (2024) have already improved substantially.[36]

We map task-level AI exposure to sectoral exposure, based on the task composition of different sectors, described in detail in Annex 4.1. This reveals that the most exposed sectors are knowledge-intensive services that rely strongly on cognitive tasks, such as Finance, ICT services (including telecoms), Publishing and Media, and Professional services (Figure 4). The least exposed sectors include sectors with a strong manual component, such as Agriculture, Mining and Construction. This pattern confirms earlier results on sectoral exposure to non-Generative AI (Felten et al., 2021 and Annex Figure A1), suggesting that Generative AI and LLMs will further expand the effects of previous non-Generative AI.[37] Note that the more optimistic scenario with expanded AI abilities shows substantially higher exposure for each sector, while the ranking of sectors is largely preserved.

[33] Acemoglu (2024) uses an indicator of Eloundou et al (2024) that captures mostly those subtasks with a high potential for automation by LLMs as opposed to augmentation. This leads to lower average exposure (around 20%) than implied by the overall, baseline exposure measure in Eloundou et al (2024), which is also used in our calculations (around 35%).

[34] While the concept of exposure at the task level may suggest that tasks are equally important, in practice more important tasks – called "core tasks" – receive a large weight when computing occupational and sector level exposure (Annex 4.1).

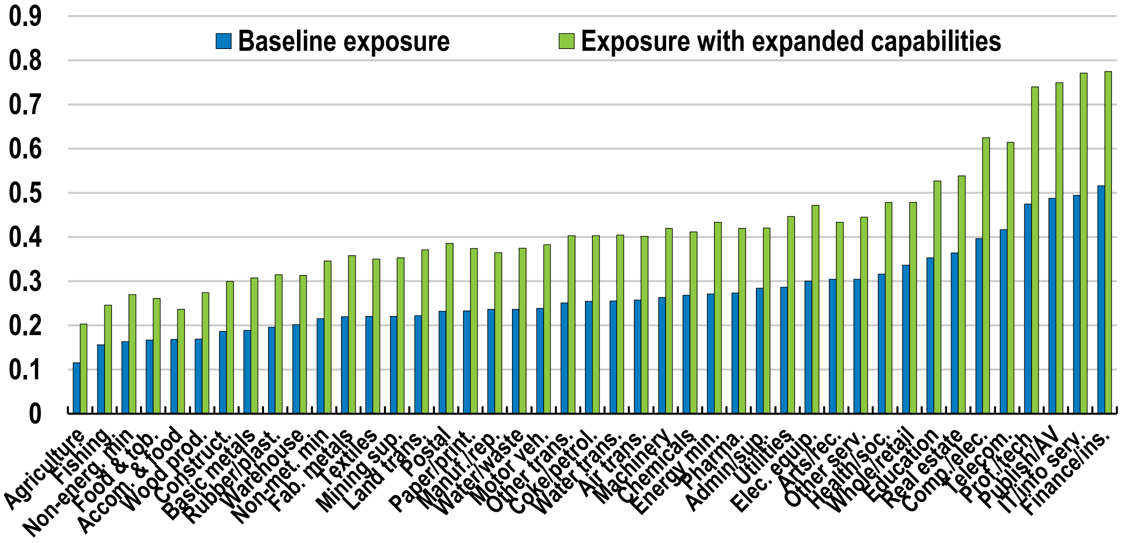
[35] In the case of humans, they use enlisted experienced annotators that previously worked on ChatGPT's development (Ouyang et al, 2022). ChatGPT and human estimates are very close in magnitude and consistent in terms of sectoral variation.

[36] For instance, the length of the interactions allowed in the LLM is now substantially larger than what was available at the time of the study of Eloundou et al (2024).

[37] To the extent that Generative AI can help with activities that have a strong physical element through providing *advice* or *guidance* with decisions about how to carry out those tasks (e.g. a plumbing or a farming activitiy) these low exposure figures in highly manual task intensive tasks can be seen conservative.

Figure 4. Sectoral AI exposure: the share of tasks that are affected by AI

Based on current AI capabilities (*baseline*) and expanded AI capabilities



Notes: The graph reports the baseline measure of sectoral exposure to AI gains (labelled as *beta* in the source study Eloundou et al., 2024) and an alternative measure that includes among the exposed tasks also the ones where performance gains are achievable if additional software is developed on top of current LLMs (labelled as *gamma* in Eloundou et al., 2024). Calculations are based on the US task-occupation-sectoral structure.
Source: Authors' calculations.

Finally, we consider the case where AI is combined with or integrated into robotics technologies (using sensors, fine motor skills, etc.) to carry out a range of physical tasks as well. The most advanced, or futuristic, among such solutions seem to be in early stage and probably far from cost effectively scalable[38], but there are already some current applications that leverage this possibility, including by relying on previous, non-Generative AI (drones, autonomous vehicles, automated assembly lines). This can be thought of as an important upside risk to exposure, and to quantify this we calculate another cross-sectoral exposure measure by computing an exposure to robotics technologies (based on the manual intensity of tasks and occupations within sectors) and adding that to the exposure to Generative AI.[39] More specifically, we combine an established definition of routine manual tasks (Acemoglu and Autor, 2011) with estimates of the intensity of manual tasks at the occupation level (Autor and Dorn, 2013) to define exposure to industrial robots (similarly to De Vries et al., 2020).[40] The resulting manual task intensive sectors – including agriculture and large parts of manufacturing – are highly exposed to robotics technologies (up to 60-80%, Figure 5). By contrast, exposure is weak (10-20%) in sectors intensive in cognitive task – such as knowledge intensive services – where Generative AI plays a stronger role. The joint exposure to AI and

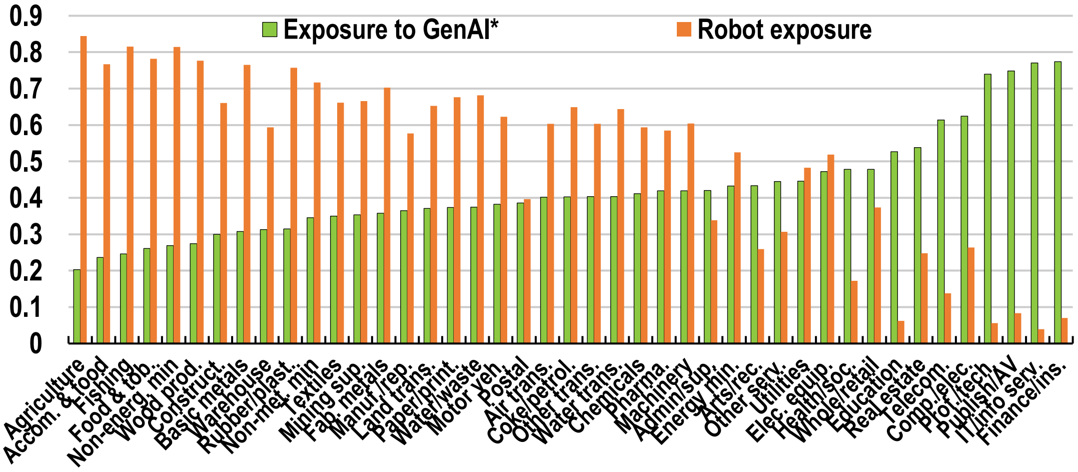
[38] See the recent case of an OpenAI powered autonomous humanoid robot which will work on a car manufacturing assembly line (Forbes Magazine, 2024).

[39] In sectors where the sum of the two different types of exposures exceeds one, we cap the combined measure – AI integrated with robotics technologies – at 1.

[40] In particular, an occupation is defined as "Manual intensive" if the share of manual tasks fall into the top tercile across all occupations. This threshold is somewhat arbitrary and making it less stringent could increase the share of manual intensive tasks. However, that would not affect our total exposure since the sum of robot and GenAI exposure reaches 100% already for most sectors. On the other hand, by using a more narrow set of manual tasks as our definition could yield a lower exposure to robots. In this sense, the values can be seen as an upper bound.

robotics – obtained as the sum of the two exposure measures – will be used in one of our scenarios denoted “*AI integrated with robotics technologies*”.

Figure 5. Sectoral exposure to Generative AI and robotics technologies



Note: *GenAI denotes the exposure measure based on Eloundou et al. (2024), expanded capabilities (as shown in Figure 4, “Exposure with additional software”; see details there). Robot exposure is obtained by the share of occupations in sectors that are in the upper tercile in terms of routine-manual task intensity, combining Acemoglu and Autor (2011), Autor and Dorn (2013) and following De Vries et al. (2020). Calculations are based on the US task-occupation-sectoral structure.
Source: Author’s calculations.

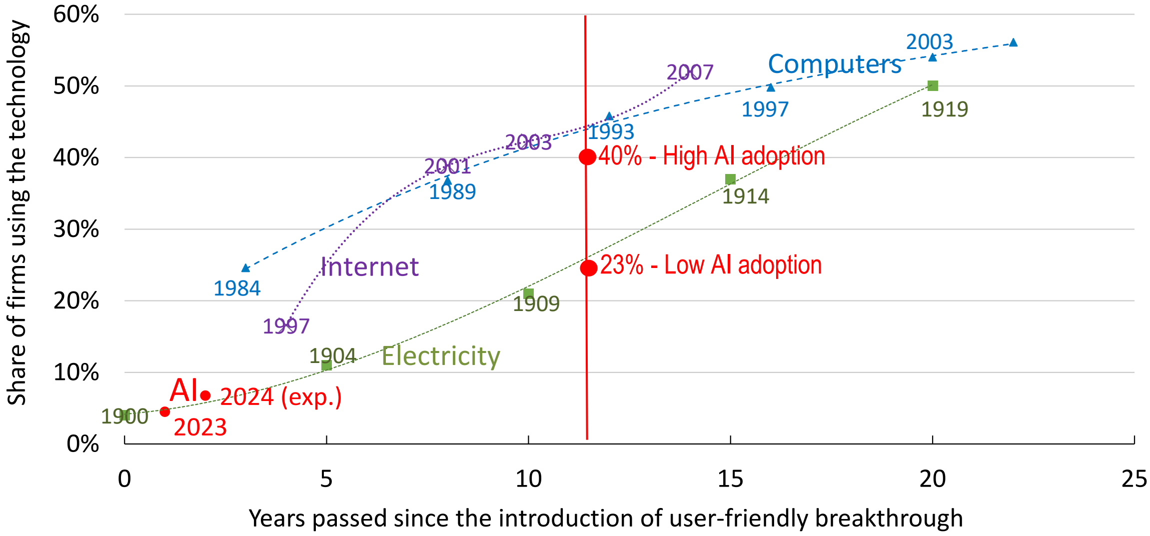
2.2.3. AI adoption: following the path of previous GPTs?

When evaluating the technology’s impact over a relatively long horizon, we need to make assumptions about its diffusion in the economy – the degree to which it is used or *adopted* among firms and workers. The assumptions of the literature shown in Table 1 range between 23% and about 50% of AI adoption 10 years from now, using various justifications.

Consistent with the literature, we focus on a 10-year horizon. To choose realistic AI adoption rates over our horizon, we consider the speed at which previous major GPTs (electricity, personal computers, internet) were adopted by firms. Based on the historical evidence, we consider two possible adoption rates over the next decade: 23% and 40% (Figure 6). The lower adoption scenario is in line with the adoption path of electricity and with assumptions used in the previous literature about the degree of cost-effective adoption of a specific AI technology – computer vision or image recognition – in 10 years (Svanberg et al., 2024; also adopted by Acemoglu, 2024). The higher adoption scenario is in line with the adoption path of digital technologies in the workplace such as computers and internet. It is also compatible with a more optimistic adoption scenario based on a faster improvement in the cost-effectiveness of computer vision in the paper by Svanberg et al. (2024).

Figure 6. Mapping AI's future adoption path with that of previous General Purpose Technologies

Share of firms using the technology, in the United States



Note: The 2024 value for AI is the expectation (exp.) as reported by firms in the US Census Bureau survey.
*We consider for the introduction of the user-friendly breakthrough variant of the technology the following: for electricity, development of electric motor; for PC, introduction of IBM PC; for AI, launch of ChatGPT. For more details, see the sources.
Source: For PC and electricity, Briggs and Kodnani (2023); for AI, United States Census Bureau, Business Trends and Outlook Survey.

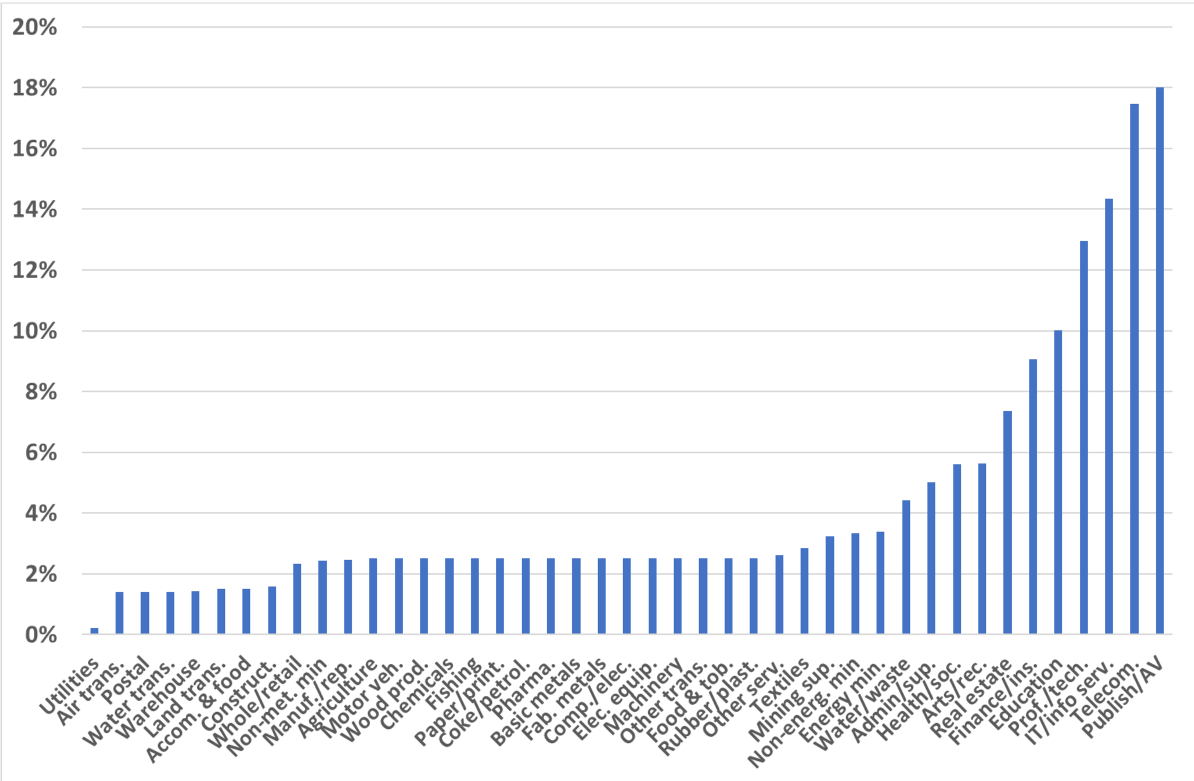
On the one hand, the assumption of a 40% adoption rate in 10 years can still be seen as somewhat conservative, since AI might have a quicker adoption rate than previous digital technologies, due its user-friendly nature. For example, when looking at the speed of another, also relatively user-friendly technology, the internet, its adoption by *households* after 10 years surpassed 50% (Figure A2 in the Annex). On the other hand, a systemic adoption of AI in the core business functions – instead of using it only in isolated, specific tasks – would still require substantial complementary investments by firms in a range of intangible assets, including data, managerial practices, and organisation (Agrawal, A., J. Gans and A. Goldfarb, 2022). These investments are costly and involve a learning-by-doing, experimental phase, which may slow down or limit adoption. Moreover, while declining production costs were a key driver of rising adoption for past technologies, there are indications that current AI services are already provided at discount prices to capture market shares, which might not be sustainable for long (see Andre et al, 2024). Finally, the pessimistic scenario might also be relevant in the case where limited reliability of AI or lack of social acceptability prevents AI adoption for specific occupations. To reflect this uncertainty, our main scenarios explore the implications of assuming either a relatively low 23% or a higher 40% future adoption rate.[41]

[41] Measuring *current* adoption rates of AI is also not straightforward. For instance, the survey of the Census Bureau asks a more specific, more narrow question about AI (was it used in core production in the last 2 weeks) which could drive the lower adoption rates obtained among US firms (around 5%) than in the EU and UK (around 10-15%) whose statistical agencies ask about AI use more generally. Differences across surveys could also reflect differences in the choice of definition about what counts as AI (Generative AI or other types of AI). Even so, within the EU, two different surveys about the same AI subfield – Natural Language Processing – yield about 5-fold differences, as documented by Hoffmann and Nurski (2021). Calvino and Fontanelli (2023) presents evidence from 11 OECD countries based on harmonised statistical code in the context of the *AI diffuse* project. Bick, Blandin and Deming (2024) presents much higher adoption rates among individuals than the official statistics, which discrepancy can be explained by the latter assessing systemic, regular use in business functions. To harmonise across countries, in Section 3.4 when we extend

The discussion up to now (captured in Figure 6) illustrates our assessment of *economy-wide* adoption rates of AI over the next 10 years. However, adoption rates will likely differ *across sectors*. In fact, current adoption rates already differ starkly across various activities, possibly reflecting a different degree of applicability and potential gains (Figure 7). Indeed, a comparison with Figure 4 on sectoral exposure rates confirms a close relationship with adoption, with knowledge intensive services (ICT and professional services in particular) showing very high exposure and adoption rates, while physical task intensive activities rank low on both measures. This positive association will motivate one of our main scenarios in which we consider the possibility that sectoral productivity gains from AI are very unevenly distributed and concentrated in knowledge intensive services with both high exposure and adoption.

