Fear of missing out: Global linkages and the cross-country distribution of the gains from AI *

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Abstract

How does international trade shape the cross-country distribution of welfare gains from Artificial Intelligence (AI), and can laggard countries free-ride on adoption abroad? Building on task-level evidence on AI's productivity benefits, we construct harmonized cross-country estimates of AI adoption in 45 industries across 76 economies and embed projected country-sector productivity gains into a global multi-sector general equilibrium trade model. Under medium-paced diffusion, AI raises real welfare gains significantly but with large cross country differences, ranging from 0.1 to 0.95 percentage points annually. A novel welfare decomposition separates each country's gains into domestic productivity, foreign productivity transmitted through trade, and a reallocation component capturing shifts in competitiveness. Trade channels are quantitatively important, especially for open economies importing AI-intensive services. However, counterfactual experiments in which individual countries forgo adoption while the rest of the world adopts reveal that competitiveness losses largely offset the benefits of cheaper imports — leaving welfare gains near zero for most non-adopters and negative for commodity exporters and countries specializing in AI-exposed services. Domestic adoption is the primary determinant of who benefits.

Keywords: Artificial Intelligence; Input-Output Networks; Productivity; International Trade.

JEL Codes: C67, D57, F00, F16, F17.

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1 Introduction

Artificial intelligence (AI) holds the promise to substantially raise productivity and living standards, although there is wide disagreement about the magnitude and timing of these gains.[1] Projections across countries further suggest that AI-driven growth may be highly uneven, reflecting differences in country-level exposure to AI and projected adoption rates (Filippucci et al., 2025; Bergeaud, 2024; Misch et al., 2025). Yet existing studies typically assess these gains by focusing on *domestic* drivers of productivity growth — task-level performance improvements, sectoral exposure, and adoption rates — without accounting for the role of international linkages. In an integrated global economy, a country's production and consumption possibilities depend not only on domestic productivity but also on productivity developments *abroad*.

In this paper, we study how international trade interacts with AI adoption to shape aggregate welfare gains from AI, measured as increases in real welfare gains. Countries that trade with leading AI adopters or rely heavily on imports of highly AI-exposed goods and services may benefit from foreign AI-driven productivity gains through lower import prices for both final and intermediate goods. This raises a central question: does participation in global value chains allow late-adopting countries to reap substantial welfare gains by "free-riding" on AI-driven productivity gains abroad? Or is domestic AI adoption a prerequisite for substantial welfare gains, such that countries lagging in adoption risk missing out – or even losing – in a world where others adopt?

We address this question in four steps. First, we construct new harmonized estimates of current AI adoption in core business functions across 76 economies and one economy representing rest-of-the-world, combining official surveys with out-of-sample predictions based on digital infrastructure, skills, and innovation capacity.[2] Second, building on experimental evidence on task-level AI performance (Brynjolfsson et al., 2025; Peng et al., 2023; Noy and Zhang, 2023; Dell'Acqua et al., 2023) and existing measures of sectoral AI exposure (Eloundou et al., 2024), we project country-sector productivity gains over the next decade

[1] Acemoglu (2025) projects relatively small macroeconomic growth impacts from AI over the next 10 years. In contrast, Trammell and Korinek (2023) view fast and accelerating growth due to the appearance of Artificial General Intelligence (AGI) – AI that matches or surpasses human capabilities in all cognitive tasks – as a distinct possibility in the foreseeable future. Focusing on *current* AI capabilities, recent estimates suggest more moderate but still significant contributions to total factor productivity growth in the coming years, reaching around 0.6 percentage points annually (Aghion and Bunel, 2024; Filippucci et al., 2024a).

[2] The calculations cover all 76 economies that are present in the OECD's 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.

under alternative adoption scenarios calibrated to the diffusion paths of previous general-purpose technologies (Comin and Hobijn, 2010; Comin and Mestieri, 2018). Third, we feed these productivity shocks into a multi-country, multi-sector general equilibrium trade model calibrated to global input-output data (Yamano et al., 2023), and derive a novel welfare decomposition (Proposition 1) that separates each country's gains into domestic productivity contributions, foreign contributions transmitted through trade, and a reallocation effect capturing shifts in global competitiveness. Fourth, we conduct counterfactual experiments in which individual countries forgo AI adoption while the rest of the world adopts, quantifying the scope for free-riding.

The micro-to-macro aggregation builds on experimental evidence on task-level productivity gains from AI in areas such as coding and customer service, combined with estimates of the share of AI-exposed tasks across sectors. These estimates are integrated with projections of country-specific AI adoption paths over the coming decade, derived from harmonized 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 centers, workforce skills, innovation, and internet penetration. This approach allows us to project AI-driven productivity gains across sectors for a large set of countries, including all OECD and G20 countries.

Further, to account for the role of international linkages, we augment the aggregation approach by introducing trade in intermediate and final goods, which can affect the global distribution of AI-driven welfare gains. Trade in intermediate and final goods can affect AI-driven welfare gains in several ways. On the one hand, households consume a mix of domestic and imported goods and services, and they benefit from foreign productivity gains when AI-driven productivity growth reduces import prices. Similarly, domestic firms rely on intermediate inputs from abroad, which may become cheaper as AI raises the productivity of trading partners. This is especially relevant when importing from leading AI adopters or importing highly AI-exposed goods and services, such as financial products or ICT services.[3] On the other hand, global AI-driven productivity gains can also affect the price of a country's export basket and, in turn, its export competitiveness. This is particularly relevant when a country specializes its exports in heavily AI-exposed sectors, such as ICT services or finance, or in products that are easily substitutable across exporters, such as commodities. The importance of these trade-related channels increases with the degree of economic integration of a country with the rest of the world.

[3]In addition, imports from AI adopters may also boost local AI adoption and productivity directly through learning and spillover effects. We discuss this possibility in section D.2 of the Appendix.

In a world of global AI adoption, the realized welfare gains in a country therefore depend not only on domestic drivers of productivity gains, such as the sectoral exposure to AI and domestic adoption rates, but also on changes in prices and factor returns induced by AI adoption abroad. In particular, since real consumption growth exceeds productivity growth when the terms of trade improve (Oulton, 2023; Baqaee and Farhi, 2024), countries lagging in AI adoption may hope to benefit from productivity gains abroad via reduced import prices. However, productivity developments abroad also affect world prices for goods and services that a country produces, leaving the overall effect on real welfare uncertain. Our model simulations allow us to quantify the extent to which countries are able to "free-ride" on foreign AI-driven productivity growth and how this depends on the structure of their economies.[4]

Our results reveal wide variation across countries in expected welfare gains from AI. In our baseline scenario — where AI is assumed to diffuse through the economy at a pace similar to that observed for previous ICT technologies such as computers and the Internet[5] — these gains range from 0.1 to 0.95 percentage points in annual welfare gain over the next 10 years across OECD countries. At the upper 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 appear most favourable, based on official surveys of AI use among businesses and on factors supporting adoption capacity such as digital infrastructure, skills, and innovation capacity (for instance, Israel, Korea, Ireland and Sweden).[6]

To shed light on how trade affects the global distribution of AI gains, we proceed in two steps. First, using Proposition 1, we decompose the welfare gains predicted by our model into domestic and foreign sources and relate them to trade and adoption patterns. This decomposition demonstrates that trade can play an important role in transmitting and distributing AI-generated productivity effects across countries. Countries that rely on imports

[4]Importantly, when studying the general equilibrium effects of AI, where services — and in particular intangible capital — play a significant role, it is crucial to account for the incomplete measurement of service trade in traditional input–output statistics. Current data often underreport cross-border flows of services, especially those related to intangible assets, leading to biased estimates of economic linkages. Correcting for this missing trade helps us refine results and provides a more reliable basis for policy conclusions (see Section 4.3.1).

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

[6]Putting these results in context by comparing them with cross-country differences observed during the previous major ICT-driven technology boom provides a useful benchmark. The ICT boom contributed about 1–1.5 percentage points to labour productivity growth over the 1995–2005 period in the US, while the comparable figure was much smaller elsewhere in the OECD, particularly in Europe (Byrne et al., 2013; Bunel et al., 2024).

of heavily AI-impacted goods and services, particularly from leading AI adopters, benefit strongly through lower import prices for final and intermediate goods. However, the decomposition also reveals that welfare gains in countries with relatively low AI-driven productivity growth are partly offset by a negative allocation effect.

The presence of a negative allocation effect has important implications for the extent to which laggard countries can "free-ride" on AI-driven productivity gains elsewhere. In a second step, we therefore conduct a series of illustrative model experiments, in which we assess the scope for trade-facilitated welfare gains arising purely from AI adoption abroad, assuming no domestic adoption. In this case, countries still benefit from cheaper imports but lose competitiveness both in world markets and in their domestic markets in the face of AI-enabled import competition. The resulting loss of competitiveness generates a large and negative allocation effect that tends to offset much of the gains from foreign AI adoption, leaving overall welfare gains relatively small. In some countries, this loss of competitiveness is particularly strong, especially where export baskets consist predominantly of highly substitutable products competing with exports from other suppliers. These include commodity exporters such as Norway, Australia and Saudi Arabia. The loss of competitiveness is also very strong in countries whose exports specialise in highly AI exposed sectors such as finance (UK) or ICT services (Israel). In these countries, real consumption may even *decline* if the world adopts AI but they do not.

Historical evidence suggests that during previous waves of major technological change, such as the Industrial Revolution, cross-country income differences initially widened as early-adopting countries pulled away from others (Korinek and Stiglitz, 2021). A similar, though more muted, divergence occurred during the ICT boom of the mid-1990s, which played out primarily in the United States but yielded smaller benefits in Europe due to slower economy-wide adoption (notably in services, such as retail; van Ark et al., 2008). Our paper suggests that early signs of uneven AI adoption across countries could foreshadow a period of AI-driven productivity divergence, and that the scope for laggard countries to benefit passively from productivity gains abroad may be very limited.

