Growth Lab

AI Meets Trade: Global Linkages and the Cross-country Distribution of the Gains from AI

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Foreword

Acknowledgements

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This work is also contributing to the OECD's Horizontal Project on Artificial Intelligence "Thriving with AI: Empowering Economies, Societies and Citizens".

ABSTRACT/ RÉSUMÉ

AI meets trade: Global linkages and the cross-country distribution of the gains from AI

This paper provides estimates of expected per capita real income gains from AI over the next decade in OECD and G20 economies. It relies on a multi-country, multi-sector general equilibrium model to incorporate the role of international trade and considers different scenarios regarding AI adoption paths and AI capabilities. In our central scenario, AI-driven productivity gains vary widely across countries and are expected to raise per capita real income growth by 0.1–0.95 percentage points annually. The model's dynamics reveal a key insight: while countries lagging in AI adoption can gain from cheaper, AI-intensive imports generated by global diffusion, maintaining competitiveness - especially in highly AI-exposed sectors - ultimately requires strong domestic AI adoption. As a further channel, the paper quantifies the welfare effects generated by international knowledge spillovers boosting AI adoption of countries with relatively lower AI adoption.

Keywords: Artificial Intelligence, International trade, Productivity, Technology adoption.

JEL codes: C6, E1, F1, O3, O4, O5.

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L'IA et le commerce : liens mondiaux et distribution internationale des gains de l'IA

L'article fournit des estimations des gains attendus de revenu réel par habitant liés à l'IA au cours de la prochaine décennie dans les économies de l'OCDE et du G20. Il s'appuie sur un modèle d'équilibre général multi-pays et multi-secteurs afin d'intégrer le rôle du commerce international, et il examine différents scénarios concernant les trajectoires d'adoption de l'IA et ses capacités. Dans notre scénario central, les gains de productivité induits par l'IA varient fortement selon les pays et devraient accroître la croissance du revenu réel par habitant de 0,1 à 0,95 point de pourcentage par an. La dynamique du modèle met en évidence un point essentiel : bien que les pays en retard dans l'adoption de l'IA puissent tirer parti de l'importation à moindre coût de biens et services intensifs en IA grâce à la diffusion mondiale, le maintien de leur compétitivité – notamment dans les secteurs fortement exposés à l'IA – exige une adoption domestique solide. En outre, l'article quantifie les effets de bien-être générés par les transferts internationaux de connaissances qui stimulent l'adoption de l'IA dans les pays dont le niveau d'adoption est relativement faible.

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

Codes JEL : C6, E1, F1, O3, O4, O5.

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AI meets trade: Global linkages and the cross-country distribution of the gains from AI

By Francesco Filippucci, Peter Gal, Katharina Laengle, Matthias Schief and Muhammed A. Yildirim[1]

1. Introduction

Artificial Intelligence (AI) is expected to bring important economic gains. These may arise through higher productivity in a range of economic activities, as discussed in Agrawal, Gans and Goldfarb (2019) and in previous OECD work (Filippucci et al., 2024; Filippucci, Gal and Schief, 2024).[2] Estimates of the magnitude of these effects vary widely across studies, ranging from less than 0.1 percentage point annual total factor productivity growth boost over the next decade (Acemoglu, 2024) to about 0.6 percentage points (Aghion and Bunel, 2024; Filippucci, Gal and Schief, 2024; Bontadini et al., 2025) with even faster and accelerating growth in case AI matches or surpasses human capabilities in all cognitive tasks (Artificial General Intelligence, AGI; Trammell and Korinek, 2023).[3] Realised gains from AI - particularly those in the mid-to-

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This work is also contributing to the OECD's Horizontal Project on Artificial Intelligence "*Thriving with AI: Empowering Economies, Societies and Citizens*".

[2] For further OECD contributions in a few key areas related to AI's economic and welfare gains, see the OECD AI Principles (OECD, 2024f) at https://oecd.ai/en/ai-principles; Lorenz, Perset and Berryhill (2023) on Generative AI capabilities and risks; Calvino, Reijerink, and Samek (2025) on an overview of impacts in productivity, innovation and entrepreneurship; Calvino, Haerle and Liu (2025) on its potential as a new General Purpose Technology; OECD (2023b) on positive impacts at the workplace; Anderson and Sutherland (2024) on health and (OECD, 2023a) on education.

[3] Nordhaus (2021) also discusses this, and more recently Erdil and Besiroglu (2024) and The Economist (2025) covered this possibility. However, recent OECD work that evaluates the difference between human and AI capabilities in a range of domains concludes that current AI is still far from meeting that threshold (OECD, 2025a).

upper part of this range - could make a meaningful contribution to reviving sluggish productivity growth in OECD economies (Andre and Gal, 2024; Fernald, Inklaar and Ruzic, 2025).

However, most estimates in the literature tend to focus on the United States, with some exceptions that also provide assessments for the G7 (Filippucci et al., 2025) and for Europe (Bergeaud, 2024; Misch et al., 2025). Moreover, existing studies typically evaluate the potential gains from AI by focusing exclusively on the drivers of domestic productivity growth (micro-level gains from AI, sectoral exposure to AI and AI adoption rates) without accounting for international linkages. However, in an integrated global economy, domestic production and consumption opportunities - and hence welfare effects - also depend on productivity developments *abroad* and on changes in competitiveness following the AI shock. Accordingly, our aim is to assess how productivity growth from AI translates into global income gains *in the presence of trade* and account for the source of these gains via trade links.[4]

Previous OECD work, in particular Filippucci, Gal and Schief (2024) and Filippucci et al. (2025), have considered the implications of trade insofar as the sectoral composition of an economy also reflects specialisation patterns, but they did not account for how domestic real incomes are affected by foreign productivity developments. This paper builds on those to update and extend our previous projections to all OECD and G20 economies.[5] It derives country-sector level productivity gains from AI, which are then incorporated into a global multi-country multi-sector general equilibrium model featuring an international trade network, demand and price adjustments as well as factor reallocation across sectors (Cakmaklı et al., 2021, building on Baqaee and Farhi, 2024). The model also allows us to decompose the gains into various trade-related channels. In particular, we explicitly model how changing trade flows - arising from uneven AI-induced productivity gains and resulting price changes across countries and sectors - may affect the global distribution of welfare gains. We focus on a welfare metric that goes beyond productivity and captures consumption possibilities in an international context, which is *per capita real income*. It incorporates developments beyond domestic productivity and also depends on price effects driven by productivity developments abroad.[6]

We consider three key channels through which international trade can interact with AI adoption to induce economic gains (higher per capita real income). First, countries that trade with leading AI adopters or rely heavily on imports of highly AI exposed goods and services - knowledge intensive services such as finance and ICT services - can benefit from AI-driven productivity gains abroad through lower intermediate and final goods prices (import channel). Second, countries that specialise their exports in heavily AI exposed activities can boost their output sales by being early adopters and improve their competitiveness. However, at the same time, reductions in world prices due to AI-driven productivity growth can also negatively affect

[4] Importantly, we differ from classic "gains from trade" analyses, which compare welfare in autarky and trade equilibria. For a recent discussion on the potential role of AI in affecting the gains from trade, see WTO (2025). For another recent analysis on the cross-country differential macro-economic impacts from AI in a global context, see Cerutti et al. (2025).

[5] The calculations are done for all 76 economies that are present in the OECD's rich inter-country input-output tables (Yamano et al., 2023). However, results outside the OECD and G20 are more rudimentary and primarily serve to close the global model.

[6] Per capita real income growth may deviate from labour productivity growth (defined as GDP per worker), due either to changes in the employment-to-population ratio or to differences between real income and real output (GDP) that may arise in an open economy. Following our previous work (Filippucci, Gal and Schief, 2024), the framework used in this paper abstracts from labour utilisation changes induced by AI, and thus assumes a constant employment-to-population ratio. However, the multi-country general equilibrium nature of the model allows for the distinction between real GDP and real income developments, the latter incorporating terms-of-trade effects. In particular, improvements in the terms of trade—measured as an increase in the ratio of export to import prices—can result in real income per capita growing faster than real GDP per capita or labour productivity (Oulton, 2023; Baqaee and Farhi, 2024). Further details on model assumptions and specifications are provided in Section 3.

the export competitiveness of countries that fall behind (export specialisation channel). Hence, trade-related gains are conditional on *domestic* AI adoption, which is required to remain competitive in the face of global adoption and reap the benefits from exporting opportunities. Third, lagging countries can learn about the use of the technology through trading partners that are leading adopters (knowledge spillovers leading to faster adoption). These mechanisms allow for the transmission of the benefits from AI-driven productivity growth across borders even to places where local AI adoption capabilities are less developed.

Our results reveal wide variation across OECD countries in terms of the expected gains from AI. In the central, medium pace, scenario - where AI is assumed to diffuse in the economy following a similar pace as was observed for previous ICT technologies such as computers and the internet[7] - these gains range across countries from 0.1 to 0.95 percentage points in terms of contributions to annual per capita real income growth over the next 10 years.[8] On the high end of the range are the United States and other economies where knowledge intensive services represent a large share of the economy (for instance, Switzerland, UK, Netherlands and Luxembourg) or where conditions for AI adoption seem most favourable, based on official surveys about AI use among businesses and on factors that drive AI adoption capacity such as digital infrastructure, skills and innovation capacity (for instance, Israel, Korea, Ireland and Sweden).[9] Our underlying estimates regarding AI's contributions to annual *labour productivity* growth span a similar range, 0.1-1 percentage points over the next decade in the central scenario (medium adoption speed).[10]

The macroeconomic gains in terms of per capita real income are obtained by feeding country-sector level TFP increases due to AI into the global general equilibrium model. We then decompose the resulting model predicted gains into domestic and foreign sources and link them to trade and adoption patterns. This decomposition reveals that trade plays an important role in the transmission and distribution of the AI generated productivity effects across countries. Indeed, the sector-level TFP gains translate into lower output prices, which in turn impact downstream producers and consumers, domestically and abroad. Countries that import a lot of heavily AI-impacted goods and services, in particular from leading AI adopters, benefit through lower import prices of final and intermediate goods and services. Such gains can

[7] A faster adoption pace, similar to that of mobile phones, as well as a slower adoption pace, like that of electricity, are also considered. These lead to about 50% larger or about 40% lower gains on average, respectively.

[8] Our aim is to assess the *potential contribution* of AI to the growth in real incomes, conditional on different assumptions about AI and other features of the economy, not to forecast *overall* income growth. Overall per capita real income growth over the next decade is expected to be affected by several other factors other than AI. Our estimates also should not be simply added to existing growth projections since those typically assume already some degree of continued technological progress.

[9] Putting these results in context and comparing them with how the last major technology boom led by ICTs played out in terms of cross-country differences provides a useful benchmark. The ICT boom contributed about 1-1.5 percentage point to labour productivity over the 1995-2005 period in the US, while the comparable figure was much smaller elsewhere in the OECD, in particular in Europe (Byrne, Oliner and Sichel, 2013; Bunel et al., 2024). In comparison to the earlier literature on the aggregate growth implications of AI, the results in this paper suggest gains that are higher than what was reported by Acemoglu (2025) but lower than what was reported in early studies by McKinsey & Company (2023), Baily et al. (2023) and Briggs and Kodnani (2023). In terms of magnitude our results are closest to those of Aghion and Bunel (2024). See more detailed comparisons in Filippucci, Gal and Schief (2024) and Filippucci et al. (2024).

[10] See Annex Figure A.7. As shown by a counterfactual exercise that isolates the role of adoption rate differences from sectoral composition reveals that the former – adoption rate, which is also the more policy actionable part – plays the more important role in driving these cross-country differences (Annex Figure A.8).

account for up to half of the total welfare gains from AI in Latin American and Central Eastern European OECD economies.

However, the potential for deriving domestic real income growth entirely from foreign productivity gains should not be overstated. Productivity growth abroad not only lowers import prices but also puts downward pressure on the world prices of the goods and services that a country exports, so that the net effect on the country's terms of trade is ambiguous. To illustrate that countries cannot expect large gains by relying exclusively on foreign AI-driven productivity gains, we also evaluate by how much real incomes in each country increase if they do not adopt AI while all other countries do. This leads to no domestic productivity growth in our model, but only abroad. In this case, the non-adopter country still benefits from lower import prices, but it also loses competitiveness on world markets as other countries offer competing goods and services at lower prices. Hence, export revenues decline, which means that real consumption possibilities are not necessarily improved much despite lower import prices. This loss of competitiveness is strongest for countries that are more exposed to price competition induced by foreign AI-driven productivity gains, for example because they compete in goods and services whose productivity is more impacted by AI (knowledge intensive services).

In separate simulations, we also model international knowledge spillovers, due to learning from more AI-advanced trading partners (i.e., learning by importing). These learning effects may accelerate AI adoption and hence lead to higher domestic productivity. Under the assumption of strong knowledge spillovers, this mechanism may amount to a tripling of the productivity gains from AI for some Latin American OECD countries and also yield about a 30-40% additional boost to the productivity gains in several Central Eastern European OECD countries, given strong trade links with leading AI adopters (the United States and advanced Europe, respectively). For other countries, however, the additional gains are generally small, even when assuming substantially larger learning effects for AI adoption than found in previous literature on innovation spillovers.

Historical evidence suggests that during previous waves of major technological change such as during the industrial revolution, the cross-country income distribution widened as early adopting countries pulled away from others (Korinek and Stiglitz, 2021). This divergence was repeated, to a lesser extent, more recently during the ICT-boom of the mid-90s, which played out primarily in the United States but yielded more muted benefits in Europe due to slower adoption of the technology throughout the economy (notably in services, such as retail; van Ark, O'Mahoney and Timmer, 2008). The cross-country pattern of our estimates, which are primarily driven by current AI adoption capacities and sectoral specialisation patterns point to similar diverging tendencies as a result of AI.[11]

To avoid such international divergences and exploit the full potential from AI adoption, especially when considering the role of international linkages, policymakers have a range of options:

a) First, strengthening digital infrastructure – including AI-related data centres – along with secure energy supply, skills and innovation capacity are critical to enable domestic adoption, as mentioned in previous work (Filippucci et al., 2025). Digital infrastructure should include AI-specific data centres to ensure fast ("low-latency'') and reliable access to advanced AI models, such as frontier Large Language Models (LLMs).

b) Second, continued access to AI models developed in leading countries requires low barriers to digital services trade (Del Giovane et al., 2025). Moreover, the spread of open-source AI models can contribute to broader and more affordable access across and within countries - even in places without substantial local AI development or where top AI models are not accessible (Andre et al., 2025). For broad global access to leading AI models, international coordination, mutual trust, and model inter-operability are also key.

[11] See Annex Figure A.9.

c) Third, countries need to work towards lowering international trade barriers, especially for late adopters, to benefit from cheaper final good and intermediate imports as well as knowledge spillovers.
d) Finally, for a more accurate and internationally comparable measurement of progress on AI, official statistical surveys on AI use among firms and workers should be conducted in a fully harmonised manner across countries.[12]

Our quantitative analysis does not consider several channels that may be relevant for the impact of AI in an international context. First, AI may reduce trade costs by helping to overcome language- and regulatory differences across countries (Del Giovane et al., 2025). This in turn may expand or redirect international trade. However, the magnitude and direction of this channel is uncertain at this stage given the lack of systematic empirical evidence.[13] Second, AI-driven automation may prompt multinational firms to reshore production and service provision (e.g. customer services) and rely less on foreign labour.[14] This is feasible and relevant only if local AI capacity is sufficiently developed - which reinforces the main policy lesson from our findings regarding the critical importance of *domestic* AI adoption capacity. Third, to upgrade and strengthen digital infrastructure, global trade in ICT equipment (chips, memory, etc.) would also need to expand - which may also affect relative incomes across countries. Finally, to the extent that restrictive trade policies persist – including in digital services trade that lead to a fragmented global market of AI models and applications – or trade policy uncertainty prevails, our analyses might overstate the importance of trade in shaping the distribution of AI gains.[15] More generally, such restrictions may hamper an efficient specialisation and adjustment to the AI driven global productivity shock, prompted by its asymmetric nature across countries and sectors.[16]

Besides these trade related aspects, we also do not consider the production or the supply of AI, neither the costs of AI production. Such a perspective may be warranted as long as competition in the AI-producing sector ensures that productivity gains are passed on to the AI users in the form of low prices. This may be the relevant scenario over our 10-year horizon unless strong and persistent monopolistic features emerge

[12] For example, through further supporting the ongoing efforts of the OECD's Working Party on Digital Economics, Measurement and Analysis, which has long promoted harmonised measurement of the digital economy.

[13] Previous evidence on machine translation by Brynjolfsson, Hui and Liu (2019) shows positive effects on trade in a specific context. Given that Generative AI based language models further improve on translation capacity, and it helps interpreting complex legal texts to comply with local regulations, this channel can be a particularly interesting one to consider in future research.

[14] The reshoring of production may of course occur independently of AI, due to higher import tariffs and other trade barriers, which is outside of our scope.

[15] Our calculations rely on the economic structures in 2019 since the inter-country input output tables are not yet available for post-pandemic years. To the extent that trade - in particular AI impacted knowledge intensive services trade - has expanded since then, our results could also be understated somewhat. On the other hand, more recent disruptions to trade could imply less intensive trade links than in 2019 data.

[16] Earlier work assessed the possibility that uneven sectoral productivity growth could limit aggregate growth through a Baumol effect (Filippucci, Gal and Schief, 2024). The model described in section 4 of this paper, which extends the earlier modelling approach to a multi-country trade setting, also allows for Baumol-type effects. However, since the focus of this paper is on the role of trade, the Baumol effect is not analysed separately here. To the extent that international trade allows to decouple domestic sectoral consumption and domestic sectoral production it adds a margin of adjustment to uneven sectoral productivity growth, in addition to the reallocation of factors. Hence, the limiting role of uneven sectoral productivity growth for aggregate welfare growth is expected to be smaller when accounting for the role of trade.

on the AI production market despite the current dynamism.[17] Productivity gains arise in our model from the integration of AI in the production of goods and services, not from improvements in the production of AI (model training, model inference, etc.). Nevertheless, we do not consider the extent to which energy supply challenges can slow down the expansion of digital infrastructure, thereby hindering AI development and diffusion.[18] In addition, environmental concerns due to the rising energy needs from expanding AI hardware infrastructure could also limit AI use, which the calculations do not consider either. This paper also does not comment on the valuations of AI developer firms, which depend not only on expected productivity gains among AI users but also on also on the extent to which market power enables AI producers to earn profits above competitive levels.

The next section presents a high-level overview of the methodology. Section 3 discusses the determinants of the sector-level productivity gains in a “local”, domestic context, while Section 4 describes the trade related channels. For both of these steps, the details are explained in the Annexes. Section 5 presents the results and illustrates the main mechanisms. The final section concludes.

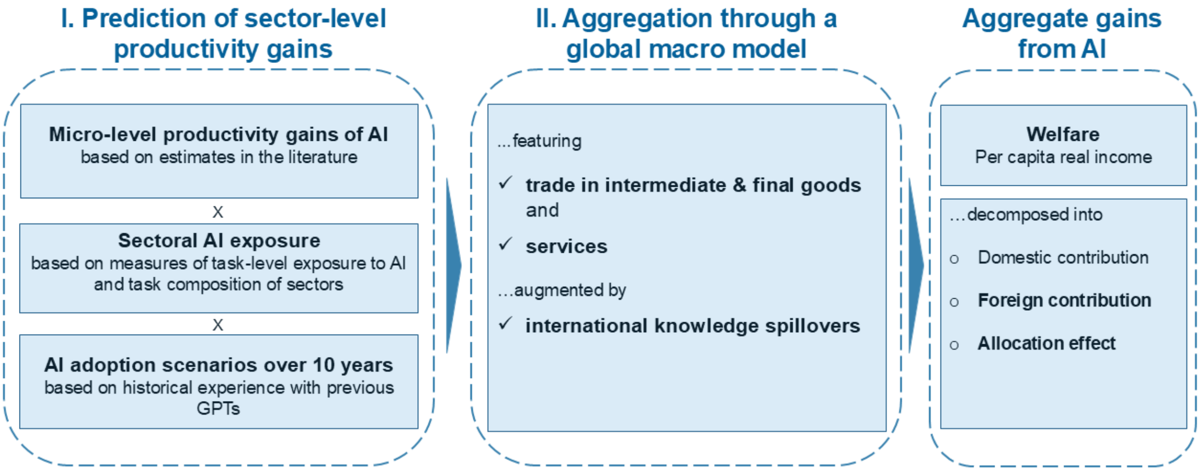
2. The macroeconomic gains from AI in an international context: from tasks to sectors and countries

This section provides an overview of the steps we take to arrive at projections of the gains from AI in a global context, accounting for cross-country and cross-sectoral differences in AI exposure and adoption, as well as for the role of international linkages. Our methodology takes a micro-to-macro approach and relies on two broad steps. First, an aggregation of task level gains from AI to sector-level gains, building on the work of Acemoglu (2025) and previous OECD research (Filippucci et al., 2024, 2025; Filippucci, Gal and Schief, 2024). In a second step, these sector-level productivity gains from AI are combined with a global multi-sector general equilibrium model to derive predictions on per capita real income effects from AI for the OECD and G20 economies, featuring a global trade network, as described in Cakmaklı et al. (2021) (Figure 1).

[17] See also Andre et al. (2025) documenting dynamic market developments in the AI producing sector.

[18] Preliminary back-of-the-envelope calculations suggest that the International Energy Agency’s projections for energy consumption by data centres over the next decade are broadly consistent with the energy demand implied by the projected AI adoption paths assumed in this paper (International Energy Agency, 2025). More discussion on AI related infrastructure investments is left for future work.

Figure 1. The macroeconomic gains from AI in an international context: a micro-to-macro framework



Note: Step I. is inspired by Acemoglu (2025), adapted to our sector-level framework which has also been applied in Filippucci, Gal and Schief (2024; Filippucci et al., 2025). Step II. and the decomposition of per capita real income builds on the multi-sector model developed in Cakmaklı et al. (2021) and building on Baqaee and Farhi (2024).
Source: Authors' elaboration.

The first step starts from experimental evidence on task-level productivity gains from AI in areas such as coding and customer service, which we combine with estimates of the share of AI-exposed tasks across different sectors. These estimates are further integrated with projections of country-specific AI adoption paths over the coming decade, which we derive relying on harmonised estimates of current adoption rates, historical adoption patterns of earlier general-purpose technologies, and data on key drivers of AI diffusion, such as the per capita number of data centres, workforce skills, innovation, or internet penetration. This approach allows us to predict AI-driven productivity gains for different sectors within a large set of countries, including all OECD and G20 countries.[19]

Further, to account for the role of international linkages, the second step of our methodology consists in augmenting the aggregation approach by allowing for two key channels: (i) international trade in intermediate and final goods that can affect the global distribution of AI-driven welfare gains and (ii) international knowledge spillovers driven by learning from trading partners that are more ahead in terms of AI adoption.

International trade in intermediate and final goods and services affects the global distribution of AI-driven welfare gains through cross-country differences in the composition of import and export baskets. To the extent that AI-driven productivity growth reduces the cost of imported final goods, consumers can benefit from foreign productivity gains. Similarly, domestic firms rely on intermediate inputs from abroad, which may also become cheaper as AI boosts productivity in trading partner countries (Figure 1, rightmost box,

[19] Since the inter-country input output tables (Yamano et al., 2023) and the global model cover 76 countries plus the rest of the world, for realism and completeness we also derived more rudimentary estimates for the remaining countries beyond OECD and G20 countries. As the calculations for these countries serve mainly to close the model globally, we refrain from presenting these results. For more details about the methodology, see Annex A.4.

"Foreign contribution").[20] However, since domestic real income also depends on firm revenues from exports, foreign productivity growth that puts pressure on world market prices can also undermine a country's competitiveness. The extent of these effects depends on the relative pace of a country's AI adoption and exposure to the AI shock, as well as the substitutability of the export product in world markets (Figure 1, rightmost box, "Allocation effect"). These features are captured by the multi-country general equilibrium model through the elasticities of substitution in production and in consumption and through the underlying international production network.

Beyond these channels, we separately model international knowledge spillovers through cross-border influences on AI adoption rates. Specifically, a country's AI adoption rate may increase in response to higher adoption in in trading partners, if imported intermediate goods and services incorporate AI applications that encourage domestic firms to adopt AI solutions themselves.

3. Determinants of sector-level productivity gains

To estimate sector-level productivity gains over the next decade, this paper adapts the analytical framework proposed by Acemoglu (2025) to a sectoral setting, as done in our previous works (Filippucci, Gal and Schief, 2024; Filippucci et al., 2025; for more details on methodology, see these papers). The empirical implementation integrates three key components for each country *c* and sector *i* to obtain sectoral productivity gains over the coming 10 years ($\textit{Sectoral productivity gains}_{ic,[t,t+10]}$): (1) average micro-level productivity gains from AI at the task-level (*Micro level gains)*, (2) the average exposure of tasks within sectors to AI ($\textit{Exposure}_{ic}$), and (3) forecasts of future AI adoption across firms within each country (Δ $\textit{Adoption rate}_{c,[t,t+10]}$). Formally, the relationship may be expressed as follows:

$$\textit{Sectoral productivity gainsic}, [t,t+10] = \textit{Micro level gains} \times \textit{Exposureic} \times \Delta\ \textit{Adoption rate}_{c,[t,t+10]} \qquad (1)$$

The subsections below elaborate on the assumptions made to quantify these components across different economies.

3.1. Micro-level performance gains from AI

Most recent studies on aggregate AI gains rely on evidence of micro-level performance improvements among workers or firms that adopt AI. In this context, micro-level studies conducted in experimental settings show that AI tools significantly improve worker performance across various tasks, although to different degrees.[21] Performance gains range from 14% in customer service to 56% in coding, with other tasks like professional writing and business consulting also benefiting, with gains around 40-45%. Recognising the risk that these experiments may not be fully indicative of productivity gains when AI is

[20] Correspondingly, the domestic contribution to welfare gains consists in cheaper final and intermediate goods for consumers and producers due to domestic productivity gains.

[21] These micro-level studies focus on AI support for customer services (Brynjolfsson, Li and Raymond, 2025), the effect of AI coding assistants on software developers (Peng et al., 2023; Cui et al., 2024; Gambacorta et al., 2024), 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) and the performance improvement with Large Language Models assisting with general writing (Haslberger, Gingrich and Bhatia, 2023). Yet more recent studies focus on legal services and find very large effects between 34% and 140% (Schwarcz et al., 2025). Briggs and Kodnani (2023) rely on firm-level studies which estimate an average gain of about 2.6% additional annual growth in workers' productivity.

taken up at a larger scale in real life contexts, we take a conservative stance: the micro-level gains underlying this paper are based on the three most precisely estimated impacts finding an average baseline effect of 30%.[22] Since much of the estimated effects capture time-savings of workers in the completion of tasks while also using capital - computers, office space, etc. - we assume these gains refer to total factor productivity (for more details see Filippucci, Gal and Schief (2024) and Annex Figure A.1).

3.2. The exposure of different sectors to AI

While the evidence discussed in the previous section highlights that AI can significantly boost productivity for certain tasks, its benefits may not extend equally to all others. To identify which tasks are exposed to AI, this analysis follows the same approach of previous work in Filippucci, Gal and Schief (2024), similar to the one of Acemoglu (2025), which relies on task-level AI exposure estimates provided by Eloundou et al. (2024) for each task in the O*NET database.