Figure 7. Current differences in adoption rates of AI across sectors are large

AI adoption rates among firms by sector, in the United States



Note: The graph reports the share of firms by sector that report a regular use of AI technologies. US data are matched to ISIC industries based correspondence tables based on employment weights.
Source: US Census Business Trends and Outlook Survey (BTOS), average across waves between June and August 2024; for agriculture, a previous (December 2023) wave was used and increased by the average rise in adoption (33%) until mid-2024.

2.2.4. *The resulting sector-level productivity gains*

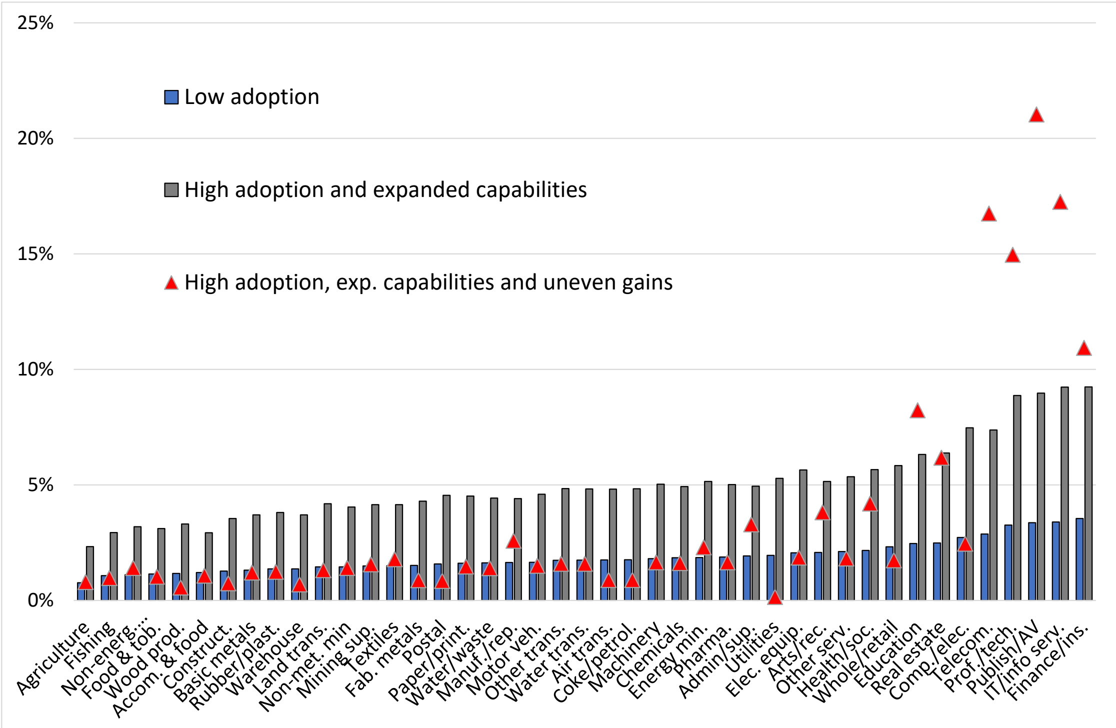
AI driven sectoral productivity gains are obtained by multiplying micro level gains with exposure and adoption (using equation 1) and are reported as the overall percentage increase in productivity over a 10-year horizon (Figure 6). They range between 1% for highly manual intensive activities (agriculture, fishing, mining) to nearly 4% in knowledge intensive services in the "*Low adoption*" case (23%). Differences across

adoption rate predictions to other countries beyond the US, we rely on preliminary results from an international survey among firms conducted by the OECD Global Forum on Productivity (OECD, 2024b).

sectors reflect heterogeneity in the baseline sectoral exposure measure, while the overall low gains reflect the low level of adoption in this scenario.

Allowing for "*High adoption* (40%) *and expanded capabilities*" (i.e. including tasks that can be performed by AI if using additional software) raises the gains but changes the ranking of exposed sectors only slightly. The implied sector-level gains in the lowest exposed sectors and the highest exposed ones vary gradually with the ranking of the sectors, ranging from slightly above 2% to almost 10% over ten years in the high adoption and expanded capabilities scenarios (Figure 8).

Figure 8. Implied sectoral total factor productivity gains from AI over a 10-year horizon



Note: The bars show the sector-by-sector value added based total factor productivity gains implied by equation 1 under various assumptions for adoption, capabilities (exposure) and micro-level gains. Low adoption assumes 23%, high adoption assumes 40% of firms adopt AI. Expanded capabilities refer to higher exposure which takes into account future potential AI capabilities when complementary digital tools become available. Uneven gains aim to get closer to the much higher dispersion and skewness observed in the data. See more details in sections 2.2.1-2.2.3.
Source: Authors' calculations.

These patterns imply AI productivity effects that vary only by a few percentage points across sectors. By contrast, the disparity of *actual* sectoral TFP growth observed during the period of the ICT boom in the US (1995-2005) is much more extreme, reaching several-fold (nearly 600%) growth in the most impacted sector (computer manufacturing) (Figure A3 in the Annex).[42] Such high TFP growth disparities, which are also observed in other countries over the same period – although to a less extreme degree; see the UK in the same figure in Annex – are suggestive of large and concentrated long-term gains of ICT in a few sectors. These sectoral productivity gains are much more uneven than what is implied by current cross-sectional variation coming from AI exposure measures (as we do in equation 1 used in our main scenarios).

[42] The large contribution of ICT producing sectors (e.g. computer manufacturing) to the ICT driven productivity boom starting in the mid-90s is analysed in Fernald (2015) and Gordon and Sayed (2020).

To better reflect the large historically observed dispersion in sectoral productivity gains as well as current, highly uneven adoption rates of AI across sectors, we also introduce a third case (also shown on Figure 8): "*High adoption*, *expanded capabilities and uneven gains*". In this case, we assume that the relative adoption rates across sectors in 10 years will be the same as today (section 2.2.3; Figure 7), while we ensure that the *average* level of sectoral productivity gains is the same as in the scenarios with more even sectoral gains.[43] By keeping the (value added share weighted) average gain fixed and by only increasing the variation across sectors, we can isolate the role of sectoral productivity dispersion.[44] This case leads to productivity gains in the most impacted sectors – knowledge intensive services – that amount to around 10-20% over 10 years.

2.3. A simple multi-sector general equilibrium model with input-output linkages

To predict how sectoral productivity gains translate into aggregate productivity growth, we need to understand how the structure of the economy changes in the wake of the sectoral productivity shocks. We will focus on changes in the sectoral allocation of factors, changes in input-output linkages between sectors, and changes in the relative sectoral output prices; under various assumptions regarding demand responses and factor reallocation.

Since we want to account for the role of cross-sectoral input-output linkages in our analysis, we turn our estimates of value-added based sectoral productivity gains into corresponding estimates of gross-output based productivity gains. The difference between value-added based productivity growth $Sectoral\ Productivity\ Growth^{VA}_{j,[t,t+10]}$ (defined in equation 1) and gross-output based productivity growth $Sectoral\ Productivity\ Growth^{GO}_{j,[t,t+10]}$ in a given sector reflects the sector's reliance on intermediate inputs:[45]

$$Sectoral\ Productivity\ Growth^{GO}_{j,[t,t+10]} = Sectoral\ Productivity\ Growth^{VA}_{j,[t,t+10]} \times (1 - Intermediate\ Input\ Share_{j,t}) \quad (2)$$

[43] This is still far from what was observed in the data during the ICT boom (several-fold increases), which motivates our more extreme case for sectoral growth dispersion in one of the alternative scenarios, to be discussed among the results in Section 3.2.

[44] Uneven sectoral gains could also be motivated by assuming micro-level gains that vary by different tasks and sectors: ICT activities are dominated by programming where AI is delivering larger performance benefits (more than 50%), while customer services are less impacted (at 14%). However, an exact matching of AI types to sectors is complicated by the fact that the current micro-level studies cover only a subset of tasks where AI might be used.

[45] Downscaling the expected productivity gains when moving to a gross output based definition of productivity is consistent with the notion that AI may lead to a smaller proportional increase in gross output when intermediate inputs play a more important role in the production process. For instance, one may expect that integrating AI in car manufacturing can improve the efficiency with which workers and assembly line machinery (i.e. labour and capital) assemble components (intermediate inputs) but that AI does not allow to assemble more cars from the same amount of components. On the other hand, one can also think of examples where AI does improve the efficiency of intermediate inputs, for example by improving their sourcing and timing which allows for just-in-time manufacturing, or by improving quality control which results in fewer defective parts and reduced waste. To the extent that AI improves the productivity of not only capital and labour but also intermediate inputs, our estimates of AI-induced productivity gains could be considered conservative.

2.3.1. The model structure

Our model corresponds to the multisector general equilibrium model in Baqaee and Farhi (2019), which features input-output links and which we calibrate to match OECD input-output tables. The specifics of the model are as follows. In each sector, i, gross output is produced by combining a single factor L_i (representing both labour and capital)[46] and a composite of intermediate inputs $\hat{X}_i$ according to

$$y_i = A_i \left(\omega_i L_i^{\frac{\theta-1}{\theta}} + (1-\omega_i)\, \hat{X}_i^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}, \tag{3}$$

where A_i denotes the level of gross-output based total factor productivity in sector i, and θ is the elasticity of substitution between factors and intermediate inputs.[47] The composite intermediate good is in turn given by

$$\hat{X}_i = \left(\sum_{j=1}^{N} \gamma_{ij}\, x_{ij}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{4}$$

where x_{ij} is output from (upstream) sector j used by (downstream) sector i as intermediate input, γ_{ij} are weight parameters over upstream sectors that add up to one, $\sum_{j=}^{N} \gamma_{ij} = 1$, and ε is the elasticity of substitution across intermediates.

Final demand Y is represented by a constant elasticity of substitution (CES) aggregator over sectoral final consumption c_i (obtained as the difference between sectoral total output y_i and total use by other sectors as intermediates $\sum_{j=1}^{N} x_{ji}$):

$$Y = \left(\sum_{i=1}^{N} \alpha_i\; c_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{5}$$

where $\sum_{i=1}^{N} \alpha_i = 1$ and σ is the elasticity of substitution across final consumption outputs.

The model requires specifying three distinct structural elasticities: the elasticity of substitution in consumption, σ, the elasticity of substitution between factors (labour and capital) and intermediate inputs in production, θ, and the elasticity of substitution between different intermediate inputs, ε. We choose these parameters based on relevant estimates from the literature. We then calibrate the share parameters ω_i, α_i

[46] An important question is whether output can be produced with higher capital intensity following the introduction of AI. This depends on whether the technology is labour or capital augmenting. Given current AI capabilities and its early use, it is very difficult to determine to what extent AI augments or substitutes human capabilities, as Autor et al (2024) also stresses in their concluding remarks and in line with conclusions in OECD (2023c). In addition, which of the two effects dominate also crucially depends on policy choices about AI's development and use (Acemoglu, Autor and Johnson, 2023). A related important question is whether productivity gains in a given profession or sector will lead to employment growth or shrinkage. In equilibrium, this depends on the demand for the output of that activity and the labour required to satisfy that demand. Our model captures these two opposing forces by modelling increased demand when prices decline following the rise in productivity, as well as the reduced labour requirement to produce a given output following the rise in productivity.

[47] An alternative modelling strategy is to have A_i represent value-added based productivity that augments factors but not intermediates, i.e. having A_i multiply L_i. The two approaches imply quantitatively similar results for the aggregate productivity gains from AI.

and , γ_{ij} to match observed sectoral factor shares, expenditure shares as well as the economy-wide input-output table, respectively.

Solving the model implies finding equilibrium prices and quantities and determining the implied sectoral allocation of intermediate inputs and factors at given sectoral productivity levels. The difference in aggregate real output between the pre- and post AI equilibria yields our model-based prediction for the aggregate TFP gains from AI. We then decompose the growth rate in aggregate TFP as follows:

$$\frac{\Delta \mathrm{TFP}}{TFP} = \underbrace{\sum_{i \in I} s_{i0}^{VA} \frac{\Delta \mathrm{A_i}}{\mathrm{A_i}}}_{Direct\ effect} + \underbrace{\sum_{i \in I} (\lambda_{i0} - s_{i0}^{VA}) \frac{\Delta \mathrm{A_i}}{\mathrm{A_i}}}_{Role\ of\ I-O\ links\ (I-O\ multiplier)} + BaumolEffect \qquad (6)$$

where s_{i0}^{VA} is the initial nominal value added share of sector *i* and λ_{i0} is the initial Domar weight - defined as sector *i* 's nominal gross output over GDP ($\frac{p_{i0} y_{i0}}{P_0 Y_0}$).[48] Capital accumulation is not modelled explicitly, so to obtain labour productivity effects from TFP effects, we apply a multiplier of 1.5 consistent with standard growth models with a Cobb Douglas production function and a capital and labour share of 1/3 and 2/3, respectively.[49]

The direct effect is the sum of the sectoral productivity gains with each sector weighted by its value-added share. The I-O multiplier is constructed by first computing the sum of the sectoral productivity gains with each sector weighted by its gross sales over GDP (i.e., its Domar weight) and then subtracting the direct effect. The input-output multiplier arises as one sector's productivity gains also helps to expand the productive capacity of other sectors by lowering the input prices that they face. Finally, the Baumol effect – which captures the role of structural change – is derived by subtracting the sum of the direct and indirect effects from the overall macroeconomic effect. In this we follow Baqaee and Farhi (2019) who interpret Baumol's growth disease as the discrepancy between within-sector productivity growth, aggregated at fixed nominal output shares and actual aggregate productivity growth.

In Annex 1, we use a simplified model without input-output linkages to derive two key insights that also apply to our main model. The first insight is that aggregate productivity gains are diminished if productivity growth differs starkly across sectors. The second insight is that differential growth rates slow down aggregate productivity growth more if demand is relatively inelastic (goods are strong complements), and if factors of production cannot easily be reallocated towards sectors where they are most needed. These mechanisms will be illustrated by the model predictions discussed under various scenarios (Section 3.1-3.2).

2.3.2. Assumptions on structural elasticities and calibration to the input-output tables

On the production side, we assume that the elasticity of substitution between factors and intermediate inputs is 0.5, following Atalay (2017) and Baqaee and Farhi (2019). Further, we assume that the elasticity of substitution between intermediate inputs is 0.0008. This low value is justified by the relatively strict

---

[48] We abstract from modelling changes in the aggregate employment rate (or unemployment) which can be motivated by our long (10-year) long horizon focus.

[49] A multiplier of 1.5 is consistent with the historical ratio of labour productivity growth to TFP growth over the past five decades in the US (Bergeaud, Cette and Lecat, 2016). This is similar to Acemoglu (2024) who also focuses on TFP and obtains labour productivity effects by applying a simple multiplier capturing capital deepening based on recent capital share data from the US, resulting in a somewhat higher multiplier of 1.75. Modelling capital explicitly would allow to separately study the cross-sectoral reallocation of labour and capital, which would allow for an additional margin of adjustment across sectors even if labour allocation is assumed to be limited, thereby reducing the drag from the Baumol effect.

technical requirements that are needed to produce a given good or service and is in the neighbourhood of what Baqaee and Farhi (2019) use.[50]

Finally, for the elasticity of substitution in consumption, we consider different scenarios (summarised in Table 2 in the next section). In our baseline scenario, we assume an elasticity of 0.72 so that the final goods produced in different sectors are gross complements (i.e. the relative demand for the goods and service produced across different sectors reacts less than one-to-one to changes in relative sectoral output prices).[51] As an alternative scenario, we consider the possibility that demand is extremely inelastic so that even a steep drop in prices would only lead to a small increase in demand. In our context of AI-driven productivity shocks, we interpret this case as a demand rigidity in the face of AI, or simply low additional demand for AI-powered goods and services. To study this possibility, we set the elasticity to a very low level of 0.01.

Given these assumptions on structural microeconomic elasticities, we calibrate all the weight parameters in the model to match observed sectoral factor shares, value-added shares, as well as empirical input-output tables which we visualise in Figure 9 for the United States. The figure highlights the important role of a number of knowledge intensive services (finance, ICT services and professional services) as inputs to the production in many other activities. This is significant since it is exactly these sectors that are highly exposed to AI (Figure 4 on exposure), implying substantial spillover gains to their downstream sectors (Calligaris et al, 2023; Acemoglu, Akcigit and Kerr, 2023).[52]

An important question is how sectoral productivity gains translate to macro level gains depending on whether factors of production (labour and capital) can easily be reallocated across sectors. To highlight the role of factor mobility, we consider the extreme cases: one where factors are perfectly mobile and can be reallocated across sectors at no cost, and one where each sector can only use the factors available prior to the AI-driven productivity gains. In the second case, all the adjustments must occur through changes in the input-output structure of the economy as well as through changes in relative prices.[53]

[50] They use 0.001 which we downscale by 20% given our more aggregate sectoral structure available in cross-country IO tables – 40 sectors – compared to what Baqaee and Farhi (2019) use – more than 80 sectors. The idea is that the production structure of intermediates is even more restricted (implying even lower elasticities of substitution) when a more course aggregation is considered. However, keeping the original value barely changes the model predictions.