Related Literature

This study contributes to the literature quantitatively estimating the medium-term aggregate productivity effects of AI, typically Generative AI (such as Large Language Models). Acemoglu (2025) introduces a tractable and influential framework in which aggregate AI gains equal the product of task-level productivity improvements, the value-added share of

AI-exposed tasks, and the projected adoption rate, yielding modest estimates of about 0.06 percentage points of annual TFP growth for the United States. Using the same framework with more optimistic assumptions, Aghion and Bunel (2024) estimate gains of up to 0.68 percentage points per year.[7] This approach has been extended to Europe (Bergeaud, 2024), to G7 economies (Filippucci et al., 2025), and to broad groups of countries globally (Cerutti et al., 2025), but always evaluating each country in isolation. We contribute along two dimensions. First, we provide, to the best of our knowledge, the first harmonized estimates of AI-driven productivity gains spanning 76 individual economies, highlighting large cross-country variation driven by differences in both sectoral exposure and forecasted adoption. Second, and more importantly, we embed these country-sector productivity projections in a global general equilibrium trade model, allowing welfare gains to reflect not only domestic drivers but also the transmission of productivity shocks through international trade. Our baseline estimates for the United States are closer to the optimistic side of the debate and comparable to the productivity gains experienced during the ICT boom (Byrne et al., 2013).[8]

We also contribute to a growing literature studying whether general-equilibrium effects can substantially alter the aggregate impact of automation. Filippucci et al. (2024a) highlight large heterogeneity in AI exposure across sectors, implying that with non-unitary elasticities of substitution the Hulten-theorem approximation may be poor due to potentially important general-equilibrium effects. In a multi-sector model, they empirically test the hypothesis that sectoral heterogeneity can dampen aggregate gains through a *Baumol effect* (Aghion et al., 2017), finding that the drag can be high if factor reallocation is limited in the medium run. Similarly, Jones and Tonetti (2025) argues that automation gains may materialize slowly because of "weak links," i.e., elasticities of substitution across tasks below one, and Gans and Goldfarb (2026) highlights how asymmetric task-level improvements can create bottlenecks when aggregating to occupations. These contributions operate in closed-economy settings. We extend this literature to a multi-sector, multi-country framework in which the structure of input-output links across country-sectors shapes the aggregate impact of AI. Under our baseline projection of global AI adoption, general-equilibrium effects are modest for most countries. However, they become quantitatively large — and welfare-reducing — when a country forgoes adoption while its trading partners do not, as competitiveness losses generate

[7] Using different methodologies, even higher gains are projected by Briggs and Kodnani (2023) and McKinsey & Company (2023).

[8] A related literature studies the longer-term implications of continued advances in AI technology (Trammell and Korinek, 2023; Nordhaus, 2021). We also leverage results from applied microeconomic studies offering experimental or quasi-experimental estimates of task-level performance improvements from AI (Brynjolfsson et al., 2025; Peng et al., 2023; Noy and Zhang, 2023; Dell'Acqua et al., 2023; Haslberger et al., 2023), AI adoption (Calvino and Fontanelli, 2023) and from the literature on the pace of global technology diffusion (Comin and Hobijn, 2010; Comin and Mestieri, 2018).

substantial negative reallocation effects.

Relatedly, our paper builds on a large literature studying how productivity shocks propagate through international trade. In multi-country trade models such as Eaton and Kortum (2002) and Caliendo and Parro (2015), productivity improvements in one country affect others through changes in relative prices and trade patterns. An insight from this literature is that countries can benefit from foreign productivity gains through trade linkages, but may also lose if they compete to supply similar goods (Kleinman et al., 2024). Whether countries can "free ride" on productivity gains abroad through improved terms of trade is a key empirical question, invoked in recent policy debates on geographically concentrated digital innovation (Krugman, 2026). The textbook Ricardian model supports this view, implying that productivity gains worsen a country's own terms of trade and benefit its partners, but in modern trade models this prediction depends on substitution patterns (Corsetti et al., 2008).[9] We adopt the multi-country general equilibrium frameworks of Çakmaklı et al. (forthcoming) and Baqaee and Farhi (2024) but apply them to a novel setting — the global diffusion of AI — and derive a welfare decomposition (Proposition 1) that allows us to separate domestic, foreign, and reallocation contributions at the country level. Using the model calibrated with realistic elasticities, we find that most countries gain little from foreign AI adoption absent domestic adoption. Because AI affects a broad range of industries and countries simultaneously, the bottlenecks that would generate terms-of-trade gains for non-adopters are unlikely to arise. This highlights the importance of domestic technology adoption for welfare growth.

The paper proceeds as follows. Section 2 presents the micro-to-macro framework for projecting sector-level productivity gains, including our harmonized cross-country AI adoption estimates. Section 3 introduces the multi-country general equilibrium trade model and derives the welfare decomposition. Section 4 presents the results and illustrates the main mechanisms. Section 5 concludes.

2 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, further extended by Filippucci et al. (2024b, 2025). The empirical implementation of this micro-to-macro

[9]This is also the reason why trends in output-based real GDP may not reflect trends in welfare, a well-known challenge when comparing the evolution of growth across countries (Feenstra et al., 2015).

framework integrates three key components: (1) micro-level productivity gains from AI at the task level, (2) the degree of exposure of tasks within sectors to AI, and (3) forecasts of future AI adoption by firms for each sector. For a given sector i of country c, the relationship may be expressed as follows.

$$\begin{aligned} &\textit{Sectoral Productivity Gains}_{ic,[t,t+10]} \\ &= \textit{Micro Level Gains} \times \textit{Exposure}_{ic} \times \Delta \textit{Adoption Rate}_{c,[t,t+10]} \end{aligned} \tag{1}$$

Given that current adoption rates are not negligible and have shown strong recent dynamics (see Section 2.1), some AI-driven gains may have already been realized. Unlike most previous work, which focuses on the total gains arising from the expected *level* of adoption, this paper's calculations focus on the gains that are still to emerge due to the expected *rise* in adoption.[10] The subsections below elaborate on the assumptions made to quantify these components across different economies.

2.1 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 particular, micro-level studies conducted in experimental settings show that AI tools significantly improve worker performance across various tasks.[11] Performance gains range from 14% in customer service to 56% in coding, with other tasks such as professional writing and business consulting also benefiting. Recognizing the risk that these experiments may not be fully indicative of productivity gains when AI is adopted at scale in real-life settings, we take a conservative stance: the micro-level gains underlying this paper are based on the three most precise estimates, which yield an average baseline effect of 30%. Since much of the estimated effects capture time savings

[10] 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). 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 rates across all sectors.

[11] These micro-level studies focus on AI support for customer services (Brynjolfsson et al., 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), as well as the performance improvement with Large Language Models assisting with general writing (Haslberger et al., 2023). 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 et al. (2024a) for a detailed overview of considered surveys and harmonization efforts.

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 et al. (2024a) and Figure A.1 of the Appendix).

2.2 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 et al. (2024a), in turn based on 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 at least 50% faster with the assistance of AI, given the capabilities of LLMs as of 2023. This is the median estimate of Eloundou et al. (2024).[12] 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. 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.[13]

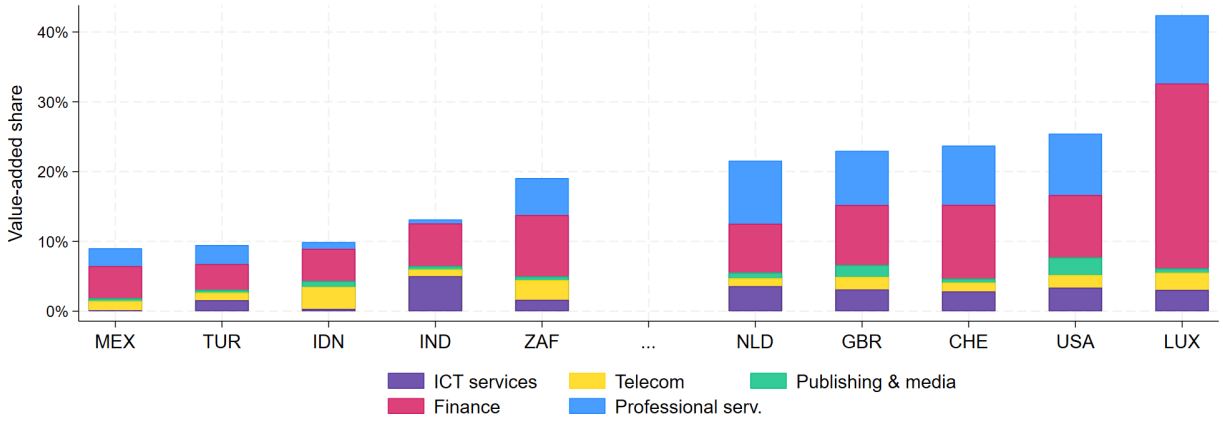
Across economies, the share of tasks that could benefit from AI-driven productivity gains ranges from 20% in India to 40% in Luxembourg under the baseline AI capabilities scenario, and from just over 30% to 60% under the expanded capabilities scenario (Figure A.2 of the Appendix). Cross-country variation in AI exposure stems from two factors. First, and more 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

[12] 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 more sensitive to prompt variation.

[13] Given the task-level exposure classification, average exposure is first calculated for each detailed occupation using task compositions from the O*NET database, then aggregated to detailed sectors using country-specific occupation-industry mappings. For more details, see Section B.1 of the Appendix.

Mexico, Türkiye, and Indonesia (Figure 1 of the Appendix). Second, to a lesser extent, differences may also exist within specific sectors across countries in the extent to which they employ AI-exposed occupations. [14]

Figure 1. The share of the 5 most AI-exposed sectors in GDP, in the lowest and the highest AI-exposed countries



NOTES: 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. Global average baseline exposure by sector: ICT services 52%, Finance 48%, Publishing and Media 47%, Professional Services 45%, and Telecom 43%.

2.3 Estimating current and future AI adoption

Realising productivity gains from AI likely requires adoption in core functions and at high intensity. However, the accurate identification of such AI adoption faces significant data challenges, in light of the lack of sufficiently comparable data on current AI adoption across countries.[15] To address these shortcoming, we harmonised and introduced adjustment procedures when compiling AI adoption data for 76 countries (and 18 industries) extending our previous calculations that were done 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, which also builds on and extends Filippucci et al. (2025) and Filippucci et al. (2024a).

[14]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 of the Appendix), reflecting different incidence of workers employed in occupations with higher AI exposure, such as managers, professionals, or clerks (Figure A.4 of the Appendix).

[15]Some statistical agencies include questions in their official surveys on several types of AI use. Their figures reveal substantially lower than overall adoption rates when AI adoption in core business operations is considered: for instance, in 2024, the respective figures are about 3% and 14% in Europe, 4 and 9% for the United States (see Annex B in Filippucci et al. (2025)).

2.3.1 Current AI adoption

The lack of harmonised AI adoption data – especially data that captures the intensity of AI use in core business functions – is primarily due to to differences in official statistics regarding (i) the purpose of AI use asked in their survey, (ii) the time period the statistics refer to, (iii) firm size coverage, (iv) industry coverage, and (v) the survey design, i.e., the definition of a statistical unit and exemplary use cases of AI. To address these discrepancies, we harmonise existing surveys that provide sufficiently comparable information to capture high-intensity, regular AI use by firms in core business functions (production and service provision) by relying on additional questions from the survey on the type of AI use and through a series of imputations across size classes, industries and time periods.

Further, we generate out-of-sample predictions for countries where these correction steps are not feasible due to unavailable or highly incomparable survey data compared with the majority of considered countries.[16] 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). This approach exploits the econometric relationship between AI adoption and its determinants reflecting countries' underlying capacity for AI adoption in core business functions, while mitigating measurement error arising from residual comparability issues in the harmonised data.[17]

Following this empirical strategy, the estimates of current high-intensity AI adoption by firms in core business functions average 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 assumption (see also Figure B.10 of the Appendix).[18] The estimates of current AI adoption in core business functions form the basis for the extrapolation into the future over a 10-year time horizon, presented in the next subsection.

[16] See B.2 of the Appendix and Annex B in Filippucci et al. (2025) for a detailed summary of the underlying steps.