Specifically, tasks will be considered as exposed following two criteria. The first criterion, referred to as *baseline exposure*, categorises a task as exposed if it can be performed significantly faster with the assistance of AI, given the capabilities of LLMs as of 2023.[23] This baseline exposure scenario corresponds to the median estimate of Eloundou et al. (2024).[24] The second measure, labelled *expanded capabilities* exposure, classifies tasks as AI-exposed if the same performance gain can be achieved with additional software built on top of LLMs, as of 2023.[25] This measure is interpreted as a more forward-looking indicator, better suited to capturing the rapidly evolving capabilities of LLMs and average AI exposure over the projection horizon. Aggregate AI exposure is calculated as the share of tasks within a country's economy that are exposed to AI.[26]

[22] Despite this conservative stance, this figure is subject to both upside and downside risks. A potential downside risk is that firms might find it harder than expected to successful scale-up and integrate AI solutions in their core functions. Challapally et al. (2025) highlights that while many firms experiment with AI solutions, so far few succeed in moving beyond pilots and successfully integrating AI to reap substantial productivity gains. However, over a ten-year horizon, there is scope for learning from early adopters and for diffusion of best practices. Productivity growth may therefore be relatively modest initially, as firms experiment with re-designing production processes, and then accelerate as successful lessons are adopted more widely (a J-curve effect), although we do not explicitly model this adjustment path. Conversely, a longer-term upside risk may arise from the emergence of new types of economic activities that integrate AI more effectively, or from the entry of new firms whose business models fully embed data collection – a key ingredient of AI – into their operations (Agrawal, Gans and Goldfarb, 2022).

[23] Specifically, it categorises tasks as exposed to AI if they can be performed at least 50% faster, which is conservatively high figure.

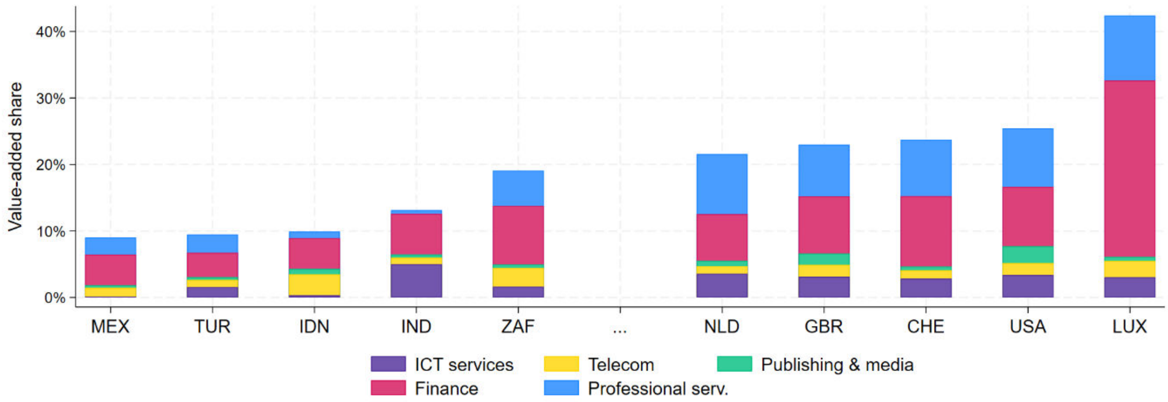
[24] Eloundou et al. (2024) provide two types of exposure estimates: one based on human ratings of O*NET's Detailed Work Activities (DWAs), and another using GPT-4 API assessments. We rely on the human-coded measures, which the authors present as their baseline, noting that the GPT-based estimates, while more granular, are less robust and somewhat sensitive to prompt variation.

[25] Going beyond these expanded capabilities, Filippucci, Gal and Schief (2024) also considered AI in combination with robotics technologies. However, the extent to which advances in generative AI (underlying the spread of technologies such as ChatGPT) can also lead to breakthroughs in robotics technology over the near term remains uncertain, as well as their magnitude in terms of the productivity impact in the tasks where they would be used. For this reason, the role of robotics technologies combined with AI are not examined in this paper.

[26] Given the task-level exposure classification, average exposure is first calculated for each detailed occupation using task compositions from the O*NET database, which are then turned into sector level exposure using weights based on employment across each occupation. When aggregating across sectors, value added weights are used. For more details, see Annex A.2

Across OECD and G20 economies, the share of tasks that could benefit from AI-driven productivity gains ranges from 20% in India to 40% in Luxembourg under the baseline AI capabilities scenario, and from just over 30% to 60% under the expanded capabilities scenario (Annex Figure A.2). Cross-country variation in AI exposure stems from two factors. First, and most importantly, some sectors that are relatively intensive in AI-exposed tasks account for a larger share of value-added in some countries. For instance, ICT, telecommunications, publishing/media, finance, and professional services account for 20–40% of value added in the Netherlands, the UK, Switzerland, the US, and Luxembourg, but only about 10% in Mexico, Türkiye, and Indonesia (Figure 2).[27] Second, to a lesser extent, differences may also exist within specific sectors across countries in the extent to which they employ AI-exposed occupations.[28]

Figure 2. The share of the 5 most AI-exposed sectors in GDP in the lowest and the highest AI-exposed countries



Note: The figure reports value-added shares of 5 most AI-exposed sectors in OECD and G20 countries, using 2019 data (pre-pandemic) from OECD STAN dataset.

3.3. *Estimating current and future AI adoption among firms*

Measuring systematic, regular AI use of firms (*AI adoption*) across OECD and G20 countries faces significant data challenges. Considering the lack of sufficiently comparable and timely data on current sector-level AI adoption across all the 76 countries required in our modelling framework, our preferred measure is based on AI use in core business functions and at high intensity.[29] We compute it after

[27] More broadly, these sectors have the following average baseline exposure in G20 and OECD economies: ICT services 52%, Finance 48%, Publishing and Media 47%, Professional Services 45%, and Telecommunication services 43%.

[28] For example, AI exposure in the construction sector ranges from around 10% to approximately 20% across OECD and G20 economies in the baseline exposure scenario (Figure A.3 in the Annex), reflecting different incidence of workers employed in occupations with higher AI exposure, such as managers, professionals, or clerks (Annex Figure A.4).

[29] To assess productivity gains in our framework, following the logic of Equation 1, our ideal AI adoption would capture AI use intensity in all business functions and tasks where AI can be used – i.e. in all of the AI-*exposed* tasks. However, that is not feasible in practice given how statistical agencies collect questions in their surveys on several types of AI use. Nevertheless, they capture AI use in *core business operations* – such as production of goods and services – which we consider as our preferred proxy measure for AI adoption. Their values are substantially lower than overall – that is, *any type of* – AI use: for instance, in 2024, the respective figures are about 3% and 14% in Europe, 4 and 9%

harmonisation and adjustment steps, extending our previous calculations for the G7 (in Filippucci et al., 2025). This section also outlines the empirical strategy for projecting our preferred AI adoption measure over the next decade.

3.3.1. Current AI adoption in core business functions: aiming for cross-country comparability

The lack of harmonised AI adoption data – especially data that captures high intensity AI use in core business functions of firms – primarily refers to differences in official statistics regarding (i) the purpose and type of AI use, (ii) the time period the statistics refer to, (iii) the coverage of the sample in terms of firm size and sectors and (iv) the survey design, i.e., the definition of a statistical unit and exemplary use cases of AI.

To address these discrepancies, we proceed in several steps. First, we *harmonise*, to the extent possible, existing surveys of countries where the official surveys on AI use among firms are sufficiently comparable in measuring high-intensity, regular AI use by firms in core business functions (production and service provision – for countries covered by Eurostat, Canada, Israel and the United States). Second, for the remaining set of the total 76 countries required for the global model, we *impute* sectoral adoption rates by using out-of-sample predictions from a simple regression model based on structural explanatory variables from three key domains relevant for AI adoption capacity: digital infrastructure, skills and innovation capacity. The selection of specific variables is based on their a statistically significant link with AI adoption as well as the availability of cross-country comparable indicators across the full set of countries (see Annex A.3 and Annex B in Filippucci et al. (2025) for a detailed summary of the underlying steps).[30]

Our preferred adoption rate estimates are calculated as the average of the *harmonised* values (derived from official survey data) and the *imputed* values (obtained from out-of-sample predictions), to mitigate measurement error arising from residual comparability issues in the partially harmonised AI adoption data. Note that our approach yields very low figures for India and China, the largest non-OECD economies, while several ad-hoc cross-country surveys indicate adoption in China and India about 50% higher than in the US (see Figure A.15). Hence, besides the low-adoption scenario (as predicted by the model), we also consider a high-adoption scenario (50% above US levels) for both of them, focusing on the latter in most discussions of the results.

Following this empirical strategy the estimates of current high-intensity AI adoption by firms in core business functions averages 4% across OECD countries ranging between about 0.2% for Mexico and about 7% for Ireland while non-OECD G20 AI adoption averages 3% ranging between 0.04% for India under the low adoption assumption and about 9.3% for China and India under the high adoption

for the United States (see Annex B in Filippucci et al. (2025)). See Calvino and Fontanelli (2023) and Calvino, Costa and Haerle (2026) and who have focused on stylised facts that emerge at the firm level regarding the type of AI use.

[30] A key assumption behind the regression-based predictions – which are fitted for countries where sufficiently harmonised AI adoption data is available – is that the estimated relationship is stable outside this group of countries. However, for less developed economies, the role of different AI adoption drivers may differ from those estimated on this group of countries, hence the adoption rate estimates for countries whose values we impute based on these predictions are surrounded by more uncertainty. An overview of the full set of considered variables across the three domains, as well as their cross-country availability, is provided in Table A.1 in the Annex.

assumption (see also Figure 4).[31] The estimates of current AI adoption in core business functions form the basis for the extrapolation over a 10-year time horizon in the future, presented in the next subsection.

3.3.2. Future AI adoption: following the path of previous General Purpose Technologies

Evaluating the impact of AI over the next 10-years requires making assumptions about the path and speed along which the technology is adopted by firms. We follow Filippucci et al. (2025) and consider previous major general purpose technologies (GPTs) and assume an S-shaped adoption path which typically reflects the slow gradual uptake of new technologies, followed by rapid adoption before reaching a plateau as saturation occurs.[32] Adoption rates for newer technologies are accelerating (Comin and Mestieri, 2018; Tankwa et al., 2025, Figure A.17 in the Annex), as reflected in the diffusion uptake of past GPT such as electricity, Information and Communication Technology (ICT) tools (including computers and the internet), and mobile phones which reached adoption levels of 23%, 40%, and 60 % respectively, 10 years after the user-friendly breakthrough of these technologies (Figure 3). Given that AI adoption rates have risen strongly in several countries over the past two years, some AI driven gains may have already been realised. This paper's calculations focus on the gains that are still to emerge due to the expected *rise* in adoption, in contrast to most previous work – including our previous papers - which focuses on the total gains that arise from the expected *level* of adoption.[33]

Drawing on the historical adoption paths of electricity, computers, the internet, and more recently mobile phones, this analysis outlines three AI adoption scenarios, at slow, medium, and fast pace. While recent adoption trends, falling access costs, and the user-friendly nature of language-based Generative AI suggest faster uptake,[34,35] deeper integration into core business functions will probably still require major investments in data, skills, and business process reorganization (Brynjolfsson, Rock and Syverson, 2021). Therefore, we focus mostly on the medium-paced adoption case in the analysis but also present the findings for the other two cases.

In the calculations of this paper, the curve for each country's AI adoption trajectory is pinned down by the current adoption rate of the country – as described in the previous subsection – and assumptions on the shape of the curve, which are assumed to be the same across countries but vary across the three scenarios. This approach leads to cross-country differences in AI adoption, with faster initial uptake causing divergence across countries, followed by convergence as countries near saturation. Over the projection

[31] Several ad-hoc cross-country surveys that also touch on AI use as for example conducted by the Japan Ministry of Internal Affairs and Communications (2024) or the Global Forum on Productivity's survey on labour shortages (OECD, 2024d) are consistent with the relative position of country-level estimates of AI adoption derived in this paper (for details see Figure A.16 in the Annex).

[32] Historically, GPTs have demonstrated S-shaped adoption curves. See the example of the internet (Figure A.18 in the Annex) and Hall, 2009; Geroski, 2000; Tankwa et al, 2025, building on Griliches, 1957, and Rogers, 1962).

[33] Current adoption rates among firms vary substantially by sector in each country, with knowledge intensive services such as ICT and Professional, scientific and technical activities typically reporting adoption rates that are substantially larger (up to 25 percent) than manufacturing and other more manual intensive activities (less than 5 percent) (see Annex B, Figure B.4 in Filippucci et al. (2025)). For simplicity, our calculations assume that these differences - in percentage points - remain the same over the projection horizon, driven by a parallel increase in adoption rate in all sectors.

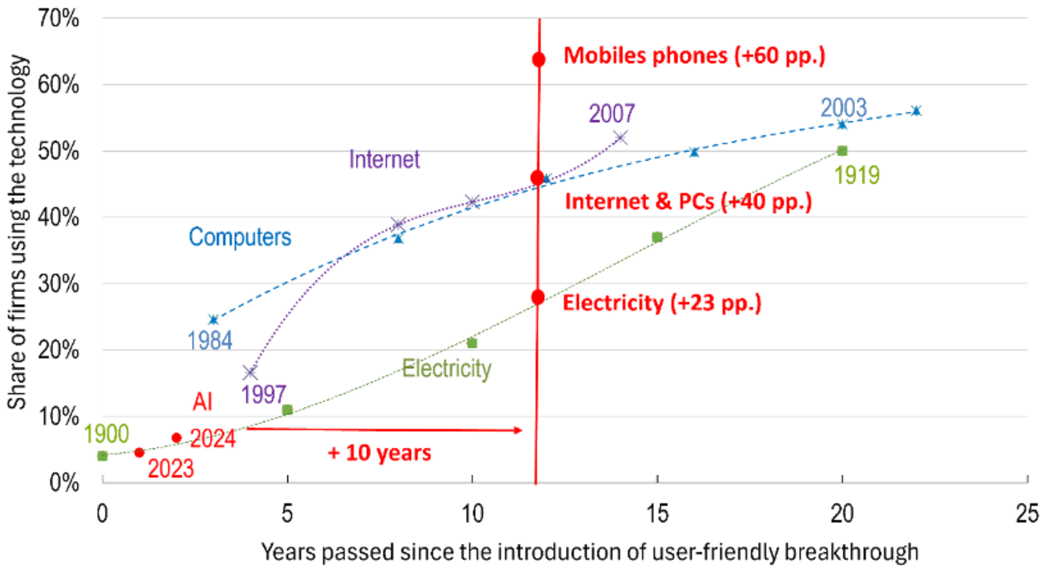
[34] For instance, AI adoption among businesses increased by about 50% between 2024 and 2025 both among EU countries and in the United States in official data. Assuming the continuation along such S-shape paths leads to an adoption rate of about 60% in 10 years, similar to that of mobile phones.

[35] New evidence shows that the quality-adjusted cost of AI models is declining exponentially (about 80% over the past two years; Andre et al., 2025), mirroring past trends observed in computational costs and computer memory (Figure A.5 in the Annex).

horizon of 10 years, it turns out that the diverging forces dominate, leading to wider difference in adoption than currently observed (see illustration on Figure A.19 in the Annex for the example of the United States and Chile).

Figure 3. Mapping AI's future adoption path with that of previous General Purpose Technologies

Share of firms* using the technology, in the United States



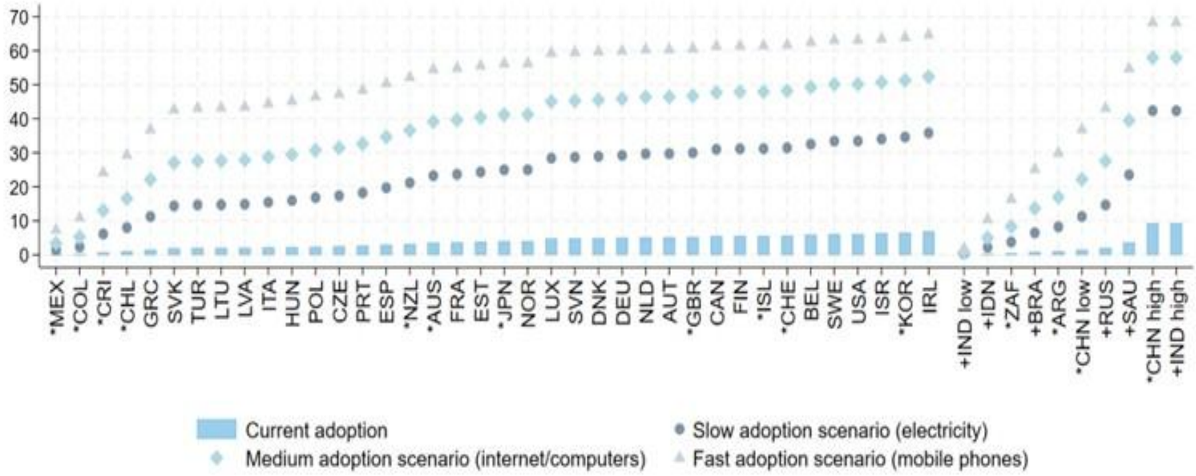
Note: *For mobile phones, the share of individuals is shown due to the lack of data on firms.
Sources: For computers and internet: United States Census; for electricity adoption of businesses: Woolf (1987) and Our World in Data; for mobile phone use of individuals: International Telecommunication Union; for AI: United States Census Bureau, Business Trends and Outlook Survey (BTOS). Beyond the United States, similar S-shaped adoption trends are observable in the case of internet use across several OECD economies (see Figure A.18 in the Annex).

Accordingly, AI adoption in 2034 is expected to range from about 30% in the slow adoption scenario to 60% in the fast adoption scenario for several leading AI adopter countries including Ireland, Korea, Israel and the United States. Lower AI adoption levels are predicted for Latin American countries including Mexico, and Colombia, where AI adoption in 2034 is expected to range between 2% to 10% depending on the scenario (Figure 4). These differences across countries in terms of future projected adoption rates reflect the ranking of estimates for current AI adoption levels mostly driven by differences across structural variables such as digital infrastructure, skills and innovation as well as the sectoral composition of the economy – in which Ireland, Korea, Israel and the United States show the highest AI adoption today.[36]

[36] Countries with low current levels of AI adoption may either "catch-up" by learning from early adopters or remain behind due to persistent adoption barriers that explain lower AI adoption rates today. Given the presence of both upside and downside risks for follower countries, the projections in this paper are based on the assumption that these risks even out, and countries differ only in the *timing* but not the *shape* of the AI adoption paths. This will result in the S-shape curves for each country to be placed in parallel, either to the left (for early adopters) or to the right (for late adopters).

Figure 4. The expected increase in AI adoption varies a lot across countries

Current and future adoption (in 10 years) based on the S-shaped adoption paths of previous GPTs, % of businesses



Note: Current adoption rates are taken from official national statistics after harmonisation steps (CAN, EU, ISR, NOR, TUR, USA) or when this is not possible, using predictions as a function of the digital infrastructure, skills, and innovation (marked by "*"). For countries for which these predictors are not available, more simplified predictions are implemented, based on a reduced set of variables including per capita real GDP and per capita internet use (marked by "+"). See Annex A.3 for details on the underlying harmonisation and prediction strategy. "CHN low" and "IND low" as well as "CHN high" and "IND high" refer to scenarios expecting low or high AI adoption in the two countries, respectively (see subsection 3.3).
Source: Authors' calculations.

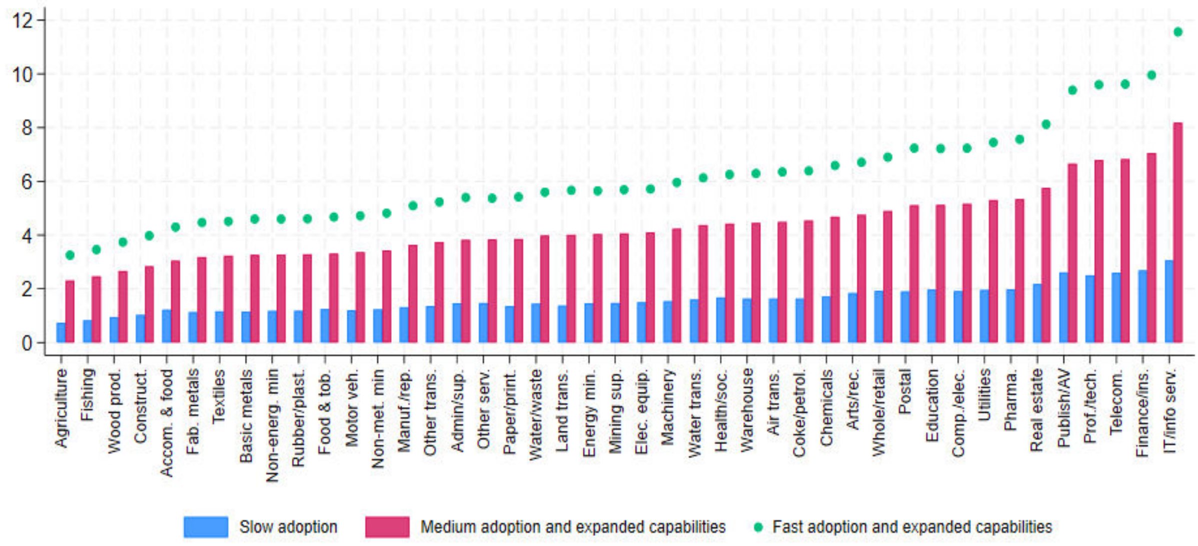
3.4. Predicted sector level productivity gains

Projections of sector-level TFP gains over the next decade are obtained by multiplying estimates of micro-level productivity gains, sectoral exposure to AI, and projected AI adoption rates, following equation 1. Significant differences in projected productivity gains exist across sectors, reflecting the fact that some sectors are much more exposed to AI than others. Depending on the scenario, projected cumulative TFP growth ranges from a low 1% in manual intensive industries (e.g., Agriculture, Fishing, or Wood) to over 10% in knowledge-intensive services, such as Professional and Technical Services, Telecommunications, Finance, or IT Services (Figure 5).[37] These results are qualitatively in line with Filippucci et al. (2025).

[37] The projected productivity gains are subject to both up- and downside risks that our current framework does not capture or quantify. On the upside, the projected productivity gains may underestimate AI's full potential, as broader innovations in organisational structures and business models could generate additional improvements by reconfiguring existing tasks or creating entirely new ones. Conversely, downside risks include the emergence of "bad" tasks with negative social value (e.g., manipulative algorithms, addictive content) (Acemoglu, 2025) and potential productivity losses from misuse, such as AI-enabled cyberattacks.

Figure 5. The projected AI-driven productivity gains vary across sectors

Projected sector-level total factor productivity gains under different scenarios (cumulative over 10 years, in percent)



Note: Calculations follow the description in Section 3, in particular equation 1. Sectoral TFP values are obtained as the simple average across OECD members.
Source: Authors' calculations.

4. How to capture the role of international linkages in shaping macroeconomic AI gains?

In this section, we develop the intuition for the analysis of the role of international trade in the distribution of AI-generated welfare gains. A central point of departure for our analysis is the observation that AI induced sectoral TFP gains imply changes in sectoral prices. These price changes affect domestic and foreign producers and consumers, and they can lead to a reallocation of factors and shifts in the production and consumption patterns. Ultimately, productivity gains and the associated price changes determine real income, which is the relevant welfare metric in an international context. Importantly, welfare gains in a country depend not only on domestically generated productivity gains from local AI adoption, but also on changes in the prices of exported and imported goods and services and on reallocation effects.[38] For example, per capita real income growth can exceed productivity growth when terms of trade improve, that is, when the ratio of export to import prices increases (Oulton, 2023; Baqaee and Farhi, 2024).[39] Countries

[38] In addition, global linkages may also affect patterns of current AI use, which then in turn affect our adoption projections. This channel will be examined in Sections 4.2 and 5.2 by modelling trade partner based knowledge spillovers or learning effects regarding adoption.

[39] Per capita real income growth may deviate from labour productivity growth (defined as GDP per worker), due either to changes in the employment-to-population ratio or to differences between real income and real output (GDP) that may arise in an open economy. Following our previous work (Filippucci, Gal and Schief, 2024), the framework used in this paper abstracts from labour utilisation changes induced by AI, and thus assumes a constant employment-to-population ratio. However, the multi-country general equilibrium nature of the model allows for the distinction between

with comparatively low domestic AI-driven productivity gains may therefore hope to benefit from AI-driven productivity gains abroad that tend to reduce their import prices. At the same time, productivity developments abroad can also affect world prices for goods and services that the country exports, leaving the overall effect on per capita real incomes uncertain.

To account for the role of international linkages in transmitting AI gains across borders, we consider three channels (Table 1). First, since households consume a mix of domestic and imported goods and services, consumers can benefit from foreign productivity gains when AI-driven productivity growth reduces the cost of imports. Similarly, domestic firms rely on intermediate inputs from abroad, which may become cheaper as AI increases the productivity of trading partners. This is especially true when importing from leading AI adopter countries or importing highly AI exposed goods and services, such as financial products or ICT services. However, we also consider a second channel according to which global AI-driven productivity gains can also affect the price of a country's export basket and impact its export competitiveness. This is all the more relevant when the country's exports are concentrated in heavily AI exposed sectors, such as ICT services or finance, or if exported goods and services are easily substitutable by other countries' exports. Moreover, as a third channel, we consider the possibility that importing from AI adopters can also boost local AI adoption, and hence directly lift domestic productivity and welfare gains, through knowledge spillovers.[40] The relevance of these trade-related channels increases with the degree of a country's economic integration with the rest of the world.

Table 1. AI and international trade: the main channels

<table>
<tr><th>Import channel</th><th>Export channel</th></tr>
<tr><td>(Channel 1) Benefitting from cheaper intermediate and final goods from abroad</td><td rowspan="2">(Channel 2) Changes in competitiveness of exports, e.g. if specialising in heavily AI exposed sectors (finance, ICT services, etc.)</td></tr>
<tr><td>(Channel 3) International knowledge spillovers leading to faster AI adoption, e.g. if importing from leading AI adopter countries</td></tr>
<tr><td colspan="2">Degree of trade openness (import and export intensity)</td></tr>
</table>

Note: For more details, see Section 4.

To quantify the role of these trade related channels from AI on a country's per capita real income, we use a multi-sector, multi-country general equilibrium trade model that reflects the global trade network, in the spirit of Baqaee and Farhi (2024) and Çakmaklı et al. (2021). Employing a general equilibrium framework is essential, as the global distribution of AI-driven welfare gains depends on the induced equilibrium changes in quantities, prices, and trade patterns. The model also enables us to explore illustrative counterfactual scenarios to shed light on the importance of the channels related to changes in competitiveness on global markets.

real GDP and real income developments, the latter incorporating terms-of-trade effects. In particular, improvements in the terms of trade—measured as an increase in the ratio of export to import prices—can result in real income per capita growing faster than real GDP per capita or labour productivity (Oulton, 2023; Baqaee and Farhi, 2024).

[40] This channel is generated outside of our global general equilibrium model and is introduced separately in subsection 4.2.

4.1. A global country-sector general equilibrium model

We employ a static multi-country, multi-sector general-equilibrium model with international production networks that builds on Çakmaklı et al. (2021) and Baqaee and Farhi (2024). We use the model to evaluate how heterogeneous, country–sector-specific productivity improvements (derived in Section 3.) translate into changes in real incomes across countries as they filter through domestic and international production networks, reallocating expenditure and reshaping trade patterns. Our application therefore differs from classic "gains from trade" analyses, which compare welfare in autarky and trade equilibria. Instead, we ask how productivity growth from AI translates into income gains across the globe *in the presence of international trade in final and intermediate goods and services*.