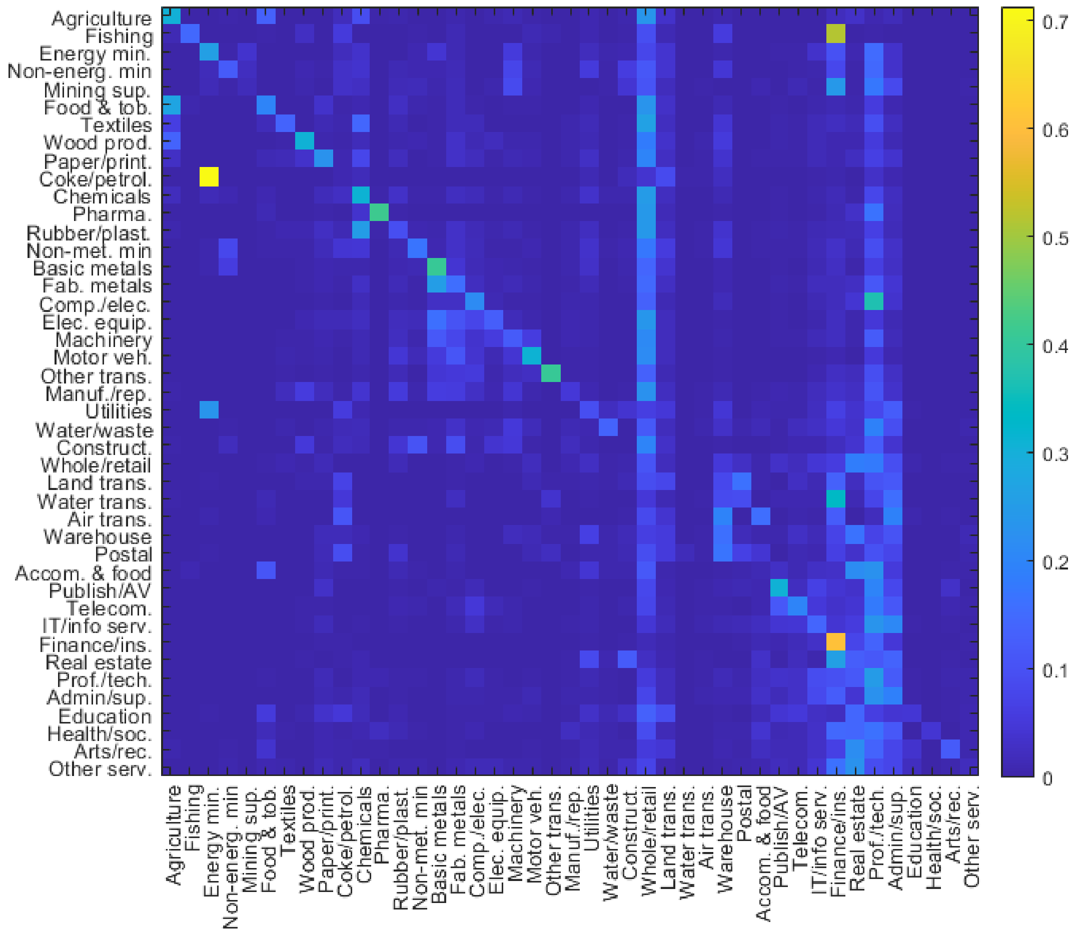
[51] Again, for similar arguments related to a courser sectoral structure, we use a 20% lower figure than in Baqaee and Farhi (2019).

[52] We use the latest available data from 2019 for the calibration exercise. This could downplay the importance of the ICT sector, given the COVID-19 pandemic related surge in digital technology use – hence potentially lower the AI driven productivity boost to the extent its benefits are transmitted across the economy through ICT.

[53] Extending our 10-year horizon to longer periods would be compatible with higher elasticities on the production side and greater factor mobility, as there is more room for the economy to adjust. Currently, we do not model partial factor mobility or differentiation between types of factors (labour and capital). These extensions would result in scenarios that fall between the two extremes of full factor mobility and restricted mobility. This is true for the case of allowing capital to move more freely than labour: it would provide an additional adjustment channel for the economy compared to the fully restricted capital mobility case and would also yield a scenario in between the two extreme cases.

Figure 9. Illustrating input-output linkage intensities across detailed sectors

The case of the US (2019)



Note: Each cell of this heatmap shows the share of the row sector's intermediate inputs that are sourced from the given column sector. By construction, the values in each row sum to 1. As an example, sector Coke/petrol. (*c19* in the ISIC Rev 4 classification system "Manufacture of coke, and refined petroleum products") sources the vast majority of its intermediate inputs from sector *Energy minerals* (*b05*, "Mining and quarrying, energy producing products"). Similarly, many sectors source a significant share of their intermediate inputs from sector *Prof./tech. (m*, "Professional, scientific and technical activities"). Note that beyond the *composition* of intermediate inputs, sectors also differ in their *overall* intermediate input use intensity which is not shown in this chart. Public administration is (ISIC Rev4. O) is omitted, following Baqaee and Farhi (2019), and given that public sector issues are outside the scope of our analysis.
Source: OECD Input-Output tables, United States.

3. Model estimates of AI's impacts on aggregate productivity

3.1. Main scenarios

Table 2 summarises our main scenarios and the underlying assumptions, which reflect various combinations of the model ingredients (parameters), estimates from the literature (on exposure and micro-level gains) and experience with previous GPTs (on adoption), as discussed in Section 2. We annualise the 10-year overall TFP gains predicted by the model to derive annualised growth rates, which for ease of exposition we interpret as additional percentage point boosts to aggregate TFP, relative to a baseline aggregate TFP growth.[54] The next subsection will present a few additional scenarios that isolate further the role of certain structural features and illustrate the effect of more extreme assumptions (see Table 3).

Table 2. Main scenarios and underlying assumptions

Scenarios	*1. Low adoption*	*2. High adoption and expanded capabilities*	*3. Scenario 2 with adjustment frictions and uneven gains across sectors*
Assumptions			
Micro-level gains from AI	30%	30%	30%
Exposure to AI	Eloundou et al. (2024), baseline	Eloundou et al. (2024), expanded AI capabilities	As in 2.
AI adoption	23%	40%	Uneven across sectors following current adoption rate differences, while keeping the cross-sectoral average gain unaffected
Factor allocation across sectors	Mobile / fully flexible	Mobile / fully flexible	Restricted
Demand	Standard	Standard	Inelastic
Results for aggregate annual TFP growth (in p.p.)			
Direct effect	0.14	0.37	0.38
Input-output multiplier	0.09	0.25	0.24
Baumol effect	0.00	0.00	-0.08
Total effect	0.24	0.62	0.53
Results for annual labour productivity growth (in p.p.)* *Total effect*	0.36	0.93	0.8

Note: See more details in the text. Assumptions for the elasticity of substitution across intermediate inputs and between intermediates and factors remain the same across the three scenarios and are described in subsection 2.3.1. The numbers are rounded to the nearest 2-digit decimal.
* The labour productivity growth effects are calculated by assuming a standard multiplier of 1.5 to account for capital accumulation (see Section 2.3.1).
Source: Authors' calculations.

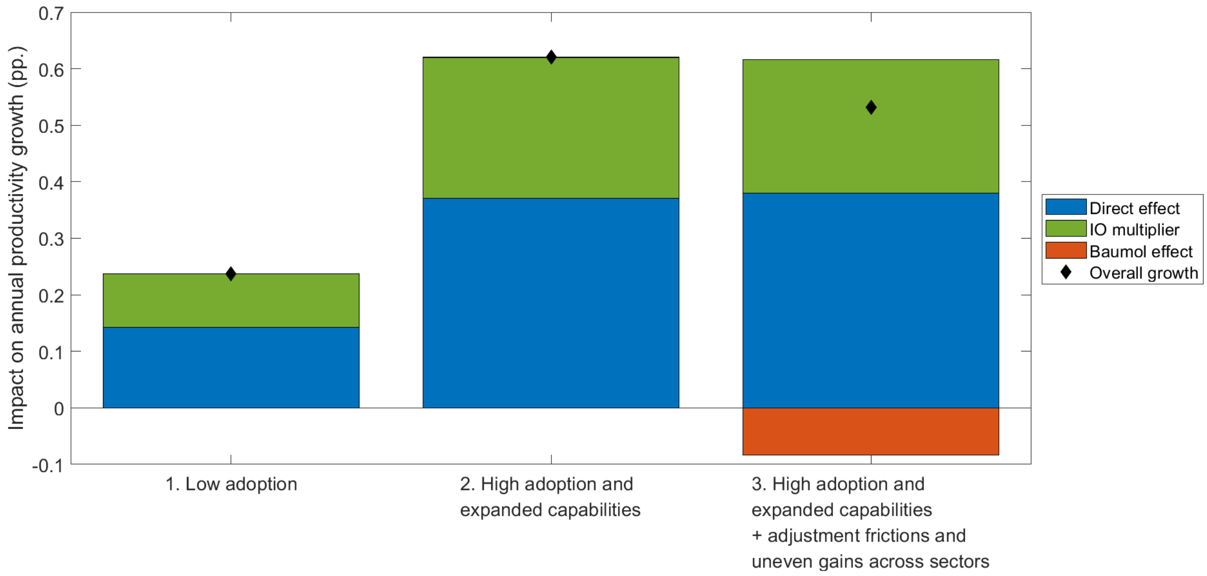
Figure 10 shows the estimated effects of AI on aggregate TFP for our main scenarios, reported as *annualised* growth over a 10-year horizon. The results in Figure 10 come from a calibration of the model to the US economy. In the first scenario with "*Low adoption*" (at 23%), we project AI to generate a 0.24 percentage points boost to annual TFP growth over the next 10 years. The direct effect of productivity increases at the sectoral level accounts for slightly more than 0.14 percentage points of annual growth. This direct effect is compounded by an input-output multiplier effect as productivity gains in one sector benefit the other sectors through reduced costs of intermediate inputs. Our estimates of the macroeconomic productivity gains from AI are somewhat larger than what Acemoglu (2024) has found, owing primarily to the fact that we use a more comprehensive measure of exposure from Eloundou et al.

[54] Note that given the low growth rates involved in the calculations, a percent increase can also be interpreted as a percentage point boost because the two are nearly identical.

(2024) and that we interpret the documented microeconomic gains as total cost savings rather than only labour cost saving. Compared to Briggs and Kodnani (2023) who project around 1pp annual TFP growth increase[55], our estimates are significantly smaller both due to lower adoption and lower exposure assumptions (see Table 1). For a more extended comparison of our estimates with those in the literature – in terms of the labour productivity effects – see Figure A.10 in Annex A.

Figure 10. Main results on long-run aggregate TFP gains from AI

Annualised productivity growth impacts over 10-years (in percentage points, calibrated for the US)



Note: See details in the text (Table 2) for the description of the three scenarios.
Source: Author's calculations.

In the second scenario with "*High adoption and expanded capabilities*", we consider the possibility of higher adoption rates (40%) and expanded AI capabilities (i.e. more tasks exposed to AI). In this case, the direct effect of sectoral productivity gains alone implies 0.37 percentage points of annual TFP growth over the next 10 years. Accounting for spillovers along input-output linkages increases the annual TFP gains to about 0.61 percent. Hence assuming higher adoption and exposure results in larger differences from Acemoglu's (2024) main estimate but still substantially lower than Briggs and Kodnani (2023).

In the third scenario, which adds "*adjustment frictions and uneven gains across sectors*", we consider various impediments that could limit the extent to which sectoral productivity gains translate into macroeconomic productivity growth. First, we consider the possibility that sectoral productivity gains are more unevenly distributed (see Figure 8 and the discussion in Section 2.2).[56] Further, we restrict the sectoral reallocation of labour and capital, but assume that firms continue to be able to freely adjust their use of intermediate inputs. Finally, we also introduce the possibility that demand for products and services from AI-powered sectors is limited (see for details Subsection 2.3.1). With these adjustment frictions in

[55] Implied when applying a standard capital multiplier of 1.5 in an inverse manner, to their baseline 1.5pp annual labour productivity growth effect.

[56] In the scenario with uneven sectoral gains, we keep the value-added share weighted mean of sectoral productivity gains fixed so that the direct effect of AI (the blue bar) remains constant.

place, and under uneven sectoral gains, our model predicts that aggregate productivity growth drops by about one-sixth relative to the frictionless benchmark due to Baumol's growth disease.

Interestingly, the Baumol effect arises only in the third scenario. This is the case because the assumed productivity gains in the first two scenarios are relatively evenly distributed across sectors (see Figure 4). In addition, these scenarios also assume a frictionless economy in which factors and intermediate inputs can be freely reallocated to sustain production in less-AI exposed sectors, and where demand is relatively elastic with consumers willing to substitute the consumption of goods and services produced in less AI exposed sectors with the consumption of output from sectors that experience strong productivity gains.

During previous GPT waves, in particular during the ICT boom episode, highly uneven productivity performance resulted in a substantial drag on aggregate productivity growth (Box 1). Over the very long term, spanning multiple technological waves across several decades, a similar phenomenon has been observed as productivity growth in manufacturing outpaced productivity growth in services, and the associated Baumol effect implied a persistent moderate drag, on the order of 0.3-0.5 percentage points per year.[57] With AI, the performance boost in some knowledge intensive services may significantly outpace others, which may yield a similar disparity of performance improvements across sectors and act as a drag on aggregate growth. As Aghion, Jones and Jones (2019) put it when assessing the potential of AI to significantly accelerate growth: *"Economic growth may be constrained not by what we do well but rather by what is essential and yet hard to improve".* Our analysis aligns with this view, suggesting that for AI to generate larger and more sustained productivity gains in the long run, AI would need to improve productivity across a wide range of activities.[58]

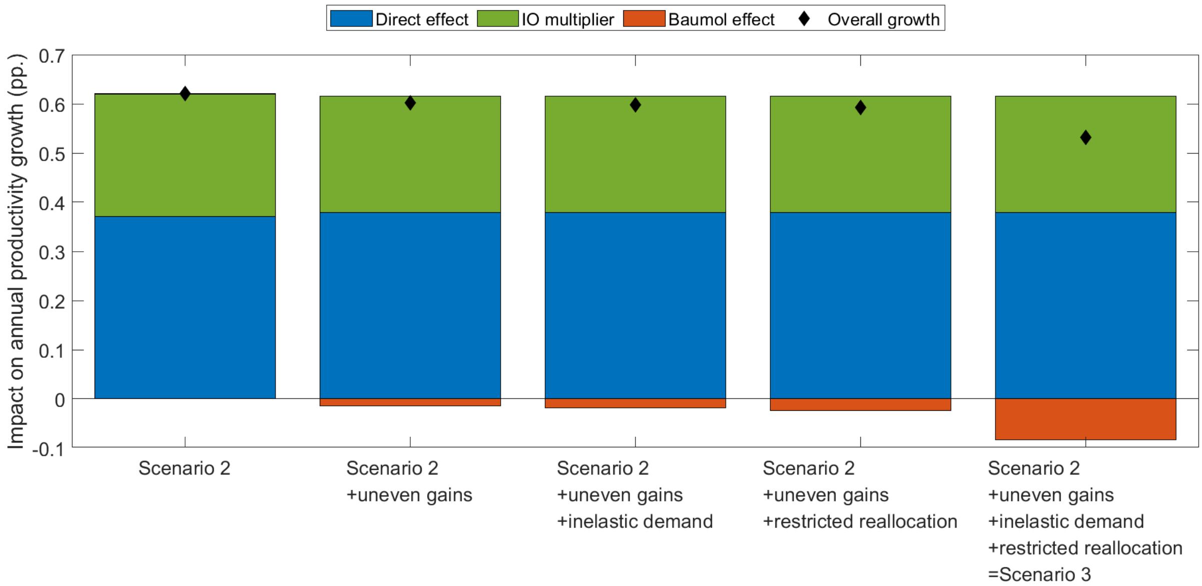
Figure 11 presents auxiliary scenarios that shed light on the relative importance of uneven sectoral gains, inelastic demand, and reallocation frictions in producing the Baumol effect. The figure shows that a large Baumol effect appears only when we assume inelastic demand and significant frictions on top of uneven sectoral gains. The reason is that in the absence of reallocation frictions, the economy can better accommodate uneven sectoral productivity growth by redeploying capital, labour, and intermediate inputs to increase output also in the sectors of the economy that did not benefit from strong productivity gains yet produce goods and services that consumers value (non-AI exposed activities).

[57] Nordhaus (2008) cites a 0.5pp per year drag over 1950-2000, and Baqaee and Farhi (2019) mention a cumulative 19pp over 70 years (approximately 0.3 pp pear year).

[58] AI may accelerate the rate of growth through raising the productivity of research and innovation itself, which our framework does not allow to investigate.

Figure 11. The role of different assumptions about sectoral gains, demand, and reallocation frictions

Annualised productivity growth impacts over 10-years (in percentage points, calibrated for the US)



Note: For Scenario 3 and Scenario 3 (last bar), see Table 3. For more details about the intermediate cases, see the text.
Source: Authors' calculations.

Box 1. How factor reallocation and changes in relative output prices affect aggregate productivity growth: exploring the drivers of Baumol's growth disease

As some sectors experience higher productivity growth than others, both historical experience as well as the model in this paper suggest that labour will tend to reallocate from the high- to the low-growth sector (historically, from manufacturing to services) and that the low-growth sector grows as a share of GDP (Nordhaus, 2008). Rising GDP shares of low-growth sectors imply that aggregate productivity grows less than what might be expected given sectoral productivity gains. This phenomenon is typically called "Baumol's growth disease".