[17] Importantly, our approach yields low figures for India and China, although several cross-country surveys indicate adoption in China and also India about 50% higher than in the US (see Figure B.5). Hence, we consider for them both a low-adoption scenario (as predicted by the model) and a high-adoption scenario (50% above US levels), with the focus in our presented scenarios being on the latter.

[18] 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, 2024c) are consistent with the relative position of country-level estimates of AI adoption derived in this paper (for details see Figure B.6 of the Appendix).

2.3.2 Future AI adoption

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 GPTs and assume an S-shaped adoption path which typically reflects the gradual uptake of new technologies, followed by rapid adoption before reaching a plateau as saturation occurs.[19] Adoption rates for newer technologies are accelerating (Comin and Mestieri, 2018; Tankwa et al., 2025, Figure B.7 of the Appendix), as reflected in the diffusion uptake of past GPTs 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 2).

Drawing on these 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, a systemic integration into core business functions will still likely require major investments in data, skills, and business process reorganization (Brynjolfsson et al., 2021).[20,21] Therefore, we focus mostly on the medium-paced adoption case in the analysis but also present the baseline 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 rates of countries (which vary across countries) and assumptions on the shape, i.e., adoption speed, parameters (which are assumed to be the same across countries).[22] This approach leads to cross-country differences in adoption, with faster initial uptake causing divergence, followed by convergence as countries near saturation.

[19] Historically, GPTs have demonstrated S-shaped adoption curves. See the example of the internet (Figure B.8 of the Appendix) and Hall, 2009; Geroski, 2000; Tankwa et al, 2025, building on Griliches, 1957, and Rogers, 1962).

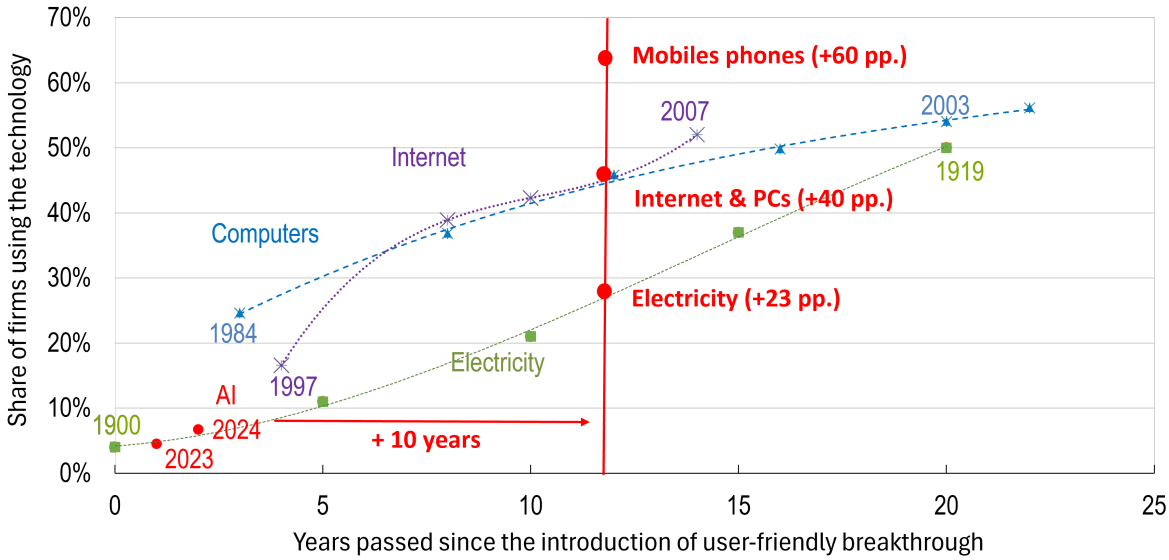
[20] For instance, AI adoption among businesses increased by about 50% from one year to the next both among EU countries and in the United States in official data. Assuming the continuation along such S-shape paths leads to an adoption rate of about 60% in 10 years, similar to that of mobile phones.

[21] 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 of the Appendix).

[22] Specifically, 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 our central, medium speed adoption scenario, the adoption path is modelled by fitting a logistic function with a logistic growth parameter similar to that observed for personal computers and the internet (see also Figure B.9 of the Appendix).

Over the projection horizon of 10 years, it turns out that the first impact dominates, leading to wider differences in adoption than currently observed, as illustrated by Figure B.9 of the Appendix.

Figure 2. Mapping AI's future adoption path with that of previous General Purpose Technologies



NOTES: Share of firms using the technology, in the United States. For mobile phones, the share of individuals is shown due to the lack of data on firms. Beyond the United States, similar S-shaped adoption trends are observable in the case of internet use across several economies (see Figure B.8 of the Appendix). SOURCE: 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).

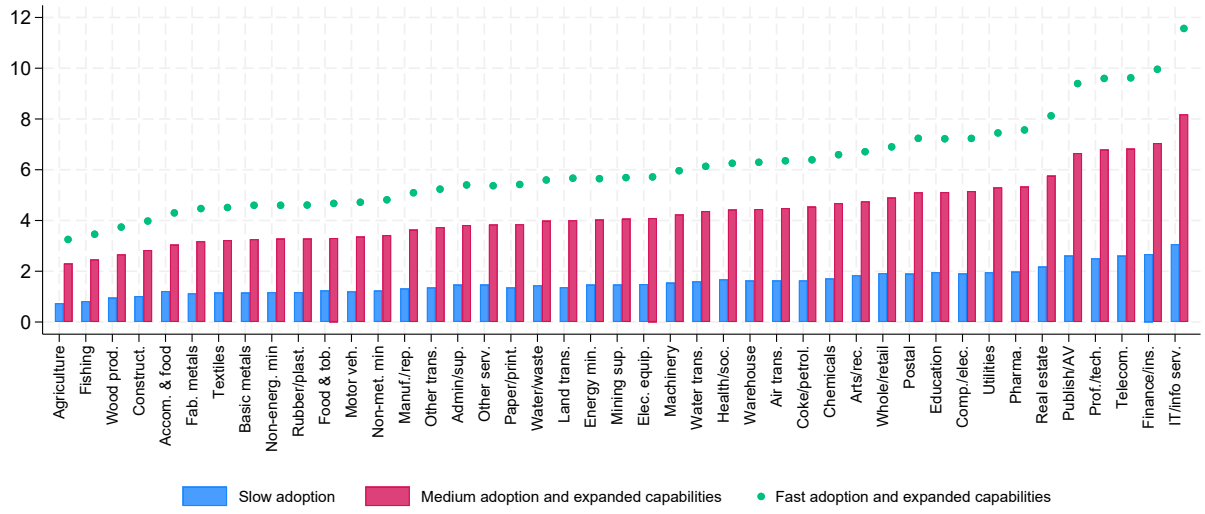
Accordingly, AI adoption in 2034 is expected to range from about 30% in the slow adoption scenario to 60% in the fast adoption scenario for several countries including Ireland, Korea, Israel and the United States, while lower AI adoption levels are predicted for Latin American countries including Mexico, and Columbia, where AI adoption in 2034 is expected to range between 2% to 10% (Figure B.10 of the Appendix). These differences across countries in terms of future assumed adoption rates reflect the ranking of estimates for current AI adoption levels – in which Ireland, Korea, Israel and the United States show highest AI adoption across countries.[23]

[23]Considerable uncertainties around these projections remain: 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 countries differ in the *timing* but not the *shape* of the AI adoption paths - the S-shape curves for each country are shifted in

2.3.3 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, IT Services, or Finance.[24] These results are qualitatively in line with Filippucci et al. (2025).

Figure 3. The projected AI-driven productivity gains vary across sectors



NOTES: Projected sector-level total factor productivity gains under different scenarios (cumulative over 10 years, in percent). Calculations follow the description in Section 2, in particular equation 1. Sectoral TFP values are obtained as the simple average across OECD members.
SOURCE: Authors' calculations.

parallel to the left (early adopters) or to the right (late adopters).

[24]The projected productivity gains can be subject to both up- and downside risks. 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.

3 The role of international linkages in shaping macroeconomic AI gains

The methodology to derive sectoral growth projections (Section 2) is based on country-specific information on AI exposure and the likely AI adoption path, and reflects the role of global trade only insofar as that specialisation shapes the sectoral composition of different economies.[25] To account for the role of international linkages in transmitting AI gains across borders through various channels, we augment the aggregation approach by allowing for trade in intermediate and final goods. International trade linkages have the potential to affect the global distribution of AI-driven welfare gains and can moderate cross-country differences.

To quantify the role of trade related channels from AI on a country's welfare, 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. (forthcoming). 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.

3.1 A global country-sector general equilibrium model

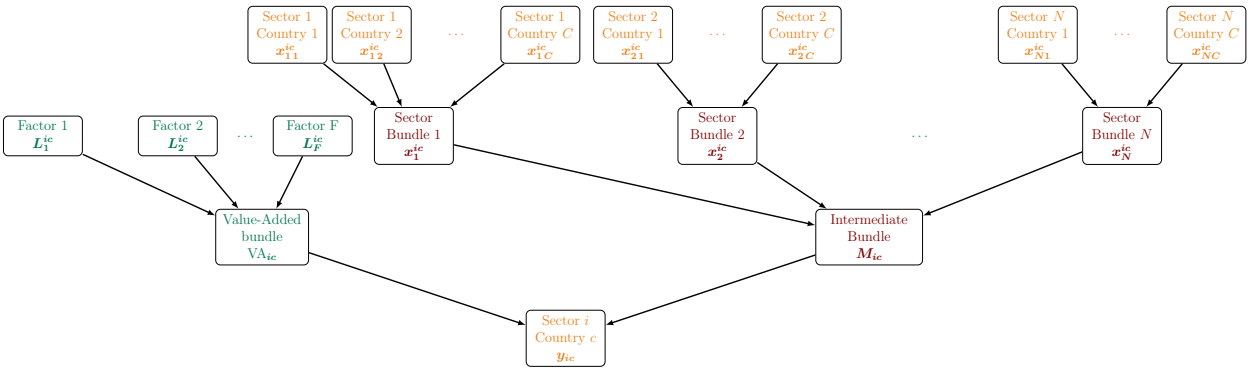
Our economic model builds on the frameworks developed by Çakmaklı et al. (forthcoming) and Baqaee and Farhi (2024). The model incorporates input–output shares, consumption shares, and industrial structure to capture the world economy realistically. Both the production and consumption sides of the model follow a similar nested constant-elasticity-of-substitution (CES) structure, which we describe in detail below.

3.1.1 Production

Figure 4 illustrates the production side of our model. Each node represents either a bundled good or a factor of production. To illustrate the structure, consider the Turkish automotive industry, corresponding to the bottom node in the figure. This industry uses both factors, forming the value-added bundle, and goods, forming the intermediate bundle.

[25] In addition, global linkages may also affect patterns of current AI use, which then in turn affect our adoption projections. This channel is examined in Section D.2 of the Appendix by modelling trading partner based spillovers or learning effects regarding AI adoption.