The model is calibrated to observed input–output shares, consumption shares, and sectoral value- added shares to realistically capture the world economy. Production in each sector features constant returns to scale and cost minimization with nested constant elasticity of substitution (CES) technologies. Sectors in different countries thus stand in imperfect competition with each other, where the strength of the competition is governed by the cross-elasticity of substitution (Armington elasticities). Representative households in each country have homothetic preferences and allocate expenditure across consumption varieties at given prices. Real income is measured by deflating nominal income with a cost-of-living index consistent with these preferences.[41] The model abstracts from several features that are important in certain contexts but that we omit here for tractability: we do not model heterogeneous firms or firm entry and exit (akin to perfect competition within sectors); we abstract from modelling changes in the aggregate employment rate (or unemployment) which can be motivated by our long (10-year) horizon focus; there is no intertemporal optimization and endogenous savings decision that governs capital accumulation; we do not model a government that could run a fiscal or trade deficit; and we do not model endogenous markups or changes in trade costs.[42]

Below we explain details on the production and consumption sides of the model and how the model is solved. We provide a mathematical description in Annex Section A.4.

4.1.1. Production

The production of sectoral output is modelled as a double-nested structure encompassing two layers. On the first layer, sectoral output is produced by combining factors, i.e., capital and labour, with an intermediate input bundle. Factors are employed domestically with labour being mobile between sectors within a country while capital is assumed to be sector specific.[43] This approach reflects the fact that capital can be tied up in specific sectors in the form of fixed assets, thus preventing its flexible transfer to other sectors. On a second layer, the intermediate bundle is composed of inputs from different sectors which in turn contain input varieties from different source countries. Cost minimization ensures that in equilibrium, labour is allocated optimally across sectors and the sourcing of intermediate input is optimal given equilibrium prices.

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[41] Given homothetic preferences, national income deflated by the (model-implied) exact cost of living index - i.e., what we call per capita real income – can be used as a welfare measure.

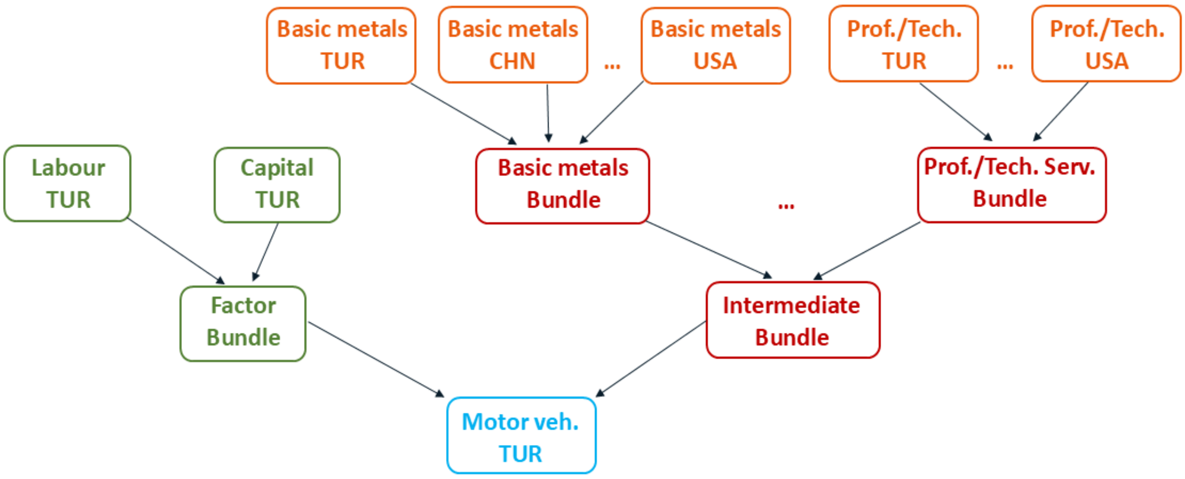
[42] The model is calibrated to the OECD inter-country input-output tables without explicitly modelling trade costs.

[43] This specification can be seen as an intermediate case between the two extreme cases discussed in our previous work: full factor mobility and fully sector-specific factors (Filippucci, Gal and Schief, 2024). In alternative, unreported specifications, we also allow some factors to be sector-specific and others to be mobile across sectors within a country.

This double-nested production structure allows us to map different degrees of complementarity and substitutability between inputs by assigning different elasticities of substitution along the different layers.[44] For example, on the first layer, the factor bundle is – partly – complementary to the intermediate bundle (the elasticity of substitution between them is smaller than one). On the second layer, we assume inputs to be complementary across different sectors (e.g., it is difficult to substitute steel with plastics in automotive production) while varieties within sectors are assumed to be more substitutable.

Figure 6 illustrates the production side of the model using the example of the Turkish automotive industry. Accordingly, the Turkish automotive industry uses Turkish capital and labour along with an intermediate bundle composed of inputs from several other sectors, such as basic metals, plastics, and business services. Each of these intermediate sector bundles is itself an aggregation of varieties sourced from different countries – e.g., basic metals sourced from Türkiye, China, the United States and other sources.

Figure 6. Production Structure – an example focused on Turkish motor vehicle manufacturing



Note: This figure illustrates the structure of inputs used in the production process for a specific sector (motor vehicle manufacturing) in a specific country (Türkiye). Each node in this figure represents either a bundle of production factors, goods and services, or varieties thereof with arrows indicating input to a downstream sector. Each layer of aggregation - ranging from sectoral varieties and bundles to intermediate goods and factors of production is combined using CES functions, each with its own elasticity parameter.
Source: Authors' elaboration based on Çakmaklı et al. (2021).

We model AI gains as a TFP shock that alters productivity at the sectoral level. An increase in productivity implies that producers can generate higher levels of output using the same amount of inputs.[45] When upstream sectors experience TFP gains, their output prices fall, reducing the cost of intermediates for downstream users, who then re-optimise their input mix given relative prices.

[44] Aggregation of factors or intermediate inputs into bundles occurs via a CES aggregator.

[45] Following Filippucci, Gal and Schief (2024), we think of AI as boosting value added based TFP, given that much of the micro-literature evaluating gains from AI identified overall time savings in the completion of tasks which is consistent with using less labour and capital to produce the same amount of value added. However, AI is assumed not to improve the productivity of intermediate inputs - such as materials use in assembling a good. 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.

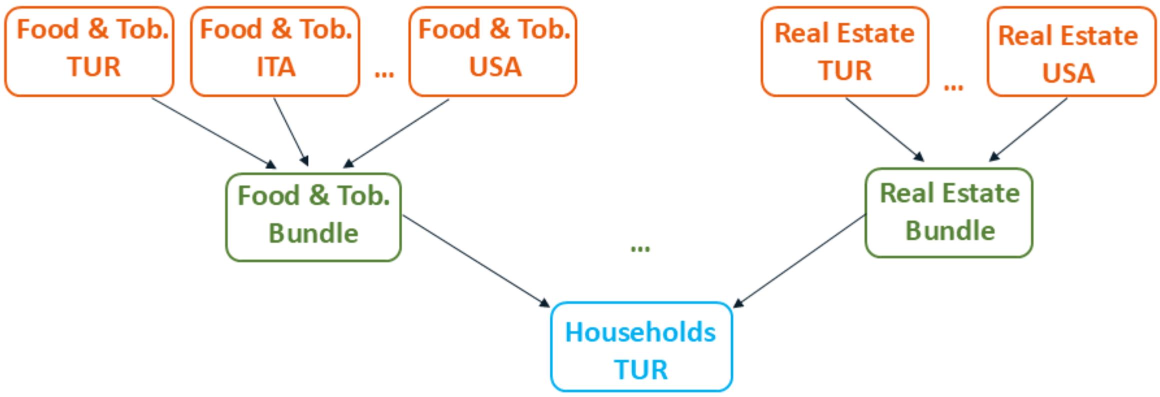
Returning to our example, the output of the Turkish automotive industry can serve as an input to other industries anywhere in the world (via their automotive sector bundles) or be consumed as a final good. In the next section, we explain the structure of the consumption bundle.

4.1.2. Consumption

Similar to production, the consumption side follows a nested CES structure with consumers in each country represented by a representative household. At the first layer of the nesting structure, households allocate their budgets across sectors by choosing among sectoral consumption bundles, taking relative prices into account.[46] At the second layer of the nesting structure, these sector consumption bundles are composed of varieties from different countries. The elasticities at this level are expected to be higher than those in the first layer, reflecting the greater substitutability among international varieties compared to cross-sector consumption. Such elasticities across countries tend to be higher in non-differentiated, homogeneous goods such as commodities, while lower in specialised products and services, such as knowledge intensive services (ICT services, finance, etc.) (Caliendo and Parro, 2015).

Figure 7 illustrates the consumption side of the model for Turkish households. Accordingly, these households allocate their budget across sectors such as food and tobacco or real estate. This corresponds, for example, to choosing among different varieties of food, such as food items of Turkish, Italian, or US American origin, to form the overall food and tobacco bundle.

Figure 7. Consumption structure – an example focused on Turkish households



Note: This figure illustrates the structure of consumption decisions in a specific country (Türkiye). Similar to Figure 6, the aggregation of consumption bundles is carried out using CES functions with varying elasticities. All bundles are specific to each country.
Source: Authors' elaboration based on Çakmaklı et al. (2021).

4.1.3. Market clearing conditions, equilibrium and solution

The model assumes an efficient economy in which markets of goods and services clear globally: each good produced is used either as an intermediate input or as a final consumption good, domestically or internationally. Within each country, factor markets also clear; thus, all labor, whether sector-specific or mobile, and all capital is fully utilized within the country. Endogenous equilibrium outcomes determine

[46] In the special case when the consumption aggregator is Cobb-Douglas, this implies that price elasticities equal one. Hence the expenditure shares on each type of goods are fixed. In this Cobb-Douglas case, this layer would reflect the fixed expenditure shares across these categories.

factor allocations, sourcing of intermediate inputs, consumption patterns, factor returns (wages and rents), and prices.

In the pre-AI equilibrium, we calibrate the model such that all good and factor prices are normalized. We then introduce AI adoption shocks in the form of the country-sector level TFP gains, as computed in Section 3 – under different scenarios, corresponding to varying speeds and channels of AI adoption (see further below in Section 5 in Table 2). After feeding the AI adoption shocks to the model, we solve for the new equilibrium. To do so, we divide the adoption shock into small increments, solve the model linearly at each step, and re-calculate the equilibrium, similar to the Euler method. By making the shock increments smaller, we better approximate the exact solution. Aggregate welfare gains are computed by comparing per capita real incomes pre and post AI adoption.

4.1.4. Data and calibration

We use the OECD ICIO table for the year 2019 to calibrate the input and consumption shares in our model (Yamano et al., 2023).[47] The OECD ICIO tables include 76 countries, plus an aggregate entity representing the rest of the world and cover 45 sectors in each country spanning the entire global economy. Elasticity parameters are taken from Çakmaklı et al. (2021), di Giovanni et al. (2023), and Baqaee and Farhi (2024), and are reported in Table A.3 in the Annex along with their references. These elasticities are commonly used in the literature and are estimated with careful research designs that exploit either tariff changes or natural experiments. We obtain these elasticities from Caliendo and Parro (2015), who estimate them using tariff increases. The elasticities tend to be higher for more homogeneous goods, such as coke, petroleum, or energy and mining products, and lower for more differentiated products, such as motor vehicles.

4.2. Learning from suppliers: Knowledge spillovers affecting AI adoption across countries

The integration of national economies into global production networks not only means that per capita real income growth can differ from productivity growth, but also that domestic productivity developments may be influenced by productivity developments abroad (Grossman and Helpman, 1991; Coe and Helpman, 1995). An important source of productivity spillovers in our setting can arise through cross-country influences on AI adoption rates depending on global connections. The country-specific AI adoption projections presented in Section 3.3 assume that the *timing* of AI adoption differs across countries, with some lagging behind compared to others. However, the *shape* of the adoption path is assumed to be the same in each country. This reflects the idea that the technology is globally available, and countries will go through the same process of rolling it out in the economy.

However, there may be cross-border spillovers in the use of the technology that arise due to trading patterns. For example, we may expect AI adoption rates to be larger, all else equal, for countries that source a disproportionate share of their intermediate inputs from AI-advanced countries.[48] Such patterns

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[47] We are constrained to this year since there were no post-pandemic global input-output matrices available when the quantitative analysis for this paper was undertaken. Given further increases in digitalisation during the pandemic, the importance of the ICT sector may be understated. However, given recent trade disruptions, the strength of trade linkages across some partners can be weaker than represented by the 2019 global input-output data.

[48] We acknowledge that this represents only one possible channel of knowledge spillovers. For instance, *exporters* may also experience spillovers when exporting to technologically more advanced destinations. However, such spillover parameters are only sparsely documented in the literature, and this channel therefore lies outside the scope of our analytical framework. Moreover, FDI flows from technologically advanced countries may likewise generate knowledge spillovers. While section 5.2 describes how the specific case in which knowledge spillovers arise within multinational firms is captured by accounting for the corresponding service trade flows, other knowledge spillover in the context of

could be the outcome of downstream firms learning about AI solutions when interacting with their suppliers (e.g., a retail firm sourcing from an AI-intensive logistics hub adopting similar AI systems for inventory management). They could also arise because of technological dependencies that shape incentives (e.g., making effective use of AI-boosted intermediate inputs may require integrating AI software in downstream production processes).[49] In addition, multinational enterprises (MNEs) can be an important driver of cross-country productivity spillovers given that AI adoption rates among subsidiaries may be more aligned with that in the multinational's home country.[50] For the technical implementation and the details of these channels, see Section 5.2 where the related results will also be discussed.

5. Results

The expected macroeconomic welfare gains from AI are presented through a set of scenarios (Table 2). The three main ones capture three sets of assumptions regarding AI adoption (slow, medium and fast, in Scenarios A1, A2 and A3; Section 3.3) and AI exposure (baseline capabilities in A1 and expanded capabilities in Scenarios A2 and A3; Section 3.2).

Three additional illustrative scenarios serve to shed light on the role of international trade. First, we shut down all domestically generated AI gains, one-by-one for each country, as a hypothetical scenario to isolate the role of foreign generated AI gains (Scenario B1). Second, we allow for trade-related knowledge spillovers that affect AI adoption. In particular, we consider both a scenario with relatively weak spillovers (Scenario B2) as well as a scenario with stronger spillovers (Scenario B3) (see more in Section 5.2). Moreover, given the important role of services trade in assessing AI-related gains through global linkages and the issue of underreported services trade in international statistics, Scenario B1 (gains under foreign AI adoption only) and Scenarios B2 and B3 (effects of AI spillovers on top of the baseline results) apply corrections for this issue.[51]

FDI are not analysed further in this paper. General issues related to AI-driven infrastructure investment will be taken up in future OECD work.

[49] Similarly, it may be the case that downstream sectors are "technologically close" to their upstream sectors and can therefore benefit from the development of complementary tools that were originally developed for AI adoption in the upstream sectors (Helpman and Trajtenberg, 1996; Carvalho and Voigtländer, 2014).

[50] At a more fundamental level, the S-shape patterns that underpins the calculations in Section 3.3 reflect two opposing forces. On the one hand, future AI adoption may be inhibited by the same frictions that explain lower AI adoption rates today, so that laggard countries may experience *flatter* adoption paths than leaders. On the other hand, laggard countries may be able to learn from the experience of other countries that have already achieved higher levels of AI adoption, allowing them to achieve a *steeper* adoption path compared to the leading countries ("catching up"). In the first part of the S-shape curve, it's the former, while in the second part, it's the latter effect that dominates (see Figure A.19 in Annex A.3.). The calculations in this section boost the latter effect in a way that is linked to trade with more advanced adopters.

[51] In brief, these corrections account for the presence of foreign multinationals and the importance of intangible assets in their operations. For the full description, see Annex A.5.

Table 2. The assumptions underlying the scenarios presented in the paper

		A1. Slow adoption and baseline capabilities	A2. Medium adoption and expanded capabilities	A3. Fast adoption and expanded capabilities	Illustrative scenarios B1. Same as Scenario A2 but without domestic AI-gains	B2. Scenario A2 with knowledge spillovers through trade	B3. Same as Scenario B2 but with *faster* spillovers
Prediction of sector level productivity gains	**Micro-level gains from AI**	30%					
	Exposure to AI	Eloundou et al. (2024), baseline	Eloundou et al. (2024), expanded AI capabilities				
	AI adoption path (on average, approximately)	As electricity (+23%)	As previous ICTs (+40%)	As mobile phones (+60%)	+40% global and +0% domestic	+40% +learning from trading partners	+40% +*fast* learning from trading partners
Global macro model	**Labour mobility**	Mobile within countries, but not across countries					
	Capital mobility	Sector- and country-specific capital					
	Production, consumption and trade elasticities	High					
	Accounting for services trade	Standard (as reported in OECD ICIO tables)			Standard	Corrected	Corrected

Note: See section 3 for more details on the prediction of sector-level productivity gains. Percentage numbers in brackets refer to the expected increase of different metrics within 10 years. See section 4 for details on the global macro model applied in this paper.
Source: Authors' elaboration.

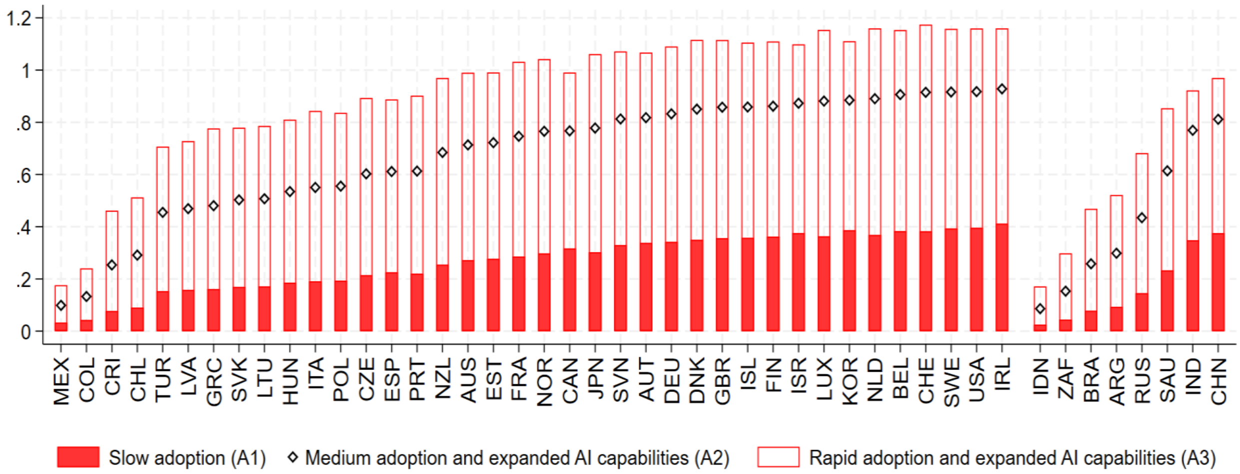
5.1. Estimates on the macroeconomic gains from AI across the OECD and the G20

The projected welfare gains from AI - expressed in terms of percentage point contributions to annual per capita real income growth over the next 10 years - differ significantly across economies and scenarios (Figure 8). Across OECD countries, these range from 0.03 to 0.4 percentage points under the slow adoption scenario (Scenario A1), from 0.1 to 0.95 percentage points under the medium adoption and expanded capabilities scenario (Scenario A2) and from 0.2 to 1.2 percentage points under the rapid adoption and expanded capabilities scenario (Scenario A3).[52]

[52] Aggregate per capita real income gains include the impact of capital accumulation, which in our case are calculated outside of the model by applying a simple 1.5 multiplier on top of the TFP induced real income per capita changes. This is a simplistic assumption that aims to account for the long-run multiplier observed between labour productivity and TFP growth, as was done in our previous works (Filippucci, Gal and Schief, 2024; Filippucci et al., 2025).

Figure 8. AI's macroeconomic gains will vary widely across countries

Predicted per capita real income gains due to AI over the next 10 years, percentage points (annualised)



Note: For the description of scenarios, see Table 2.
Source: Authors' calculations.

Differences across scenarios reflect both the pace of AI adoption and the sectoral composition of national economies. For instance, estimates are comparably low in Latin American countries, such as Mexico and Colombia, at around 0.03-0.2 across the three scenarios (Scenarios A1-A3), consistent with their relatively lower value added share of knowledge-intensive service sectors and a larger emphasis on manufacturing, which is less impacted by current AI technology.[53] In contrast, Luxembourg, Switzerland and the United States, with a greater reliance on AI-impacted sectors such as finance and ICT, show welfare gains from 0.4 to 1.2 percentage points across scenarios. The estimated effects in non-OECD G20 economies also range widely, with the lowest gains expected for Indonesia and South Africa (0.05-0.25 across scenarios) and the highest ones for India and China (0.4-1 across scenarios[54]).

In comparison to the earlier literature on the aggregate growth implications of AI, the results in this paper suggest gains that are higher than what was reported by Acemoglu (2025) but lower than what was reported in early studies by McKinsey & Company (2023), Baily et al. (2023) and Briggs and Kodnani (2023). In terms of magnitude our results are closest to those of Aghion and Bunel (2024).[55] To put findings into perspective, comparing our results with the most recent technology driven boom - led by ICTs – provides a useful benchmark. The ICT boom contributed about 1-1.5 percentage points to annual labour productivity growth over the 1995-2005 period in the US, while the comparable figure was much smaller elsewhere in the OECD, in particular in Europe. This gap in performance was attributed to lower adoption

[53] As highlighted in Section 3.3 and Annex Figure A.14, it should also be noted that the underlying AI adoption values for Latin American countries are derived entirely from model-based estimates.

[54] The adoption scenarios for IND and CHN presented here correspond to the high adoption assumption described in section 3.3.1.

[55] Since most of these studies focus on productivity effects, as we have also done in our earlier work (Filippucci, Gal and Schief, 2024; Filippucci et al., 2024), Annex Figure A.7. shows aggregate labour productivity gains consistent with our productivity growth projections from this Section.

of ICTs in lagging countries, not only in core digital sectors but in some services such as retail (van Ark, O'Mahoney and Timmer, 2008).[56]

Moreover, our results suggest that AI is likely to increase existing cross-country differences in income per capita across the OECD (Annex Figure A.9). This is explained by the strong positive correlation found between AI adoption and economic development, and by the fact the most exposed sectors – knowledge intensive services – represent a larger share of economic activity in richer countries. A simple counterfactual exercise shows that among these two, it is the more policy actionable part – AI adoption – which is the more important driver of cross country differences: if countries were to adopt AI to the same extent as the United States, even the countries benefitting the least from AI would see their labour productivity gains at about 0.7 percentage points per year, instead of about 0.1, when using their actual adoption rates (Annex Figure A.8). Indeed, facilitating the diffusion of AI through enhanced digital infrastructure – including AI-related data centres – alongside a secure energy supply, a suitably skilled workforce, and strengthened innovation capabilities is critical to supporting effective domestic adoption.

5.1.1. Dissecting aggregate effects: price changes induced by the AI shock and the role of trade specialisation

In an integrated world economy, per capita real income growth in any given country depends not only on domestic productivity gains, but also on productivity developments abroad which can affect the domestic economy through trade. In our model, foreign productivity improvements contribute to determining world market prices and thus influence the terms at which products are imported and exported.

Welfare gains may thus be impacted by these AI-induced price changes. On the one hand, lower import prices raise domestic per capita real income, as consumers gain access to the same goods at lower cost. On the other hand, productivity improvements abroad can also put pressure on export prices and undermine the ability of domestic producers to remain competitive in global markets. To understand the welfare implication of AI-driven productivity growth, the discussion below will consider how the initial productivity shock transmits into output price declines which in turn impacts export and import price declines, depending on the structure of the economy regarding output specialisation and trade patterns.

The decline in output prices following the AI-induced TFP increase is a key step to generate real income gains. Prices in the model adjust after different countries and sectors experience AI-driven productivity gains, following market-clearing conditions in each sector.[57] Sectors that benefit more from AI adoption are expected to experience stronger output price declines, since they can produce more output with the same amount of input (Figure 9). These include the most AI exposed sectors, such as knowledge intensive services - financial services, IT and information services, professional and technical services, publishing / AV and telecommunication services. The lowest declines are expected in more manual intensive sectors where AI exposure is low - for instance, fishing, agriculture, construction and low-tech manufacturing such as textiles.[58] Relatively homogeneous goods such as commodities (in the mining sector) experience relatively stronger price declines than the inverse of TFP increases. This is due to their high cross-elasticity

[56] The less dynamic technology adoption observed in Europe might be explained by a weaker business reorganisation capacity. This may arise in the context of stronger labour regulations, as recently suggested by Schoefer (2025).

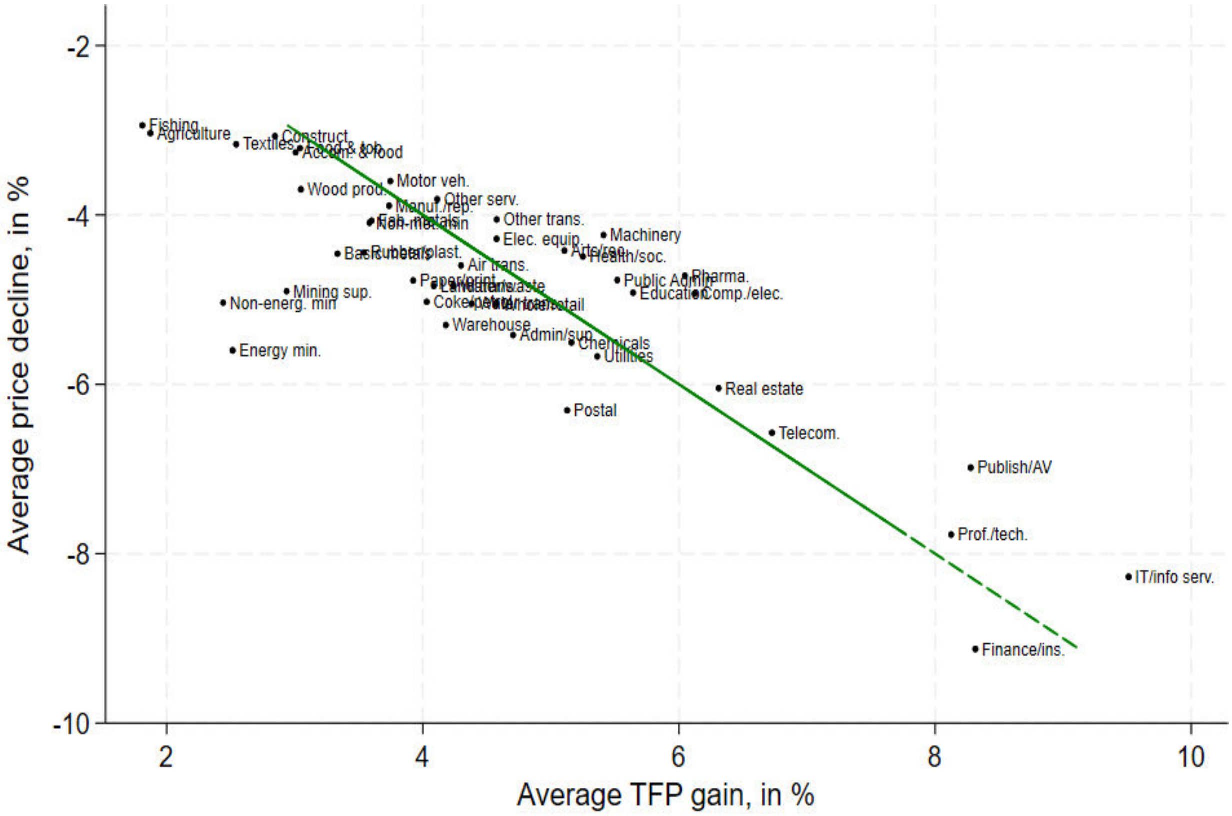
[57] Real income growth in the model is derived as the inverse of the growth rate of the price level.