What are the drivers of this drag? To shed light on this issue, Annex 2 derives an aggregate labour productivity (LP) growth decomposition, which yields the following relationship:

$$\underbrace{\frac{LP_t - LP_0}{LP_0}}_{\substack{Aggregate\ real \\ LP\ growth}} = \underbrace{\sum_{j\in J} s_{j0}^{VA}\left(\frac{LP_{jt} - LP_{j0}}{LP_{j0}}\right)}_{Within-industry\ effect} + \underbrace{\sum_{j\in J} \Delta w_{jt}\frac{LP_{jt}}{LP_0}}_{Labor\ reallocation\ effect} + \underbrace{\sum_{j\in J} w_{jt}(\Delta p_{jt})\frac{LP_{jt}}{LP_0}}_{Valuation\ effect} \quad (7)$$

where s_{j0}^{VA} is the initial (nominal) value added share of sector j, LP_{jt} is real labour productivity in sector j that is normalised to 1 in period 0, and $\Delta w_{jt} = \frac{L_{jt}}{L_t} - \frac{L_{j0}}{L_0}$ is the change in the employment share of sector j.

Since labour tends to move from high to low growth sectors, the labour reallocation term tends to be negative. Would preventing the reallocation of factors to low-growth sectors therefore improve aggregate productivity growth? On the one hand, preventing labour from moving to the low growth sector increases aggregate productivity growth by setting the second term in equation (6) to zero. On the other hand, preventing factor reallocation also affects relative output prices and aggregate productivity growth through a valuation effect (the third term). Using a simple general equilibrium model, we show in Annex 1 that not allowing for reallocation implies that the additional drag going through the valuation effect exceeds the gains from labour remaining in the high-growth sector. Hence, preventing the reallocation of factors to low-growth sectors can increase rather than decrease the Baumol effect.

The interpretation is that without factor reallocation equilibrium in the goods markets must be achieved entirely through changes in relative output prices. Specifically, the prices in the sectors with higher productivity growth need to decline more to ensure that demand meets the increased supply. As a result, even though output evaluated at initial prices would be larger if factors were kept in the high-growth sector, aggregate real GDP growth would be lower because the implied changes in relative output prices would lead to a steeper reduction in the output share of the high-growth sectors. We also confirm this interpretation in the model (see Figure A7 in Annex 3).

To demonstrate the importance of accounting for changes in relative output prices in practice when aggregating long-run sectoral productivity growth, we implement this decomposition formula on EUKLEMS & INTANProd data over the 12-year period from 1995 to 2007 in the US, which includes what is often characterised as the ICT driven boom (Fernald, Inklaar and Ruzic, 2024). Our calculations show that the Baumol drag has a quantitatively important effect on aggregate real labour productivity growth over a medium- to long run period (in line with findings by Nordhaus (2008) and Baqaee and Farhi (2019) over longer horizons preceding our sample) and that the valuation effect in particular plays on important role (Figure 12).[59] In fact, using a formula that does not account for the valuation effect but only the labour reallocation effect would result in a higher aggregate real labour productivity growth (53.5% - 13.1% = 40.4%) than the correct aggregate (26.9%), by about 50%, which is a large discrepancy.

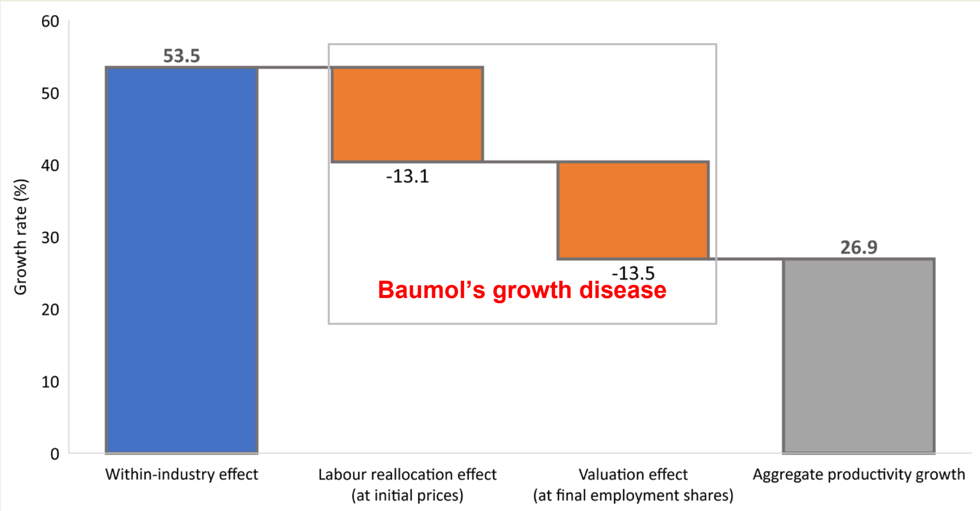
Together, the labour reallocation and the valuation effects imply that sectors with large productivity gains, on average, saw their share of GDP moderately decline over the period 1995-2007.[60] Many other OECD countries have experienced a similar phenomenon (Annex Figure A4), although to a lesser degree since the US productivity performance was more concentrated in certain sectors (ICT) compared to other countries – which led to a stronger Baumol effect in the US.[61]

[59] The label “Baumol effect”, as used here, refers to the discrepancy between aggregate productivity growth and within-industry productivity growth. Alternatively, one could reserve the label for the effect of reallocation from high to low-growth sectors and distinguish it from the effect of reallocation across sectors with different productivity *levels*, which we do not do here (Tang and Wang, 2004).

[60] Note that reallocation of factors from high to low-growth sectors is a longer-term sector-level phenomenon. Other types of reallocation dynamics operate at the sub-sectoral level and over shorter horizons. See Calligaris (2023) for a recent analysis of the effect of productivity on employment at various levels of aggregation.

[61] Note also that the Baumol effect appears to have been particularly pronounced in the period 1995-2007, with much smaller effects found when the decomposition is applied to more recent time periods.

Figure 12. Decomposition of aggregate labour productivity growth covering the ICT boom period in the US (1995-2007)



Note: Decomposition using equation (7). The sum of the labour reallocation and valuation effect can be considered as the drag arising through Baumol's growth disease. An alternative decomposition that evaluates labour reallocation at final prices assigns an even large role for the valuation effect.
Source: Authors' calculations using the EUKLEMS & INTANProd database.

3.2. Additional scenarios

In addition to our three main scenarios discussed above, we also consider two additional scenarios with more extreme assumptions. Scenario 4, titled "*Large and concentrated gains in most exposed sectors*" (Table 3 and Figure 13), assumes that the variation in sectoral gains is even larger than in our third main scenario. Specifically, it assumes that the top four exposed sectors – ICT services, publishing, professional services and finance – experience a 100% micro level gain instead of the previously assumed 30%; while all other sectors have only the minimum gains that were measured in micro studies (14%; see Figure 3 in Section 2.2.1). Two observations motivate this choice as a plausible case, even if less likely than our main scenarios. First, in our review of the micro-level literature (Figure 3), a central task in ICT services, coding, received more than a 50% productivity boom in controlled experiments by Peng et al. (2023) and Gambacorta et al. (2024), which could increase further with future improvements in AI capabilities. Second, during the previous, ICT driven boom, *sectoral* productivity gains reached *several fold* increases in the most impacted activities, such as computer manufacturing (US) or ICT services (UK) (Figure A3 in the Annex).

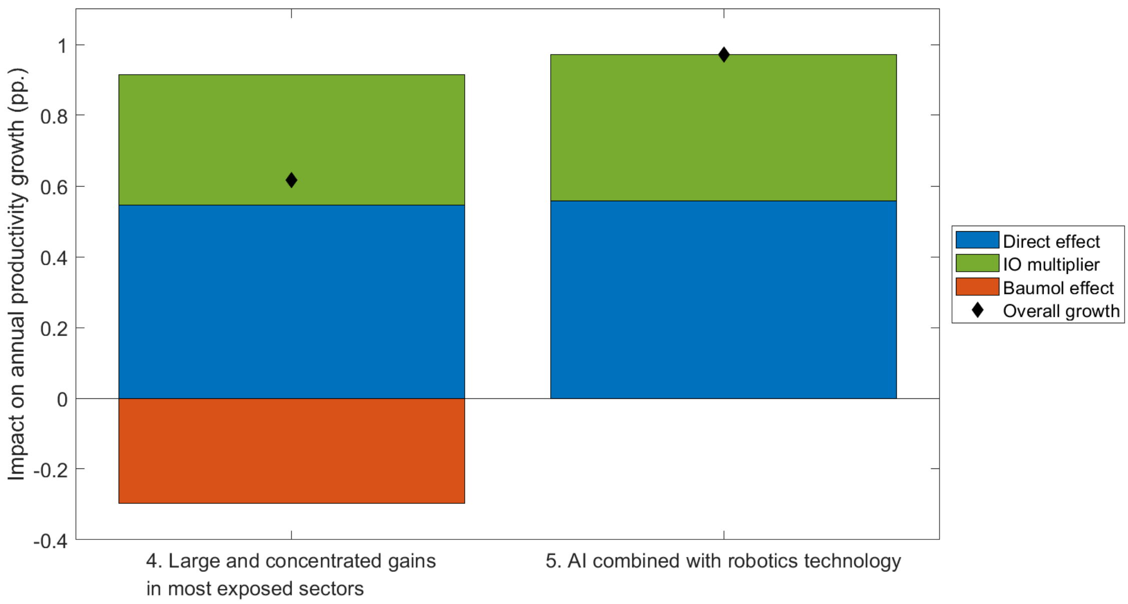
Table 3. Additional illustrative scenarios and their underlying assumptions

Scenarios	*4. Large and concentrated gains in most exposed sectors**	*5. AI combined with robotics technology*
Assumptions		
Micro-economic performance gains	100% in the three most exposed sectors and 14% in all other sectors	30%
Exposure	Eloundou et al. (2024)	Eloundou et al. (2024) expanded capabilities, combined with the share of physical tasks**
Adoption	40%	40%
Factor allocation across sectors	Restricted	Restricted
Demand	Inelastic	Inelastic
Results for aggregate annual TFP growth (in p.p.)		
Direct effect	0.55	0.56
Input-output multiplier	0.37	0.41
Baumol effect	-0.30	0.00
Total effect	0.61	0.97
Results for annual labour productivity growth (in p.p.)* *Total effect*	0.92	1.4

Note: See more details in the text. The numbers are rounded to the nearest 2-digit decimal. *We select the four most exposed sectors, which are ICT services, finance, professional services and publishing and media. **The share of physical tasks is taken as a proxy measure for capturing the potential impact of robots in production. See more in Section 2.2.2 describing assumptions about AI exposure. ***The labour productivity growth effects are calculated by assuming a standard multiplier of 1.5 to account for capital accumulation (see Section 2.3.1).
Source: Authors' calculations.

Figure 13. Large and concentrated AI gains vs. widespread gains due to integration with robotics technology

Annualised productivity growth impacts over 10-years (in percentage points, calibrated for the US)



Note: These estimates correspond to Scenario 4 and 5 as defined in Table 3.
Source: Authors' calculations.

This scenario shows an important drag through the Baumol effect (around 0.3 percentage points; the red bar), which amounts to a decline of about a third of the productivity boost given by the direct and I-O multiplier effects (0.92 pp; the sum of the blue and green bars). This arises due to the combination of uneven sectoral gains *and* limited reallocation and unresponsive demand. These are not negligible risks given historical experience on the size of the Baumol effects (Box 1), the strong concerns about AI's especially disruptive role in labour markets and the difficulties in managing those (Acemoglu, Autor and Johnson, 2023; OECD, 2023c) and the low social acceptability of AI in certain economic activities which can limit demand (Cazzaninga et al, 2024).

Finally, Scenario 5 (Figure 13) illustrates the situation where AI will be combined with or integrated into robotics technologies, denoted "*AI combined with robotics technology*". We estimate the resulting aggregate TFP gains amount to nearly 1 percentage point annual gains, a large number, without any drag from Baumol type effects, given the very widespread and relatively equal productivity gains across sectors.

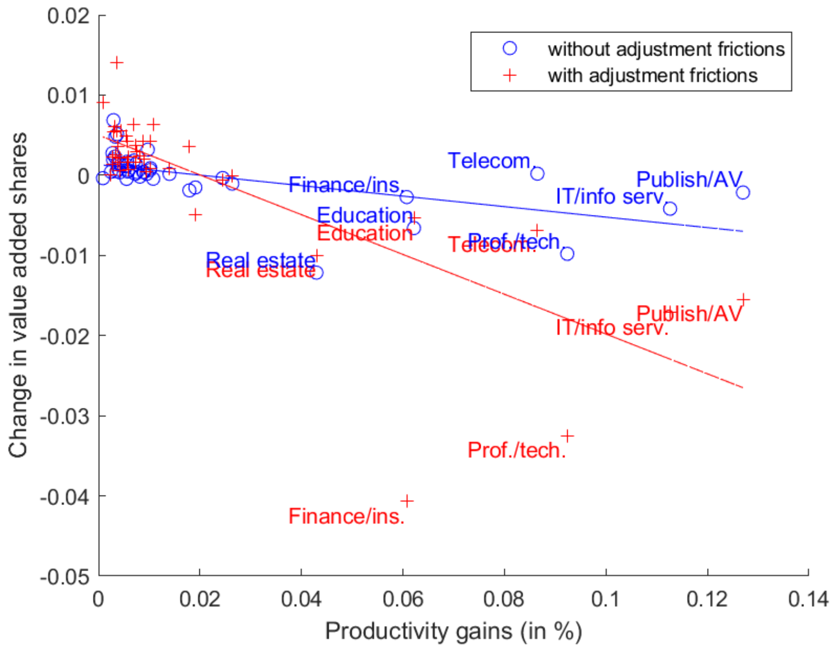
3.3. Sectoral patterns

The sectoral granularity of the model predictions can be used to illustrate some key mechanisms at play that give rise to the Baumol effect in some of our scenarios. In particular, the importance of frictions can be illustrated through sector-level outcomes.

Figure 14 plots the change in sectoral value-added shares against sectoral productivity growth rates, separately for a scenario with and without adjustment frictions arising from limited sectoral reallocation of factors and very inelastic demand. In both scenarios, sectors with larger productivity gains tend to experience declining nominal output shares. This reflects both falling relative prices as well as factor reallocation away from these sectors as less labour is needed to meet demand in these sectors. Clearly, however, the negative correlations are stronger in the presence of frictions, indicating that the economy is less able to translate (uneven) sectoral productivity growth into aggregate productivity gains. The reason is that with inelastic demand and without cross-sectoral reallocation of labour and other factors, prices would need to fall more strongly to induce sufficient demand for the increased output from the sectors with large productivity gains (see Annex 1 for a formal argument). This relative price decline more than offsets the increased production, leading to a larger drop in the most exposed sector's nominal value-added share.

Figure A8 shows the sectoral contributions to aggregate productivity and further disaggregate them into direct effects and indirect effects going through lowered input prices.

Figure 14. Sectoral correlations of productivity gains and changes in value-added shares



Note: The case with reallocation frictions and inelastic demand corresponds to Scenario 3 (Figure 8 and Table 2). The case without frictions and rigidities assumes that that factors can freely be reallocated across sectors and that the elasticity of substitution in demand is high (Figure 11, 2nd bar). In both cases, a sector's productivity growth is derived under the assumption of high adoption rates, expanded capabilities and uneven gains, and downscaled by the sector's factor share.
Source: Authors' calculations.

3.4. *Country-specific results*

The results presented so far pertain to the US context, given that most current estimates on AI's micro-level impacts (on productivity and exposure) originate from there. However, under the assumption that task-level gains from AI and tasks performed by workers in different occupations are the same across countries, we can extend the results to other countries using I-O tables and the occupation composition of sectors, in combination with assumptions about future AI adoption. More specifically, we rely on the following three sources of cross-country variation to obtain country specific predictions for a few major economies with readily available data.[62]

First, we estimate country specific future AI adoption rates by relying on the currently observed adoption rate differences across countries. These reflect cross-country differences in digital infrastructure, human capital, and other structural features, as also captured by the AI Preparedness index compiled by Cazzaniga et al. (2024) and illustrated by its strong correlation with observed adoption rates across countries (Figure A9 in Annex 3).[63] Accordingly, we extrapolate the *relative differences* in adoption rates across countries over the next 10 years and use the US future adoption rate (Section 2.2.3, Figure 4) as

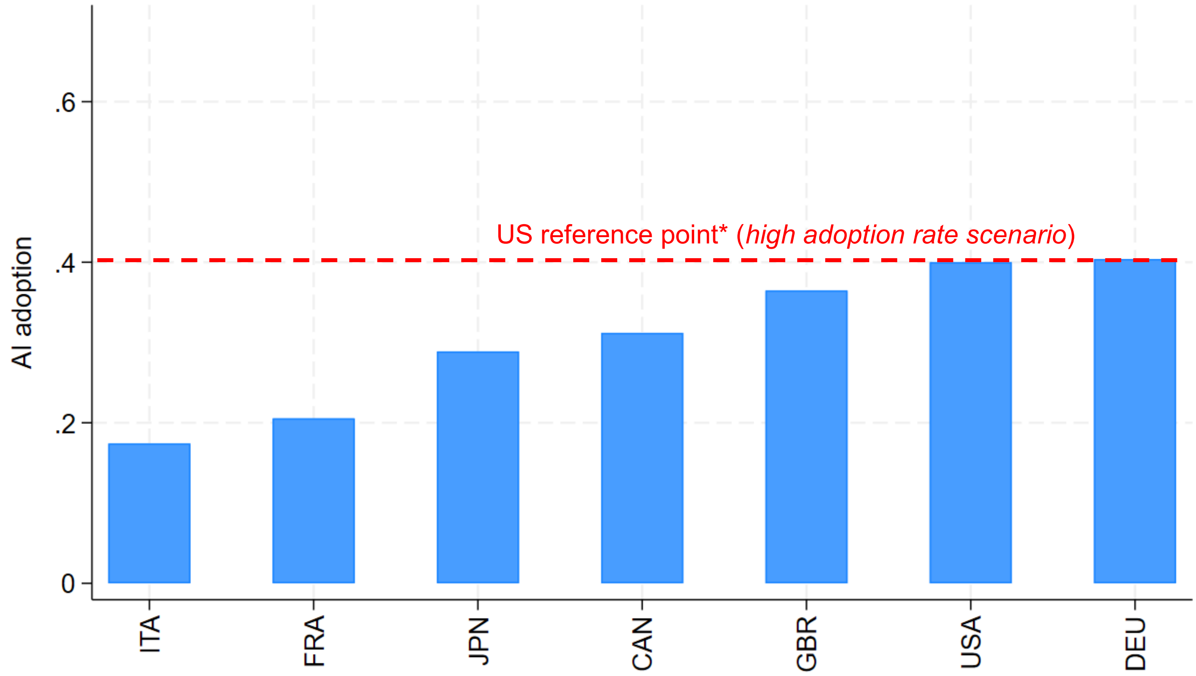
[62] This covers the set of G7 economies, which can potentially be extended in future work which would account explicitly for international trade linkages.