Figure 4. Production Structure



NOTES: This figure illustrates the structure of inputs used in the production process for sector i in country c. 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. The notation associated with each input is shown at the bottom of the corresponding box. Adapted from Çakmaklı et al. (forthcoming).

The value-added bundle consists of factors of production such as labour and capital. In our main scenarios, labour is mobile while capital remains fixed across sectors, representing an intermediate case between the two extreme assumptions considered in our previous work: full factor mobility and fully sector-specific (immobile) factors (Filippucci et al., 2024a).[26] However, factors are not allowed to move *across* countries; in our example, all factors used in the Turkish automotive industry are specific to Türkiye.

The intermediate bundle is composed of intermediate sector bundles. For instance, the Turkish automotive sector requires inputs from several other sectors, such as basic metals, plastics, and business services. Each intermediate sector bundle is itself an aggregation of varieties sourced from different countries. For example, the steel bundle used by the Turkish automotive industry includes steel from Türkiye, China, Germany, the United States, and other countries.

We adopt this double-nested structure because sectoral outputs are generally complements when used as intermediate inputs by downstream sectors; for example, it is difficult to substitute steel with plastics in automotive production. By contrast, varieties within the same sector but sourced from different countries are more likely to be substitutes. Finally, the value-added bundle is also complementary to other inputs. This flexible structure allows us to capture varying degrees of complementarity and substitutability by assigning different elasticities of substitution to each bundle.

[26] In alternative, unreported specifications, we also allow some factors to be sector-specific while others are mobile across sectors within a country.

We model the AI shock 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.[27]

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

Formally, production takes place at the sectoral level by combining a value-added bundle, consisting of the factors of production, with an intermediate goods bundle using a CES production function.[28]

$$y_{ic} = \frac{A_{ic}}{\overline{A}_{ic}} \left[\alpha_{ic}^{\frac{1}{\phi}} \left(\frac{\text{VA}_{ic}}{\overline{\text{VA}}_{ic}} \right)^{\frac{\phi-1}{\phi}} + (1-\alpha_{ic})^{\frac{1}{\phi}} \left(\frac{M_{ic}}{\overline{M}_{ic}} \right)^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}. \tag{2}$$

where i and c denote industries and countries, respectively. Here, y_{ic} is output, A_{ic} is TFP, VA_{ic} is value added bundle, M_{ic} captures the bundle of intermediate inputs, ϕ is the elasticity of substitution between the value-added bundle and the intermediate bundle, and α_{ic} is the value added share in total output. Variables with bar on top represent the normalizations for a calibrated CES representation. The corresponding price index is

$$p_{ic} = \frac{\overline{A}_{ic}}{A_{ic}} \left[\alpha_{ic} \left(p_{ic}^{\text{VA}} \right)^{1-\phi} + (1-\alpha_{ic}) \left(p_{ic}^{M} \right)^{1-\phi} \right]^{\frac{1}{1-\phi}}, \tag{3}$$

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

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

$$\text{VA}_{ic} = \left[\sum_{f \in \mathcal{F}} \left(\frac{\Omega_f^{ic}}{\alpha_{ic}} \right)^{\frac{1}{\eta}} \left(\frac{L_f^{ic}}{\overline{L}_f^{ic}} \right)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \quad p_{ic}^{\text{VA}} = \left[\sum_{f \in \mathcal{F}} \frac{\Omega_f^{ic}}{\alpha_{ic}} \left(w_f \right)^{1-\eta} \right]^{\frac{1}{1-\eta}}, \tag{4}$$

where η is the elasticity of substitution between different factors of production, $\mathcal{F}$ is the set

[27] Following (Filippucci et al., 2024a), we interpret AI as boosting value-added-based TFP, since much of the micro literature identifies gains from AI as time savings in task completion, consistent with using less labour *and* capital to produce the same amount of value added. AI is therefore assumed not to improve the productivity of intermediate inputs, such as materials used in assembling a good.

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

of all factors, Ω_f^{ic} is the share of factor f in inputs of sector ic and w_f if the wage (price) of factor f.

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

$$\Omega_j^{ic} \equiv \frac{1}{1-\alpha_{ic}} \sum_{m \in \mathcal{C}} \Omega_{jm}^{ic}, \qquad M_{ic} = \left[\sum_{j \in \mathcal{J}} (\Omega_j^{ic})^{\frac{1}{\varepsilon}} \left(\frac{x_j^{ic}}{\overline{x}_j^{ic}} \right)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}}, \quad p_M^{ic} = \left[\sum_{j \in \mathcal{J}} \Omega_j^{ic} \left(p_j^{ic} \right)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}. \tag{5}$$

Here, Ω_j^{ic} captures the share of sector j among all intermediate inputs of sector ic, and p_j^{ic} is the corresponding sectoral price index. We assume that all sectoral intermediate bundles are complements, i.e., their elasticity of substitution ε follows $0 \leq \varepsilon < 1$.

Sectoral intermediate bundles are formed by combining varieties sourced from different countries. We define the matrix $\Xi^{\mathcal{J}}$ to capture the share of bundle j for sector ic supplied by country m. The sectoral intermediate bundle and its price index are given by

$$\Xi_{jm}^{ic} \equiv \frac{\Omega_{jm}^{ic}}{\Omega_j^{ic}}, \qquad x_j^{ic} = \left[\sum_{m \in \mathcal{C}} (\Xi_{jm}^{ic})^{\frac{1}{\xi_j}} \left(\frac{x_{jm}^{ic}}{\overline{x}_{jm}^{ic}} \right)^{\frac{\xi_j - 1}{\xi_j}} \right]^{\frac{\xi_j}{\xi_j - 1}}, \qquad p_j^{ic} = \left[\sum_{m \in \mathcal{C}} \Xi_{jm}^{ic} \left(p_{jm} \right)^{1-\xi_j} \right]^{\frac{1}{1-\xi_j}}. \tag{6}$$

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 greater than 1, so that varieties sourced from different countries are substitutes.

3.1.2 Consumption

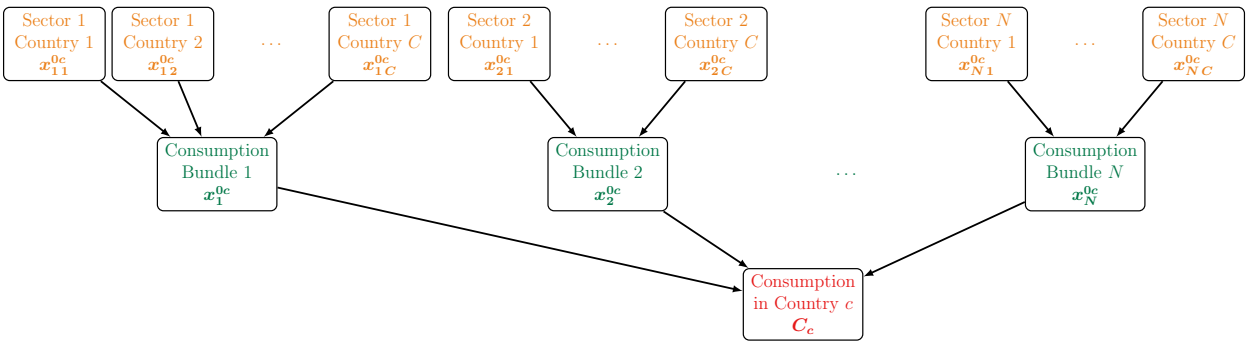
As depicted in Figure 5, the consumption side also follows a nested CES structure, similar to the production side. In this case, the bottom node represents a household in a given country. For illustrative purposes, consider households in Türkiye. At the first level of the nesting structure, Turkish households choose among sectoral consumption bundles, allocating their budgets across sectors such as housing, automobiles, food, and others.[29]

The top layer captures varieties within a given sector originating from different countries. For

[29] In the special case where the consumption aggregator is Cobb–Douglas, price elasticities equal one, implying fixed expenditure shares across goods. In this case, this layer reflects fixed expenditure shares across these categories.

Turkish consumers, for example, this corresponds to choosing among different car varieties, such as German, French, or American cars, to form the overall car bundle. Elasticities at this level are expected to be higher than those in the first layer, reflecting greater substitutability among international varieties than across-sector consumption. Such cross-country elasticities tend to be higher for non-differentiated, homogeneous goods such as commodities, and lower for specialised products and services, such as knowledge-intensive services including ICT services and finance (Caliendo and Parro, 2015).

Figure 5. Consumption Structure



NOTES: This figure illustrates the structure of consumption decisions in country c. Similar to Figure 4, the aggregation of consumption bundles is carried out using CES functions with varying elasticities. All bundles are specific to each country. Adapted from Çakmaklı et al. (forthcoming).

Mathematically, households in country c maximize utility first at the sectoral level:

$$\Omega_j^{0c} \equiv \sum_{m \in \mathcal{C}} \Omega_{jm}^{0c}, \qquad C_c = \left[\sum_{j \in \mathcal{J}} (\Omega_j^{0c})^{\frac{1}{\sigma}} \left(\frac{x_j^{0c}}{\overline{x}_j^{0c}} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

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

$$p_{0c} = \left[\sum_{j \in \mathcal{J}} \Omega_j^{0c} \left(p_j^{0c} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}, \quad \text{for } (\sigma = 1) : \log p_{0c} = \sum_{j \in \mathcal{J}} \Omega_j^{0c} \log p_j^{0c}, \tag{7}$$

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

Sectoral consumption bundles are formed by combining varieties sourced from different coun-

tries. The sectoral consumption bundle and its price index are given by

$$\Xi_{jm}^{0c} \equiv \frac{\Omega_{jm}^{0c}}{\Omega_{j}^{0c}}, \qquad x_j^{0c} = \left[\sum_{m\in\mathcal{C}} (\Xi_{jm}^{0c})^{\frac{1}{\xi_j^0}} \left(\frac{x_{jm}^{0c}}{\overline{x}_{jm}^{0c}}\right)^{\frac{\xi_j^0-1}{\xi_j^0}}\right]^{\frac{\xi_j^0}{\xi_j^0-1}}, \qquad p_j^{0c} = \left[\sum_{m\in\mathcal{C}} \Xi_{jm}^{0c} \left(p_{jm}\right)^{1-\xi_j^0}\right]^{\frac{1}{1-\xi_j^0}}. \tag{8}$$

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

Market Clearing and Equilibrium

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:

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

3.1.3 First-Order Approximation: Decomposing Welfare Gains

Since the world as a whole is a closed economy, Hulten's Theorem (Hulten, 1978) extends to the global economy, implying that the change in global welfare is given by

$$\mathrm{d}\log W_{\text{World}} = \sum_{i\in\mathcal{J}} \sum_{c\in\mathcal{C}} \lambda_{ic}\, \mathrm{d}\log A_{ic}. \tag{9}$$

However, welfare effects may differ across countries. Moreover, for each country, we are interested in relating welfare gains to productivity changes in domestic and foreign industries. Using the envelope theorem, we extend Hulten's theorem to obtain a first-order approximation to country-level welfare changes, stated in the following proposition:

Proposition 1. *The first-order welfare change for country m following a productivity shock is given by*

$$\mathrm{d}\log W_m = \underbrace{\sum_{i\in\mathcal{J}} \lambda_{im}^m\, \mathrm{d}\log A_{im}}_{\textit{Direct domestic productivity gains}} + \underbrace{\sum_{i\in\mathcal{J}} \sum_{c\neq m\in\mathcal{C}} \lambda_{ic}^m\, \mathrm{d}\log A_{ic}}_{\textit{Direct productivity gains from abroad}}$$

$$\underbrace{\underbrace{-\sum_{f\in\mathcal{F}}\Lambda_f^m\,\mathrm{d}\log\Lambda_f}_{\textit{Local–global mismatch}}+\underbrace{\frac{1}{\chi_m}\sum_{f\in\mathcal{F}_m}\Lambda_f\,\mathrm{d}\log\Lambda_f}_{\textit{Local factor income change}}}_{\Delta\ \textit{allocation}}, \tag{10}$$

where W_m denotes real welfare in country m, λ_{ic}^m is the local Domar weight defined as the mth row of the matrix $\Omega^0\,\Psi$ ($\lambda^m \equiv [\Omega^0\,\Psi]_m$), $\Lambda_f^m \equiv \lambda^m\,\Omega^F$ is the vector of local Domar weights for factors, and $\mathcal{F}_m$ denotes the set of factors belonging to country m.