[58] The negative 45-degree line is shown in Figure 9 for reference. If all elasticities in the model were equal to one and the share of expenditures on each product would be constant (i.e., "Cobb-Douglas case"), price changes would exactly match the inverse of TFP changes, and the points on the figure would lie along the negative 45-degree line.

of demand across varieties which induces stronger competition among producers and leads to lower prices.[59]

Figure 9. Large TFP gains lead to large declines in output prices

Average change in prices and TFP across sectors over the next 10 years, in %



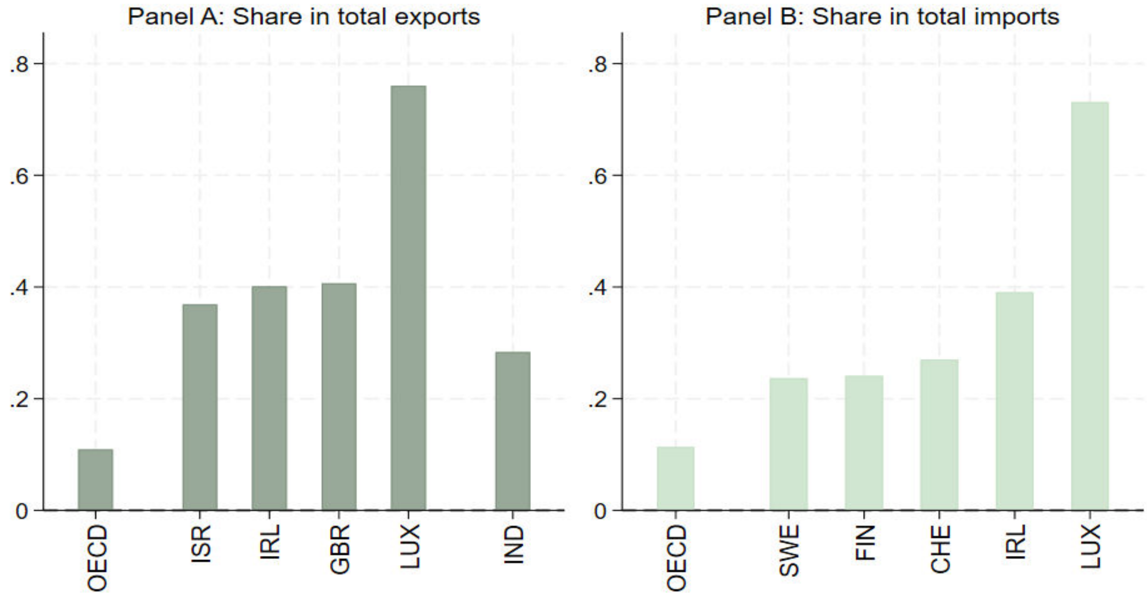
Note: This figure shows the average price decline and TFP gains from AI across sectors for Scenario A2 as presented in Table 2. Averages are obtained by aggregating country-sector values weighted by respective value-added shares of country-sectors in the world market of a given sector.
Source: Authors' calculations.

The extent to which these price developments translate into the welfare gains of different countries depends on the composition of their export and import baskets. Countries whose export or import baskets contain a relatively large share of sectors that are particularly exposed to AI are more likely to experience sharper declines in export and import prices. It is in these countries where export and import price changes are most impacted by the AI shock. For instance, exports of highly AI exposed sectors account for about three quarters of total exports in Luxembourg and for about 40% in the United Kingdom, Ireland, and Israel, followed by India at nearly 30% (Figure 10, Panel A). For Luxembourg, these sectors also make up for three quarters of its import basket followed by Ireland (40%), Switzerland, Finland, and Sweden (all three around 25%).

[59] See also Figure A.6 in Annex which shows that the distribution of prices in higher elasticity goods converges to the higher end of the TFP distribution.

Figure 10. The most impacted countries by the AI shock in terms of exports and imports

The shares of the Top 5 AI exposed sectors in the exports and imports of countries, in %



Note: This graph shows the export (Panel A) and import (Panel B) shares of countries in the five most AI exposed sectors, i.e., financial services, IT and information services, professional and technical services, publishing / AV and telecommunication services. Shares are shown for countries with the largest export and import shares of respective sectors.
Source: Authors' calculations.

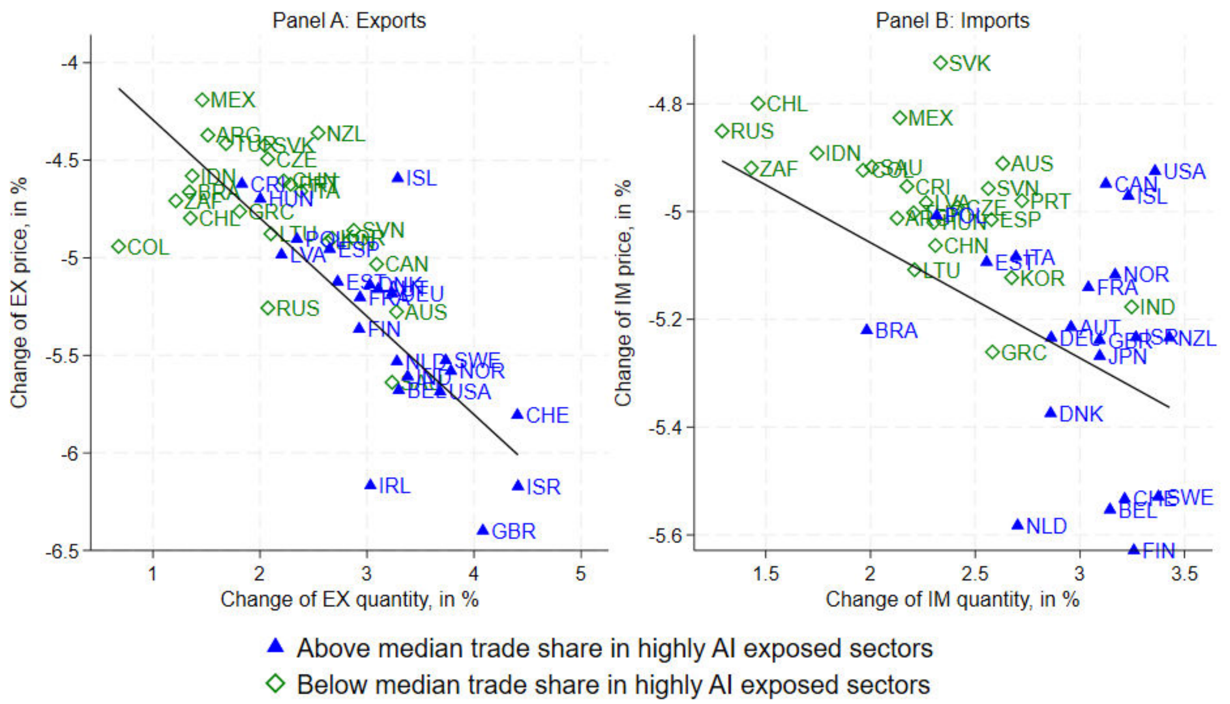
The varying intensity of the AI induced TFP shocks and price changes across country–sectors, together with cross-country differences in the composition of export and import baskets, leads to divergent export and import prices and, ultimately, to differing trade quantities across countries.[60] Figure 11 confirms this: export and import prices tend to fall more - while quantities tend to increase more - for countries whose trade composition was more sensitive to the AI shock (marked by blue triangles). These include the United Kingdom, Ireland, Israel, as well as Switzerland and the United States regarding exports, and Belgium, the Netherlands, Sweden, Switzerland and Finland in terms of imports. These price and quantity changes in turn determine the transmission and distribution of AI generated gains through trade, which will be discussed in more detail in the next subsections through a decomposition of the per capita real income gains and counterfactual experiments.[61]

[60] As a result, divergent export and import price movements affect countries' terms of trade. Improvements in the terms of trade are typically associated with welfare gains, and deteriorations with welfare losses. In our setting, however, the sources of welfare gains are more nuanced: in countries with high AI adoption, a relative decline in export prices, i.e., a worsening of terms-of-trade, can occur alongside welfare gains due to increased production.

[61] Interestingly, import price changes following the rise of AI are distributed more evenly across countries, whereas export price changes vary more widely. This pattern reflects the fact that export baskets are often concentrated in a few dominant industries, that can be more or less affected by AI, while import baskets tend to be more diversified, averaging out differential impacts across sectors.

Figure 11. Trade price and quantity changes reflect import and export specialisation patterns of countries

Changes of export- and import prices and quantities, in %



Note: This figure shows the change of the export and import price indices and respective quantities of individual countries in Scenario A2 (Table 2). 'Highly AI exposed sectors' as indicated by the legend refers to financial services, IT and information services, professional and technical services, publishing / AV and telecommunication services). Price indices were computed for the initial product basket (export or import composition). For visualisation purposes, Luxembourg is omitted from both panels (with prices falling by 7.5%) and Ireland (price decline of more than 6%) omitted from the right panel.
Source: Authors' calculations.

5.1.2. *Welfare gains from AI adoption with international trade: a decomposition*

The AI induced changes in world market prices and trade volumes, illustrated in the previous subsection (Section 5.1.1), impact per capita real incomes across countries through different channels. To assess the contribution of these different channels we introduce a three-term decomposition that allows us to separately identify the domestic and foreign contributions of AI adoption as well as global allocation effects (see equation A.12 in Annex A.4).[62] The **domestic contribution** to welfare gains arises from lower prices of domestically produced goods and services, which make consumption more affordable for households. The **foreign contribution** captures the benefits from cheaper imports when other countries adopt AI. The remaining gains capture what we call the **allocation (competitiveness) effect**. It reflects whether

[62] To quantify the role of these different channels, we calculate the total exposure of consumers to domestic and foreign productivity gains via the "Leontief inverse" matrix of global input-output links, which captures all direct and indirect linkages in global value chains. Sector-level AI productivity gains are weighted by "local Domar weights", which measure each sector's total (direct and downstream) contribution to households in a given country. Local Domar weights are calculated by multiplying the vector of consumption shares in a country with the Leontief inverse matrix. See Annex A.4 for more details.

domestic producers gain or lose competitiveness - reflected in relative changes in global sales - as relative prices and trade patterns adjust, an adjustment with important implications for real incomes across countries.

Box 1. Decomposing AI induced welfare gains with international trade

- **Gains from domestic adoption**
  - Higher productivity.
  - Higher productivity in producing goods and services for domestic consumption *directly* benefits domestic consumers.
  - Higher productivity in producing goods and services for the export market *indirectly* benefits domestic consumers.

  Example: Consider German consumers. Productivity gains in Germany's automotive sector directly reduce car prices at home; gains upstream (e.g. German steel or chemicals supplying autos) also pass through to households. Gains can travel via value chains as well: a productivity improvement in Germany's chemical industry can lower costs in China's plastics industry, whose outputs are used in German cars. All benefits to German households that originate in German industries are counted in the "domestic contribution".
- **Gains from foreign adoption**
  - Sectoral composition and import partners lead to access to cheaper final and intermediate goods in real terms through global value chains.
  - Higher benefits if trading with higher AI adopting countries.
  - Higher benefits if importing more in AI-impacted sectors.
  - Technological spillovers: partnering with leading AI adopter countries.

  Example: German consumers benefit when Türkiye's automotive sector becomes more productive, lowering the price of Turkish cars. Because Türkiye's automotive firms source inputs abroad, improvements in China's steel industry likewise reduce costs that feed into Turkish vehicles and, ultimately, German import prices. These direct and upstream foreign effects are grouped in the "foreign contribution".
- **Re-allocation effects & competition**
  - Relatively lower AI adoption leads to competition with lower prices.
  - Specialising in non-differentiated products with high elasticities of substitution across exporters (commodities) makes the competition stiffer.
  - Tradable industries face more competition globally.
  - More potential benefits if export basket is formed by AI intensive sectors.
  - The higher the domestic productivity increase, the higher the export quantities.

  Example: If sectoral productivity changes left expenditure and input shares unchanged, aggregate welfare gains would equal the sum of domestic and foreign terms. In reality, heterogeneous shocks and elasticities of substitution different from one induce reallocating effects. For example, if Türkiye's plastics industry does not adopt AI while other countries' plastics producers do, Turkish plastics lose market shares and labour moves to other activities. The resulting real-income effects are captured by the "allocation" term.

This decomposition takes into account the network structure of global trade linkages, the benefits of integration into global value chains as well as the differential AI adoption of countries and industries. The decomposition accounts for the network structure of trade, participation in global value chains and heterogeneous AI adoption across countries and industries. For a detailed discussion of these channels, illustrated by examples, see Box 1.

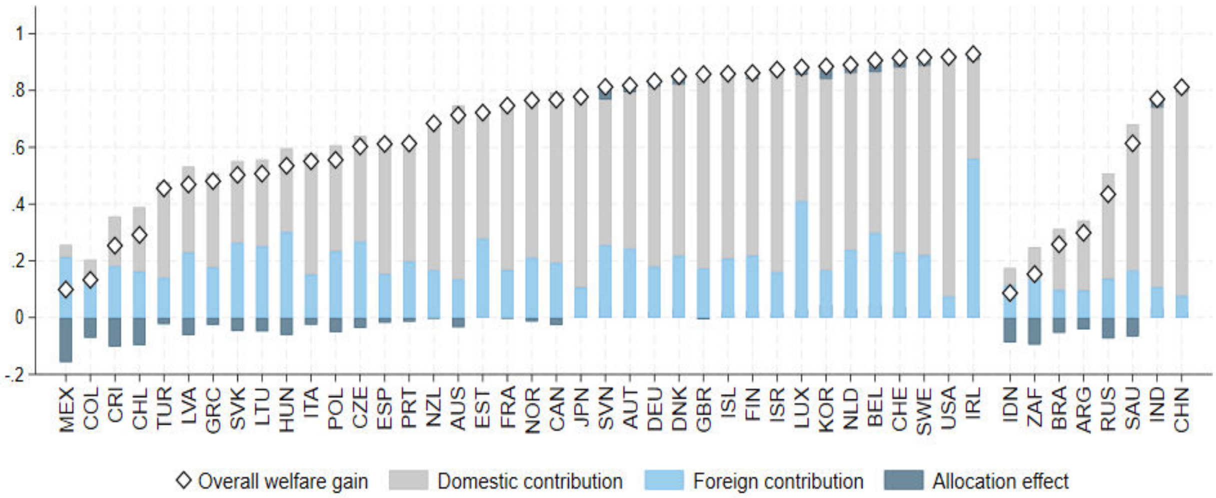
Results (Figure 12) show that the benefits from foreign AI adoption vary considerably across countries. These differences are partly driven by changes in import prices but also depend on trade openness, as explained in the previous subsection. As expected, highly open economies such as Luxembourg and Ireland, whose import baskets are dominated by AI-intensive sectors - ICT services and professional services -, obtain larger foreign gains of around 3-4 percentage points. By contrast, countries with lower AI adoption in Europe and Latin America (e.g., Latvia and Greece or Mexico and Colombia) capture more modest benefits from foreign adoption, around 1-1.5 percentage points. Nevertheless, compared to their total welfare gains, these still amount to a substantial contribution, up to 50% (Central Eastern European countries) or even higher (for Latin American countries).

While consumers always benefit from lower prices through higher real income–captured by the positive bright blue part in Figure 12, the overall impact through trade depends on how well domestic producers can remain competitive in global markets under these conditions (the sum of the foreign gains and the allocation effect). Countries such as Mexico, Colombia, and Costa Rica benefit from foreign adoption but also lose competitiveness, with lower prices inducing large negative reallocation (competitiveness) effects. By contrast, higher-AI-adopting countries tend to display slightly positive allocation effects.[63]

[63] Overall, the allocation effects shown in Figure 12 tend to be small, owing to the fact that in the central scenario all countries experience at least some productivity gains, which limits the extent to which the production network adjusts. For the same reason, the results are also broadly robust to different choices of elasticities. In the next subsection, we consider scenarios in which the productivity gains differ more starkly across countries and where the allocation effects play a larger role. For these results, the choice of elasticities can matter quantitatively, even if the qualitative findings would remain unchanged under different assumptions regarding the various elasticities of substitution in production and consumption.

Figure 12. The role of trade in driving the welfare gains from AI

Decomposing predicted per capita real income gains from AI over the next 10 years, percentage points (annualised)



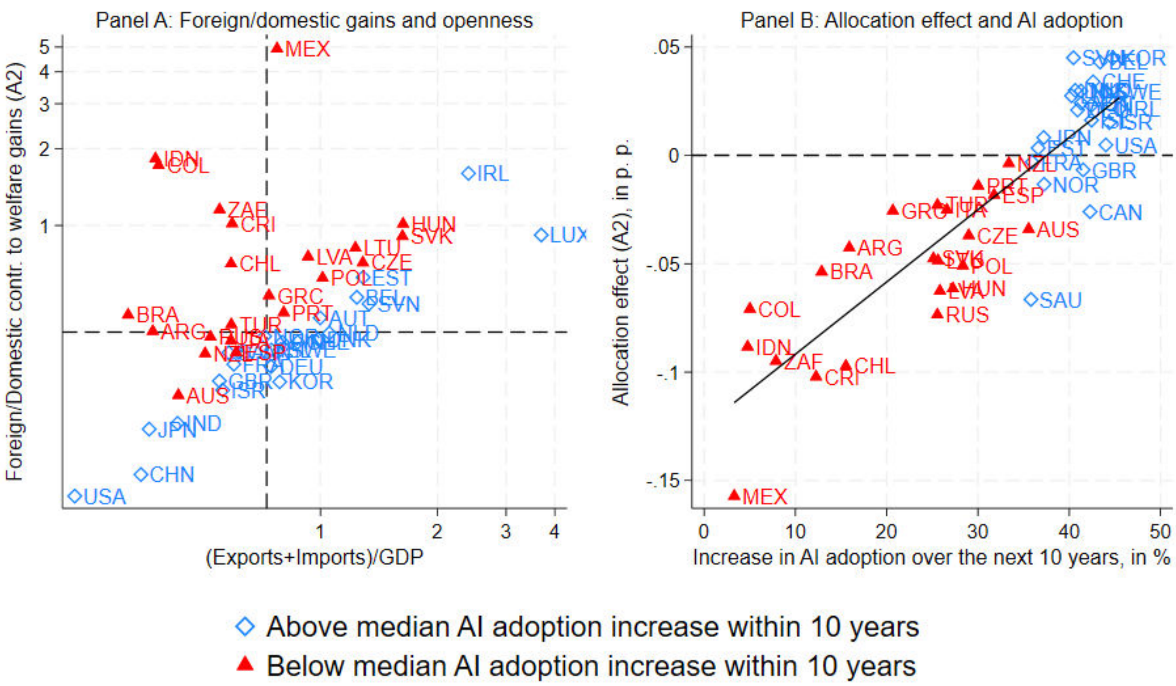
Note: The figure decomposes overall welfare gains (A2) into three components: "Domestic contribution" capture AI gains accruing to domestic demand from the price declines of domestically produced goods and services; "Foreign contribution" is conditional on AI adoption and capture gains accruing to domestic demand from reduced import prices; "Allocation effect" includes gains or losses coming from changing global demand for domestically produced goods and services. For details, see Annex A.4., and equation A.12 therein.
Source: Authors' calculations.

To visualise the complex role of openness and AI adoption in driving the size of the foreign contribution, Figure 13 Panel A, plots the ratio of foreign to domestic gains against the trade openness of countries. Among high–AI-adopting economies (blue dots), the share of foreign gains rises systematically with greater trade openness. By contrast, in lower–AI-adopting countries (red triangles) such as Mexico, Indonesia, Colombia, South Africa, and Costa Rica, the contribution of foreign gains to total gains is large - even when trade openness levels are not particularly high. Hence openness raises the importance of foreign-generated AI gains, but the relationship is more nuanced when AI adoption is low: then the type of openness (trade specialisation regarding partner countries and sectors) starts to matter more. Given that many of these countries rely on AI impacted sectors in their imports, in line with less developed local knowledge intensive services (finance, ICT and professional services), the relative contribution of foreign generated AI gains are high for them.

Panel B of Figure 13 captures the more monotonic positive relationship between the speed of adoption and the size of the competitiveness effects across countries. The positive link stems from these fast-adopter countries boosting global sales as a result of their improved price competitiveness. Their improved competitiveness is caused by the relatively larger positive TFP shock that they experience.

Figure 13. Foreign contributions and allocation effects due to AI correlate positively with trade openness and adoption rates

Ratio of foreign over domestic gains and trade openness, in %



Note: In Panel A, the vertical dashed line represents the median value of trade openness while the horizontal dashed line represents the median ratio of foreign and domestic contributions to welfare gains. The axes of Panel A are on log scales.
Source: Authors' calculations.

The substantial foreign contribution from the AI shock in most countries may suggest that countries can rely primarily on the foreign benefits of AI adoption while remaining "idle" (i.e. not adapting) domestically. However, the allocation effect - which captures competitiveness gains or losses - also depends crucially on domestic AI adoption. In particular, not introducing the technology while competitors do can induce a loss of competitiveness and can induce a large negative allocation effect. To quantify the importance of this issue, the next subsection presents a counterfactual experiment with our model.

5.1.3. Counting on foreign productivity gains? Assessing the scope for real income gains without domestic AI adoption through model experiments

This section examines the extent to which domestic AI adoption constitutes a necessary condition for substantial welfare gains from AI. Given the challenges in building AI capacity and diffusing the technology broadly, we ask the following question: can countries that do not adopt AI hope to benefit from its diffusion elsewhere through access to cheapened intermediate inputs and final consumption goods and services? To answer this question, we consider a series of modelling experiments, one-by-one for each country (Scenario B1, presented in Figure 14): what happens to per capita real income in a given country if it does not adopt AI, while all other countries do? In these experiments, productivity in the focal country is not directly affected by AI. Hence any changes to its per capita real income will arise from AI gains transmitted through international linkages.

On average, these experiments show that AI related gains arising only through the AI adoption of trade partners are modest in the absence of domestic adoption (Figure 14, diamonds). The median OECD country is projected to experience a boost in per capita real income growth only by approximately .03 percentage points annually over ten years, thanks solely to AI adoption abroad. The large differences with respect to AI gains in global adoption (Scenario A2) emerge because in this current illustrative scenario (Scenario B1), countries find it more difficult to compete with increasingly productive trade partners, both in domestic markets (due to stronger import competition) and in foreign markets (due to cheaper exports of trade partners), inducing a strongly negative allocation effect that almost fully offsets the gains from cheaper imports for most countries.

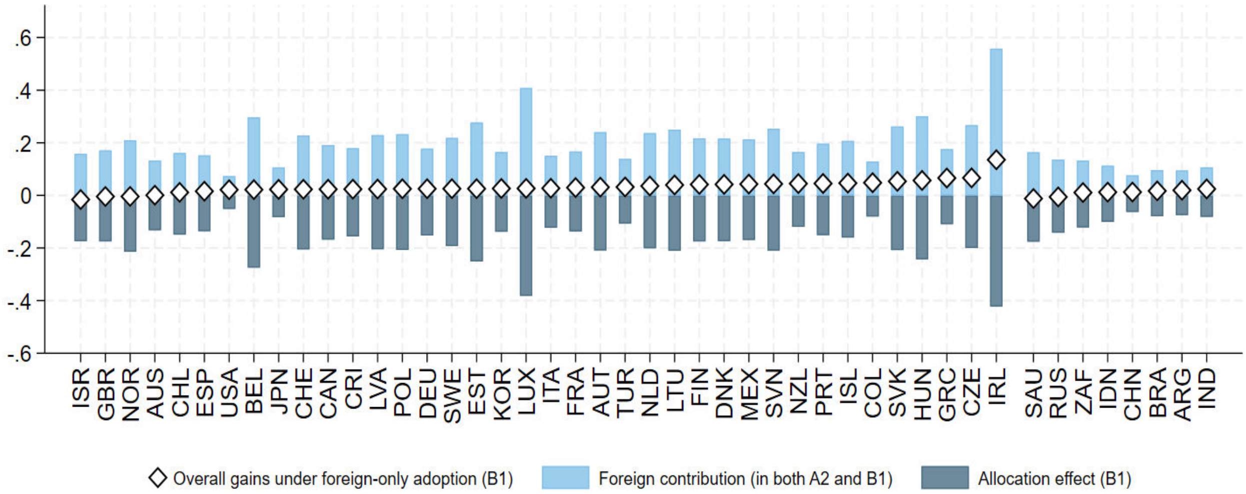
This can be seen by the decomposition on Figure 14, which shows the role of lower import prices – called the foreign contribution (brighter area - the same as in the baseline, central Scenario A2) and the allocation, or loss of competitiveness, effect (darker area). This loss is particularly pronounced for small open economies such as Ireland or Luxembourg, whose export baskets are highly exposed to AI and lose market share when not adopting domestically.

Such losses can also arise in situations where countries highly specialise in heavily AI exposed industries, such as finance (in the case of the United Kingdom) and ICT services (Israel) (also Figure 10, Panel A). In these countries, missing out on AI leads to a strong competitiveness loss on both domestic markets (through stronger import competition) and on foreign markets (through lower prices on world markets), amounting to about 0.2 percentage point loss, that is, about a quarter of the total gains in the central scenario. Conversely, this magnitude also captures the size of the competitiveness-related gains that they experience when they *do adopt*. For these countries, domestic AI adoption is therefore a necessary condition for remaining competitive in world markets. Similarly, the loss is also pronounced for countries that face particularly strong export competition due to the high substitutability of their exports (e.g., commodity exporters such as Norway or Australia (among OECD countries) or Saudi Arabia (among the G20).[64]

[64] See also Figure A.10 in the Annex, which shows the share of the mining/oil sector (a highly substitutable commodity) in the exports of selected countries.

Figure 14. Relying only on foreign generated AI gains leads to moderate gains from AI due to a loss in competitiveness

Predicted per capita real income gains due to AI over the next 10 years in two scenarios, percentage points (annualised)



Note: This graph decomposes sources of the welfare gains when a country does not adopt AI but other countries do (Scenario B1) and compares to the baseline scenario where there is adoption both domestically and abroad (Scenario A2). The "foreign contribution" is the same under global adoption (A2) and foreign only adoption (B1). The "Allocation effect" captures the loss of global sales and lower export prices in case a country does not adopt AI domestically.
Source: Authors' calculations.

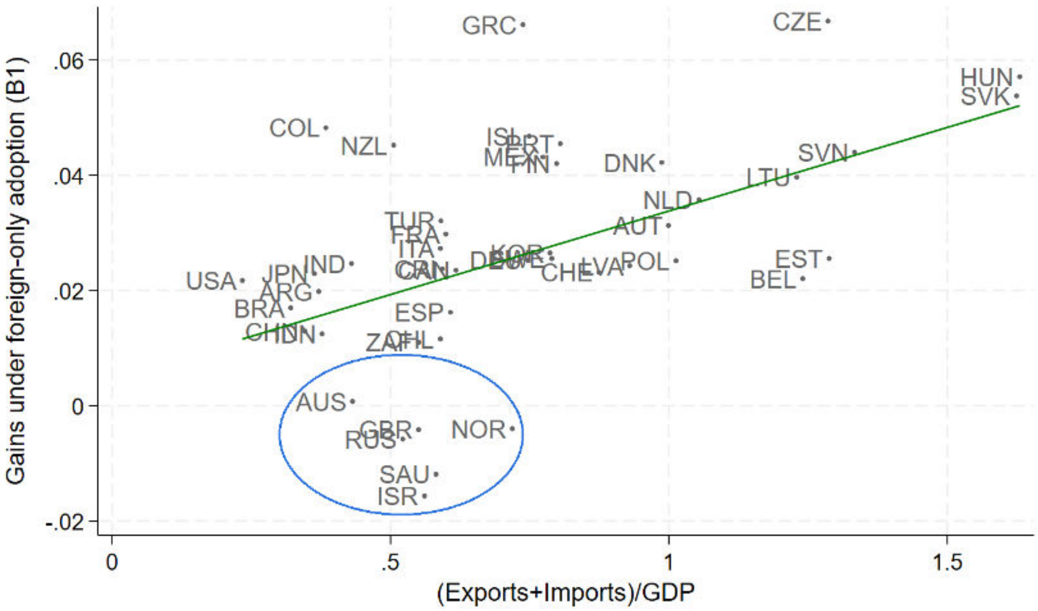
Indeed, for the countries whose trade specialisation is such that they are most impacted by the AI shock, missing out on AI adoption strongly undermines global competitiveness, as shown by the group of countries within the blue circle in Figure 15. For these countries the gains when not adopting locally are much weaker than what is implied by their level of openness, due to the large loss-of-competitiveness effect given their sectoral specialisation in trade.