[63] The relationship is strong but imperfect, as the Figure shows: current adoption rates are lower than what is implied the AI readiness index for some countries (France and Japan), which may indicate that adoption is expected to rise faster in the future than assumed by our experiment. This would lead to correspondingly higher predicted productivity gains for these countries than what is shown on Figure 16.

the reference point.[64] As a consequence, earlier adopting countries will preserve their lead in the future, consistent with having more advanced digital capacity, skills and regulatory stance with new technologies. The implied cross-country differences in future adoption rates are large and range from less than 20% in Italy to 40% in Germany (Figure 15).

Figure 15. AI adoption rate assumptions across countries

The share of firms assumed to adopt AI in 10-years



Note: *The US future adoption rate assumption is taken from Figure 6 on adoption. This serves as a reference point to derive the numbers for the other countries, based on the observed cross-country variation in *current* adoption rates, which correlates very strongly with the AI Preparedness Index compiled by Cazzaninga et al. (2024). See more details in the text.
Source: Authors' calculations relying on Eurostat (for capturing variation within European countries) and preliminary results from the Global Forum on Productivity survey on AI use in companies (for capturing the variation across US, Europe, Canada and Japan; OECD, 2024b).

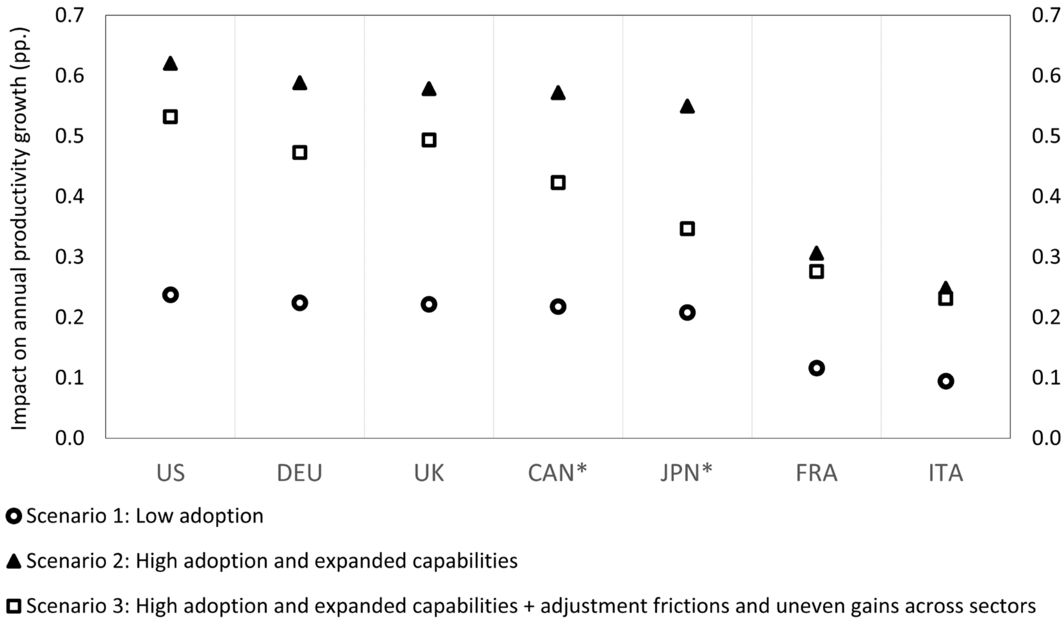
Second, we consider country specific economic structures as captured by the variation in sectoral value-added shares, reflecting country specificities in both production and demand, and I-O linkages.

[64] For instance, if a given country has a current AI adoption rate that is half of the US, it will be assumed to be half of the US in 10 years as well. To estimate cross-country differences in AI adoption taking into consideration differences in country-specific surveys, we combine two data sources: official Eurostat data, measuring differences within the EU, and preliminary results from an OECD Global Forum on Productivity survey among firms in several countries, which serves as a globally harmonised measure to capture differences between the EU and non-EU OECD countries (OECD, 2024b). See more details in Annex 4.2.

Third, we derive country-specific sectoral exposure to AI, captured by the different occupation composition of sectors across countries (Annex Figure A5), which are particularly important in some sectors (e.g. in ICT manufacturing; Annex Figure A6). [65]

Figure 16. Comparing aggregate gains across countries

The estimated impact of AI on aggregate annual TFP growth by country (in percentage points)



Note: *Underlying sectoral AI exposure rates use numbers from the US due to the lack of suitable internationally harmonised data on the occupational composition of sectors. Cross-country differences depend to a large extent on assumptions about differences in future adoption rates, which are derived from current adoption rates and are subject to considerable uncertainty.
Source: Authors' calculations.

Figure 16 compares the aggregate productivity gains for the largest OECD economies (G7) with that of the US under the three main scenarios: *1. Low adoption; 2. High adoption and expanded capabilities;* and *3. Adding adjustment frictions and uneven sectoral gains to scenario 2*. The results show that the combined effect of the underlying cross-country differences leads to substantial variation in aggregate predicted productivity gains from AI. In scenarios 1 and 2, similar sized TFP gains arise in Germany to the ones obtained for the US (at 0.25 and 0.6 percentage points per year, respectively), while in France and Italy, the gains would be about half of that (0.1 and 0.3), largely mirroring adoption rate differences.[66] However, differences in economic structures – in particular, a larger share of knowledge intensive services – are

[65] Data on the employment composition of sectors by detailed occupation are sourced from Eurostat Labour Force Surveys and US Census Current Population Survey.

[66] Given notable successes of developing highly capable Generative AI models in France (e.g. Mistral), it may seem surprising to see low predicted gains at the macro level there. One missing feature from our framework that could explain this is the lack of an explicit accounting for AI "production" itself. In essence, the micro level gains in that AI supplying sector – ICT services – are assumed to be the same as in other sectors; in France as well as in other countries, given the lack of country specific micro level estimates on micro level gains. When country specific estimates of micro-level gains become available this can be refined.

strong enough to compensate in the case of Canada, which results in similar sized predicted gains to Germany despite lower implied future adoption rates.

In the third scenario with adjustment frictions, differences in the sectoral structure of the economy play an even stronger role, resulting in substantial drops in the predicted aggregate gains for Germany and in particular Japan. This finding is in line with their relatively more important reliance on manufacturing and less on knowledge intensive services, which are strongly impacted by AI (see exposure differences across sectors in Section 2.2.2).[67]

These results should be seen as illustrations driven by the assumptions. Future work can refine the methodology and further expand the set of countries, potentially by taking into account the role of openness through cross-country links and introduce different consumption and production elasticities related to that.68 Nevertheless, the current results underline the crucial role of fast and widespread adoption in driving stronger economic gains from AI, along with sectoral economic specialisation patterns. Importantly, policies can influence both levers and hence can have a first order impact on shaping the aggregate productivity benefits from AI and how they play out differently across countries.

4. Concluding remarks and potential extensions

All in all, while the potential aggregate productivity gains from AI are significant, they depend on several conditions, where government policies have a key role to play. First and foremost, they should enable fast and widespread adoption in places where AI can make a positive impact on productivity and thereby improve societal well-being.[69] Surveys among firms indicate several factors that could limit AI adoption, relating to the ability as well as the willingness (or incentives) to adopt (Hoffmann and Nurksi, 2021). In terms of abilities, skills, digital infrastructure, and data access are crucial. Open borders for digital services facilitate access to the globally most advanced AI models. Robust digital infrastructure and clear regulations regarding data usage, accountability and lower overall uncertainty about the technology are essential. Maintaining healthy competition in the market of AI provision is key to ensure high quality and low prices of access (Andre et al, 2024). A related competition issue can arise if companies using AI manage to increase their market power – similar to what happened with digital intensive firms (Aghion and Bunel, 2024; Calligaris, Criscuolo and Marcolin, 2024) – which may lead to lower supply and higher prices in the short run and may hurt innovation in the longer run. Safety, reliability, and privacy must be also addressed to build trust in AI technologies, both among firms and consumers, which is a key demand side channel to enable strong macro-level productivity gains. Social dialogue will also play in important role in the acceptability of AI in the workplace and to foster investment in skills that are complementary to AI.[70]

Further, policies also play a role by helping workers transition to sectors and roles where they are most valued in the new AI landscape. This includes effective retraining programs and other active labour market

[67] For the case of France and Italy, the presence of frictions and uneven gains play a relatively less important role, given that they increase non-linearly with the size of the gains in the frictionless scenario and that the gains in that scenario are smaller to begin with.

[68] Demand elasticities in reality may be larger in more open economies, at least among tradable goods and services, potentially affecting the reallocation results (Baumol effect).

[69] Not all applications of AI may be welfare enhancing, even if they could improve measured productivity. Examples could potentially include AI-powered social media that leverage cognitive biases to the detriment of the user (Acemoglu, 2024).

[70] Lane, Williams and Broecke (2023) find that workers who work in companies that consult them about the adoption of new technologies were far more positive about the impact of AI on their performance.

policies. Moreover, well-functioning capital markets are needed to ensure the productive allocation of capital – including intangible assets such as data, a key complement to AI.

The importance of policies, institutions, and economic structures in reaping the benefits of technological change is also illustrated historically when looking at the ICT driven boom around 1995-2005. It resulted in large productivity gains in the US and in a few other countries, whereas their growth benefits were smaller in Europe (Byrne et al, 2013; Bunel et al, 2024). The limited ICT-related gains in Europe are often ascribed to an adoption challenge (less successful integration of digital tools in sectors with strong potential for ICT gains, such as retail), combined with stronger impediments to within sector reallocation in Europe (Van Ark, O'Mahoney and Timmer, 2008).

Other ongoing megatrends, such as demographic changes and aging populations in particular, also impact AI adoption. On one hand, older populations may be slower to adopt new technologies, potentially leading to skill obsolescence. On the other hand, labor shortages resulting from aging demographics may drive increased adoption of AI and robotics to compensate for the shrinking size of the workforce. However, slower reallocation and mobility due to aging could present additional challenges.

Future research could focus on various extensions to the framework used here to further refine the analysis of AI's impact on productivity growth. First, international input-output tables could be leveraged to incorporate trade linkages and expand the country coverage. Second, a more refined analysis of future AI adoption across countries and its policy and structural drivers could broaden and strengthen our cross-country results. Third, considering AI's large energy requirements, future research could investigate what implications AI adoption will have for energy use and planning and global decarbonisation efforts, under various assumptions about energy efficiency and other technological improvements. Fourth, evaluating the risks associated with excessive concentration in the AI market (Aghion and Bunel, 2024) is crucial, as maintaining competitive markets is essential for fostering AI diffusion and encouraging ongoing innovation.

The model itself could also be enriched to sharpen the understanding of a few channels affecting AI's impact. For instance, incorporating sector- or time-varying demand elasticities could provide a more nuanced view of how AI adoption influences different parts of the economy. Modeling physical capital accumulation explicitly and exploring its complementarities with AI can yield additional insights.[71] Incorporating innovation-boosting effects, while less straightforward, could reveal how AI adoption might lead to broader and longer-term gains in productivity.[72] In addition to productivity, labour market implications – such as the effects of AI on employment and wages – could be further explored with a more detailed modelling of labour inputs which also helps exploring the links with ongoing demographic changes (ageing).

[71] A further extension could be to investigate the contribution of increased investment in AI producing industries to labour productivity. For instance, ICT investments contributed to sustaining labour productivity growth during the ICT revolution in the US, even if TFP improvements from ICT technologies were also of central importance (Gordon and Sayed, 2020).

[72] Yet, AI could also hamper innovation, for instance if AI-driven increase in fraud and hallucinations due to lack of regulation damages trust and the circulation of ideas.

References

Acemoglu, D. (2024) “The Simple Macroeconomics of Artificial Intelligence”, *Economic Policy, 2024;, eiae042, https://doi.org/10.1093/epolic/eiae042*

Acemoglu, D., U. Akcigit and W. Kerr (2016), “Networks and the Macroeconomy: An Empirical Exploration”, NBER Macroeconomics Annual, Vol. 30/1, pp. 273-335.

Acemoglu, D. and D. Autor (2011), "Skills, Tasks and Technologies: Implications for Employment and Earnings,"*Handbook of Labor Economics*, in: O. Ashenfelter & D. Card (ed.), Handbook of Labor Economics, edition 1, volume 4, chapter 12, pages 1043-1171, Elsevier.

Acemoglu, D., D. Autor and S. Johnson (2023), *Can we Have Pro-Worker AI? Choosing a path of machines in service of minds,* MIT Shaping the Future of Work Initiative, Policy Memo.

Acemoglu, D., D. Autor and C. Patterson (2024) “Bottlenecks: Sectoral Imbalances and the US Productivity Slowdown,” *NBER Macroeconomics Annual*, University of Chicago Press, vol. 38(1), pages 153-207.

Acemoglu, D. and P. Restrepo (2018), "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment," *American Economic Review,* 108 (6): 1488–1542.

Acemoglu, D. and P. Restrepo (2019), "Artificial Intelligence, Automation, and Work," in: *The Economics of Artificial Intelligence: An Agenda*, p. 197-236, University of Chicago Press

Aghion, P. and S. Bunel (2024), “AI and Growth: Where Do We Stand?”, https://www.frbsf.org/wp-content/uploads/AI-and-Growth-Aghion-Bunel.pdf

Aghion, P., B. Jones and C. Jones (2019), “Artificial Intelligence and Economic Growth”, in: *The Economics of Artificial Intelligence: An Agenda*, p. 237-82, University of Chicago Press

Agrawal, A., J. Gans and A. Goldfarb (2023), "The Turing Transformation: Artificial intelligence, intelligence augmentation, and skill premiums". *National Bureau of Economic Research Working Papers* No. *31767.*

Agrawal, A., J. Gans and A. Goldfarb (2022), “Power and Prediction: The Disruptive Economics of Artificial Intelligence”, *Harvard Business Review Press*

Agrawal, A., J. Gans and A. Goldfarb (2019), “Economic Policy for Artificial Intelligence”, *Innovation Policy and the Economy*, Vol. 19.

Akcigit, U. and S. T. Ates (2021), "Ten Facts on Declining Business Dynamism and Lessons from Endogenous Growth Theory." *American Economic Journal: Macroeconomics,* 13 (1): 257–98.

Aldasoro, Iñaki, S. Doerr, L. Gambacorta and D. Rees (2024), "The impact of artificial intelligence on output and inflation," BIS Working Papers 1179, Bank for International Settlements.

Alderucci, D. et al. (2020), *Quantifying the Impact of AI on Productivity and Labor Demand: Evidence from U.S. Census Microdata*, https://www.aeaweb.org/conference/2020/preliminary/paper/Tz2HdRna.

Andre, C. and P. Gal (2024), “Reviving productivity growth: A review of policies”, *OECD Economics Department Policy Paper*, No. 1822., OECD Publishing, Paris, Andre, C., M. Betin, P. Gal and P. Peltier (2024), “Competition in the market of Artificial Intelligence: monitoring developments by new indicators”, *forthcoming*.

Andrews, D., C. Criscuolo and P. Gal (2016), "The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy", *OECD Productivity Working Papers*, No. 5, OECD Publishing, Paris, https://doi.org/10.1787/63629cc9-en.

Artificial Intelligence Commission of France (2024), IA : Notre Ambition pour la France, https://www.gouvernement.fr/actualite/25-recommandations-pour-lia-en-france.

Atalay, E. (2017), "How Important Are Sectoral Shocks?", *American Economic Journal: Macroeconomics*, 9 (4): 254–80.

Autor, D., C. Chin, A. Salomons and B. Seegmiller (2024), “New Frontiers: The Origins and Content of New Work, 1940–2018”, *The Quarterly Journal of Economics*, Volume 139, Issue 3, August 2024, Pages 1399–1465, https://doi.org/10.1093/qje/qjae008

Autor, D. and D. Dorn (2013), "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, American Economic Association, vol. 103(5), pages 1553-1597, August.

Baily, M., E. Brynjolfsson and A. Korinek (2023), *Machines of mind: The case for an AI-powered productivity boom*. Brookings Institution, https://www.brookings.edu/articles/machines-of-mind-the-case-for-an-ai-powered-productivity-boom/

Baqaee, D.R. and Farhi, E. (2019), The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten’s Theorem. Econometrica, 87: 1155-1203. https://doi.org/10.3982/ECTA15202

Baumol, W.J. (1967). “Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis”?*The American Economic Review*. 57 (3): 415–426.