The proof of this proposition is provided in Section C.1 of the Appendix. The entries of the local Domar weight λ_{ic}^m capture how strongly consumption in country m depends on industry i in country c, both directly and indirectly. Λ_f^m denotes the share of factor output used to satisfy demand in country m relative to country c's GNE and is related to the global Domar weights through $\sum_m \chi_m \Lambda_f^m = \Lambda_f$.

The local–global mismatch term in Equation 10 arises from differential exposure of countries' income baskets to sectoral productivity changes. If all countries consume goods in the same global proportions (i.e., when all rows of Ω^0 are identical), then $\Lambda_f^m = \Lambda_f$ for all factors f. Since world GDP is given by

$$\mathrm{GDP}_W = \sum_{f\in\mathcal{F}}\Lambda_f = 1 \quad \Rightarrow \quad \mathrm{dGDP}_W = 0 = \sum_{f\in\mathcal{F}}\mathrm{d}\Lambda_f = \sum_{f\in\mathcal{F}}\Lambda_f\,\mathrm{d}\log\Lambda_f,$$

the local–global mismatch term equals zero when all countries demand the same shares of industry–country pairs worldwide. In other words, this term captures the divergence between global and local demand structures.

The local factor income change term, by contrast, equals zero if all nested CES functions on the production side take the Cobb–Douglas form. In that case, the share of world income accruing to factor f remains constant because income is distributed upstream according to fixed expenditure shares. Deviations from the Cobb–Douglas structure, arising from differential elasticities between the value-added bundle and the intermediate input bundle as well as across factors within the value-added bundle, move this term away from zero.

Therefore, a useful benchmark is the case in which there are no demand differences across countries and the production side consists of Cobb–Douglas technologies. Under these as-

sumptions, the change in welfare in country m is given by

$$\mathrm{d}\log W_m = \underbrace{\sum_{i\in\mathcal{J}} \lambda_{im}^m \,\mathrm{d}\log A_{im}}_{\text{Direct domestic productivity gains}} + \underbrace{\sum_{i\in\mathcal{J}}\sum_{c\neq m\in\mathcal{C}} \lambda_{ic}^m \,\mathrm{d}\log A_{ic}}_{\text{Direct productivity gains from abroad}} \tag{11}$$

Note that this formulation still incorporates network effects. For example, a productivity gain in the Turkish steel industry is attributed to domestic gains in Türkiye even if the steel is used by the German transportation industry, which is in turn consumed by Turkish households.

3.1.4 Solving the General Equilibrium Model

Our solution methodology follows closely Çakmaklı et al. (forthcoming). To provide intuition, we rewrite the market-clearing conditions as:

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

Dividing both sides by world GDP, GDP_W, and defining global Domar weights as $\lambda_{ic} \equiv p_{ic}y_{ic}/\mathrm{GDP}_W$, we obtain

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

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

Writing Domar weights and expenditure shares as row vectors, the system can be expressed in matrix notation as

$$\lambda = \lambda\,\Omega + \chi\,\Omega^0 \quad \Rightarrow \quad \lambda = \chi\,\Omega^0\,\underbrace{[I-\Omega]^{-1}}_{\equiv\Psi} = \chi\,\Omega^0\,\Psi, \tag{12}$$

where Ψ denotes the Leontief inverse.

Similarly, from the factor market-clearing conditions, $\Lambda = \lambda\,\Omega^F$ where $\Lambda_f \equiv w_f L_f/\mathrm{GDP}_W$ is the factor Domar weight and Ω^F is the factor share matrix. We also define $\Psi^F \equiv \Psi\,\Omega^F$.

Proposition 2. *Given the TFP shocks to sectors* $\mathrm{d}\log A_{ic}$ *in country* c *in sector* i *and the*

multi-level CES framework described in Section 3.1, the changes in the factor Domar weights satisfy:

$$\mathrm{d}\log\Lambda = \mathrm{d}\log\Lambda\, D\, \hat{\Lambda}^{-1} + B\, \hat{\Lambda}^{-1},$$

where $D = D_1 + D_{21} + D_{22} + D_{23} + D_{31} + D_{32} + D_{33} + D_{34} + D_{41} + D_{42} + D_{43}$, *and* $B = B_{21} + B_{22} + B_{23} + B_{31} + B_{32} + B_{33} + B_{34} + B_{43}$ *such that:*

$$\begin{aligned}
D_1 &= \hat{\Lambda}\,\Phi\,\Omega^0\,\Psi^F \\
D_{21} &= \Psi^{F\prime}\,(1-\widehat{\xi^0})\,\widehat{\chi\Omega^0}\,\Psi^F & B_{21} &= -\mathrm{d}\log A\,\Psi'\,(1-\widehat{\xi^0})\,\widehat{\chi\Omega^0}\,\Psi^F \\
D_{22} &= \Psi^{F\prime}\,(\widehat{\xi^0}-\sigma)\,\left[(1_{C\times C}\otimes I_N)\odot\left(\Xi^{0\prime}\,\hat{\chi}\,\Omega^0\right)\right]\,\Psi^F & B_{22} &= -\mathrm{d}\log A\,\Psi'\,(\widehat{\xi^0}-\sigma)\,\left[(1_{C\times C}\otimes I_N)\odot\left(\Xi^{0\prime}\,\hat{\chi}\,\Omega^0\right)\right]\,\Psi^F \\
D_{23} &= (\sigma-1)\,\Psi^{F\prime}\,\Omega^{0\prime}\,\hat{\chi}\,\Omega^0\,\Psi^F & B_{23} &= -(\sigma-1)\,\mathrm{d}\log A\,\Psi'\,\Omega^{0\prime}\,\hat{\chi}\,\Omega^0\,\Psi^F \\
D_{31} &= \Psi^{F\prime}\,(1-\hat{\xi})\,\widehat{\lambda\Omega}\,\Psi^F & B_{31} &= -\mathrm{d}\log A\,\Psi'\,(1-\hat{\xi})\,\widehat{\lambda\Omega}\,\Psi^F \\
D_{32} &= \Psi^{F\prime}\,(\hat{\xi}-\varepsilon)\,\left[(1_{C\times C}\otimes I_N)\odot\left(\Xi'\,\hat{\lambda}\,\Omega\right)\right]\,\Psi^F & B_{32} &= -\mathrm{d}\log A\,\Psi'\,(\hat{\xi}-\varepsilon)\,\left[(1_{C\times C}\otimes I_N)\odot\left(\Xi'\,\hat{\lambda}\,\Omega\right)\right]\,\Psi^F \\
D_{33} &= (\varepsilon-\phi)\,\Psi^{F\prime}\,\Omega'\,\hat{\lambda}\,(1-\hat{\alpha})^{-1}\,\Omega\,\Psi^F & B_{33} &= -(\varepsilon-\phi)\,\mathrm{d}\log A\,\Psi'\,\Omega'\,\hat{\lambda}\,(1-\hat{\alpha})^{-1}\,\Omega\,\Psi^F \\
D_{34} &= (\phi-1)\,\Psi^{F\prime}\,\hat{\lambda}\,\Omega\,\Psi^F & B_{34} &= -(\phi-1)\,\mathrm{d}\log A\,\Psi'\,\hat{\lambda}\,\Omega\,\Psi^F \\
D_{41} &= (1-\eta)\widehat{\lambda\Omega^F} \\
D_{42} &= (\eta-\phi)\,\Omega^{F\prime}\,\hat{\lambda}\,\hat{\alpha}^{-1}\,\Omega^F \\
D_{43} &= (\phi-1)\,\Psi^{F\prime}\,\hat{\lambda}\,\Omega^F & B_{43} &= -(\phi-1)\,\mathrm{d}\log A\,\Psi'\,\hat{\lambda}\,\Omega^F.
\end{aligned} \tag{13}$$

Here, A represents the vector of industry-level TFP shocks arising from AI adoption, $\odot$ and $\otimes$ denote the Hadamard and Kronecker products respectively, $1_{C\times C}$ is a $C\times C$ matrix of ones, I_N is the N-dimensional identity matrix, ξ and ξ^0 collect the sectoral elasticities of substitution for production and consumption (each matched to the corresponding sector-industry pair), and the caret ($\widehat{\ }$) operator places the entries of the underlying vector along the main diagonal of a conformable matrix. Because the composite D matrix is singular by construction, we pin down the price level by requiring that aggregate nominal output is fixed, i.e., $\sum_f \Lambda_f\,\mathrm{d}\log\Lambda_f = 0$, which requires:

$$D_{1,1} = 0, \quad D_{f>1,1} = -\Lambda_f \quad \textit{and} \quad B_1 = 0.$$

Proof sketch. The proof proceeds by totally differentiating the factor Domar weight identity

$$\Lambda = \chi\,\Omega^0\,\Psi^F,$$

which yields four terms corresponding to changes in country income shares ($d\chi$), consumption

expenditure shares ($d\Omega^0$), intermediate input shares ($d\Omega$), and factor input shares ($d\Omega^F$). Each term is then expressed as a function of $\mathrm{d}\log\Lambda$ and the exogenous TFP shock $\mathrm{d}\log A$.

The first term captures the *income channel*: a change in factor Domar weights alters country income shares χ through the mapping Φ, which feeds back into factor demand via $\Omega^0\,\Psi^F$, producing D_1.

For the remaining three terms, the key intermediate step is the generalized Shepard Lemma, which in the presence of TFP shocks relates price changes to both factor price changes and productivity changes:

$$\mathrm{d}\log p = -\mathrm{d}\log A\,\Psi' + \mathrm{d}\log\Lambda\,\Psi^{F'}.$$

This decomposition implies that every price-mediated channel generates two components: a D matrix that captures how factor price changes propagate through substitution patterns, and a B vector that captures the direct effect of TFP improvements on prices and, consequently, on expenditure and input shares.