To rule out the possibility that our results on foreign contributions to AI induced welfare gains are subject to a downward bias due to insufficient statistical measurement of services trade, for instance due to the presence of foreign affiliates of large services firms (banks, ICT services, etc.; see Cernat, 2024) [65], we conduct a robustness check. In particular, we account for under-measured services trade by considering the presence of multinational firms and the degree of intangible capital intensity (given their role in unmeasured services trade) across different countries and sectors. The results of this robustness check affect the magnitude of the reported estimates only marginally, indicating that this statistical discrepancy plays a minor role in our findings. A detailed description of our correction approach, as well as comprehensive results, is provided in Annex A.5.

[65] According to estimates by Cernat (2024) this so-called "mode 3" international service trade, which involves local subsidiaries, amounts to nearly double of the recorded - "mode 1" - service component. A related phenomenon is the Dark Matter in international finance and trade (Hausmann and Sturzenegger, 2014) which refers to the large returns on foreign assets by the US, driven presumably by the large share of intangible assets in US outward investments, which are hard to capture.

Figure 15. Missing out on AI adoption undermines competitiveness in global markets for countries specialised in the most impacted sectors from the AI shock

Welfare gains from AI under foreign-only adoption (Scenario B1) in relation to trade openness



Note: This graph shows the relationship between gains under foreign-only adoption (B1) and the degree of trade openness by countries. As described in the text, the countries within the blue circle exhibit a strong trade specialisation either in AI-impacted sectors (financial services, IT and information services, professional and technical services, publishing / AV and telecommunication services) such as Israel or the United Kingdome, or in goods with high substitutability (mining and coke/petroleum) such as Australia, Norway, or Saudi Arabia. Ireland and Luxembourg show very high values for trade openness compared to the other countries in the sample and are therefore not displayed for visualization purposes. Corresponding values are as follows: Gains under foreign-only adoption: 0.14 (IRL), 0.03 (LUX); Trade openness: 2.4 (IRL), 3.7 (LUX).
Source: Authors' calculations.

5.2. The role of international knowledge spillovers through boosting AI adoption

To investigate the potential role of knowledge spillovers, this section presents results from a separate scenario in which we consider the possibility that cross-country knowledge spillovers regarding technology use - AI adoption - are systematically related to trade patterns. Specifically, we augment the AI adoption rates of Section 3.3, which assumed a uniform S-shaped adoption path for each country, with an additional spillover term that depends on exposure to global AI adoption via intermediate input trade and foreign firm ownership as follows:

$$\Delta Adoption_{ic} = \Delta\overline{Adoption}_c + \beta \sum_{c' \in C} \sum_{i' \in I} \omega_{ic}^{i'c'} \left(Adoption_{c'} - Adoption_c\right) \mathbf{1}_{Adoption_{c'} > Adoption_c} \qquad (2)$$

In this expression, $\Delta Adoption_{ic}$ is the projected increase in the AI adoption rate of sector *i* in country *c* over the next decade, accounting for international knowledge spillovers. It is the sum of the baseline increase in the AI adoption rate in country *c* without accounting for international spillovers – $\Delta\overline{\mathrm{Adoption}}_{\mathrm{c}}$ (in percentage points, as computed in Section 3.3) – and a spillover term that depends on the global upstream linkages - capturing imports - between sectors and their relative current AI adoption rates. $\mathcal{C}$ and I represent the set of countries and sectors, respectively, and the weight $\omega_{ic}^{i'c'}$ in the spillover term captures the relative proportion of inputs sourced from upstream sector *i'* in country *c'*, expressed as a share of gross output of the downstream sector *i* in country *c*. The weights are multiplied by an indicator function $\mathbf{1}_{Adoption_{c'} > Adoption_c}$ that equals 1 if the current AI adoption rate in country c' exceeds that in country *c*, and is zero otherwise. This ensures that spillovers occur only from countries with currently higher AI adoption to countries with currently lower AI adoption - in the spirit of learning from more advanced adopters. Hence, the projected percentage point increase in the AI adoption rate in sector *i* of country *c* is given by the medium pace adoption rate plus a trade weighted average of the adoption rates in trade partner countries from which the sector imports and that have higher adoption rates.[66]

All weights $\omega_{ic}^{i'c'}$ are computed based on input-output structures as observed in the OECD ICIO tables (for 2019) and corrected for unmeasured services trade (see Annex A.5). Finally, the parameter β governs the strength of international knowledge spillovers. Unlike the weight parameters $\omega_{ic}^{i'c'}$, β is not observed directly and has to be calibrated. We explore knowledge spillovers under two alternative calibration approaches for β, one based on evidence from patenting and the other based on likely adoption paths of country groups.

As an illustration of the extent to which trade-facilitated knowledge spillovers might change the results, we re-estimate the model under two alternative sets of AI-driven productivity shocks that allow for international knowledge spillovers in AI adoption rates (Figure 16). Both spillover scenarios are computed following the approach described in Section 4.2, but they differ in how the *strength* of international spillovers is calibrated, as explained below.

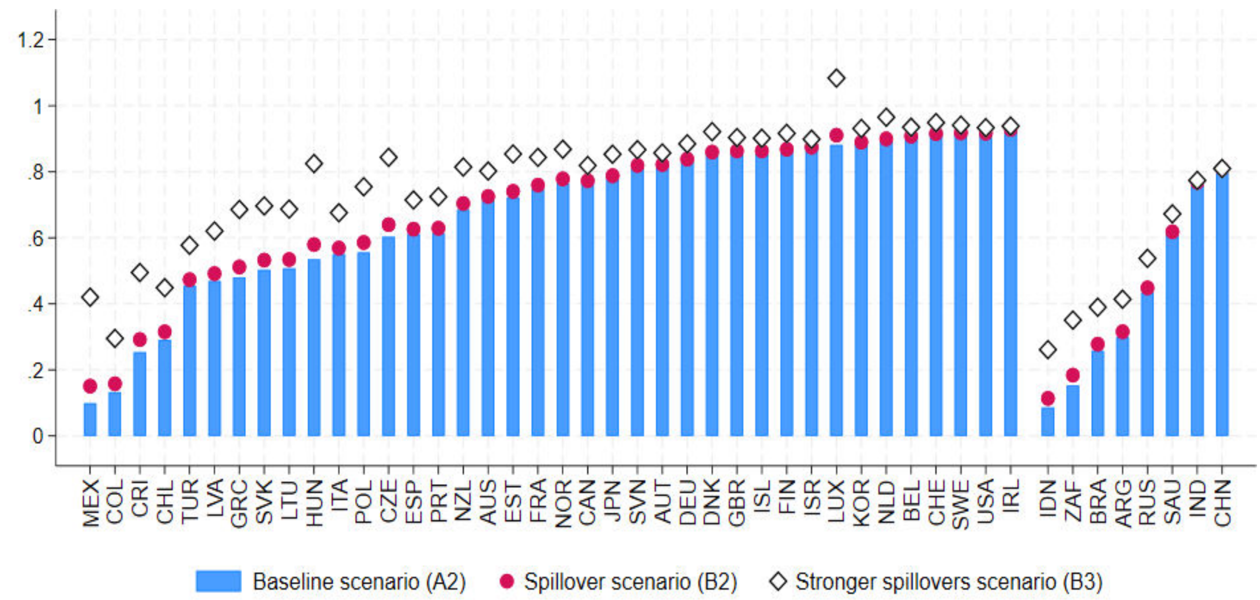
Spillover Scenario B2 assumes that AI adoption spillovers are of comparable magnitude to documented knowledge spillovers reflected in patenting dynamics. Hence, this spillover scenario starts from an empirical estimate of the strength of international spillovers in patenting taken from the literature and calibrates the parameter β in equation (2) to match that value.[67] While β governs the overall strength of the spillover channel, the implied size of the adoption gain for a given country depends on the country's exposure to foreign AI adoption through intermediate input trade. The resulting spillovers in Scenario B2 are relatively modest (Figure 16), with the largest adoption gains observed in Mexico where AI adoption is currently relatively low and exposure to foreign AI adoption is high.

[66] AI usage can also spread across countries through multinational firms. Multinationals headquartered in AI advanced economies may enable their foreign subsidiaries to operate with frontier AI technologies, even when those subsidiaries are located in countries where AI adoption is generally lagging. A flipside of this phenomenon is missing intangible intermediate (service) trade between foreign and domestic affiliates of MNEs. Annex A.5 aims at correcting for such missing trade and thus provide an assessment on the size of the likely impacts of knowledge spillovers through the presence of MNEs.

[67] This calibration implies that a one standard deviation increase in trade-weighted exposure to upstream AI adoption increases future AI adoption by 0.177 standard deviations of current AI adoption, following the results for patenting spillovers reported in Berkes, Manysheva and Mestieri (2022).

Figure 16. Technology spillovers from leading AI-adopter trading partners can boost gains significantly in lagging AI adopter countries

Predicted per capita real income gains due to AI over the next 10 years, percentage points (annualised)



Note: B2 adapts spillover from previous literature on innovation (patents), and B3 uses an alternative illustrative experiment which leads to about six times as strong spillovers than in B2.
Source: Authors' calculations.

Although Scenario B2 suggests that international knowledge spillovers play only a minor role, it may understate their importance in the case of AI. Learning about AI applications from trading partners may be easier than what is assumed in Scenario B2 based on evidence from patenting. If the evidence from patenting does not translate to the context of AI adoption, the appropriate value for β in equation 2 might be larger. For instance, it may be reasonable to expect those Latin American countries - especially Mexico - which are deeply integrated through trade with the AI frontier (US) and therefore have ample learning opportunities, should see strong increases in AI adoption rates despite starting from currently relatively low levels. The fact that spillover Scenario B2 still projects that AI adoption will progress much faster in Greece (the European OECD countries with the lowest projected increases in the AI adoption rate) and other European OECD countries than in Latin American countries could therefore be viewed as unrealistic. Stronger knowledge spillovers may also affect the relative ranking of other countries in terms of AI gains, depending on their exposure to the AI frontier.

To assess the implications of stronger spillovers, the second spillover scenario (Scenario B3) scales up the parameter β – the parameter that governs the overall strength of spillovers – in equation (2). This ensures that the speed of convergence of lagging countries, especially those with strong trade links to AI advanced countries, will increase. We calibrate the strength of the spillover channel so that the projected percentage point increase in AI adoption in the four Latin American OECD countries (Mexico, Colombia, Costa Rica and Chile) corresponds to the projected change in those EU countries of the OECD that benefit the least from AI (captured by the bottom 10% of countries in EU OECD).[68]

The implied spillover dynamics in Scenario B3 are about *six times* stronger than in Scenario B2. Strong spillovers triple the projected real income gains for Mexico and lead to an increase of about 40% to 90%

[68] This stronger convergence is achieved by finding the appropriate β parameter that leads to this outcome.

for Chile, Costa Rica and Colombia. Several Central Eastern European economies as well as Greece experience an additional boost of about 30% to 40%. For other countries, where trade with leading AI adopters is relatively less important, the additional gains remain generally small. Overall, even with such spillover effects that are much stronger than those found in previous literature, the ranking of countries in terms of AI driven welfare gains remain largely unchanged.

6. Conclusions

Aggregate welfare gains from AI originate both from domestic and from international sources. This paper assesses several channels underpinning both of them and projects per capita real income gains from AI over the next ten years for OECD and G20 economies. The estimates range between 0.1 and 0.95 percentage point in terms of contributions to annual per capita real income growth over the next 10 years in our central, medium adoption speed, scenario. These results complement the existing literature, whose primary focus to date has been on productivity impacts, in a limited set of countries (most often the US): labour productivity estimates underlying the per capita income gains in our paper for the US are more moderate than the early optimistic predictions (Briggs and Kodnani, 2023) but higher than the most pessimistic views (Acemoglu, 2024) and closest to Aghion and Bunel (2024). These estimates are conditional on several assumptions and characteristics of the economies - among which the most important domestic factors are sectoral composition and preconditions to AI adoption by firms.

Regarding the importance of international trade linkages and their interaction with AI adoption, Table 3 summarises the main findings. First, importing highly AI intensive goods and services (ICT services, finance and professional services) or relying mostly on AI intensive exporters will lead to cheaper final and intermediate imports, increasing real incomes of domestic consumers (Channel 1). Second, specialising in heavily AI impacted sectors in exports and domestic production can lead to global market share increases, but this crucially depends on domestic AI adoption (Channel 2, contrast between the first and second columns). Third, technological spillovers can arise through learning from AI intensive trading partners that lead to faster AI adoption domestically (Channel 3). Finally, the degree of openness amplifies the magnitude of these channels. Hence, to the extent trade tensions remain elevated which results in less open economies, the expected gains from AI through these channels could be moderated.

Table 3. Summary of results: trade channels are important and conditional on AI domestic adoption

Effect on per capita real income gains from AI, by main channel		Domestic and foreign AI adoption scenario	No domestic but foreign AI adoption scenario
1. Import channel: benefitting from cheaper intermediate and final goods from abroad			
	If imports include a high share of heavily AI exposed goods and services or leading AI adoption partners…	+	+
2. Export channel: changes in competitiveness of exports			
	If specialising in heavily AI exposed sectors...	+	–
3. International knowledge spillovers leading to faster AI adoption			
	If importing from leading AI adoption countries	+	*N/A*
Degree of trade openness		*Amplifies channels above*	

Notes: Channel 3 under "no domestic but foreign AI adoption scenario" is not available because such a scenario would impose no domestic AI adoption, hence no role for spillovers.

To avoid international divergences due to AI and exploit the full potential of the technology, policymakers can consider a range of policy areas:

- Strengthening digital infrastructure – including AI-related data centres – along with skills and innovation capacity are critical to enable domestic adoption.
- Enabling access to AI models that are developed in leading countries and facilitate the spread of open-source AI models. Promoting international coordination, mutual trust, and model inter-operability are also key in this respect. This in turn contributes to broader and more affordable access across and within countries - even in places without substantial local AI development or where top AI models are not accessible. Also, low barriers digital services trade would further facilitate the spread of AI related gains across borders in applications that build on top of AI models.
- Preserving and deepening trade integration to maximise benefits via cheaper final good and intermediate imports and from learning spillovers.
- A more accurate and comparable measurement of progress on AI in an international context would be beneficial, building on existing official statistical surveys on AI use among firms and workers, notably through the OECD's Working Party on Digital Economics, Measurement and Analysis that has been spearheading such efforts.

Future work will take a closer look at the determinants and enablers of AI adoption from the digital infrastructure point of view, given large gaps in the buildup of digital capital across countries in the OECD (Gal et al, 2026). A further topic for analysis could include the role of AI in shaping the abilities and incentives of firms to trade, for instance through a reduction of language barriers and by facilitating adaptation to different local regulatory settings. As more empirical studies become available on the impact of AI on these aspects, and given existing estimates on the role of these barriers on trade, it will be feasible to put an empirical estimate on the expected reduction of overall services barriers reduction due to AI.

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Annex A. Supplementary material

A.1. Additional Tables and Figures

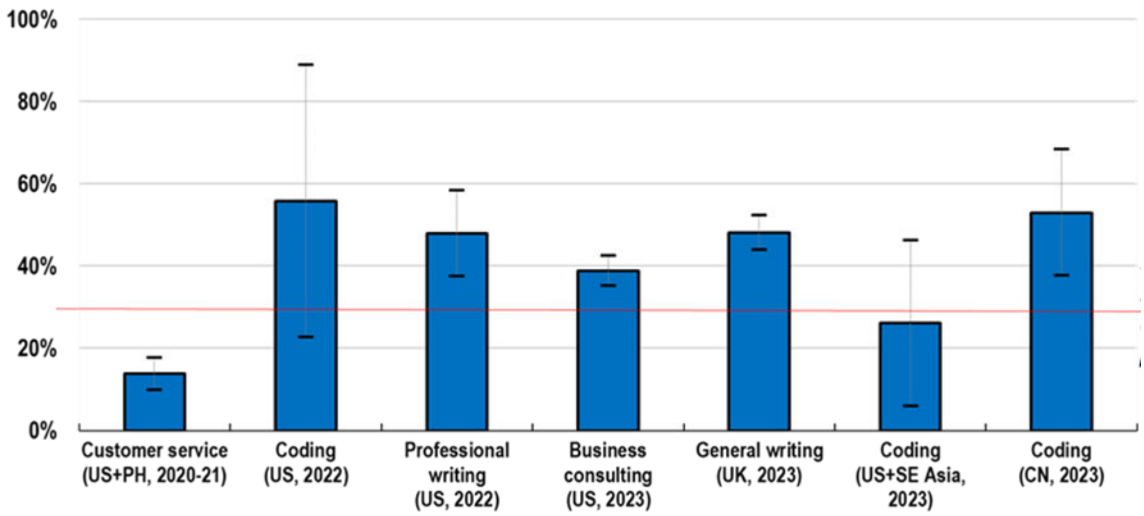
The micro-level studies are often done in an experimental setting, lending strong credibility to the estimated effects, and cover a range of activities: (i) customer services, (ii) software developers and (iii) professional writing tasks and business consulting tasks.[69] The estimates indicate that the effect of AI tools on worker performance range from 14%, for example in customer service assistance, to 56%, for example in coding.[70]Nevertheless, one may argue that these studies were carried out in the context of tasks where performance gains are most promising and may not extend to other business contexts and when AI is used at scale in real-life environments. To remain conservative, the 30% number on micro-level gains that is retained for this paper's calculations averages only the three most precise estimates – excluding the largest effects that are mostly found among programmers.

[69] Given that these task-focused studies often estimate time savings, or quantity increases in output when using the same amount of inputs – including capital – this paper interprets them as total factor productivity gains, i.e. lifting the joint productivity of labour and capital (computers, office space, etc.). An alternative interpretation of these studies considers that they produce estimates of only labour cost savings (Acemoglu, 2025) This interpretation would mean that in order to arrive at TFP gains, one would need to down-scale these gains to the share of labour, that is to around 60% of the reported productivity gains in the studies.

[70] More specifically, AI support for customer services (1st estimate on Figure A.1; Brynjolfsson, Li and Raymond, 2025), the effect of AI coding assistants on software developers (2nd, 6th and 7th estimates, respectively; Peng et al., 2023; Cui et al., 2024; Gambacorta et al., 2024), and the gains from using Large Language Models such as ChatGPT in speed and quality of professional writing tasks (3rd estimate; Noy and Zhang, 2023) or in business consulting performances (4th estimate; Dell'Acqua et al., 2023) and the performance improvement with Large Language Models assisting with general writing (5th estimate; Haslberger, Gingrich and Bhatia, 2023). Yet more recent studies focus on legal services and find very large effects between 34% and 140% (Schwarcz et al., 2025). Briggs and Kodnani (2023) rely on firm-level studies which estimate an average gain of about 2.6% additional annual growth in workers' productivity. See Annex B in Filippucci, Gal and Schief (2024) for a detailed overview of considered surveys and harmonisation efforts of this paper.

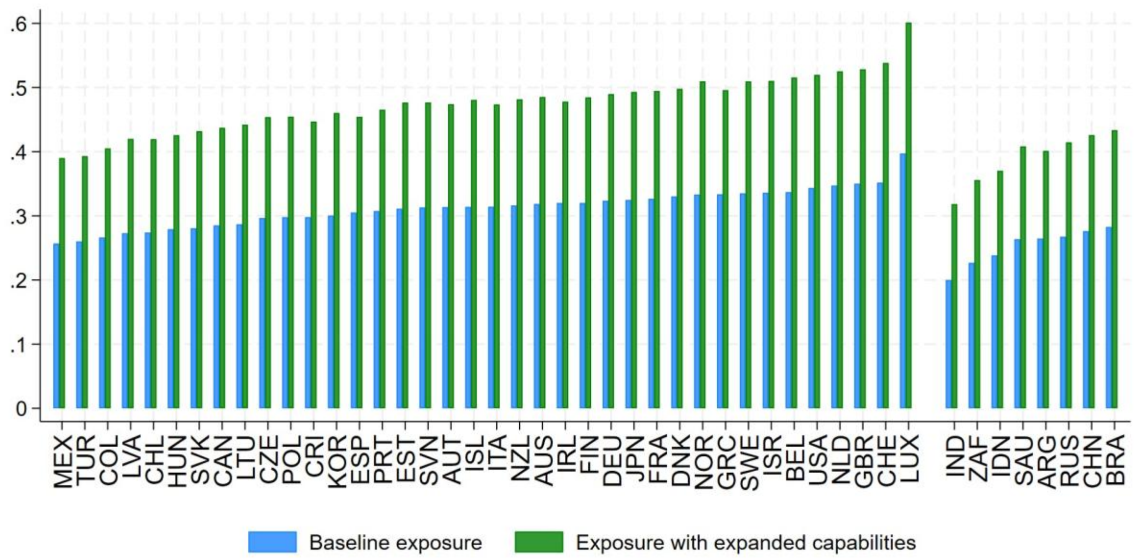
Figure A.1. Micro-level gains from Generative AI are found to be large in a range of tasks

Estimated % increase in productivity and 95% standard errors, as reported by various studies



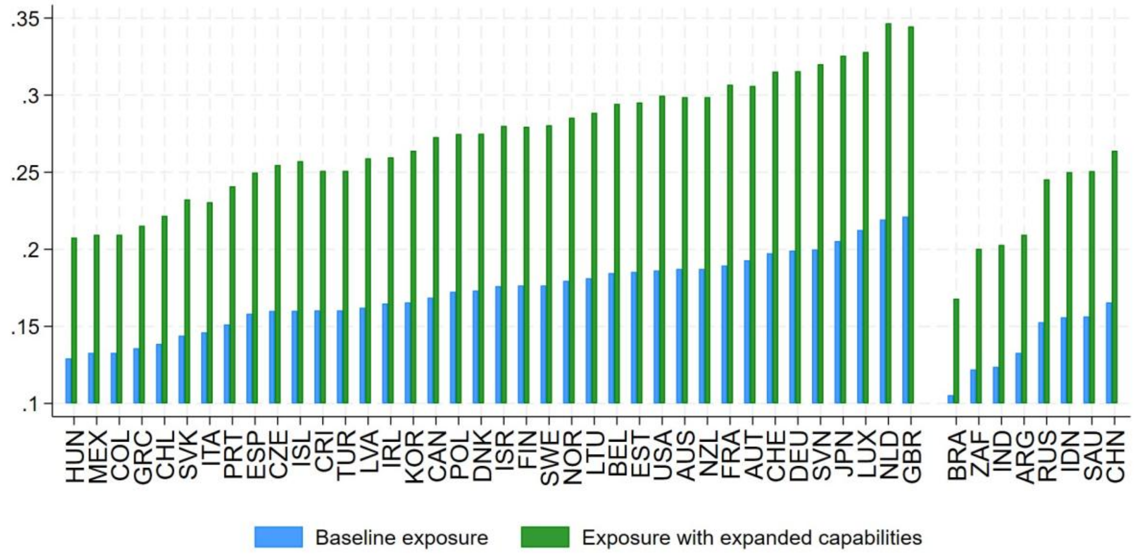
Note: The graph shows the worker-level productivity effects reported in different studies together with 95% confidence intervals. In parentheses, the reference country and year of the studies are shown.
Source: Compilation from the literature by Filippucci, Gal and Schief (2024).

Figure A.2. AI exposure in OECD and G20 countries



Note: This figure reports the average share of tasks exposed to AI across OECD economies plus the remaining of the G20. Country-level averages are obtained by mapping granular task-level exposure from Eloundou et al. (2024) (relying on LLM capabilities as of 2023) to occupations within different sectors. This approach distinguishes the occupational composition of 43 sectors (ISIC Rev. 4) which are aggregated to the country-level using respective 2019 pre-pandemic value-added shares of different sectors.
Source: Authors' calculations based on national labour force statistics combined with Eloundou et al (2024).

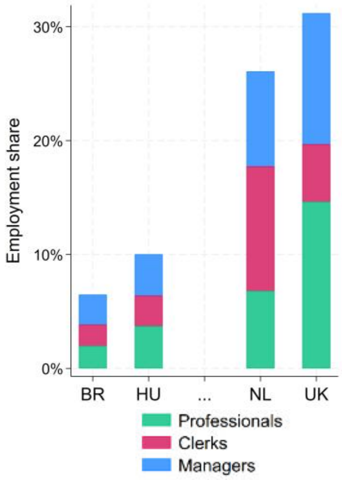
Figure A.3. AI exposure in the construction sector, OECD countries and key partners



Note: This figure reports the average share of tasks exposed to AI in the Construction sector (ISIC rev. 4 sector F) across OECD economies plus Argentina, Brazil, China, Indonesia, India, Russia, Saudi Arabia, and South Africa. Country-level averages are obtained by mapping granular task-level exposure from Eloundou et al. (2024) (relying on LLM capabilities as of 2023) to occupations within different sectors. This approach distinguishes the occupational composition of 43 sectors (ISIC Rev. 4) which are aggregated to the country-level using respective 2019 pre-pandemic value-added shares of different sectors.
Source: Authors' calculations based on national labour force statistics combined with Eloundou et al (2024).

Figure A.4. Employment share of specific occupations, in lowest vs. highest AI-exposed countries

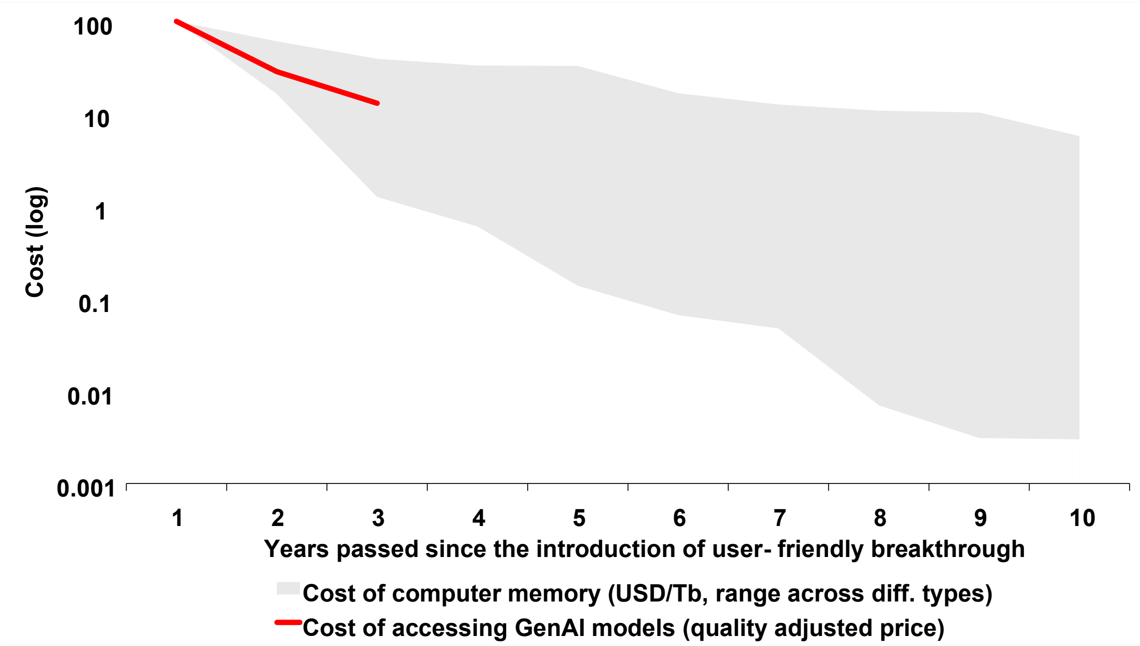
Employment share of occupations in the ISCO groups of Managers, Professionals and Clerical Support Workers (relatively high AI-exposure occupations), construction sector, in lowest vs. highest AI-exposed countries



Note: The figure reports employment shares of highest and lowest two countries by exposure in the construction sector, among OECD and G20 countries for which data on sectoral composition are available.
Source: Authors' calculations based on national labour force statistics combined with Eloundou et al (2024).