Bergeaud, A. (2024), “The Past, Present and Future of European Productivity”, paper prepared for the ECB Forum on Central Banking “Monetary policy”in an era of transformation”, 1-3 July 2024, Sintra, Portugal

Ben-Ishai, G. J. Dean, J. Manyika, R. Porat, H. Varian and K. Walker. (2024), “AI and the Opportunity for Shared Prosperity: Lessons from the History of Technology and the Economy”, *arXiv preprint arXiv:2401.09718*.

Berlingieri, G., S. Calligaris, C. Criscuolo and R. Verlhac (2020), "Laggard firms, technology diffusion and its structural and policy determinants", *OECD Science, Technology and Industry Policy Papers*, No. 86, OECD Publishing, Paris, https://doi.org/10.1787/281bd7a9-en.

Besiroglu, Tamay and Marius Hobbhahn (2022), “Trends in GPU Price-Performance,” Technical Report, EpochAI 2022.

Bessen, J. (2018), “AI and Jobs: The Role of Demand”, *National Bureau of Economic Research Working Papers*, No. 24235.

Besson, L., A. Dozias, C. Faivre, C. Gallezot, J. Gouy-Waz, B. Vidalenc (2024), “The Economic Implications of Artificial Intelligence”, *Tresor-Economics*, No. 341, April 2024

Bick, A., A. Blandin and D. J. Deming (2024), "The Rapid Adoption of Generative AI", *NBER Working Papers* 32966, National Bureau of Economic Research, Inc.

Briggs, J. and D. Kodnani (2023), “The Potentially Large Effects of Artificial Intelligence on Economic Growth”, *Goldman Sachs Economics Research.*

Brynjolfsson, E., D. Li and L. Raymond (2023), “Generative AI at Work”, *National Bureau of Economic Research Working Papers* No. 31161.

Brynjolfsson, E., Rock, D., & Syverson, C. (2021), “The productivity J-curve: How intangibles complement general purpose technologies”, *American Economic Journal: Macroeconomics*, 13(1), 333-372.

Bunel, S., G. Bijnens, V. Botelho, E. Falck, V. Labhard, A. Lamo, O. Röhe, J. Schroth, R. Sellner, J. Strobel and B. Anghel (2024), "Digitalisation and productivity," Occasional Paper Series 339, European Central Bank.

Byrne, D. M., S. D. Oliner and D. E. Sichel (2013). "Is the Information Technology Revolution Over?," *International Productivity Monitor*, Centre for the Study of Living Standards, vol. 25, pages 20-36, Spring.

Calligaris, S., F. Calvino, R. Verlhac and M. Reinhard (2023), "Is there a trade-off between productivity and employment?: A cross-country micro-to-macro study", *OECD Science, Technology and Industry Policy Papers*, No. 157, OECD Publishing, Paris, https://doi.org/10.1787/99bede51-en.

Calligaris, S., C. Criscuolo and L. Marcolin (2024), "Mark-ups in the digital era", Centre for Economic Performance, London School of Economics, https://cep.lse.ac.uk/_NEW/PUBLICATIONS/abstract.asp?index=10858.

Calligaris, S., Chaves, M., Criscuolo, C., De Lyon, J., Greppi, A., Pallanch, O., (2024), "Exploring the evolution and the state of competition in the EU", Protecting competition in a changing world, European Commission.

Calvino, F. and L. Fontanelli (2023), "A portrait of AI adopters across countries: Firm characteristics, assets' complementarities and productivity", *OECD Science, Technology and Industry Working Papers*, No. 2023/02, OECD Publishing, Paris, https://doi.org/10.1787/0fb79bb9-en.

Causa, O., et al. (2022), "Getting on the job ladder: The policy drivers of hiring transitions", *OECD Economics Department Working Papers*, No. 1710, OECD Publishing, Paris, https://doi.org/10.1787/0304c673-en.

Cazzaniga, M. et al. (2024), "Gen-AI: Artificial Intelligence and the Future of Work", *IMF Staff Discussion Notes* No. 2024/001

Council of Economic Advisers (2024), Economic Report of the President, https://www.whitehouse.gov/wp-content/uploads/2024/03/ERP-2024.pdf.

Cui, Kevin Zheyuan, Mert Demirer, Sonia Jaffe, Leon Musolff, Sida Peng, and Tobias Salz (2024), "The Productivity Effects of Generative AI: Evidence from a Field Experiment with GitHub Copilot.", https://mit-genai.pubpub.org/pub/v5iixksv/release/2

Czarnitzki, D., G. Fernández and C. Rammer (2023), "Artificial intelligence and firm-level productivity", *Journal of Economic Behavior & Organization*, Vol. 211, pp. 188-205.

Damioli, G., V. Van Roy and D. Vertesy (2021), "The impact of artificial intelligence on labor productivity", *Eurasian Business Review*, Vol. 11, pp. 1-25.

Demmou, L. and G. Franco (2021), "Mind the financing gap: Enhancing the contribution of intangible assets to productivity", *OECD Economics Department Working Papers*, No. 1681, OECD Publishing, Paris, https://doi.org/10.1787/7aefd0d9-en.

De Vries, G. J., Gentile, E., Miroudot, S. and K. M. Wacker (2020), "The rise of robots and the fall of routine jobs," *Labour Economics*, Elsevier, vol. 66(C).

Decker, R. A., J. Haltiwanger, R. S. Jarmin, and J. Miranda (2020), "Changing Business Dynamism and Productivity: Shocks versus Responsiveness." *American Economic Review*, 110 (12): 3952–90.

Dell'Acqua, F. et al. (2023), "*Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality*", *Harvard Business School Technology & Operations Mgt. Unit Working Paper* No. 24-013.

Dingel J.I., and Neiman B (2020), "How Many Jobs Can Be Done at Home?", *Journal of Public Economics,* 189: 104235

Eloundou, T., S. Manning, P. Mishkin and D. Rock (2024), "GPTs are GPTs: Labour market impact potential of LLMs", *Science 384 (6702)*, 1306-1308

Felten, E., M. Raj and R. Seamans (2021), “Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses”, *Strategic Management Journal,* Volume 42, Issue 12, December 2021, Pages 2195-2217

Fernald, J. (2015) "Productivity and Potential Output before, during, and after the Great Recession," *NBER Macroeconomics Annual, University of Chicago Press*, vol. 29(1), pages 1-51.

Fernald, J., Inklaar, R. and Ruzic, D. (2024), *The Productivity Slowdown in Advanced Economies: Common Shocks or Common Trends?,Review of Income and Wealth*. https://doi.org/10.1111/roiw.12690

Filippucci, F., et al. (2024), “The impact of Artificial Intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges”, *OECD Artificial Intelligence Papers*, No. 15, OECD Publishing, Paris, https://doi.org/10.1787/8d900037-en.

Forbes Magazine (2024), “OpenAI-Powered Humanoid Robot Fills Spot At BMW Assembly Plant”, 7 July 2024, https://www.forbes.com/sites/chriswestfall/2024/07/07/openai-powered-humanoid-robot-fills-spot-at-bmw-assembly-plant/

Furman, J. and R. Seamans (2019), “AI and the Economy”, *Innovation Policy and the Economy*, Vol. 19, pp. 161-191

Gambacorta, L., H. Qiu, S. Shan, and D. M. Rees (2024), “Generative AI and labour productivity: a field experiment on coding”, No. 1208., Bank for International Settlements Working Papers. https://www.bis.org/publ/work1208.pdf

Goldin, Ian, P. Koutroumpis, F. Lafond, and J. Winkler (2024), “Why Is Productivity Slowing Down?” *Journal of Economic Literature*, 62 (1): 196–268.

Goldman Sachs (2024), “Top of Mind”, Global Macro Research, Issue 129, June 25

Google (2024), “AI achieves silver-medal standard solving International Mathematical Olympiad problems”, DeepMind Research Blog, https://deepmind.google/discover/blog/ai-solves-imo-problems-at-silver-medal-level/

Gordon, R. J. and Sayed, H. (2020), “Transatlantic technologies: The role of ICT in the evolution of US and European productivity growth”, *National Bureau of Economic Research* Working Papers No. 27425

Haslberger, M., J. Gingrich and J. Bhatia (2023), *No great equalizer: experimental evidence on AI in the UK labor market*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4594466.

Hoffmann, M. and L. Nurski (2021) “What is holding back artificial intelligence adoption in Europe?”, *Policy Contribution* 24/2021, Bruegel

Hulten, C. R (1978), “Growth Accounting with Intermediate Inputs,” *The Review of Economic Studies*, 45 (3), 511–518.

JP Morgan (2024), “A strong economy in a fragile world”, Mid-Year Outlook.

Lane, M., M. Williams and S. Broecke (2023), “The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers”, *OECD Social, Employment and Migration Working Papers*, No. 288, OECD Publishing, Paris, https://doi.org/10.1787/ea0a0fe1-en.

Lipsey, R., K. Carlaw and C. Bekar (2005), *Economic Transformations: General Purpose Technologies and Economic Growth*, Oxford University Press, Oxford UK.

Lorenz, P., K. Perset and J. Berryhill (2023), “Initial policy considerations for generative artificial intelligence”, *OECD Artificial Intelligence Papers*, No. 1, OECD Publishing, Paris, https://doi.org/10.1787/fae2d1e6-en

McElheran, K. J. F. Li, E. Brynjolfsson, Z. Kroff, E. Dinlersoz, L. Foster and N. Zolas (2024) "AI adoption in America: Who, what, and where," *Journal of Economics & Management Strategy*, vol 33(2), pages 375-415.

McKinsey (2023), *The economic potential of generative AI*. McKinsey Report January 2023.

Nordhaus, W. D. (2008), “Baumol’s Diseases: A Macroeconomic Perspective”, *The B.E. Journal of Macroeconomics,* vol. 8, no. 1 https://doi.org/10.2202/1935-1690.1382

Nordhaus, W. D. (2021), “Are We Approaching an Economic Singularity? Information Technology and the Future of Economic Growth”, *American Economic Journal: Macroeconomics*, 13 (1), 299‑332.

Noy, S. and W. Zhang (2023), *Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence*. Science 381,187-92(2023).

OECD (2015), *The Future of Productivity*, OECD Publishing, Paris, https://doi.org/10.1787/9789264248533-en.

OECD (2019b), *Artificial Intelligence in Society*, OECD Publishing, Paris, https://doi.org/10.1787/eedfee77-en.

OECD (2023a), *Recommendation of the Council on Artificial Intelligence*, https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449.

OECD (2023b), Productivity Compendium 2023

OECD (2023c), *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*, OECD Publishing, Paris, https://doi.org/10.1787/08785bba-en

OECD (2023d), Key Issues in Digital Trade Review: OECD Global Forum on Trade 2023 “Making Digital Trade Work for All”, OECD Publishing, Paris, https://doi.org/10.1787/b2a9c4b1-en.

OECD (2024a), “Artificial intelligence, data and competition”, *OECD Artificial Intelligence Papers*, No. 18, OECD Publishing, Paris, https://doi.org/10.1787/e7e88884-en.

OECD (2024b), Survey by the Global Forum on Productivity, *forthcoming*

OECD (2024c), *Recommendation of the Council on Artificial Intelligence*, https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449

O*NET (2023), O*NET 27.2 Database.

Ouyang, Long, et al., (2022), "Training language models to follow instructions with human feedback," Advances in neural information processing systems, 35: 27730-27744.

Peng, S. et al. (2023), *The Impact of AI on Developer Productivity: Evidence from GitHub Copilot*. arXiv:2302.06590

Pizzinelli, C, A Panton, M Mendes Tavares, M Cazzaniga, and L Li, (2023), “Labor Market Exposure to AI: Cross-country Differences and Distributional Implications,” *IMF Working Paper*, International Monetary Fund 2023.

Restuccia, D., and R. Rogerson (2017), "The Causes and Costs of Misallocation", *Journal of Economic Perspectives*, 31 (3): 151–74.

Rockall, E., C. Pizzinelli and M. M. Tavares (2024), “Artificial Intelligence Adoption and Inequality.” Unpublished, International Monetary Fund, Washington, DC.

Svanberg, M., Li, W., Fleming, M., Goehring, B. and N. Thompson (2024), “Beyond AI Exposure: Which Tasks are Cost-Effective to Automate with Computer Vision?” https://ssrn.com/abstract=4700751 or http://dx.doi.org/10.2139/ssrn.4700751

Syverson, C. (2024), “Unpacking the mysteries of productivity”, *interview with McKinsey Global Institute*, 2 July 2024, https://www.mckinsey.com/mgi/forward-thinking/unpacking-the-mysteries-of-productivity

Trammell, P. and A. Korinek (2023), “Economic Growth under Transformative AI”, *National Bureau of Economic Research Working Papers* No. 31815.

Van Ark, Bart, Mary O’Mahoney, and Marcel P. Timmer (2008), “The Productivity Gap between Europe and the United States: Trends and Causes,” *Journal of Economic Perspectives*, 22 (1): 25–44.

Varian, H. (2019), “Artificial Intelligence, Economics, and Industrial Organization” in: *The Economics of Artificial Intelligence: An Agenda*, pp 399 – 422., University of Chicago Press

WEF (2023), Jobs of Tomorrow: Large Language Models and Jobs, *WEF White Papers*, September 2023.

Annex A. Auxiliary analyses, tables, and figures

1. A simple multisector general equilibrium model

Our main results are derived from a multi-sector model with a full set of input-output linkages, calibrated to OECD economies. Some of the key insights from this model, however, can also be derived from a simplified model without input-output linkages.[73] The first insight is that aggregate productivity gains are diminished when productivity growth differs starkly across sectors. The second insight is that differential growth rates slow down aggregate productivity growth more if demand is relatively inelastic, and if factors of production cannot easily be reallocated towards sectors where they are most needed.

To derive these insights, consider a simple multi-sector economy with $I \in \mathbb{N}$ sectors. In each sector, $i \in I$, output is produced linearly from labour according to

$$y_i = A_i L_i,$$

where A_i denotes the level of (labour-) productivity in sector i. Final demand is represented by a constant elasticity of substitution (CES) aggregator,

$$Y = \left(\sum_{i=1}^{N} \alpha_i \; y_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{8}$$

with $\sum_{i=1}^{N} \alpha_i = 1$ and $0 < \sigma < 1$. In this simple economy, there are no input-output linkages across sectors. By setting σ lower than 1, we assume that the goods and services produced in the different sectors are gross complements rather than substitutes. We first assume labour is mobile across sectors but relax that assumption later.

How do sectoral productivity shocks, that is changes in A_i, translate into changes in aggregate output, Y? A foundational result in the literature on the aggregation of microeconomic productivity shocks is Hulten's theorem. Hulten (1978) showed that in a competitive economy with constant returns to scale, macroeconomic productivity gains can be approximated as a weighted sum of microeconomic productivity changes at the firm or sectoral level where the weights of a given firm or sector, λ_i, is the ratio of its sales to GDP:

$$\mathrm{d} \log(Y) \approx \sum_{i \in I} \lambda_i \, d \log(\mathrm{A_i}) \tag{9}$$

In a realistic economy with input-output linkages, a part of each sector's output is used as in input in other sectors, so that sectoral sales exceed value added and the sum of the weights in the above decomposition formula is larger than 1. Such economies are characterised by a multiplier that captures the fact that a positive productivity shock in one sector also improves the productive capacity of other sectors by lowering their input prices. In the context of the simple economy studied here, sales equal value added, and Hulten's

[73] The following derivations are based directly on the notation and insights in Baqaee and Farhi (2019).

theorem implies that aggregate productivity gains can be approximated by the value-added share weighted average of sectoral productivity gains.

Hulten's theorem provides a powerful tool for aggregating microeconomic shocks that does not require any knowledge of the underlying structure of the economy. However, the approximation provided by Hulten's theorem is only exact to a first order and can therefore be strongly biased when the microeconomic shocks are large and the economy is characterised by important nonlinearities stemming from non-unitary elasticities of substitution, network linkages, or barriers to the reallocation of productive factors. In other words, Hulten's theorem ignores precisely those aspects of real economies that give rise to Baumol's growth disease.

Baqaee and Farhi (2019) extend the foundational theorem of Hulten (1978) to obtain a second-order approximation of the aggregate productivity gains which accounts for the non-linearities that are ignored in the linear approximation. In the context of our simple economy, the second-order approximation can be written as follows:

$$
\begin{aligned}
d\log(Y) \approx {} & \sum_{i\in I} \lambda_i \, d\log(\mathrm{A_i}) \\
& + \frac{1}{2}\left\{ \sum_{i\in I} \lambda_i (1-\lambda_i)\left(1-\frac{1}{\rho}\right)\left(d\log(\mathrm{A_i})\right)^2 \right. \\
& \left. + \sum_{\substack{i,j\in I \\ i\neq j}} \lambda_i\left(1-\lambda_i-\lambda_j\right)\left(1-\frac{1}{\rho}\right) \mathrm{d}\log(\mathrm{A_i})\, \mathrm{d}\log\left(\mathrm{A_j}\right) \right\}.
\end{aligned}
\tag{10}
$$

In this formulation, ρ is a general equilibrium (pseudo) elasticity of substitution that captures how the relative sales shares of any two sectors change under an exogenous productivity shock to one of the sectors. In contrast to the structural elasticity σ, the general equilibrium elasticity ρ depends on the constraints we impose on the economy. For example, whether labour can be freely reallocated across sectors affects the size of ρ.

Importantly, the second term on the right-hand side captures the drag on aggregate growth stemming from the tendency of sectors with low productivity growth to experience increasing nominal output shares relative to sectors with high productivity growth. Hence, this term can be interpreted as a quantification of the importance of Baumol's cost disease.