The second and third terms decompose the *expenditure substitution channel* and the *input substitution channel*, respectively. Within each, the nested CES structure produces three layers of substitution: (i) within-sector substitution across country varieties, governed by ξ^0 (or ξ); (ii) across-sector substitution within the consumption (or input) bundle, governed by σ (or ε); and (iii) substitution across broad aggregates, governed by σ (or ϕ). Each layer yields a separate D and B pair.

The fourth term captures the *factor substitution channel*, which operates through three analogous layers: within-factor-type substitution (η), substitution between factors and intermediates (ϕ), and the price feedback through the Leontief inverse. Since the first two sub-terms involve $\mathrm{d}\log w$ directly (not through prices), they contribute only D matrices (D_{41}, D_{42}). The third sub-term passes through good prices and generates both D_{43} and B_{43}.

Collecting all terms, the system can be solved in closed form:

$$\mathrm{d}\log\Lambda = B\,\hat{\Lambda}^{-1}\,(I - D\,\hat{\Lambda}^{-1})^{-1} = B\,(\hat{\Lambda} - D)^{-1}.$$

The full derivation, including the element-by-element construction of each matrix, is provided in Section C.2 of the Appendix. □

The economic interpretation of each matrix in Proposition 2 parallels Çakmaklı et al. (forthcoming), with one important distinction. In the earlier framework, the exogenous shocks—

labor supply declines and sectoral demand shifts—entered the system as additive terms that were independent of endogenous price responses. Here, the TFP shock enters through the price system itself, so that *every* substitution channel that responds to relative price changes is also directly affected by the productivity improvement. Concretely:

- D_1 encodes the income channel: higher factor Domar weights raise country incomes, which feed back into final expenditure and factor demand through the round-by-round propagation in Ψ^F.
- D_{21}–D_{23} and B_{21}–B_{23} govern expenditure-side substitution. The D matrices reflect how endogenous price changes redirect consumer spending across varieties and sectors, while the B vectors reflect the direct price reductions from TFP gains that trigger those same substitution margins.
- D_{31}–D_{34} and B_{31}–B_{34} govern input-side substitution through the same three-layer CES structure, operating through intermediate demand rather than final demand.
- D_{41}–D_{43} and B_{43} govern factor market adjustments. D_{41} and D_{42} reflect the direct response of factor demand to own-price changes and within-industry factor substitution. D_{43} and B_{43} capture how industry-level price changes—driven by both endogenous wage movements and exogenous TFP shocks—alter the relative cost of factors versus intermediates.

Once $\mathrm{d}\log\Lambda$ is obtained, all other equilibrium objects—good prices, Domar weights, input-output shares, the Leontief inverse, and real expenditure—can be updated. In particular, the welfare change of country c is:

$$\mathrm{d}\log W_c = \mathrm{d}\log\chi_c - \mathrm{d}\log p_{0c}, \tag{14}$$

which provides our measure of the welfare impact of AI-driven productivity gains.

The nature of B vector also gives us the following corollary:

Corollary 1. *Since all B sub-vectors have $\mathrm{d}\log A$ terms in the left-most side, we can write:*

$$\mathrm{d}\log\Lambda = \mathrm{d}\log A\,\tilde{B}\,(\hat{\Lambda} - D)^{-1},$$

where $\tilde{B}$ is a matrix that is obtained by the remainder of the terms of $B = \mathrm{d}\log A\,\tilde{B}$ vector.

This corollary carries several implications. First, the equilibrium factor price response is linear in the productivity shock: the matrix $\tilde{B}(\hat{\Lambda}-D)^{-1}$ is a fixed transmission matrix determined entirely by pre-shock equilibrium objects—input–output shares, consumption shares,

elasticities, and the Leontief inverse—so that doubling the AI shock doubles the response. Second, since $(\hat{\Lambda} - D)^{-1}$ needs to be inverted only once, each counterfactual experiment reduces to a single matrix multiplication, lowering the computational cost from $\mathcal{O}(n^3)$ to $\mathcal{O}(n^2)$ per scenario. Third, because $\mathrm{d}\log A$ is a row vector indexed over country–sector pairs, the equilibrium response decomposes additively as $\mathrm{d}\log\Lambda = \sum_{ic} \mathrm{d}\log A_{ic}\ \tilde{b}_{ic}\ (\hat{\Lambda} - D)^{-1}$, enabling a clean attribution of factor price changes to individual country–sector shocks and creates a second-order refinement to the domestic versus foreign decomposition in Proposition 1. Fourth, since welfare satisfies $\mathrm{d}\log W_c = \mathrm{d}\log\chi_c - \mathrm{d}\log p^{0c}$ and both terms are linear in $\mathrm{d}\log\Lambda$ and $\mathrm{d}\log A$, the welfare change collapses to $\mathrm{d}\log W_c = \mathrm{d}\log A\ \mu_c$ for a precomputable vector μ_c that serves as a country-specific sufficient statistic encoding the full general equilibrium sensitivity of country c to every productivity shock worldwide.

Finally, the linearity holds only at first order; for large shocks—cumulative TFP gains exceeding 10% in some sectors—higher-order corrections may matter, but the factorization facilitates efficient iterative updating of $\tilde{B}$ and D at the new equilibrium point. Hence, by splitting the shocks into smaller shocks and solving the model sequentially help us capture the non-linearities. We introduce productivity shocks under different scenarios, corresponding to varying speeds and channels of AI adoption. After introducing a given shock, we solve for the new equilibrium and compare it to the pre-shock baseline to assess welfare gains or losses from AI adoption.

3.2 Input-Output Data and Model Calibration

We use the OECD ICIO table for 2019 to calibrate the input and consumption shares in our model (Yamano et al., 2023).[30] The OECD ICIO table includes 76 countries, plus an aggregate entity representing the rest of the world, and covers 45 sectors in each country, spanning the global economy.

We follow Çakmaklı et al. (forthcoming), di Giovanni et al. (2023), and Baqaee and Farhi (2024) in selecting elasticity values and report these elasticities and their sources in Table 1. Following Atalay (2017), we use an elasticity of 0.6 between the value-added bundle and the intermediate input bundle, implying complementarity between them. We also use the same elasticity between factors of production that form the value-added bundle (Oberfield and Raval, 2021). Note that these values are on the higher side compared to Baqaee and Farhi (2019). For the elasticity of substitution between sectors, we use 0.2 based on Boehm et al.

[30] We are constrained to this year because post-pandemic global input–output matrices are not yet available. Given further increases in digitalisation during the pandemic, the importance of the ICT sector may therefore be understated. In addition, recent trade disruptions may imply weaker trade linkages across some partners than those captured by the 2019 global input–output data.

(2019). On the consumption side, we assume an elasticity of 1 (i.e., Cobb–Douglas) across sectors. For Armington elasticities governing substitution between varieties sourced from different countries, we use the estimates provided by Caliendo and Parro (2015) in both the consumption and production blocks.

Table 1. 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	0.2	Boehm et al. (2019)
ξ_i	Sector level input bundle EoS	> 1	Caliendo and Parro (2015)
σ	EoS of consumption among sectors	0.9 – 1	Baqaee and Farhi (2024)
ξ_i^0	Sector level consumption bundle EoS	> 1	Caliendo and Parro (2015)

NOTES: "EoS" is the elasticity of substitution.

4 Results

We present results from two complementary model experiments, and we use decompositions to clarify the mechanisms behind the welfare outcomes. In the first experiment (Section 4.1), each country-sector pair receives the AI-induced productivity gain implied by (1). We then solve for the new global equilibrium while allowing prices, factor allocations, domestic input-output linkages, and international trade in both intermediate inputs and final goods to adjust endogenously. This experiment delivers our baseline estimate of the global distribution of welfare gains under worldwide AI adoption. In the second experiment (Section 4.2), we shut down *domestic* AI adoption one country at a time, while keeping adoption in all other countries at the baseline levels from the first experiment. This counterfactual quantifies the extent to which a country benefits from productivity gains abroad through cheaper imported intermediates and final goods in the absence of domestic AI adoption. It also highlights the general equilibrium consequences of loosing competitiveness in a world of global AI adoption.

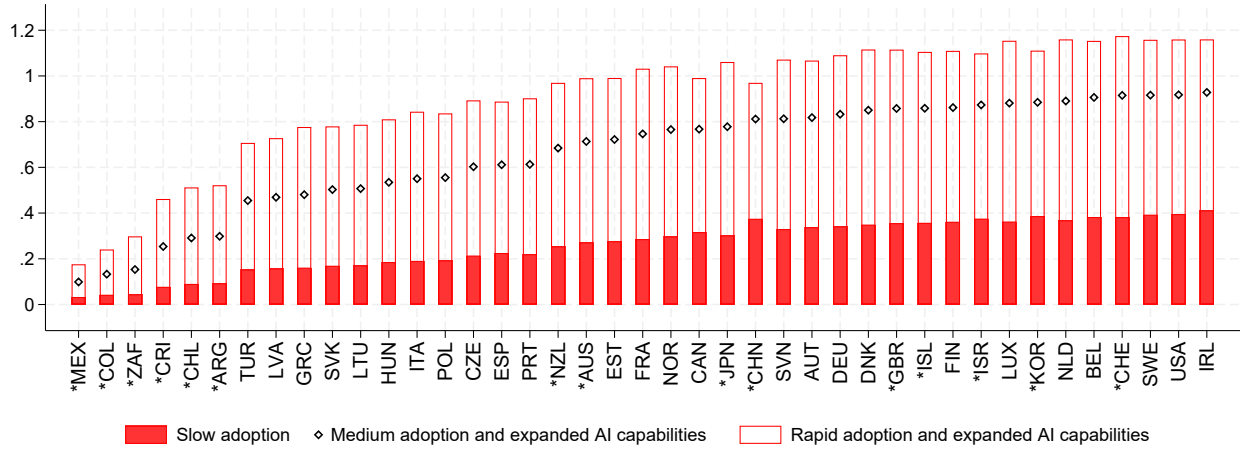
4.1 Real income gains from global AI adoption

Figure 6 shows the projected welfare gains from AI – expressed in terms of annual percentage point contributions to real welfare over the next 10 years – in OECD and G20 countries. The projected gains differ significantly across economies and scenarios. Across OECD countries, the projected gains range from 0.03 to 0.4 percentage points under the slow adoption scenario,

from 0.1 to 0.95 percentage points under the medium adoption and expanded capabilities scenario and from 0.2 to 1.2 percentage points under the rapid adoption and expanded capabilities scenario.[31]

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, Mexico and Colombia, around 0.03-0.2 across the three scenarios, consistent with having a lower share of knowledge-intensive service sectors and a larger emphasis on manufacturing which is less impacted by current AI (see again Figure 1).[32] In contrast, Luxembourg, Switzerland and the United States, with a greater reliance on AI-impacted sectors such as finance and ICT, show productivity 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) while the highest ones in India and China (0.4-1 across scenarios, in their high adoption scenarios).