Figure A.5. The AI cost decline seems comparable to what happened with other digital technologies in the past

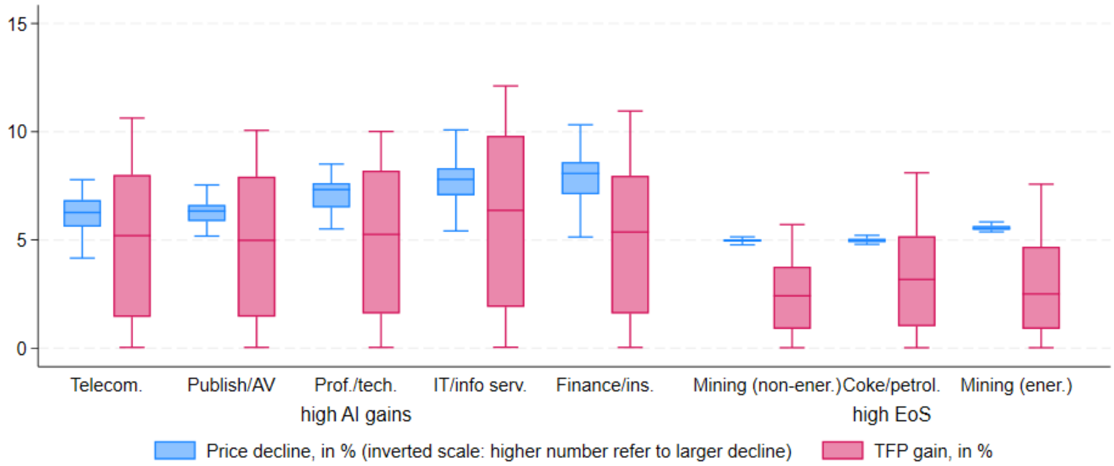
Price changes of Generative AI models versus computer memory, during the early adoption phase (in log scale)



Source: Cost of computation: Kurzweil (2024); Cost of computer memory: McCallum (2023). Cost of accessing GenAI models: Andre et al. (2025).

Figure A.6. High price declines in sectors with large TFP gains and high elasticity of substitution

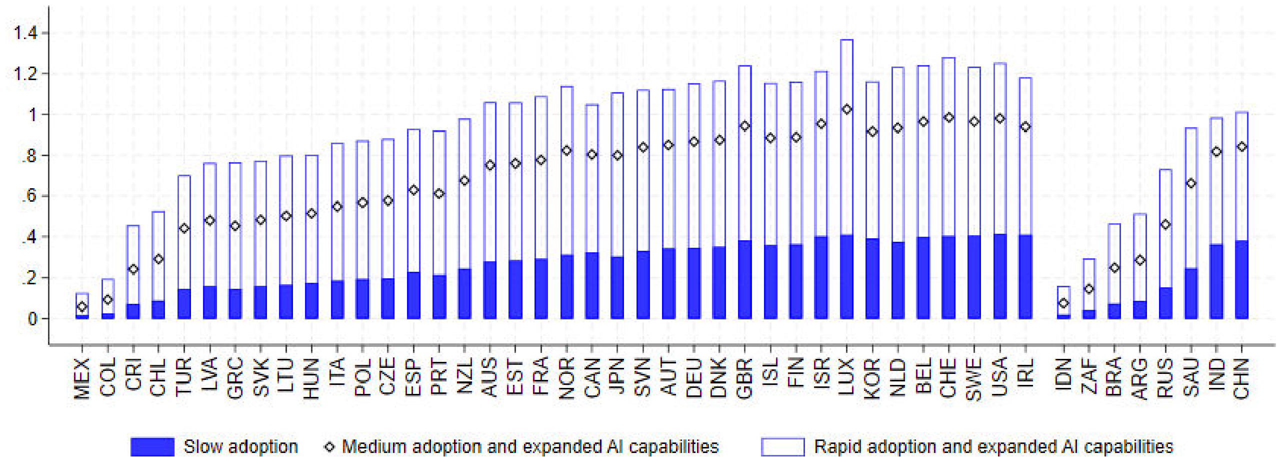
The distribution of productivity gains and price changes across countries, by sector (in %)



Note: Model output from the central scenario assuming medium adoption pace.
Source: Authors' calculations.

Figure A.7. AI-induced labour productivity growth across countries

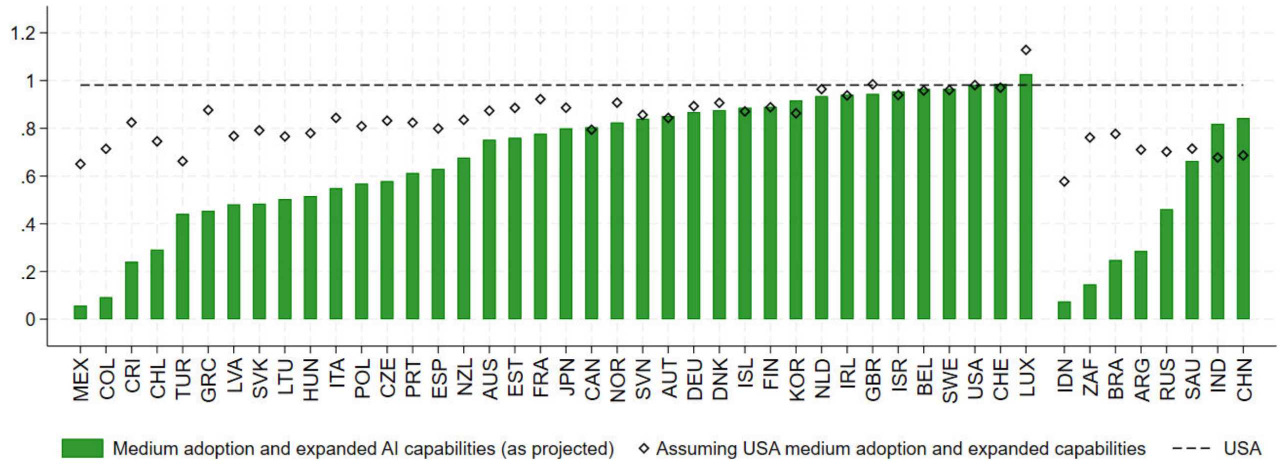
AI's predicted contribution to annual labour productivity growth over the next decade, percentage points (annualised)



Note: This figure shows the aggregate annual labour productivity growth contribution from AI, computed as the value-added weighted average of sector-level productivity growth rates, over the next decade (first order approximation). To study welfare gains in an integrated world economy, sector level productivity gains are fed into a global multi-country multi-sector general equilibrium model that accounts for price effects (including terms of trade effects) and the reallocation of factors. While labour is allowed to move across sectors, projections of welfare implications assume that aggregate labour utilisation remains the same over the 10-year time horizon. Countries are ordered by their welfare gains from AI in the central scenario. See more details in Sector 4.1.
Source: Authors' calculations.

Figure A.8. Fostering AI adoption would close a large part of the gap vis-à-vis the United States in terms of predicted labour productivity gains

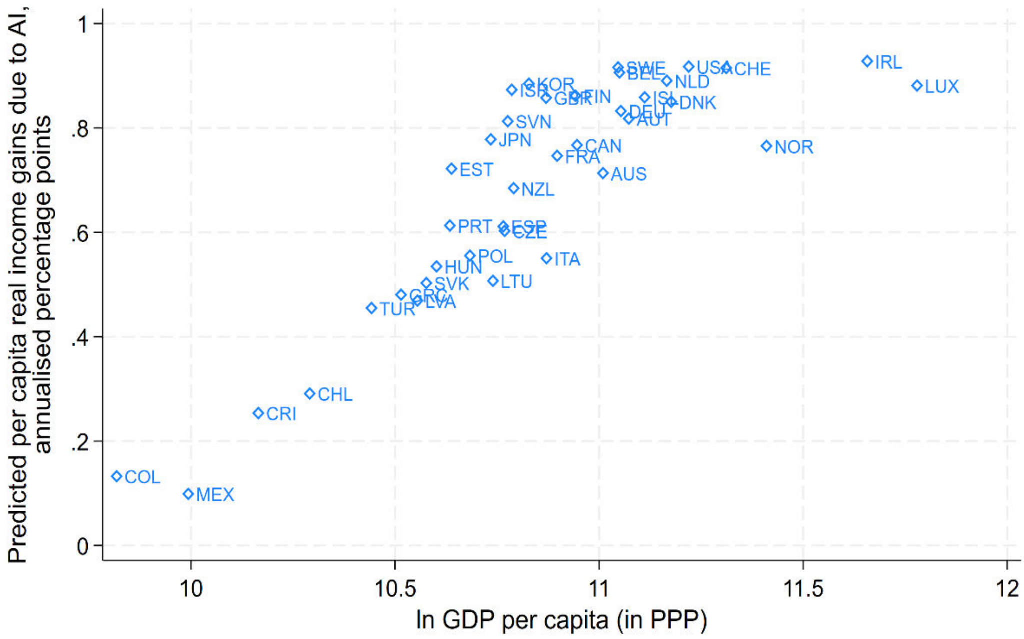
AI's predicted contribution to annual labour productivity growth over the next decade, in the central scenario and when assuming the same sectoral AI adoption level as that of the United States, percentage points (annualised)



Note: This figure shows AI's predicted contribution to annual labour productivity growth over the next decade. Solid bars present numbers based on *projected AI adoption rates per country* for the central scenario at medium adoption pace while diamonds present numbers based on the sectoral AI adoption rates of the USA.
Source: Authors' calculation.

Figure A.9. The projected AI-driven per capita income gains are larger for initially more developed countries

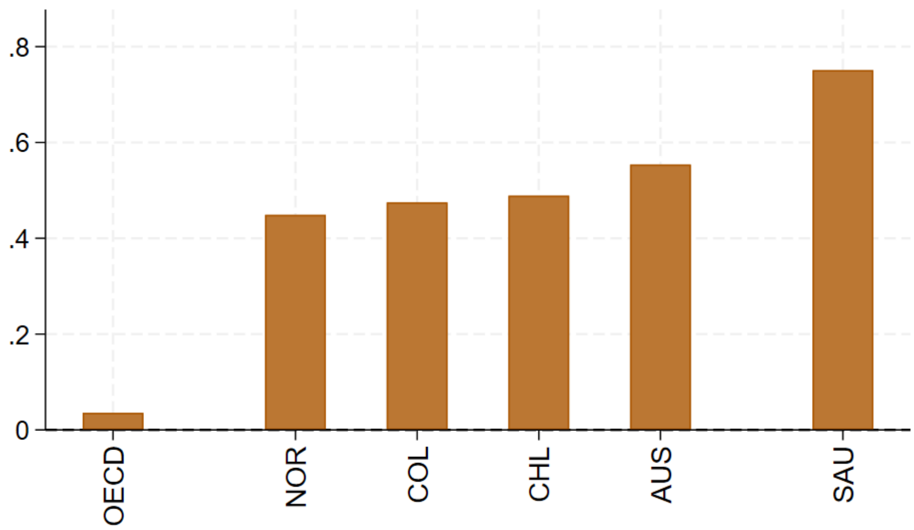
Initial GDP per capita levels (PPP based, in logs) and predicted AI-driven per capita real income gains (annualised percentage points)



Source: Authors' calculations.

Figure A.10. Top 5 Oil and Mining Exporters by Share

Mining and oil in total exports, in %



Note: This figure shows the export shares of countries in sectors with a high cross-elasticity of substitution, i.e., Mining and Coke/petroleum. Shares are shown for countries with the largest export shares of respective sectors.
Source: Authors' calculations.

A.2. Calculating sector-level exposure to AI in different countries

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.

In countries with detailed data on occupation by industry employment, occupations' exposure are then aggregated to the industry level and weighted by each industry's 2019 value-added share in the national economy. These countries include the United States, Canada, European Union member states, the United Kingdom, Australia, Costa Rica, and Brazil. 2019 is chosen as the most recent pre-pandemic year. For other countries, industry exposures are imputed using data from similar countries by per-capita income, while maintaining each country's own 2019 value-added structure for country-level aggregation. These include Argentina, Bangladesh, Belarus, Brunei, Switzerland, Chile, China, Cote d'Ivoire, Cameroon, Colombia,ˆ Egypt, Hong Kong, Indonesia, India, Iceland, Israel, Jordan, Japan, Kazakhstan, Cambodia, South Korea, Laos, Morocco, Mexico, Myanmar, Malaysia, Nigeria, Norway, New Zealand, Pakistan, Peru, Philippines, Russia, Saudi Arabia, Senegal, Singapore, Thailand, Tunisia, Türkiye, Taiwan, Ukraine, Vietnam, and South Africa. Results are reported only for G20 and OECD economies.

For the United States, 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 and United Kingdom, 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.

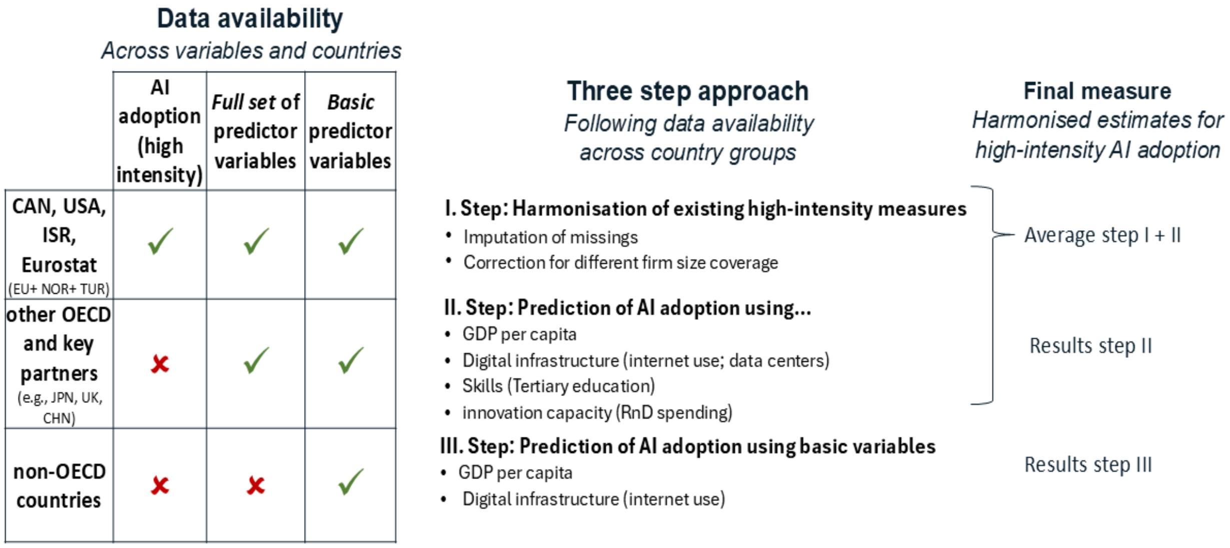
For Canada, we convert exposure for United States occupations at SOC 2010 to SOC 2018. Then, we use a crosswalk provided by Statistics Canada to convert our estimates to Canadian NOC 2016 classification, and then to NOC 2021. Two assumptions are required in this passage: that workers in each NOC 3-D are distributed following the relative employment weight of each United States SOC 6-D category with respect to the corresponding Canadian NOC 3D, and that workers are uniformly distributed workers in multiple mappings. We then collapse to the more aggregated NOC 43 categories, for which industry by occupation distribution of employment is available in LFS Canada. As Canada uses a similar NAICS classification for industries, we follow the same procedure as United States to convert NAICS into ISIC sectors.

Finally, for Australia, Costa Rica, and Brazil, we follow a similar procedure to that used for European countries. For Australia, we use data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, converting industries from ISIC Rev. 3 to ISIC Rev. 4 and occupations from ISCO-88 to ISCO-08. For Brazil, we rely on data from the PNAD Contínua, and for Costa Rica, on the Encuesta Continua de Empleo.

A.3. AI adoption calculations

This paper defines AI adoption as the integration of AI in the production process of goods or services, which constitute core business functions. This definition goes beyond the occasional reliance on AI tools by employees in isolated tasks that are not directly related to core business activities. Given the landscape of heterogenous and often incomplete AI adoption data, AI adoption in core business functions for 76 countries is obtained in a multi-stage harmonisation process based on data availability Figure A.11).

Figure A.11. Overview over most important steps in the calculation of harmonised AI adoption in core business functions



Note: This graph presents the most important steps in the calculation of harmonised AI adoption in core business functions. Based on data availability across the 76 countries of our sample, we proceed in three steps: First, harmonising existing high-intensity AI adoption measures; second, predicting AI adoption based on countries' income level, digital infrastructure, innovation capacity and skills; third, predicting AI adoption based on a basic set of predictor variables for countries with limited data availability. Finally, harmonised estimates for high-intensity AI adoption are taken from prediction steps two and three, respectively. For the first group of countries with data on high-intensity AI adoption, we average the harmonised measures with predictions (step one and two).
Source: Authors' elaboration.

Harmonisation of existing AI adoption measures and out-of-sample predictions

The ***first step*** in calculating harmonised data on AI adoption in core business functions consists in identifying surveys which capture the use of AI in production processes of goods or services. Such surveys are conducted by the Canadian Survey on Business Conditions, Eurostat[71], the United States Census

[71] Eurostat surveys cover 27 member countries of the European Union plus Norway and Türkiyë.

Bureau[72] and Central Bureau of Statistics of Israel.[73] These surveys are harmonised in terms of their coverage of industries and firm sizes.[74] More precisely, data harmonisation consists in excluding micro firms (with less than 10 employees)[75] and to impute data for sectors that are not covered in certain countries (e.g., Agriculture in Eurostat) based on observed differences across sectors in countries where data is available.

Some discrepancies remain despite these efforts – particularly due to the time reference and the design of surveys.[76] To mitigate those, and also to obtain AI adoption measures in countries for which comparable data do not exist, we are pursuing an additional, ***second step***: for countries where AI adoption data exist, we link AI adoption levels in a regression model to its fundamental drivers, such as the level of economic development, digital infrastructure, skills and innovation, to impute AI adoption across countries through out-of-sample predictions. A key assumption behind the regression-based predictions – which are fitted for countries where sufficiently harmonised AI adoption data is available – is that the estimated relationship is stable outside this group of countries. However, for less developed economies, the role of different AI adoption drivers may differ from those estimated on this group of countries, hence the adoption rate estimates for countries whose values we impute based on these predictions are surrounded by more uncertainty.

The exact drivers included in the regression analysis are pinned down by the availability of cross-country comparable indicators and their ability to provide a good fit for capturing AI adoption. For this purpose, we apply the *Lasso* (least absolute shrinkage and selection operator) method for variable selection across more than 30 variables using both logarithmic and absolute specifications, and considering alternative functional forms including linear, squared, and interaction terms to select variables that jointly provide the best fit for AI adoption, i.e., being either individually or jointly statistically significant. Table A.1 provides an

[72] We note that US Census BTOS data are considered “experimental,” distinguishing them from other Census surveys like the Annuel Business Survey (ABS) in terms of sample design, size, and statistical adjustments such as nonresponse correction. At the time of writing, the most recent ABS results on AI use were from 2021. Given the rapid adoption of generative AI models following the release of ChatGPT in late 2022, we prioritise timely data and therefore rely on BTOS for our analysis.

[73] For a more detailed information of the precise wording of surveys by Eurostat and the statistical offices of Canada and the US, see Filippucci et al. (2025). Israel recently also conducted a survey on the use of AI in companies, with a questionnaire very similar in wording to the Eurostat survey. To include findings from a 2025 survey on AI adoption in Israel, we were harmonising the time reference of the survey with 2024 AI adoption figures considered in this paper. More specifically, we applied a ratio, derived from the US BTOS survey, comparing AI usage in the first half of 2025 to overall usage in 2024, to adjust the corresponding figures for Israel.

[74] For details on these harmonisation steps see Filippucci et al. (2025)’s Annex B.

[75] The exclusion of micro-enterprises is primarily due to data availability. Of the 30 countries for which data on AI adoption production processes of goods or services are available, only Canada and the United States provide information that covers all firms, including those below 10 employees which is required for our analysis; data in other countries refer to firms with 10 or more employees. For this reason, AI adoption values for Canada and the USA are adjusted based on the sector-level share of micro firms and the ratio of AI adoption across all firm sizes compared to those with 10 or more employees only. See Filippucci et al. (2025)’s Annex B for details on the methodology.

[76] For example, first, in the United States, official statistics surveys typically focus on the past two weeks or six months, whereas Eurostat surveys refer to the ’current situation’. Second, while national statistical institutes define a statistical unit of their surveys at least by firm size and economic activity - as it is the case in France and Germany - additional variables, such as turnover, can significantly influence findings on AI adoption across industries. Third, despite efforts in this paper’s empirical strategy to identify comparable questions on AI use, differences remain in the level of detail provided to respondents regarding specific AI use cases.

overview of the full set of considered variables from the three domains of digital infrastructure, innovation capacity, skills, along with a set of general variables such as GDP per capita.

Table A.1. Overview of variables considered as potential regressors

Domain	Variable	Source	Coverage (%)	
			Sample	OECD
General	Google trends importance of AI (index)	OECD.AI Policy Observatory	64	100
	GDP per capita (in PPP)	***OECD/World Bank***	***100***	***100***
	Share of working age population (%population)	OECD	68	100
	Startups (stock and flow: % firms)	OECD SDBS	43	74
Infrastructure	# availability zones (abs/per capita)	Ledonvirtha et al. (forthcoming)	41	63
	# data centers (abs/per capita)	***Data Center Map***	***68***	***100***
	# internet exchange points (abs/per capita)	Data Center Map	68	100
	# public clouds (abs/per capita)	Data Center Map	64	92
	AI compute capacity (abs/share/per capita)	Ledonvirtha et al. (forthcoming)	41	63
	Business download speed - diff. speed cat. (%firms)	OECD Data Kitchen [*]	37	63
	Fiber connection over total broadband subscr. (abs/per capita)	OECD.AI Observatory Index (forthcoming) [**]	50	100
	Internet use of individuals (abs/per capita)	***ITU***	***100***	***100***
	Public sector's online services (index)	UN E-Government Survey	97	100
	Total fixed broadband subscription (abs/per capita)	OECD Data Kitchen [**]	50	100
	Total mobile broadband subscriptions (abs/ per capita)	OECD Data Kitchen [**]	50	100
	Use of mobiles (abs/%population)	ITU	100	100
Innovation	# supercomputers (abs/per capita)	OECD.AI Observatory Index (forthcoming) [***]	54	100
	Business R&D expenditure (%GDP)	***OECD Main Science and Technology Indicators***	***55***	***100***
	Business R&D expenditure in ICT (%GDP)	OECD Main Science and Technology Indicators	49	95
	Economic complexity of exports (index)	Atlas of Economic Complexity	95	95
	Github project impact (%contributions)	OECD.AI Policy Observatory	66	97
	Github project popularity (%contributions)	OECD.AI Policy Observatory	68	100
	Government R&D expenditure (%GDP/per capita)	OECD Main Science and Technology Indicators	55	100
	High value datasets accessibility/availability (%total)	OECD.AI Observatory Index (forthcoming) [+]	50	92
	ICT investment (%GDP)	OECD Going Digital	39	79
	ICT patents (%IP5)	OECD Going Digital	46	82
	ICT venture capital (%GDP)	OECD Going Digital	36	71
	Top10 cited computer sc. docs (%top10 all fields)	OECD Going Digital	58	100
Skills	Digital skills among active population (score)	World Economic Forum	99	100
	High skilled share (by country/by country-sector)	ILO	92	97
	PIAAC score (literacy/numeracy/prob solv.)	OECD Survey of Adult Skills (PIAAC)	41	76
	STEM education (%age25-64)	OECD Education at a Glance 2024	55	100
	Tertiary education in workforce (abs/%popul./%age25-64)	***OECD Education at a Glance 2024***	***63***	***100***

Note: [*] from OECD ICT Access and Usage by Businesses Database; [**] from OECD Broadband statistics; [***] from Top 500 list; [+] from OECD Open Useful and Re-usable data (OURdata). All variables correspond to 2023 or the closest prior year. Variables retained in the analysis are highlighted in bold italics.

Regression results show that high-intensity AI adoption is positively correlated with real GDP per capita and digital infrastructure (Table A.2). Although these variables lose individual significance when additional regressors for innovation, skills and AI specific digital infrastructure are included, they remain jointly significant both within the full set of variables and when considered together with the individually insignificant variables. The variables presented in Table A.2 (column 3) are the most established, and comparable across countries, and are therefore used to impute AI adoption across countries through out-of-sample predictions from the regressions.