The above formula is useful to gain intuition for when to expect Baumol's growth disease to play an important role. First, it can be shown that in our model $\rho = 1/(2-\sigma)$, so that ρ is smaller than 1 whenever σ is smaller than 1, which in turn implies that the reallocation term will indeed be negative. Moreover, note that the reallocation term will more strongly negative, the lower the elasticity of substitution, σ, and the more unequal the productivity growth across sectors, as can be seen in the formula above.

Table A1 shows the size of the two terms in the above decomposition formula for different values of σ and different sectoral productivity growth rates in a stylised model with two equally sized sectors.

Table A.1. A stylised example

	$d\,log(A_1) = .4$ $d\,log(A_2) = .6$			$d\,log(A_1) = 0$ $d\,log(A_2) = 1$	
	σ = .9	σ = .1		σ = .9	σ = .1
First-order effect	.5	.5		.5	.5
Baumol effect	-.0065	-.0585		-.0125	-.1125

Source: authors' calculations

We can also consider introducing reallocation frictions to this economy. For example, consider the situation where factors cannot be reallocated between sectors. In this case, the general equilibrium elasticity is equal the structural elasticity so that we have $\rho = \sigma$. As a consequence, for any $\sigma < 1$, the general equilibrium elasticity is smaller when labour mobility is restricted relative to the case where labour can move between sectors. Hence, the Baumol effect will be larger in this case.

The interpretation is that equilibrium in the goods markets must be achieved entirely through changes in relative output prices. Specifically, the prices in the sector with higher productivity growth will need to decline more than before to ensure that demand equals the increased supply. As a result, even though output evaluated at initial prices would be larger if labour was forced to stay in the sector with the larger productivity shock, real GDP growth is lower in this case because the implied changes in relative output prices lead to larger reduction in the output share of the high productivity sector.

2. An aggregate labour productivity growth decomposition to illustrate Baumol's growth disease

To understand how restricting factor reallocation affects aggregate growth through changes in relative output prices, we derive an aggregate labour productivity growth decomposition.

The relationship between aggregate nominal value added per worker, $\frac{P_t Y_t}{L_t}$, and sectoral nominal value added per worker, $\frac{P_{jt} Y_{jt}}{L_{jt}}$, can be written as follows:

$$\frac{P_t Y_t}{L_t} = \sum_{j \in J} \underbrace{\frac{L_{jt}}{L_t}}_{\substack{\text{Industry j's} \\ \text{employment share}}} \times \underbrace{\frac{P_{jt} Y_{jt}}{L_{jt}}}_{\substack{\text{Industry j's} \\ \text{value added per worker}}} \tag{11}$$

To obtain real labour productivity, LP_t, we divide by the aggregate price index P_t to get:

$$LP_t \stackrel{\text{def}}{=} \frac{Y_t}{L_t} = \sum_{j \in J} \underbrace{\frac{P_{jt}}{P_t}}_{\substack{\text{Industry j's} \\ \text{relative ouput price}}} \times \underbrace{\frac{L_{jt}}{L_t}}_{\substack{\text{Industry j's} \\ \text{employment share}}} \times \underbrace{\frac{Y_{jt}}{L_{jt}}}_{\substack{\text{Industry j's} \\ \text{labour productivity}}} \tag{12}$$

Hence, aggregate real labour productivity growth depends on changes in sectoral real labour productivity, $\frac{Y_{jt}}{L_{jt}}$, as well as on changes in the sectors' employment shares, $\frac{L_{jt}}{L_t}$, and relative output prices, $\frac{P_{jt}}{P_t}$. In particular, for given sectoral labour productivity growth rates, aggregate labour productivity growth will be diminished to the extent that sectors with high productivity growth see their relative output price and employment share decline relative to sectors with low productivity growth. Given that aggregate productivity growth depends on how the sectoral productivity gains affect quantities *as well as* prices, we need a macroeconomic framework that allows us to understand the evolution of both types of variables in equilibrium.

It is common to see decomposition formulas that decompose yearly aggregate labour productivity growth into a "within-industry effect" and one or several "reallocation effects", and that do not explicitly account for changes in relative sectoral output prices. For example, consider the following standard decomposition of aggregate labour productivity growth:

$$\underbrace{\frac{LP_t - LP_0}{LP_0}}_{\substack{Aggregate\ real \\ LP\ growth}} = \underbrace{\sum_{j \in J} s_{j0}^{VA} \left(\frac{LP_{jt} - LP_{j0}}{LP_{j0}} \right)}_{Within-industry\ effect} + \underbrace{\sum_{j \in J} \Delta w_{jt} \frac{LP_{jt}}{LP_0}}_{Labor\ reallocation\ effect} \tag{13}$$

where s_{j0}^{VA} is the initial (nominal) value added share of sector *j*, LP_{jt} is real labour productivity in sector *j*, $\Delta w_{jt} = \frac{L_{jt}}{L_t} - \frac{L_{j0}}{L_0}$ is the change in employment share of sector *j*, and real values are derived by normalising prices to 1 at time 0. Note that the term $\frac{LP_{jt}}{LP_0}$ can be written as $\frac{LP_{j0}}{LP_0}\frac{LP_{jt}}{LP_{j0}}$, meaning it captures both the initial relative productivity of sector *j* as well as it's differential growth rate over time.[74]

Applied to yearly growth rates, or when using a fixed weight price index (e.g. with a fixed base year), this decomposition is exact. However, it is only approximative when applied to decompose growth over longer periods, since the weights in the aggregate price index are typically updated to reflect changes in the sectoral composition of the economy (chain-linking). Indeed, measures of real GDP growth rely on regularly updated weights of the various expenditure items in the construction of the aggregate price index P_t (GDP deflator) in all OECD countries and in more and more non-OECD ones.

We can augment the above formula to capture the effect of changing relative output prices on aggregate real labour productivity growth (which we label "valuation effect") by adding a third term:

$$\underbrace{\frac{LP_t - LP_0}{LP_0}}_{\substack{Aggregate\ real \\ LP\ growth}} = \underbrace{\sum_{j \in J} s_{j0}^{VA} \left(\frac{LP_{jt} - LP_{j0}}{LP_{j0}} \right)}_{Within-industry\ effect} + \underbrace{\sum_{j \in J} \Delta w_{jt} \frac{LP_{jt}}{LP_0}}_{Labor\ reallocation\ effect} + \underbrace{\sum_{j \in J} w_{jt} (\Delta p_{jt}) \frac{LP_{jt}}{LP_0}}_{Valuation\ effect} \tag{14}$$

where $\Delta p_{jt} = \frac{P_{jt}}{P_t} - 1$ captures the relative price change of sector *j*.[75] This decomposition is exact when applied to decompose aggregate real labour productivity growth over short *as well as* long time periods.

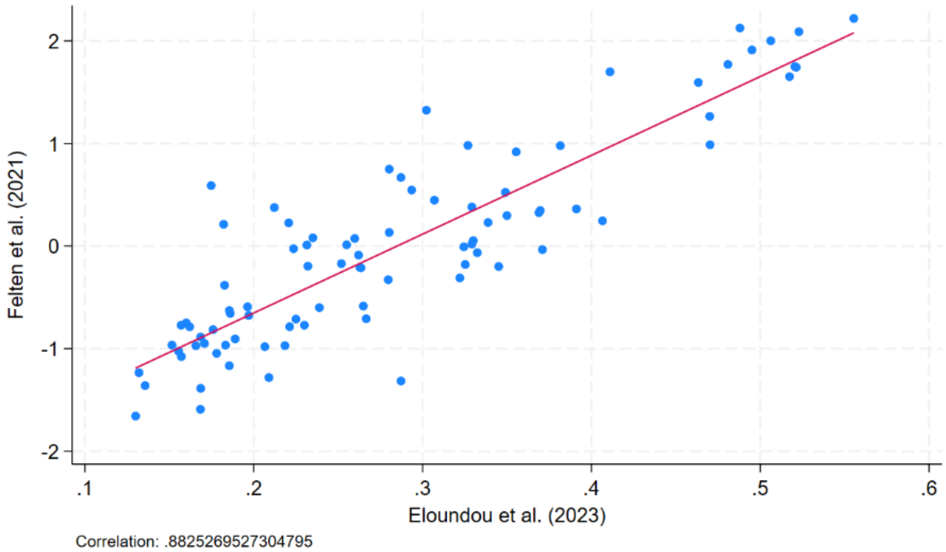
[74] This gives rise to the possibility of decomposing the affected terms further into a static and dynamic element (see Tang and Wang, 2004 and OECD, 2023b) which is not the focus of our interest here.

[75] An alternative possibility is to evaluate labour reallocation at final prices and to compute the valuation at initial employment shares, which yields an even large role for the change in relative prices term.

3. Additional tables and figures

Figure A.1. High correlation between alternative AI exposure estimates at the occupation level

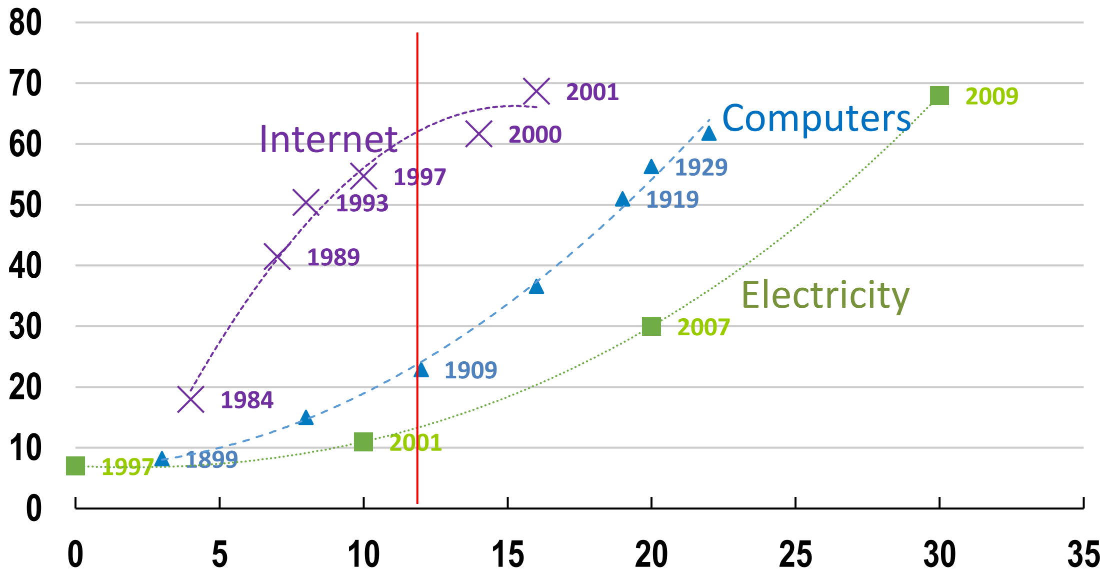
Felten et al. (2021, non-Generative AI) and Eloundou et al. (2024, Generative AI)



Note: Correlation at the US-SOC occupation level.
Source: Author's calculations using the cited sources.

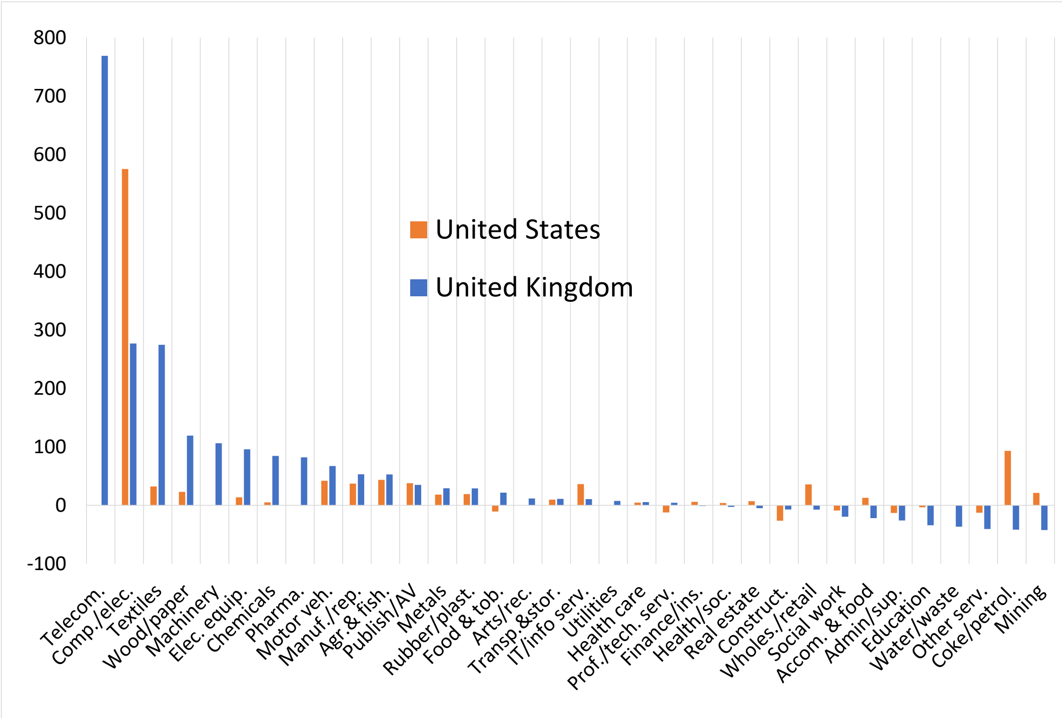
Figure A.2. The evolution of the adoption of previous General Purpose Technologies

by households (%, United States)



Note: *We consider for the introduction of the user-friendly breakthrough variant of the technology the following: for electricity, development of electric motor; for PC, introduction of IBM PC. Dotted lines represent a high-level polynomial fit on the observed dates.
Source: For PC and electricity, Briggs and Kodnani (2023).

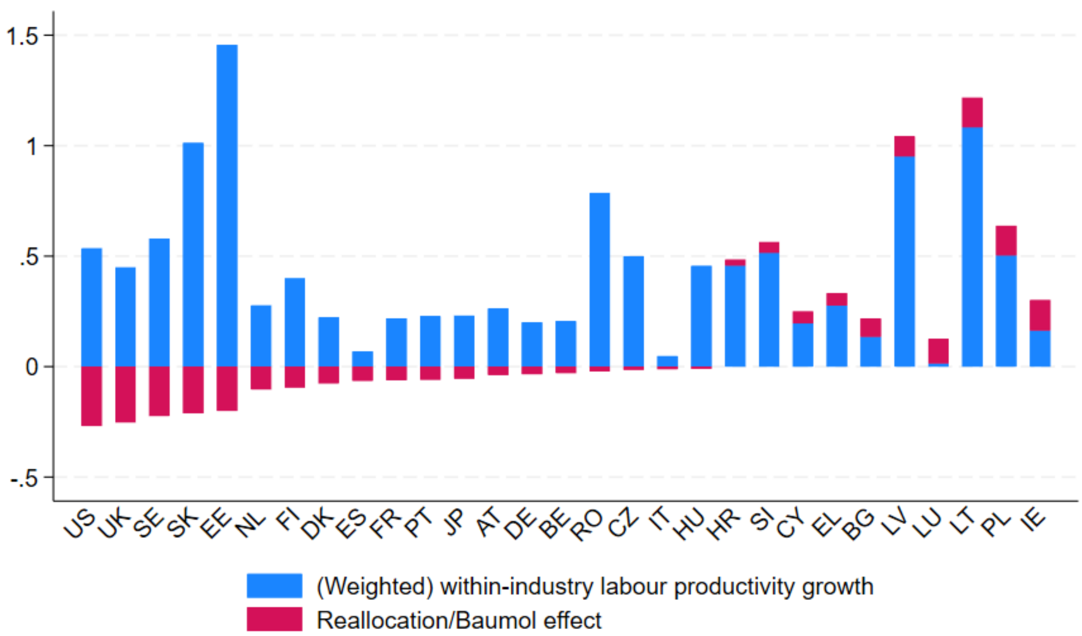
Figure A.3. Sectoral TFP growth during 1995-2005 in the US and UK (in %)



Source: EUKLEMS & INTANProd.