Figure 6. AI's macroeconomic gains will vary widely across countries



NOTES: Predicted welfare gains due to AI over the next 10 years, percentage points (annualised). This figure shows estimated welfare gains from AI-induced productivity improvements under three scenarios reflecting different paces of AI adoption (see Section 2.3.2). Countries marked with "*" are based on AI productivity estimates that draw on AI adoption figures constructed using a comprehensive set of predictor variables (see Section B.2 of the Appendix).
SOURCE: Authors' calculations.

Comparing these results with the most recent technology driven boom - led by ICTs - provides a useful benchmark. The ICT boom contributed by about 1-1.5 percentage points to annual

[31] Aggregate real welfare gains include the impact capital accumulation, although applied outside the model as a 1.5 multiple. 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 et al., 2024b, 2025)

[32] As highlighted in Figure B.10, it should also be noted that the underlying AI adoption values for Latin American countries are derived entirely from regression model based estimates.

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 of ICTs in lagging countries, not only in core digital sectors but in some services as potential ICT users, such as retail (van Ark et al., 2008).[33]

4.1.1 The sources of welfare gains from global AI adoption: a decomposition

The global adoption of AI at varying speeds and with differences across countries in exposure generates heterogeneous productivity effects and a complex response in optimal factor allocations, world market prices, and trade flows. At the core, productivity gains by domestic and foreign firms reduce production costs and, ultimately, the prices faced by both consumers and producers.

However, such price reductions create two opposing effects. On the one hand, lower prices —whether from domestic production or imports— increase consumers' welfare gain, since the same basket of goods can be purchased at a lower cost. On the other hand, falling prices—whether in local markets or global sales—intensify competitive pressures for producers. To assess the sources of domestic welfare gains in a world of global AI adoption, we decompose each country's welfare change into domestic and foreign contributions (see Proposition 1).

The *domestic contribution* captures the portion of a country's welfare gains that originates from productivity improvements in its *own* industries and accrues to domestic absorption through lower prices. These gains can be direct—for instance, higher productivity in Germany's automotive sector lowering car prices for German households—or indirect through domestic input–output linkages (e.g., productivity gains in German steel or chemicals reducing costs in downstream domestic production). Importantly, domestic-origin gains can also propagate internationally along value chains and then return through trade: for example, German productivity improvements may lower the cost of intermediates used abroad, which in turn reduces the cost of goods imported back into Germany. All welfare gains ultimately attributable to productivity changes in German industries are counted in the domestic contribution for Germany.

The *foreign contribution* captures welfare gains driven by productivity improvements *abroad* that lower the prices of imported final goods and imported intermediate inputs used in domestic production. The magnitude of this component depends on (i) how much a country

[33]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).

imports, and (ii) the extent to which its import bundle is sourced from high-adopting trading partners and concentrated in highly affected sectors. For example, German households benefit if Türkiye's automotive sector becomes more productive and Turkish car prices fall; similarly, productivity gains in upstream sectors (e.g., China's steel industry) can lower Turkish production costs and thereby further reduce German import prices. These direct and upstream foreign-origin effects are grouped in the foreign contribution.

The remaining gains correspond to what we call the *competitiveness* or *allocation* effect. 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 reallocation effects. For example, if Türkiye's plastics industry does not adopt AI while other countries' plastics producers do, Turkish plastics lose market share and labour moves to other activities within the country. The resulting real-income effects are captured by the allocation term.[34]

Hence, this decomposition takes into account the network structure of global trade linkages, the benefits of integration into global value chains, as well as differential AI adoption across countries and industries. In particular, AI productivity gains in a sector are weighted by the "local Domar weights" of industries, which quantify the direct and indirect contributions of a sector (e.g., the Turkish automotive industry) to households in a given "local" country (e.g., German consumers), in contrast to "global" aggregate gains.[35] AI-driven productivity improvements in one sector propagate downstream through input–output linkages to other industries and to households through lower consumer prices, potentially across countries. These gains therefore reflect both direct and indirect inter-industry linkages, with the importance of sectors in the network captured by the local Domar weights.

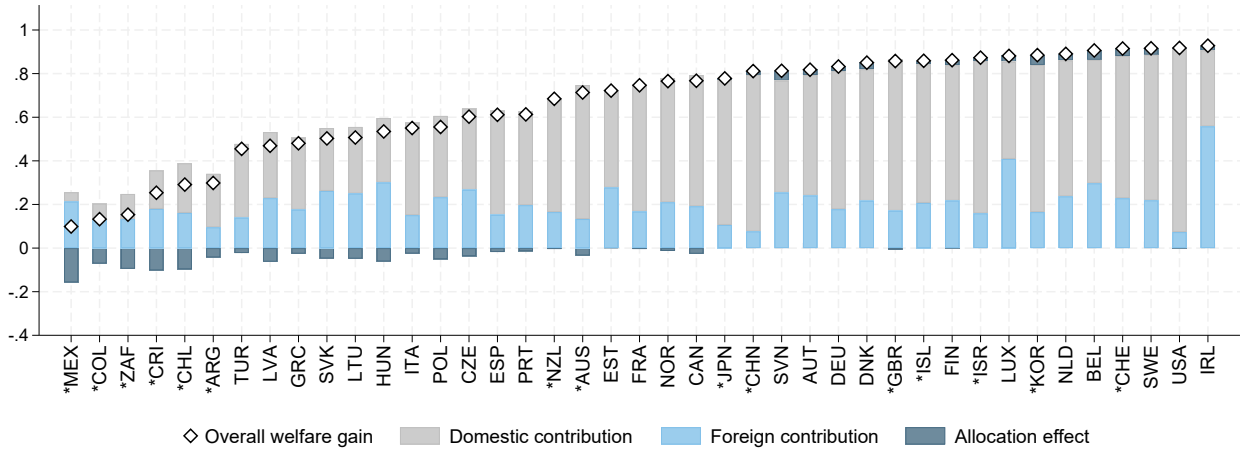
Figure 7 shows the results from this decomposition. As expected, highly open economies such as Luxembourg and Ireland, whose import baskets are dominated by AI-intensive sectors (e.g., ICT services and professional services) obtain larger foreign gains of around 3-4 percentage points. By contrast, countries 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% or even higher. While consumers always benefit from lower prices through higher real income–captured by the pos-

[34]The first order approximation would be exact if all countries consume goods in the same global proportions and all production-side CES functions take the Cobb–Douglas form, implying that intermediate input shares remain constant in production. In this case, the competitiveness (allocation) effect is zero and the the total welfare gains can be fully decomposed into domestic and foreign sources.

[35]Local Domar weights are calculated by multiplying the vector of consumption shares in a country with the Leontief inverse matrix.

itive bright blue part in Figure 7, 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 lose competitiveness, as lower prices abroad erode their market share both domestically and internationally. These countries therefore exhibit large negative allocation (competitiveness) effects. By contrast, higher-AI-adopting countries tend to display slightly positive allocation effects.

Figure 7. The role of trade in driving the welfare gains from AI

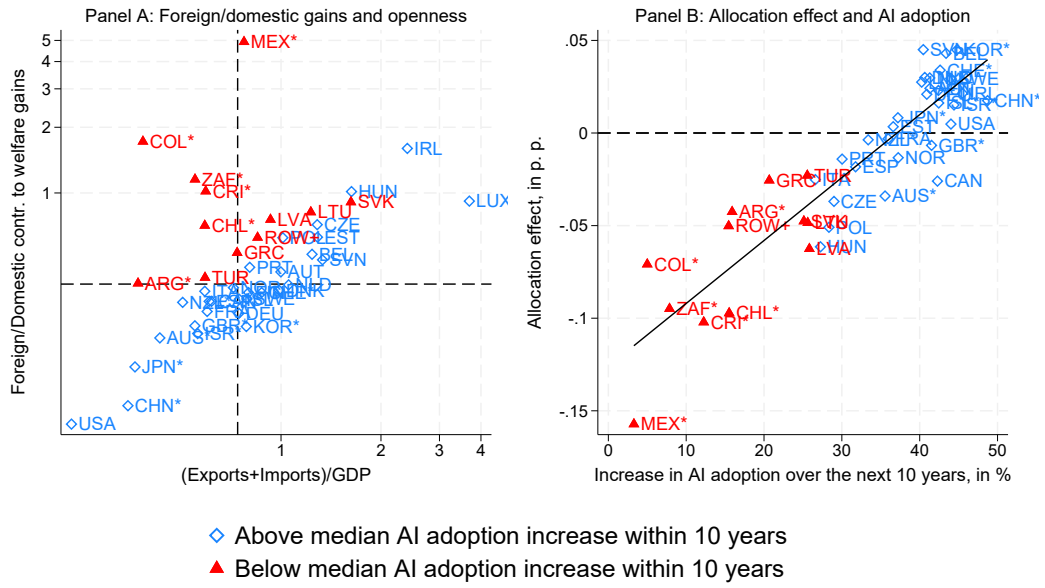


NOTES: Decomposing predicted welfare gains due to AI over the next 10 years in the baseline scenario with medium adoption pace, in percentage points (annualised). The figure decomposes overall welfare gains in the central medium adoption scenario into three components: "Domestic contribution" capture AI gains accruing to domestic demand from the price declines of domestically produced goods and services; "Foreign contribution" are conditional on AI adoption and capture gains accruing to domestic demand from reduced import prices; "Allocation effect" includes gains or losses coming from changing market shares of domestically produced goods and services. For details, see Section 3.1.3. Countries marked with "*" are based on AI productivity estimates that draw on AI adoption figures constructed using a comprehensive set of predictor variables (see Section B.2 of the Appendix).
SOURCE: Authors' calculations.

To further illustrate how openness and adoption interact, Figure 8 Panel A plots the ratio of foreign to domestic gains against trade openness. Among high–AI-adopting economies (blue markers), the share of foreign gains rises systematically with greater trade openness. By contrast, among slower adopters (red markers) 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 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 8 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 the fast-adopter countries gaining market shares as a result of the relatively larger sectoral productivity gains that they experience.