Table A.2. The econometric link between high-intensity AI adoption and its structural drivers

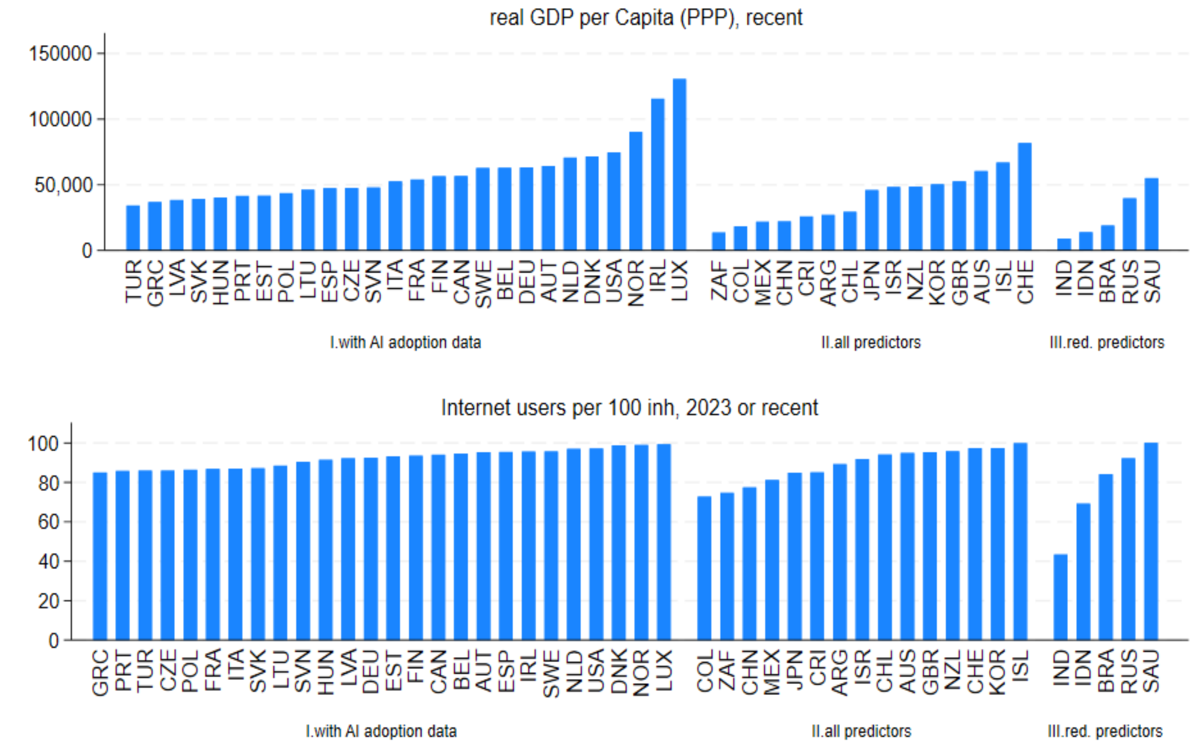
Projected sector-level total factor productivity gains under different scenarios (cumulative over 10 years, in percent)

	(1)	(2)	(3)	(4)
	AI adoption	AI adoption	AI adoption	AI adoption
real GDP pCapita (PPP), 2023	0.731***	0.270	0.093	0.071
	(0.1598)	(0.1942)	(0.1218)	(0.1647)
Internet users per 100 inh, 2023 or recent		3.574***	1.820	1.863
		(1.0367)	(1.2251)	(1.6600)
Business exp in RnD, %GDP 2023 or recent			0.284***	0.284***
			(0.0521)	(0.0884)
Tertiary educ share in popul (25-64), 2023 or recent			0.228	
			(0.2416)	
# Data Centers per 1 mn popul, 2025			0.029	0.060
			(0.0801)	(0.0897)
PIAAC prob solv score, 2023				0.541
				(1.0316)
Observations	558	558	468	396
R-squared	0.627	0.655	0.737	0.752
Sector FE	YES	YES	YES	YES
Clustering	ctry-level	ctry-level	ctry-level	ctry-level
F-test for joint significance:				
All variables	***	***	***	***
Insignificant variables only	-	-	***	**

Note: Predictors of AI adoption - capturing economic development, infrastructure, innovation capacity, and skills - were selected based on data availability (see Table A.1), the Lasso variable selection procedure, and tests of joint significance for both the full set of variables and those individually insignificant. All variables are included in natural logarithms. AI adoption refers to the final harmonised high-intensity measure pertaining. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Sources: Authors' calculations based on World Bank (2024), International Telecommunication Union (ITU) (2025), Data Center Map (2025), OECD (2024 a , b, c and OECD (2023c).

Descriptive statistics of selected variables are presented in Figures A.10 and A.11. Digital infrastructure is measured by the share of individuals using the internet and the number of data centres per capita[77], skills are represented by the proportion of tertiary educated in the population aged 25-64, while innovation is measured as the business R&D expenditure in % of GDP.

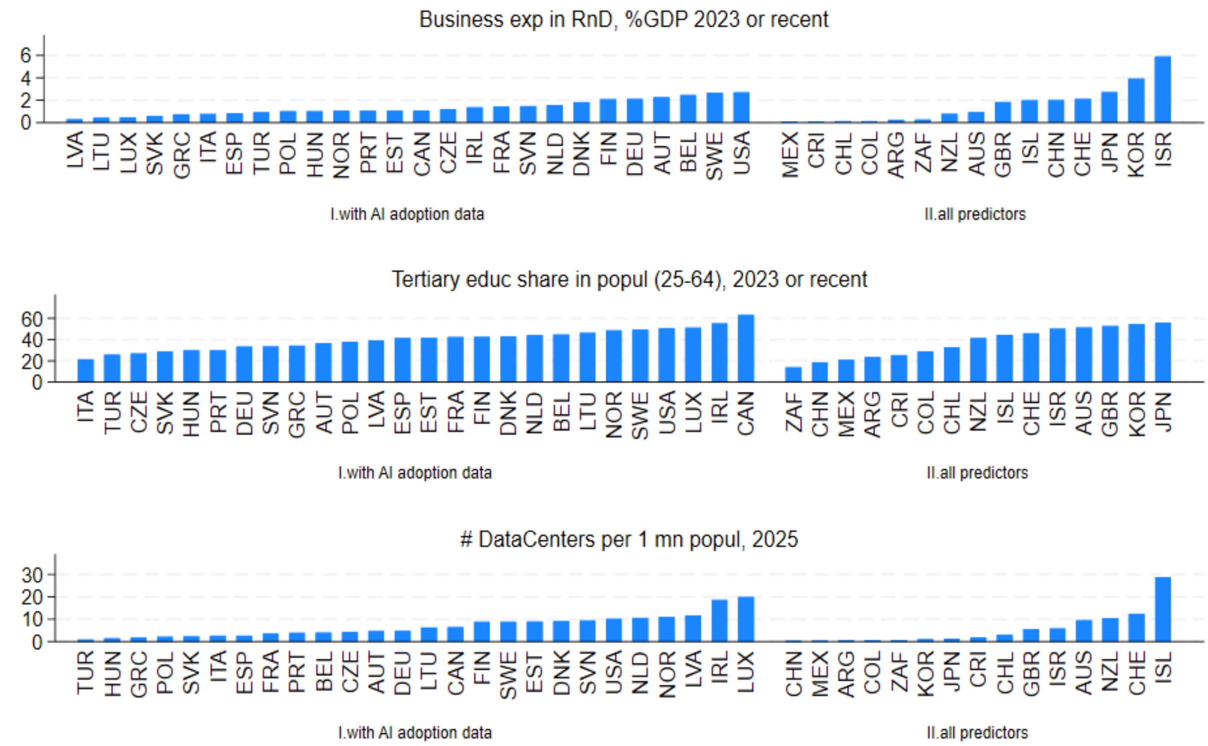
Figure A.12. AI adoption predictor variables: Descriptives statistics of *basic* predictor variables



Note: "Red. Predictors" refer to the reduced set of predictors (see Figure A.11).
Source: World Bank (2024), International Telecommunication Union (ITU) (2025).

[77] An alternative measure would have been the OECD's indicator on public cloud compute capacity for AI that aims at capturing the AI compute capacity in public clouds across regions (Ledonvirtha et al. (forthcoming)). While our chosen measure, the number of data centers from Data Center Map, is not without limitations, four factors motivated our choice: (i) Data Center Map has fewer missing values; (ii) its correlation with other relevant variables, i.e., per capita internet use and AI adoption among firms, is higher; (iii) Lasso-based variable selection in the explanation of AI adoption favours the measure from Data Center Map; and (iv) it offers a more direct alignment with our concept of interest in terms of unit of measurement - for example, the AI cloud compute indicator counts availability zones rather than data centers, and since an availability zone can encompass multiple data centers, it may not fully capture AI cloud compute capacity within a country.

Figure A.13. AI adoption predictor variables: Descriptives statistics of *additional* predictor variables

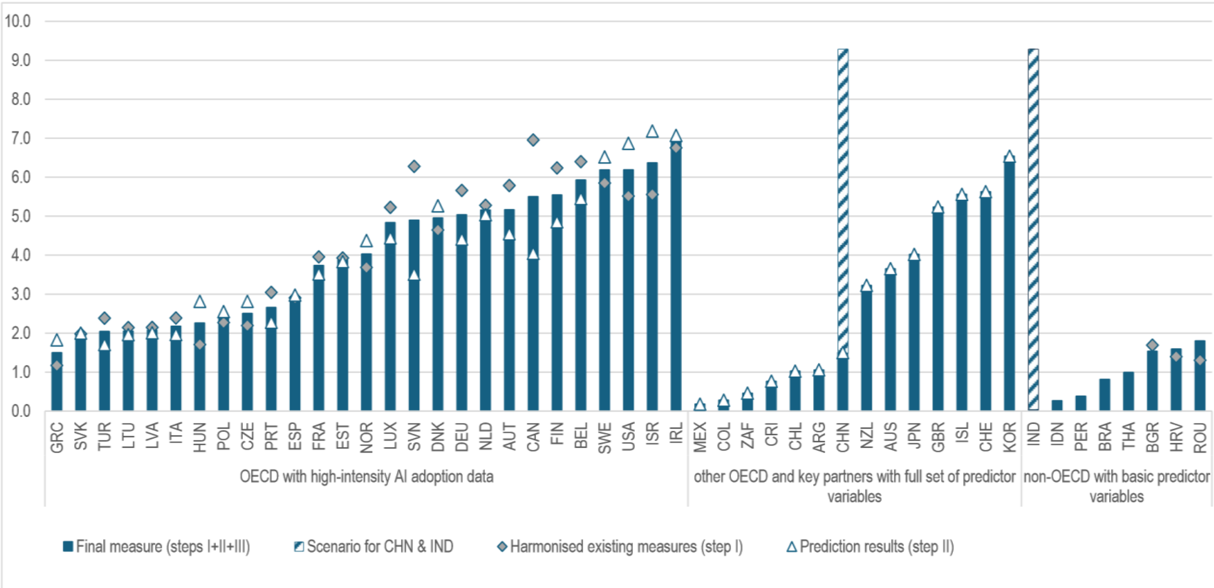


Source: OECD (2024a,b,c) and Data Center Map (2025).

Importantly, out of the 76 considered countries, 30 non-OECD countries do not have the comprehensive set of selected predictor variables. For this reason, in a ***third step***, out-of-sample predictions were derived for these countries based on a reduced set of predictor variables, i.e., the level of economic development (GDP per capita) and the digital infrastructure (internet use per capita) (Table A.2, column 2). The resulting preferred adoption rate estimates are calculated as the average of the harmonised values (derived from observed data) and the imputed values (obtained from out-of-sample predictions based on fundamental drivers) (Figure A.14).

Figure A.14. Harmonised estimates for current AI use in core business functions, 2024

Share of firms adopting AI (in % of all firms)



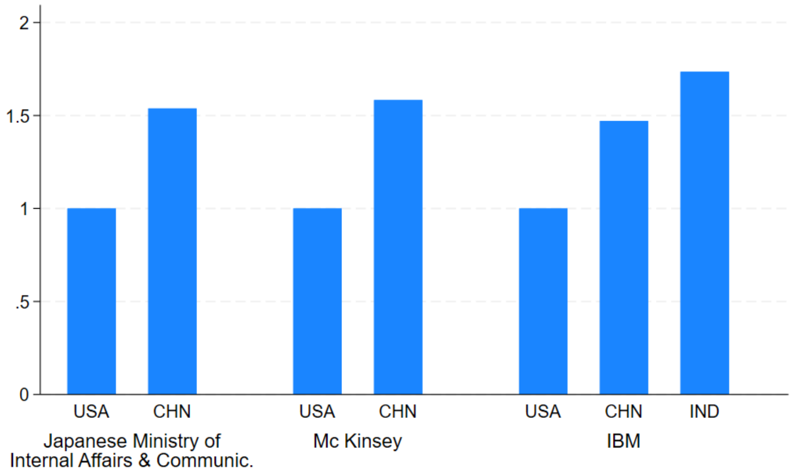
Note: For China and India, the shaded areas represent the difference between two scenarios – a scenario assuming low AI adoption and a scenario assuming high AI adoption.

Sources: Existing measures for Canada: Statistics Canada – Canadian Survey on Business Conditions (CSBC) (Statistics Canada, 2024); for EU: Eurostat Community survey on ICT usage and e-commerce in enterprises (Eurostat, 2025); for the United States: United States Census – Business Trends and Outlook Survey (BTOS) (United States Census Bureau, 2025). Predictor variables sourced from World Bank (2024), International Telecommunication Union (ITU) (2025), Data Center Map (2025), OECD (2024a,b,c).

For China and India, the results from our out-of-sample imputation strategy yield very low estimated AI adoption rates. By contrast, evidence from the literature and various surveys suggests substantially higher adoption levels in both China and India - in some cases, roughly 50% above those observed in the United States (Figure A.15). For this reason, we consider the results from our imputation strategy as a low adoption scenario while we consider a high-adoption scenario with AI adoption being 50% higher in China and India than in the US.

Figure A.15. Cross-survey comparison of AI adoption in China and India relative to the US

Country-level AI adoption relative to the US



Note: Data from Japan Ministry of Internal Affairs and Communications (2024) and McKinsey & Company (2023) referring to 2024 while data from IBM (2023) referring to 2023.
Sources: Japan Ministry of Internal Affairs and Communications (2024), McKinsey & Company (2023) and IBM (2023).

Cross validation of our preferred AI adoption estimate

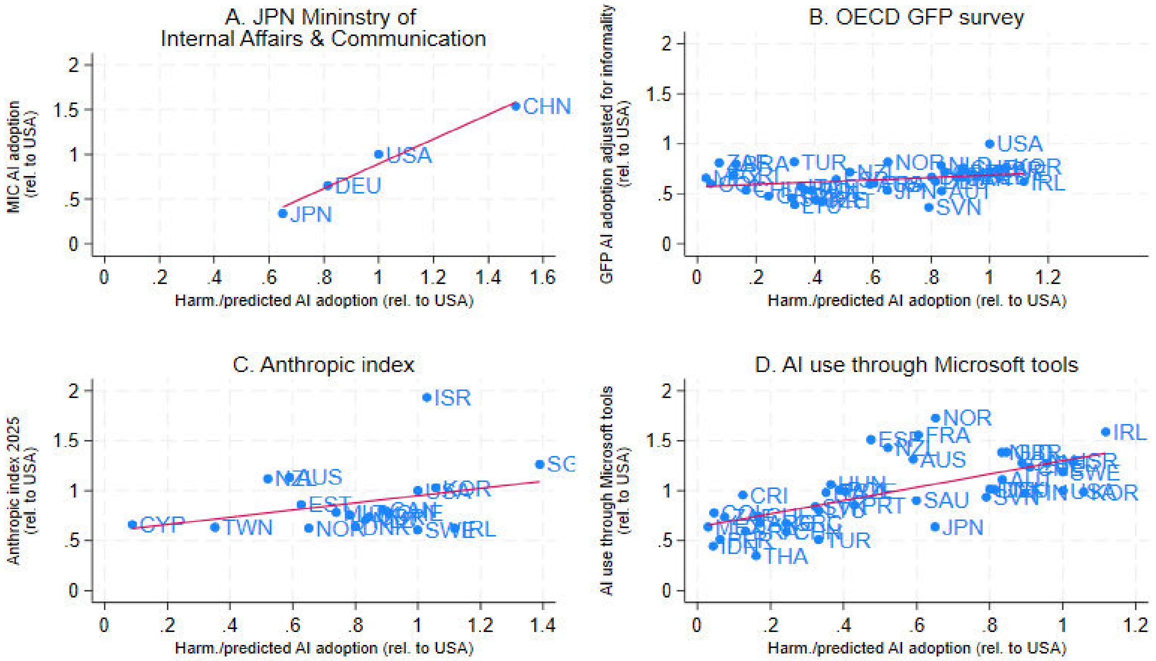
The ranking of country-level estimates of AI adoption in core business functions in this paper is broadly consistent with other sources on AI adoption. These include a survey by Japan's Ministry of Internal Affairs and Communications (covering China, Germany, Japan, and the US), the OECD's Global Forum on Productivity (GFP) employer survey on labour shortages (covering 34 OECD countries plus Brazil and South Africa), Anthropic's AI use index (covering 15 OECD countries plus 4 Cyprus, Malta, Singapore and Chinese Taipei) and estimates based on AI use through Microsoft tools (Misra et al., 2025).[78] Although these sources differ in purpose, sector coverage, and time reference, their findings on AI adoption show a positive correlation with our estimates (Figure A.16).[79]

[78] Other OECD studies such as for example, Generative AI and the SME Workforce: New Survey Evidence, which surveys SMEs in Austria, Canada, Germany, Ireland, Japan, Korea, and the United Kingdom, are not directly compared with our findings due to substantial differences in survey design. In particular, the exclusive focus on SMEs and the wording of the AI-use question ("Does anyone in your company, and please include yourself, ever use generative AI for work?") limit the scope for direct comparability, and the results should therefore be interpreted as complementary rather than directly comparable.

[79] Especially, Anthropic's AI index differs from our metrics in that it relies solely on one AI tool (Claude.ai, Anthropic's generative AI model), focuses on individual rather than firm-level usage, and refers specifically to 2025 values.

Figure A.16. AI adoption relative to the US

Comparing alternative data sources on AI adoption (vertical axes) with our current calculations (horizontal axes)



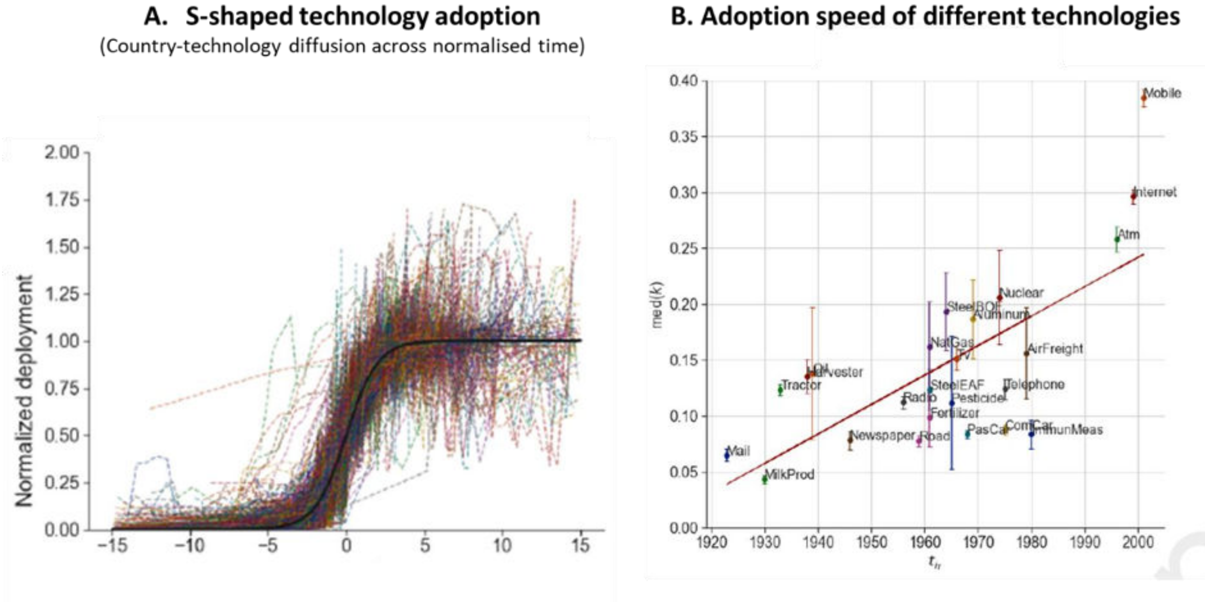
Note: This figure shows AI adoption values of different countries relative to the United States across different surveys. Importantly, while AI adoption in panels A and B considers AI adoption among firms, panel C captures the Anthropic AI usage index which is based on the share of claude.ai usage divided by the share of working-age population.
Source: Japan Ministry of Internal Affairs and Communications (2024) and OECD (2024d).

A few countries - particularly Latin American economies such as Mexico, Colombia, and Costa Rica - stand out in this pattern: in the GFP survey, their reported AI adoption rates are relatively closer to those of the United States than our estimates suggest. Relatively low AI predictions can be explained by the drivers of AI adoption, as depicted in Figures A.10, A.11 and Table A.2, which are low for most Latin American countries. In addition, this gap is largely explained by three features of the GFP survey that tend to produce higher AI diffusion figures than the predictions in this paper, which are based on structural drivers of adoption. First, the GFP survey is conducted online thereby pre-selecting firms more likely to use AI. Second, it asks about adoption over the past two years and does not specify the purpose of AI use. Third, it excludes agriculture - a sector with generally low AI adoption - thereby biasing country-level aggregates upward, especially for countries where agriculture accounts for a large share of value added.

Current AI adoption extrapolated over 10 years

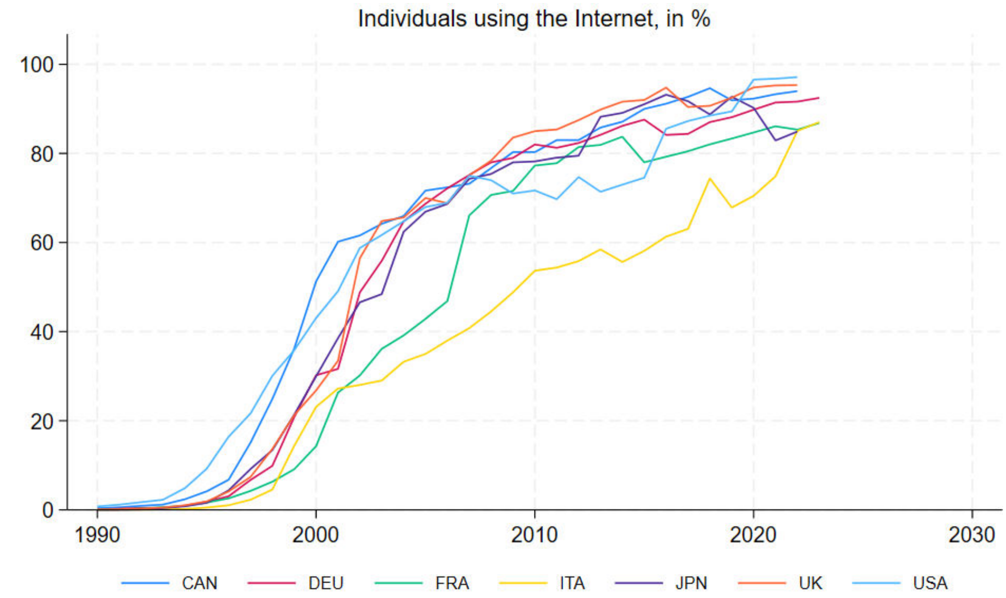
As highlighted in Section 3.3, the future adoption path of AI is expected to follow an S-shaped curve following a logistic function as motivated by the diffusion of past technologies (Figure A.17 and Figure A.18).

Figure A.17. Diffusion path of past technologies



Note: Panel A shows the adoption path of 3015 country-technology pairs. The data are normalized and plotted using non-dimensional coordinates to allow to comparisons across country-technology pairs with different adoption speeds and saturation levels. The thick black line traces the idealized logistic curve. Panel B shows the median adoption speed (parameter k) across countries for a given technology.
Source: Tankwa et al. (2025).

Figure A.18. S-shaped adoption path of past technologies: the example of the internet

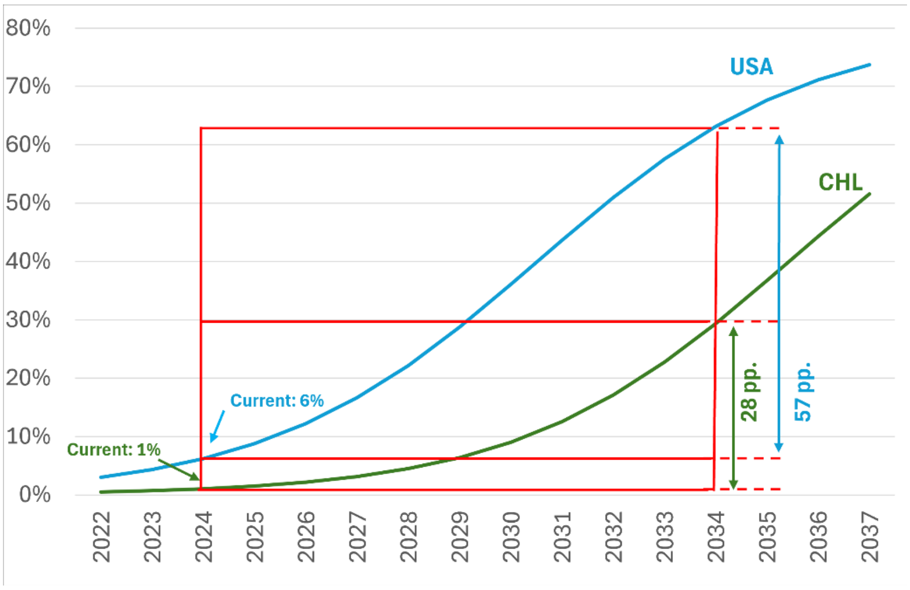


Source: International Telecommunication Union (ITU) (2025).

In this paper, AI adoption paths are modelled by fitting logistic curves to current AI adoption rates, under different assumptions on the logistic growth rate (the “speed of adoption”) and assuming a maximally achievable adoption rate of 80% in the long run. For example, for the most rapid adoption scenario, the adoption path is modelled by fitting a logistic function with a logistic growth parameter similar to that observed for mobile phones (Figure A.17). The United States and Chile have AI adoption levels of about 6% and 1% respectively, in 2024, hence their increase in AI adoption along the S-shaped path over the next 10 years differs substantially (Figure A.19 illustrates this under the fast adoption scenario, mimicking the diffusion of mobile phones). Accordingly, within 10 years AI adoption in the United States is expected to increase by 57 percentage points while AI adoption in Chile is expected to increase by 28 percentage points. This divergence is due to the fact that both countries are still on the accelerating parts of their adoption paths, during which level difference in AI adoption across countries tend to increase.

Figure A.19. Current adoption rate differences across countries are likely to drive adoption 10 years from now: United States versus Chile

Future AI adoption path assumptions following the S-shape of previous GPTs under fast adoption speed scenario (following mobile phones), % of businesses



Note: Calculations based on the adoption speed of the latest digital technology (mobile phones).
Source: Authors' calculations based on adoption speed sourced from Tankwa et al. (2025) (see Figure A.17).

A.4. Model Details

Set-up

We follow the models in Çakmaklı et al. (2021) and Baqaee and Farhi (2024) very closely. We calibrate the model in the pre-AI period[80] and quantify the changes after the productivity shocks associated with AI. In that sense, our model boils down to a two-period model solved by exact hat algebra used widely in the trade literature. We analytically solve the model using a second order approximation but by introducing small shocks and integrating the result, we approximate the non-linear solution, similar to the Euler method.

[80] The calibration is based on 2019 OECD ICIO tables including 76 countries, plus an aggregate entity representing the rest of the world and 45 sectors in each country. We construct the rest of the world by taking the bottom decile of countries' TFP distribution. The 'public administration' sector is proxied using each country's average TFP in services while the sector 'activities of households' is assumed to experience zero TFP gains from AI.

We have N countries and J industries. We denote countries with c, m, or n, and sectors (industries) with i, j, or k. Sector-country pairs are given by a combination of industry and country codes (e.g., ic). We denote consumption by households in country c with a fictional sector 0.

The total output of sector-country ic is given by y_{ic} with price p_{ic}. Suppose sector i in country c uses the good produced by sector-country jm in the amount x_{jm}^{ic}. Similarly, x_{jm}^{0c} denotes the output of jm consumed by households in country c. Let Ω denote the input-output matrix and Ω^0 the consumption share matrix. The elements of these matrices are given by:

$$\Omega_{jm}^{ic} \equiv \frac{p_{jm}x_{jm}^{ic}}{p_{ic}y_{ic}}, \qquad \Omega_{jm}^{0c} \equiv \frac{p_{jm}x_{jm}^{0c}}{E_c} \tag{A.1}$$

where E_c is the total expenditure (i.e., GNI) of country c.