Figure A.4. The contribution of the Baumol growth disease and reallocation to overall productivity growth in selected countries*

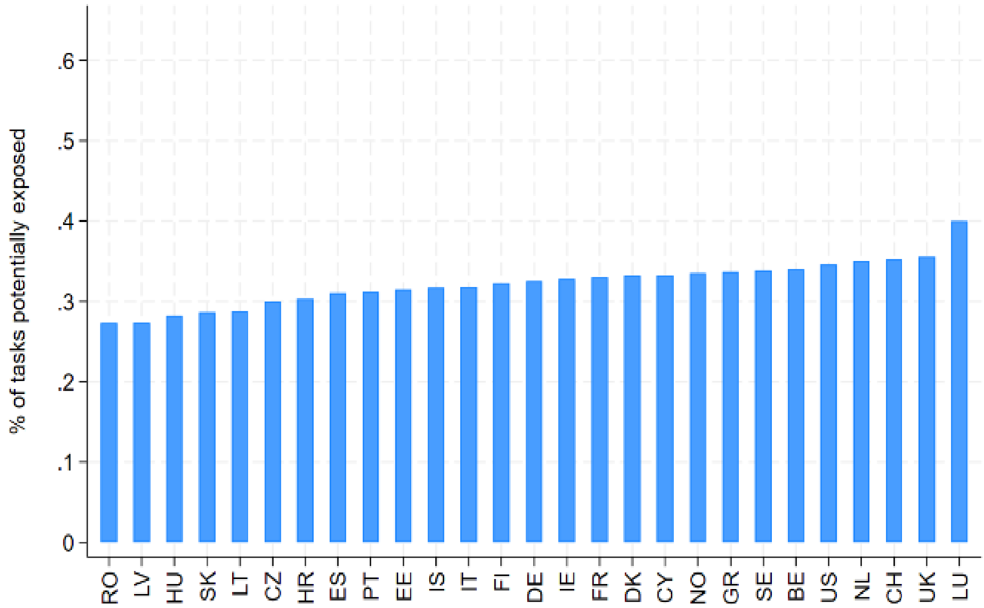
Based on labour productivity (1995-2005)



Note: *Driven by data availability. See details in Box 1.
Source: EUKLEMS & INTANProd dataset

Figure A.5. Estimated share of tasks exposed to AI by country

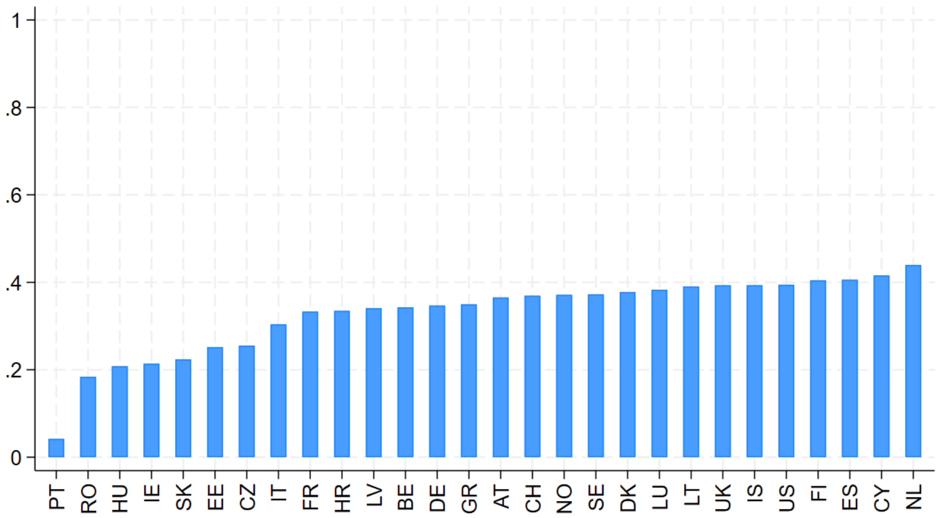
Averaged across sectors



Source: Eloundou et al. (2024) combined with Labour Force Surveys.

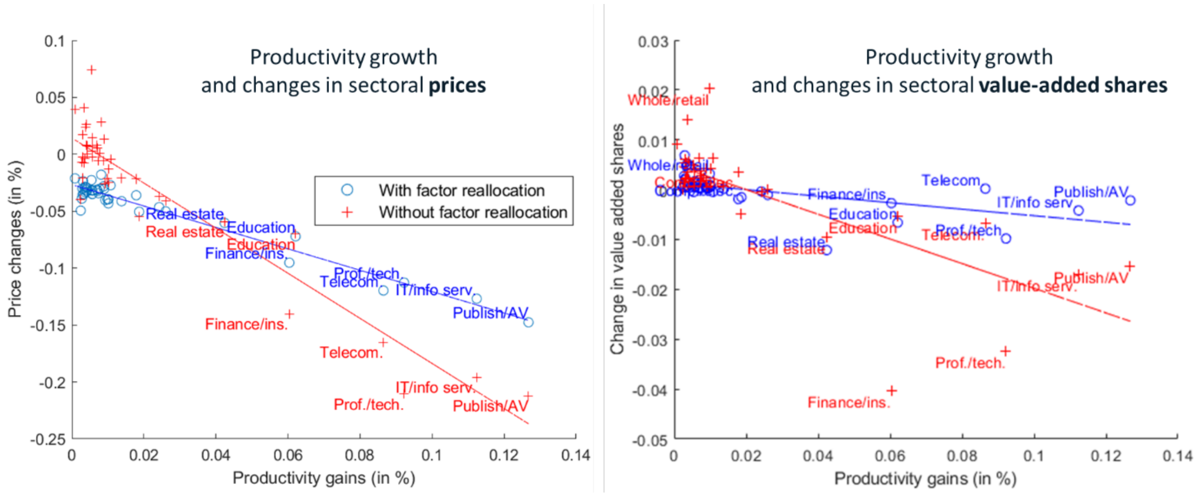
Figure A.6. Estimated share of tasks exposed to AI by country: zooming in on ICT manufacturing

in ICT producing manufacturing*



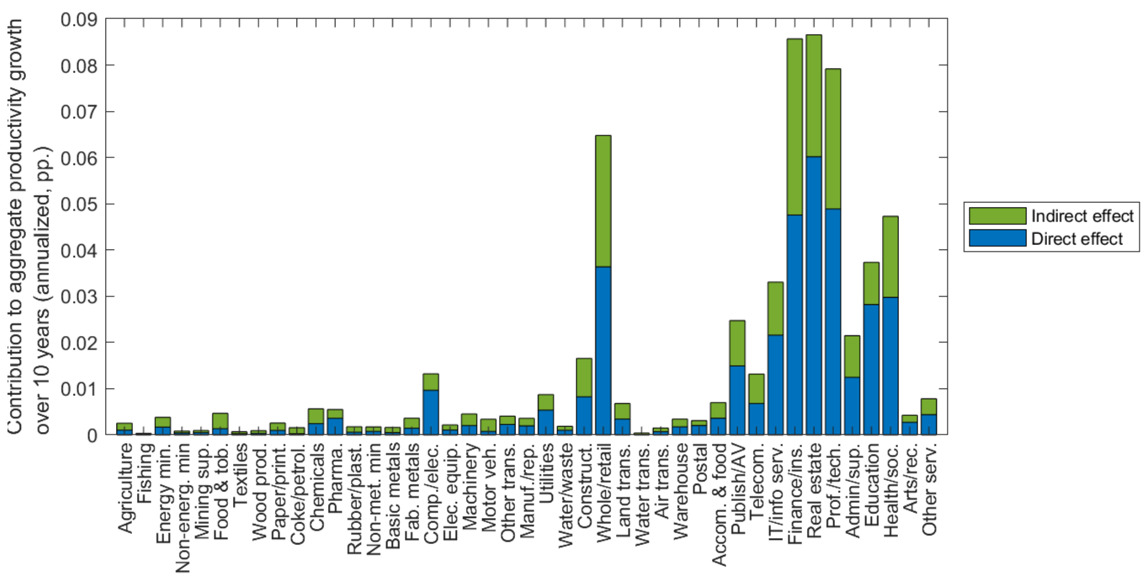
Note: * Sector C26 Manufacture of computer, electronic and optical products
Source: Eloundou et al. (2024) combined with Labour Force Surveys.

Figure A.7. Sectoral correlations of productivity gains and changes in prices and value-added shares



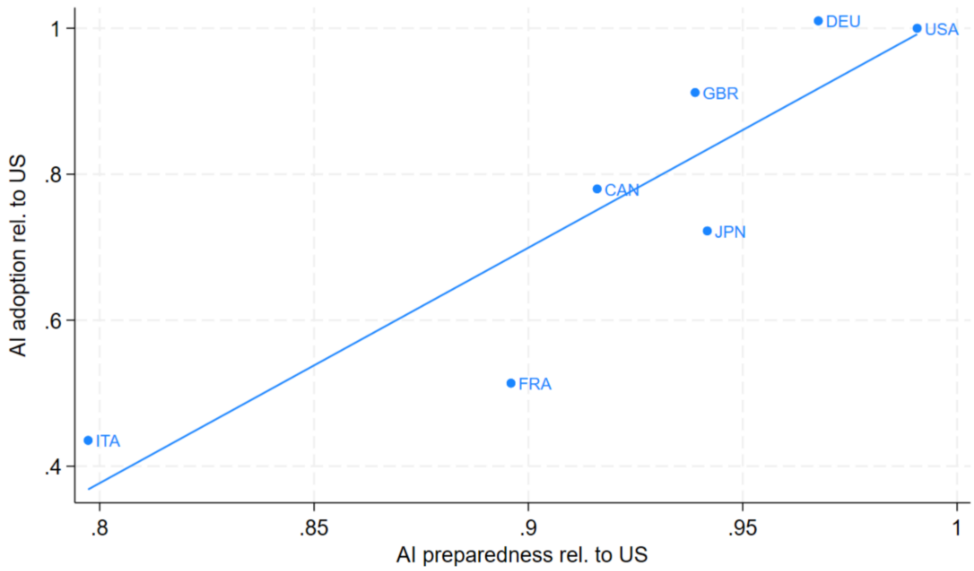
Note: The case with factor reallocation corresponds to the middle bar in Figure 11. The case without factor reallocation corresponds to Scenario 3 (Figure 10 and Table 3). In both cases, a sector's productivity growth is derived under the assumption of high adoption rates, expanded capabilities and uneven gains, and downscaled by the sector's factor share.
Source: Authors' calculations.

Figure A.8. The contribution of sectors to aggregate productivity growth



Note: Sectoral sources of aggregate productivity growth under Scenario 2. We attribute the I-O link driven *indirect effect* to the sectors which use cheaper and more abundant intermediates from upstream sectors following productivity improvements in those upstream sectors. Thereby these downstream sectors magnify the productivity gains of these upstream sectors. Note also that even if individual sectoral contributions from manufacturing are low, total manufacturing altogether represents a sizable contribution to aggregate gains.
Source: Authors' calculations.

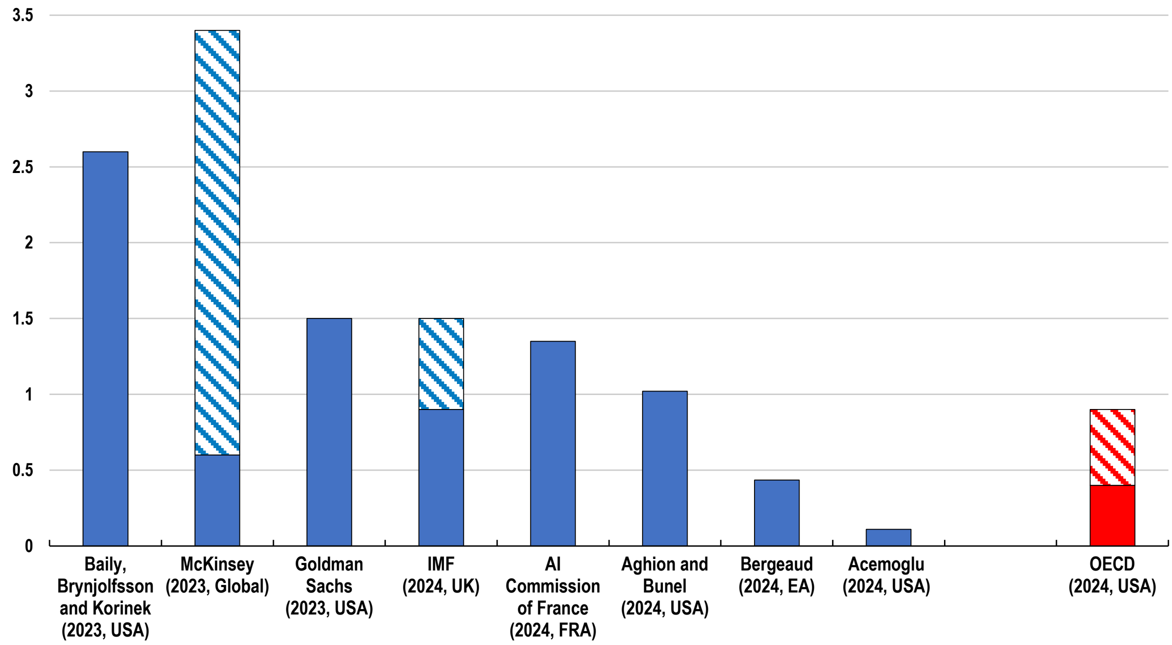
Figure A.9. Estimated AI adoption relatively to United States and AI Preparedness Index



Note: The vertical axis reports the estimated ratio between US future adoption rate and future adoption for different countries, based on the observed cross-country variation in *current* adoption rates. See more details in the text. The horizontal axis reports the AI Preparedness Index (Cazzaniga et al., 2024), again relatively to US. The AI Preparedness index assesses the level of AI preparedness across based on a set of macro-structural indicators that including digital infrastructure, human capital and labour market policies, innovation and economic integration, and regulation and ethics.
Sources: Authors' calculations relying on Eurostat (for capturing variation within European countries) and preliminary results from the Global Forum on Productivity survey on AI use in companies (for capturing the variation across US, Europe, Canada and Japan; OECD, 2024b). Cazzaniga et al. (2024)

Figure A.10. Comparing AI's predicted macro-level productivity gains across studies and this paper

Predicted increase in annual labour productivity growth over a 10-year horizon due to AI (in percentage points)



Note: When the source presents a range of estimates as the main result, the lower and upper bounds are indicated by striped areas. In cases where modelling predictions primarily focus on TFP, labour productivity is obtained using simple assumptions about the aggregate capital multiplier (Acemoglu, 2024; Aghion and Bunel, 2024; Bergeaud, 2024; our paper). The estimates refer to the countries shown in brackets.
Sources: See references at the end of the paper; for Goldman Sachs (2023), the underlying reference is Briggs and Kodnani (2023); for IMF (2024) the underlying reference is Rockall, Pizzinelli and Tavares (2024); for OECD, the range from this paper's main scenarios are shown (Table 2 last row in Section 3.1).

4. Derivation of AI exposure and adoption rates across different countries

4.1. AI exposure: from US ONET to ISIC

To derive sectoral AI exposure in terms of ISIC sectors, we start from AI exposure estimates from Eloundou et al. (2024) at the level of ONET tasks. We use both their baseline beta measure and the gamma measure, which accounts for extended capabilities. Eloundou et al. (2024) offer two types of exposure estimates: those derived from human ratings of ONET's Detailed Work Activities (DWAs) and task-level assessments using GPT-4 APIs. We focus on human-coded exposure variables. While the GPT-based measures offer more granular insights, Eloundou et al. (2024) present the human-coded estimates as their primary findings, arguing that the GPT-based results are less robust and more sensitive to prompt variations. We combine this exposure data with task-level information on manual task intensity, sourced from Acemoglu and Autor (2011).

For the US, we aggregate the task-level data to the occupational classification of SOC 2018 at the 6-digit detail. We differentiate between core and non-core, supplemental tasks in occupations and assign a double weight to core tasks (see more details in O*NET, 2023). Using the occupational composition of industries from the BLS Occupational Employment and Wage Statistics (OEWS) survey, we aggregate this information to NAICS 3-digit industries using employment weights. We then convert the NAICS 3-digit classifications to ISIC 2-digit sectors by leveraging a crosswalk from the U.S. Census Bureau, corresponding NAICS 6-digit to ISIC 4-digit industries, incorporating employment data at the NAICS 3-digit level. In cases where a single NAICS 6-digit code corresponds to multiple ISIC 4-digit codes, we first distribute the employment evenly across the NAICS 6-digit codes within each NAICS 3-digit group, then again equally across each ISIC 4-digit code corresponding to the same NAICS 6-digit code, generating unique NAICS 6-digit–ISIC 4-digit cells with their associated employment estimates. Finally, we aggregate the AI exposure to the NAICS 3-digit level and convert it to ISIC sectors using an employment-weighted average across the NAICS 6-digit–ISIC 4-digit cells.

For EU countries, we first aggregate the task-level dataset to the 8-digit O*NET-SOC 2018 occupation codes, again using core weights. We then convert these codes to SOC 2010 6-digit codes, for which a crosswalk to ISCO 2008 4-digit codes is available from the BLS. To avoid double-counting, we follow the methodology outlined by Dingel and Neiman (2020). When a SOC 2010 6-digit code maps to multiple ISCO 4-digit codes, we allocate the U.S. employment weight of the SOC across the ISCO codes proportionally to the ISCO employment shares in the respective EU country. This gives us unique SOC 2010 6-digit–ISCO 2008 4-digit cells. We then calculate the average AI exposure across all SOCs within each ISCO 3-digit category, weighted by estimated employment in the SOC 2010 6-digit–ISCO 2008 4-digit cells. Finally, we use an ad-hoc extraction of Eurostat microdata providing the composition of ISCO 3-digit occupations within ISIC 2-digit industries (with some aggregation to avoid overly granular cells with too few units) to obtain a weighted average of AI exposure within ISIC sectors.

4.2. AI adoption: harmonising across countries

To estimate AI adoption rates across different countries and sectors, we draw on a combination of sources to cover our target sample. For the U.S., our primary source is the Business Trends and Outlook Survey (BTOS), from which we use estimated AI adoption data from November 2023, as well as projected adoption for November 2024—representing one and two years after the introduction of ChatGPT. Sector-specific adoption rates for the U.S. are based on NAICS 2-digit estimates from BTOS, converted to ISIC using the methodology described earlier, which relies on the U.S. Census Bureau's crosswalk between NAICS 6-digit and ISIC 4-digit industries.

We calculate average AI adoption rates across BTOS waves from June to August 2024, with the exception of agriculture, for which we use the latest available estimate from December 2023, adjusted by the average growth in adoption (33%) up to mid-2024.

For the EU, the most recent AI adoption estimates come from Eurostat in 2023. However, Eurostat's definition of AI is broader than that used in BTOS, and the sample includes only firms with more than 10 employees. To align the two data sources, we use a global survey conducted by the OECD Global Forum on Productivity (GFP) between May and August 2024. This survey provides AI adoption estimates for the U.S. and several EU countries based on a harmonised set of questions posed to a representative sample of employers. Using the relative adoption in the EU with respect to the U.S. from the GFP data, we ensure the average AI adoption rate in the EU is comparable with that of the US. We then use cross-country variation from Eurostat's to arrive at comparable estimates for individual EU countries.