Finally, the value-added (or factor share) in country-sector pair ic is defined as:

$$\alpha_{ic} \equiv 1 - \sum_{jm} \Omega_{jm}^{ic} \equiv \frac{\sum_{f \in \mathcal{F}} w_f L_{ic,f}}{p_{ic}y_{ic}}, \tag{A.2}$$

where F is the set of all factors, including different types of labor and capital. We define Ω^F—the matrix representing the factor shares—as a matrix whose elements are given by the factor shares in the output:

$$\Omega_f^{ic} = \frac{w_f L_f^{ic}}{p_{ic}y_{ic}} \quad \text{such that} \quad \sum_f \Omega_f^{ic} = \alpha_{ic} \tag{A.3}$$

Production

As shown in Figure 6, the production is done at the sectoral level by combining a value-added bundle, which consists of the factors of production, and an intermediate good bundle using a CES production function and productivity A_{ic}.[81]J

$$y_{ic} = \frac{A_{ic}}{\overline{A}_{ic}} \left[\alpha_{ic} \left(\frac{\mathrm{VA}_{ic}}{\overline{\mathrm{VA}}_{ic}} \right)^{\frac{\phi-1}{\phi}} + (1-\alpha_{ic}) \left(\frac{M_{ic}}{\overline{M}_{ic}} \right)^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}. \tag{A.4}$$

[81] Following Baqaee and Farhi (2024), we use calibrated CES function representation.

The corresponding price index is:

$$p_{ic} = \frac{\overline{A}_{ic}}{A_{ic}}\left[\alpha_{ic}\left(P_{ic}^{\mathrm{VA}}\right)^{1-\phi} + (1-\alpha_{ic})(p_{ic}^{M})^{1-\phi}\right]^{\frac{1}{1-\phi}}, \qquad \textbf{(A.5)}$$

where P_{ic}^{VA} and p_{ic}^{M} are the prices of the value-added bundle and intermediate bundle, respectively.

The value-added bundle is composed of factors of production, with the bundle level and its price index given by:

$$\mathrm{VA}_{\mathrm{ic}} = \left[\sum_{\mathrm{f}\in\mathcal{F}} \frac{\Omega_{\mathrm{f}}^{\mathrm{ic}}}{\alpha_{\mathrm{ic}}}\left(\frac{\mathrm{L}_{\mathrm{f}}^{\mathrm{ic}}}{\overline{\mathrm{L}}_{\mathrm{f}}^{\mathrm{ic}}}\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \qquad \textbf{(A.6)}$$

$$\mathrm{p}_{\mathrm{M}}^{\mathrm{ic}} = \left[\sum_{\mathrm{f}\in\mathcal{F}} \frac{\Omega_{\mathrm{f}}^{\mathrm{ic}}}{\alpha_{\mathrm{ic}}}(\mathrm{w}_{\mathrm{f}})^{1-\eta}\right]^{\frac{1}{1-\eta}}$$

η

The intermediate bundle is formed from sectoral intermediate bundles. The sectoral intermediate bundle j used in sector ic is denoted by x_j^{ic}, with the corresponding price index p_j^{ic}. We write the sectoral intermediate bundle and its price index as:

$$\Omega s_j^{ic} \equiv \frac{1}{1-\alpha_{ic}} \sum_{m\in\mathcal{C}} \Omega_{jm}^{ic}, \qquad \textbf{(A.7)}$$

$$M_{ic} = \left[\sum_{j\in\mathcal{N}} \Omega s_j^{ic}\left(\frac{x_j^{ic}}{\overline{x}_j^{ic}}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}},$$

$$p_M^{ic} = \left[\sum_{j\in\mathcal{N}} \Omega s_j^{ic}\left(p_j^{ic}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}.$$

Here, Ωs_j^{ic} captures the share of sector j among all intermediate inputs of ic, and p_j^{ic} is the sectoral price index. We assume that all sectoral intermediate bundles are complements, i.e.,

$0 \le \varepsilon < 1.$

Sectoral intermediate bundles are formed by combining varieties coming from different countries. We define the matrix Ξ^{N} to capture the share of bundle j for sector ic fulfilled by jm. We write the sectoral intermediate bundle and its price index as:

$$\Xi_{jm}^{ic} \equiv \frac{\Omega_{jm}^{ic}}{\Omega s_j^{ic}}, \qquad \text{(A.8)}$$

$$x_j^{ic} = \left[\sum_{m\in\mathcal{C}} \Xi_{jm}^{ic} \left(\frac{x_{jm}^{ic}}{\overline{x}_{jm}^{ic}}\right)^{\frac{\xi_j-1}{\xi_j}}\right]^{\frac{\xi_j}{\xi_j-1}},$$

$$p_j^{ic} = \left[\sum_{m\in\mathcal{C}} \Xi_{jm}^{ic} \left(p_{jm}\right)^{1-\xi_j}\right]^{\frac{1}{1-\xi_j}}.$$

Here, the elasticity of substitution ξ_j is sector-specific and, in the trade literature, referred to as the trade elasticity or Armington elasticity. We assume these elasticities are larger than 1, so that all varieties coming from different countries are substitutes.

Consumption

Consumption on the household side also follows a similar structure, as shown in Figure 7. Households in country c maximize their utilities first at the sectoral level:

$$\Omega s_j^{0c} \equiv \sum_{m\in\mathcal{C}} \Omega_{jm}^{0c},$$

$$C_c = \left[\sum_{j\in\mathcal{N}} \Omega s_j^{0c} \left(\frac{x_j^{0c}}{\overline{x}_j^{0c}}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where x_j^{0c} is the sectoral consumption bundle, Ωs_j^{0c} denotes the weight of sector j in the final consumption of consumers in country c, and σ is the elasticity of substitution between sectors. The corresponding consumption price index can be written as:

$$\mathrm{p}_{0c} = \left[\sum_{j\in\mathcal{N}} \Omega \mathrm{s}_j^{0c} \left(\mathrm{p}_j^{0c}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \quad \text{for } (\sigma = 1): \log \mathrm{p}_{0c} = \sum_{j\in\mathcal{N}} \Omega \mathrm{s}_j^{0c} \log \mathrm{p}_j^{0c}, \qquad \text{(A.9)}$$

where p_j^{0c} denotes the price index for the consumption bundle j in country c. The $\sigma = 1$ case corresponds to a Cobb-Douglas utility function.

Sectoral consumption bundles are also formed by combining varieties coming from different countries. The sectoral consumption bundle and its price index can be written as:

$$\Xi_{jm}^{0c} \equiv \frac{\Omega_{jm}^{0c}}{\Omega s_j^{0c}}, \quad \text{(A.10)}$$

$$x_j^{0c} = \left[\sum_{m \in \mathcal{C}} \Xi_{jm}^{0c} \left(\frac{x_{jm}^{0c}}{\overline{x}_{jm}^{0c}}\right)^{\frac{\xi_j^0 - 1}{\xi_j^0}}\right]^{\frac{\xi_j^0}{\xi_j^0 - 1}},$$

$$p_j^{0c} = \left[\sum_{m \in \mathcal{C}} \Xi_{jm}^{0c} (p_{jm})^{1-\xi_j^0}\right]^{\frac{1}{1-\xi_j^0}}.$$

Similar to the production side, ξ_j^0 is the sector-specific Armington elasticity. We allow for this elasticity to differ from that used in the production block.

Market Clearing and Solution Methodology

Goods markets clear:

$$y_{ic} = \sum_{j \in \mathcal{J}} \sum_{m \in \mathcal{C}} x_{ic}^{jm} + \sum_{m \in \mathcal{C}} x_{ic}^{0m},$$

and factor markets clear:

$$L_f = \sum_{j \in \mathcal{J}} \sum_{m \in \mathcal{C}} L_f^{jm}.$$

Our solution methodology follows closely Çakmaklı et al. (2021) and Baqaee and Farhi (2024). We refer readers to those resources for details. To provide some intuition, we rewrite the market-clearing conditions as:

$$p_{ic} y_{ic} = \sum_{j \in \mathcal{J}} \sum_{m \in \mathcal{C}} p_{ic} x_{ic}^{jm} + \sum_{m \in \mathcal{C}} p_{ic} x_{ic}^{0m} = \sum_{j \in \mathcal{J}} \sum_{m \in \mathcal{C}} \Omega_{ic}^{jm} p_{jm} y_{jm} + \sum_{m \in \mathcal{C}} \Omega_{ic}^{0m} E_m$$

Dividing both sides by world GDP, GDP$_W$, and defining the global Domar weights as $\lambda_{ic} \equiv p_{ic} y_{ic} / \text{GDP}_W$, we can rewrite the previous equation as:

$$\lambda_{ic} = \sum_{j \in \mathcal{J}} \sum_{m \in \mathcal{C}} \lambda_{jm} \Omega_{ic}^{jm} + \sum_{m \in \mathcal{C}} \chi_m \Omega_{ic}^{0m},$$

where $\chi_m \equiv E_m / \text{GDP}_W$ is the world expenditure share of country m.

Writing the Domar weights and expenditure shares as row vectors, we can express the system in matrix notation as:

$$\lambda = \lambda \Omega + \chi \Omega^0 \quad \Rightarrow \quad \lambda = \chi \Omega^0 \underbrace{[I - \Omega]^{-1}}_{\equiv \Psi} = \chi \Omega^0 \Psi,$$

where Ψ is the Leontief inverse.

Similarly, from the factor market clearing conditions, we have:

$$\Lambda = \lambda \Omega^F,$$

where $\Lambda_f \equiv w_f L_f / \text{GDP}_W$ is the factor Domar weight, and Ω^F is the factor share matrix.

Note that the price indices in Equations A.7, A.8, A.10, A.11, and A.12 relate the prices of consumption and production bundles to upstream goods and factors. In contrast, Domar weights are determined by downstream industries. In this framework, factors do not have anything downstream and are, therefore, the terminal nodes. Since we take L_f to be exogenous and normalize world GDP to 1, log-changes in factor prices and factor Domar weights are one-to-one. Hence, as in Çakmaklı et al. (2021) and Baqaee and Farhi (2024), the entire system can be solved in terms of factor Domar weights.

First-order Linear Approximations

Since the world as a whole is a closed economy, Hulten's Theorem (Hulten, 1978) is generalized to the global economy as:

$$\mathrm{d}\log \mathrm{GDP}_W = \sum_{i\in\mathcal{J}}\sum_{c\in\mathcal{C}} \lambda_{ic}\, \mathrm{d}\log A_{ic} \tag{A.11}$$

However, the welfare of each country can be differentially affected. As shown in di Giovanni et al. (2023) and Baqaee and Farhi (2024), the first order welfare change for a country m following a productivity shock is given by:

$$\mathrm{d}\log W_m = \underbrace{\sum_{i\in\mathcal{J}} \lambda_{im}^m\, \mathrm{d}\log A_{im}}_{\text{Domestic contribution}} + \underbrace{\sum_{i\in\mathcal{J}}\sum_{c\neq m\in\mathcal{C}} \lambda_{ic}^m\, \mathrm{d}\log A_{ic}}_{\text{Foreign contribution}} \underbrace{\underbrace{- \sum_{f\in\mathcal{F}} \Lambda_f^m\, \mathrm{d}\log \Lambda_f}_{\text{Local-global mismatch}} + \underbrace{\frac{1}{\chi_m}\sum_{f\in\mathcal{F}_m} \Lambda_f\, \mathrm{d}\log \Lambda_f}_{\text{Local factor income change}}}_{\Delta\text{ allocation}} \tag{A.12}$$

where W_m is the per capita real income (welfare) in country m, λ_{ic}^m is the local Domar weight which is defined as the mth row of the matrix Ω^0 $(\lambda^m \equiv [\Omega^0\, \Psi]_m)$, $\Lambda_f^m \equiv \lambda^m$, $\Lambda_f^m \equiv \lambda^m\, \Omega^F$ is the vector of local Domar weights for the factors and $\mathcal{F}_m$ denotes the set of factors belonging to country m. The entries of the local Domar weight λ_{ic}^m capture how much consumption in the country m depends on industry i in the country c, both directly and indirectly. Λ_f^m denotes the factor output that is used to satisfy demand in the country m as a share of country c's GNE and is related to the global Domar weights with $\sum_m \chi_m \Lambda_f^m = \Lambda_f$. The domestic contribution term captures the real income gains that derive from improved domestic productivity, while abstracting from changes in expenditure shares and the production network fixed (that is, abstracting from allocation effects). Domestic productivity gains may benefit domestic consumers indirectly as the gains travel along international value chains (see example in Box 1 in Section 5.1.2). Similarly, the foreign contribution term captures the real income gains that derive from improved productivity abroad (again, abstracting from allocation effects). Finally, the allocation term captures how domestic real incomes are affected by changes in the global production network that are induced by domestic and foreign productivity gains.[82]

[82] The allocation term can be further decomposed into two sub-terms: The local-global mismatch captures the discrepancy between local and global changes in factor demands (via consumption of final and intermediate goods through the global input-output network). The local factor income change term accounts for the income change due to reallocation.

Elasticities

We follow Çakmaklı et al. (2021), di Giovanni et al. (2023), and Baqaee and Farhi (2024) for our elasticity choices and provide these elasticities and their sources in Table A.3.

Table A.3. Parameter values

Parameter	Explanation	Value	Source
ϕ	EoS between intermediates and VA	0.6	Atalay (2017)
η	EoS across factors	0.6	Oberfield and Raval (2021)
ε	EoS among intermediate inputs	0.05-0.2	Baqaee and Farhi (2019); Boehm, Flaaen and Pandalai-Nayar (2019)
ξ_i	Sector level input bundle EoS	>1	Caliendo and Parro (2015)
σ	EoS of consumption among sectors	1	Baqaee and Farhi (2024)
ξ_i^0	Sector level consumption bundle EoS	>1	Caliendo and Parro (2015)

Note: "EoS" is the elasticity of substitution.

A.5. Accounting for under-reported services trade

A substantial part of services trade is unrecorded in traditional statistics since their delivery occurs through the presence of local subsidiaries of foreign enterprises, typically multi-national ones (MNEs) (Cernat, 2024). For instance, when a domestic sector buys ICT services from US companies (say, French companies buy Microsoft services), that transaction is not reported as an intermediate services import from abroad, but as services sourced from the domestic ICT sector (say, Microsoft France). In official trade statistic, there is also no corresponding services flow recorded between the foreign headquarters and the domestic subsidiary. This missing trade link between the US headquarter and the French subsidiary could involve a range of intangibles, including R&D, software, data, as well as business processes, organisation, and managerial practices.

According to estimates by Cernat (2024) - combining the Trade in Services by Modes of Supply (TISMOS) database[83] with the OECD-WTO Trade in Value Added (TIVA) dataset [84] - this so called "mode 3" international service trade, which involves local subsidiaries, amounts to nearly *double* of the recorded - "mode 1" - service component.[85]

This under-reported trade link could be particularly relevant when assessing AI gains due to international linkages, given that AI gains are largest in (knowledge intensive) services. To gauge the quantitative significance of this issue, we leverage the idea that most of intangible capital payments in local subsidiaries of MNEs represent a missing services flow from the headquarters to the local subsidiary. This approach excludes part of value added that accrues to local labour and tangible capital since they represent the "domestically produced" component in value added. However, by attributing all intangible capital compensation as "payments" for unrecorded services flows from the foreign MNE, it represents an upper bound for the unrecorded service flows between headquarters and subsidiaries.

To derive estimates for this missing services trade, we combine measures on the share of domestic output in a sector produced by foreign owned companies from the OECD's Analytical Multi-national Enterprises

[83] https://www.wto.org/english/res_e/statis_e/gstdh_mode_supply_e.htm.

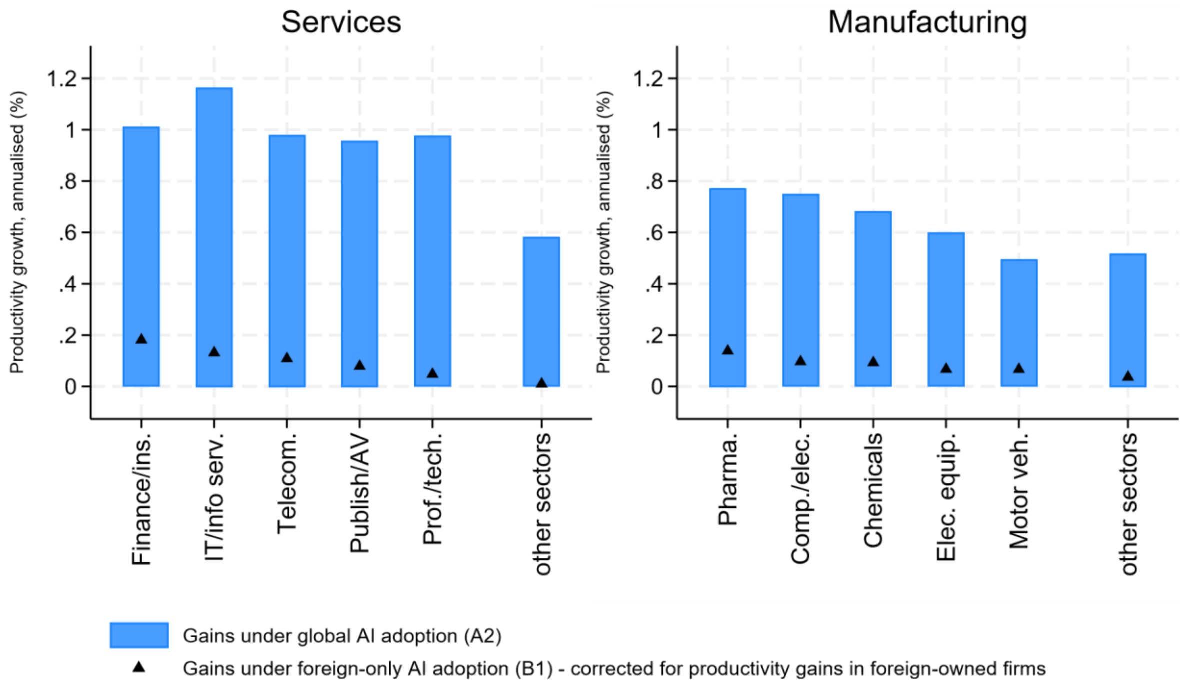
[84] https://www.oecd.org/en/topics/sub-issues/trade-in-value-added.html.

[85] A related phenomenon is the Dark Matter in international rate (Hausmann and Sturzenegger, 2014) which refers to the large returns on foreign assets by the US, driven presumably by the large share of intangible assets in US outward investments, which are hard to capture.

(AMNE) database (Cadestin et al., 2018)[86] with the share of output that is attributable to intangible capital using the EUKLEMS - IntanProd dataset (Bontadini et al., 2023). It results in an estimate for the size of the unreported service intermediate imports for each country sector, approximating it by intangible capital services flows accruing to foreign owned MNEs.

The value-added share of intangible capital of foreign companies varies widely across sectors. In services such as finance, ICT, and telecommunications, it ranges between 11 and 17 percent corresponding to about 0.1 percentage points of annual productivity growth (Figure A.20). Similarly, intangible capital in foreign-owned firms also plays an important role in some advanced manufacturing industries. For pharmaceuticals, computer/electronic equipment and chemicals, the correction for unmeasured services trade in form of MNEs' intangible capital accounts for between 13 and 17 percent corresponding to about a little bit less than 0.1 percentage points of annual productivity growth.

Figure A.20. Correcting for unreported service trade introduces foreign generated gains from AI in intangible intensive services and manufacturing industries



Note: This graph shows the average sector-level gains under global AI adoption (A2) and gains under foreign-only AI adoption (B1) which have been corrected for productivity gains in foreign-owned firms. The selected sectors are those with the largest corrected gains under foreign-only adoption.
Source: Authors' calculations.

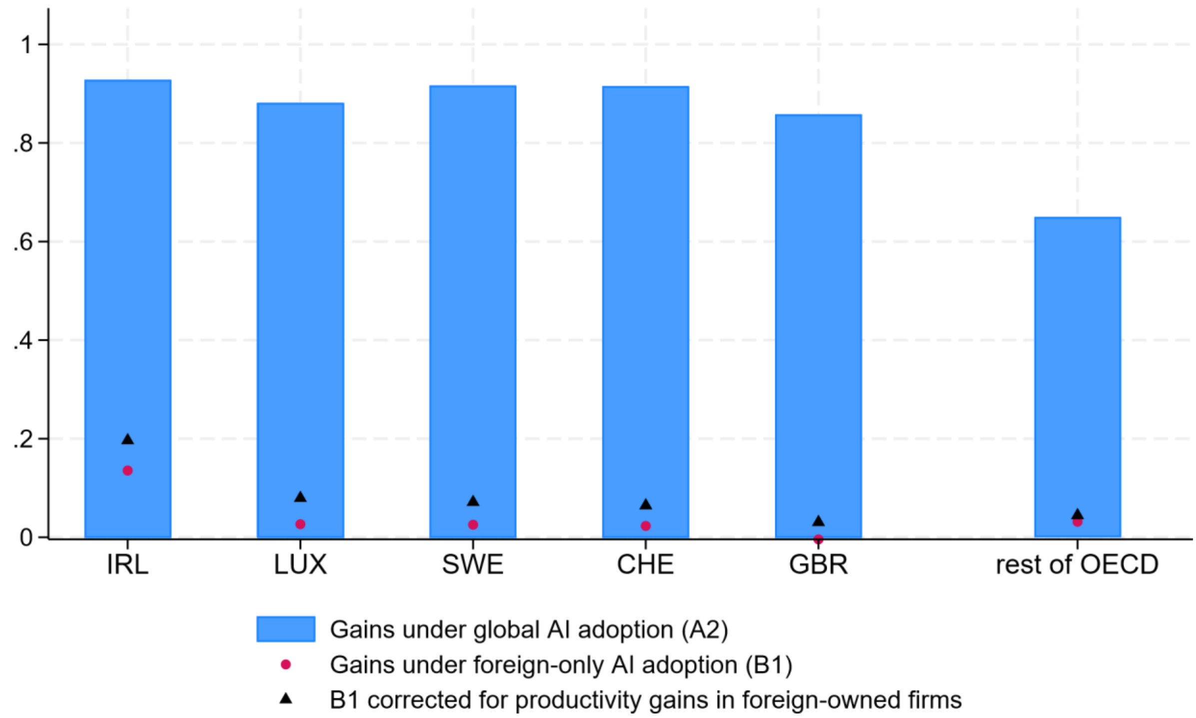
The extent to which the correction of unmeasured services trade leads to an upward adjustment of per capita real income gains from foreign linkages at the country level depends on the intensity of foreign-owned firms' presence and the value-added share of intangible capital within national sectors. Figure A.21 compares per capita real income gains from AI through international linkages based on traditional input-output statistics with per capita real income gains from AI through international linkages based on input-output statistics *corrected for gains in foreign-owned firms*. Corrected per capita real income gains from AI

[86] https://www.oecd.org/en/data/datasets/activity-of-multinational-enterprises.html

are slightly larger than gains based on common input-output statistics. For the five countries most affected by the correction (Ireland, Luxembourg, Sweden, Switzerland and the United Kingdom), per capita real income gains from AI through international linkages ultimately account for approximately 4 to 20% of total gains from AI compared to shares between close to 0 and 14% when not correcting for gains in foreign-owned firms.[87] Overall, our attempt to account for the additional impact of unmeasured services trade suggests that the gains from AI through trading with AI adopters is unlikely to account for an important fraction of the total gains that a country can achieve through domestic adoption.

Figure A.21. Correcting for unreported service trade lifts gains from foreign generated AI only moderately in a few countries

Predicted per capita real income gains due to AI over the next 10 years, percentage points (annualised)



Note: This graph shows gains under global AI adoption (A2), foreign only AI adoption (B1) and the latter, B1, corrected for productivity gains in foreign-owned firms. The selected countries are those with the largest difference between the corrected and non-correct gains under foreign-only AI adoption, i.e., the difference between the triangle and the dot.
Source: Authors' calculations.

Formally, let $CapServ_{ic}^{int}/\mathrm{VA}_{ic}$ denote intangible capital services in country c and sector i, which is expressed as a share of domestic value added as follows:

$$\frac{CapServ_{ic}^{int}}{\mathrm{VA}_{ic}} = IntanShare_{ic}\frac{CapServ_{ic}}{\mathrm{VA}_{ic}}$$

where the share of intangible capital services in total capital services $IntanShare_{ic}$ is approximated by the share of intangible investments in total investments: $IntanShare_{ic} = I_{ic}^{int}/I_{ic}^{total}$. All of these variables

[87] It should be noted that our correction of unmeasured service trade is likely to represent an upper bound. This is because all MNEs' intangible flows from their foreign affiliates are attributed to unrecorded services, whereas in practice such flows may only partly relate to services, given that the output of manufacturing industries is generally classified as goods. Even under this assumption, however, the estimated effects remain moderate.

are sourced from the EU KLEMS IntanProd dataset (Bontadini et al., 2023).

We combine this intangible capital services share with information on the importance of the presence of MNEs. In particular, we source value added generated by local subsidiaries of MNEs $VA_{ic}^{subsMNE}/VA_{ic}$, from the AMNE data (Cadestin et al., 2018). To obtain our estimate for unrecorded services intermediate imports or "imputed services imports", $\widetilde{II_{ic}}$(expressed as a share of sectoral value-added VA_{ic}) we apply this foreign MNE produced value added share with intangible capital services:

$$\text{Imputed Services Imports}_{\text{ic}} \doteq \frac{\widetilde{II_{ic}}}{\text{VA}_{ic}} = \underbrace{\frac{\text{VA}_{ic}^{subsMNE}}{\text{VA}_{ic}}}_{AMNE} \cdot \underbrace{\frac{CapServ_{ic}^{int}}{\text{VA}_{ic}}}_{IntanProd} \tag{A.13}$$

This expression is our estimate for the missing services imports, expressed as a fraction of the domestic value added generated by the importing sector. In the example above, this captures what the French ICT services sector has obtained as services from abroad, from the foreign affiliates of firms that operate in the French ICT services sector, including US headquarters.

Adjusting AI-related knowledge spillover weights for under-reporting in international services trade

Let ω_{jm}^{ic} denote the share of foreign intermediate inputs coming from country m and sector m to country c and sector i, as a share of gross output in country-sector c,i, as in equation (2), source from the OECD's inter-country input-output (ICIO) tables.[88]

We define weights that adjust for under-reported trade in services, $\widetilde{\Omega_{jm}^{ic}}$, as follows:

$$\widetilde{\Omega_{jm}^{ic}} = \Omega_{jm}^{ic} \cdot z_{jm}^{ic}, \qquad z_{jm}^{ic} := \frac{II_{jm}^{ic} + \widetilde{II_{jm}^{ic}}}{II_{jm}^{ic}}, \tag{A.14}$$

where z_{jm}^{ic} is a correction factor that adjust for the relative difference between total intermediate imports and reported intermediate imports, in proportional terms, and $\widetilde{II_{jm}^{ic}}$ is the flow unrecorded imported intermediate services inputs, II_{jm}^{ic} is the observed imported intermediate inputs. We have no information to estimate this correction for each country-sector *source* and *destination* pair specifically, but only for each destination (buying) country-sector. Hence, we assume that these proportions are the same for each country-sector source, defined by accounting for all intermediate flows coming from abroad into country-sector ic (aggregated over all sources), as follows:

$$z_{jm}^{ic} = z_{ic} := \frac{II_{ic} + \widetilde{II_{ic}}}{II_{ic}} \tag{A.15}$$

where $II_{ic}^{imp} = \sum_{m\in\mathcal{C}}\sum_{j\in\mathcal{J}} II_{jm}^{ic}$ is total imported intermediate inputs and $\widetilde{II_{ic}} = \sum_{m\in\mathcal{C}}\sum_{j\in\mathcal{J}} \widetilde{II_{jm}^{ic}}$ is total imported unrecorded intermediate services. These are obtained by combining the level of value added in country-sector cs with expression A.13:

$$\widetilde{II_{ic}} = \text{VA}_{ic}^{\text{ICIO}} \cdot \text{ImputedServicesImports}_{ic}, \tag{A.16}$$

where VA_{ic}^{ICIO} is sourced from the ICIO dataset to ensure internal consistency and avoid any issues from different value-added measurement in ICIO from AMNE.

[88] Yamano et al. (2023) and https://www.oecd.org/en/data/datasets/inter-country-input-output-tables.html.