Figure 8. More open and more advanced AI adopter countries tend to have larger welfare gains from AI through trade

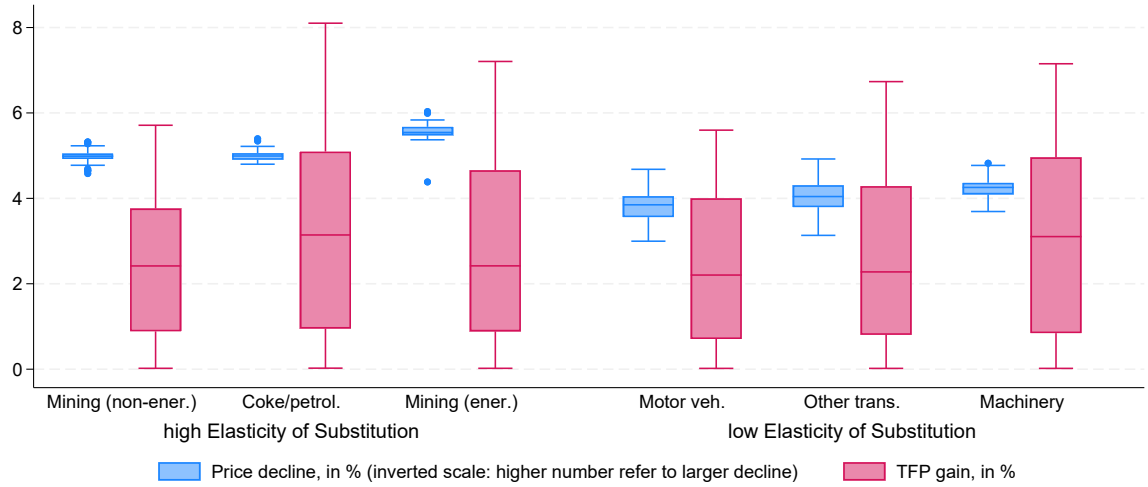


NOTES: Ratio of foreign over domestic gains and trade openness, in %. Red triangles refer to slow AI adopters (those with below median increase in AI adoption over the next 10 years). In Panel A, the vertical dashed line represents the median value of trade openness in the full sample while the horizontal dashed line represents the median ratio of foreign and domestic contributions to welfare gains in the full sample. The axes of Panel A are on log scales. Countries marked with "*" are based on AI productivity estimates that draw on AI adoption figures constructed using a comprehensive set of predictor variables (see Section B.2 of the Appendix).
SOURCE: Authors' calculations.

While AI adoption ultimately affects welfare through implied changes in equilibrium prices, the decompositions above make clear that these price responses are shaped by several forces operating jointly in general equilibrium. For example, although sectors with larger AI-driven productivity gains tend, on average, to exhibit stronger declines in output prices, equilibrium price changes are not determined solely by productivity developments within a sector but also reflect demand conditions, input–output linkages, and substitution patterns across goods and countries. As a result, even sectors with broadly similar productivity gains can display

markedly different price responses. This is illustrated in Figure 9, which compares sectors with comparable TFP gains but different elasticities of substitution across exporters. High-elasticity sectors (energy mining, non-energy mining, and coke/petroleum) display larger and less dispersed price declines. By contrast, sectors with lower substitutability (motor vehicles, other transport equipment, and machinery) exhibit smaller and more heterogeneous price responses.

Figure 9. For similar-sized TFP Gains, price reductions are larger and less dispersed in sectors with higher substitutability across exporters



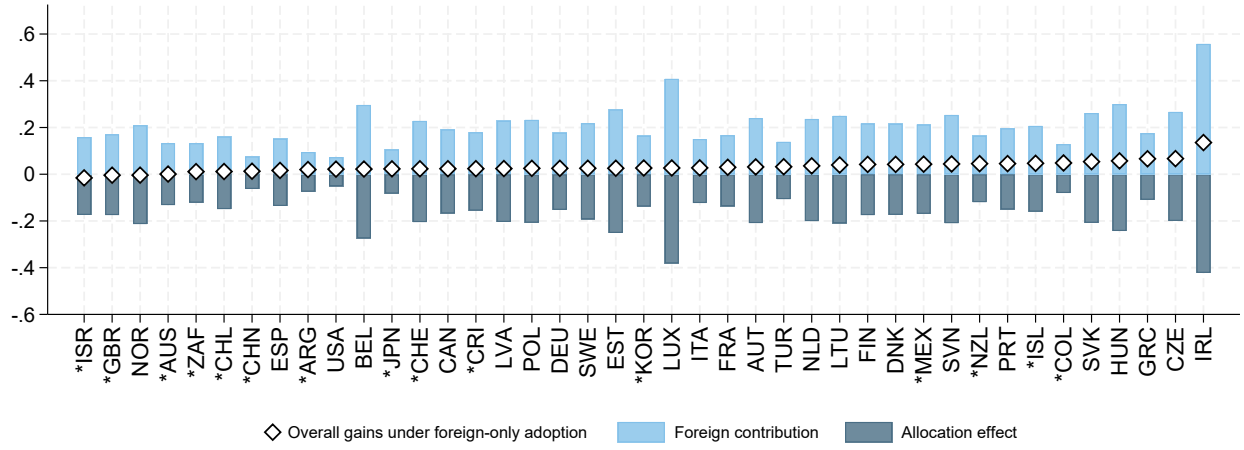
NOTES: Model output from the central scenario assuming medium adoption pace. The figure compares the three sectors with the highest Armington elasticities of substitution across varieties from different exporters (energy mining, non-energy mining, and coke/petroleum) and the three sectors with the lowest Armington elasticities (motor vehicles, other transport, and machinery).
SOURCE: Authors' calculations.

The underlying mechanism is that in sectors with high cross-country substitutability, prices are effectively pinned down in global markets. Producers compete closely with foreign suppliers, so the price of a domestic variety is disciplined by the lowest-cost producers worldwide. As a result, productivity improvements in leading countries translate directly into lower prices for all suppliers, compressing the dispersion of price changes. In contrast, in sectors with lower substitutability, varieties are more differentiated and firms retain some market power, which dampens the pass-through from foreign productivity gains to domestic export prices and allows for greater cross-country variation in price adjustments.

4.2 Real welfare gains without domestic AI adoption?

The sizeable foreign contribution in Figure 7 raises an important question: can countries that lag in AI adoption still expect significant welfare gains resulting from access to cheapened intermediate inputs and final consumption goods sourced from AI adopting countries with strong productivity gains? We now show that the answer to this question is a clear "no". Even under global adoption, Figure 7 shows that countries with relatively weak domestic adoption already tend to exhibit negative allocation effects, reflecting loss of competitiveness. Not adopting AI at all and therefore not realizing any direct domestic productivity improvements from AI *while competitors do* could induce a much larger loss of competitiveness and induce a large negative allocation effect. To quantify the importance of this issue, we re-solve the model under different sets of sector and country specific productivity shocks. Specifically, repeating for each country individually, we solve the model assuming no AI adoption in the focal country but the same sector-level productivity shocks as in Figure 7 for all other countries. We then again decompose the aggregate welfare gains into its different sources to illustrate how things are different in this case.

Figure 10. Relying only on foreign generated AI gains leads to moderate gains from AI due to a loss in competitiveness

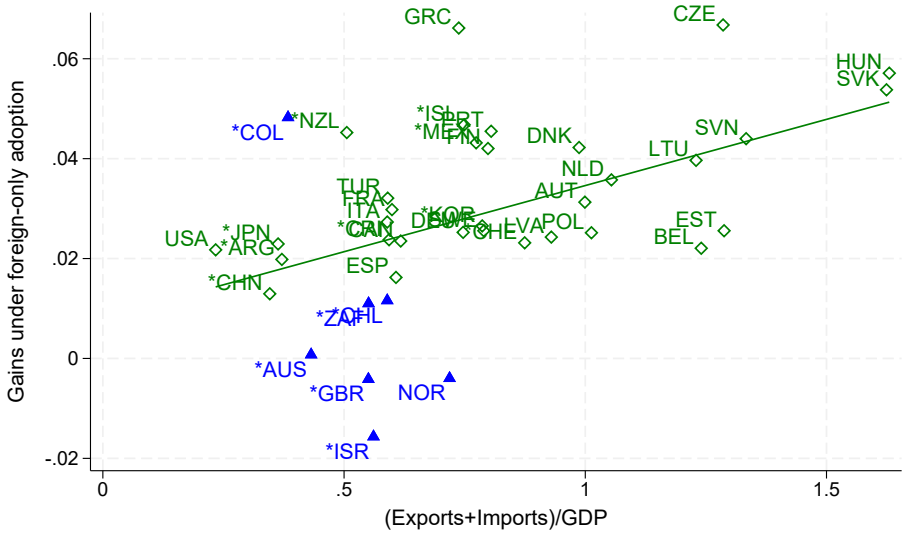


NOTES: Predicted welfare gains due to AI over the next 10 years in two scenarios, percentage points (annualised). This graph decomposes sources of the welfare gains when a country does not adopt AI but other countries do and compares these gains to the baseline scenario where there is adoption both domestically and abroad. The "foreign contribution" is the same under global adoption and foreign only adoption. The "Allocation effect" captures the loss of market shares and lower export prices in case a country does not adopt AI domestically.Countries marked with "*" are based on AI productivity estimates that draw on AI adoption figures constructed using a comprehensive set of predictor variables (see Section B.2 of the Appendix).

SOURCE: Authors' calculations.

Figure 10 shows the results. The median OECD country is projected to experience a boost in real welfare only by approximately .03 percentage points annually over ten years, thanks solely to AI adoption abroad. By construction, the domestic contribution is zero and is therefore not plotted. The foreign contribution does not depend on whether the focal country adopts AI or not and is therefore the same as in Figure 7. Crucially, however, the foreign contribution is largely offset by a much more negative allocation effect than under global adoption. The reason is straightforward: without domestic productivity improvements, domestic firms struggle to compete against increasingly productive foreign producers both at home (through import competition) and abroad (through lower-priced foreign exports). This is particularly pronounced in small open economies such as Ireland and Luxembourg: they benefit substantially from cheaper imports, but their high dependence on export performance makes the competitiveness loss especially costly.

Figure 11. Missing out on AI adoption undermines competitiveness in global markets for countries specialised in the most impacted sectors from the AI shock



NOTES: Welfare gains from AI under foreign-only adoption (scenario) in relation to trade openness. This graph shows the relationship between gains under foreign-only adoption and the degree of trade openness by countries. Blue coloured countries (triangle markers) capture those countries with a high share of sectors that are strongly impacted by the AI shock (the top 25% of countries in terms of the size of sectors with either high AI exposure, i.e., financial services, IT and information services, professional and technical services, publishing / AV and telecommunication services, or with a high cross elasticity of substitution, i.e., mining and coke/petroleum). Countries marked with "*" are based on AI productivity estimates that draw on AI adoption figures constructed using a comprehensive set of predictor variables (see Section B.2 of the Appendix).
SOURCE: Authors' calculations.

Figure 11 shows that welfare gains under foreign-only adoption tend to be larger for countries that rely more on trade, but this relationship is not universal and depends on the exact characteristics of the economy. Countries whose exports are concentrated in highly AI-exposed sectors may suffer larger competitiveness losses when global adoption pushes down world prices in those sectors. Similarly, countries exporting highly substitutable goods (e.g., commodities) can face strong price pass-through from foreign productivity gains, compressing export revenues. We illustrate this point by highlighting in blue all the countries with a high share of sectors that are either strongly affected by the AI shock (e.g., finance, ICT, professional services, publishing/AV, telecommunications - in the UK or Israel) or highly substitutable across exporters (e.g., mining, coke/petroleum - in Norway, Australia). For these counties, the positive relationship between gains under foreign-only adoption and the degree of trade integration breaks down.

Finally, it is worth pointing out that the welfare losses associated with reduced competitiveness can exceed the welfare gains from cheapened intermediate inputs and final goods sourced from abroad. In this case, the projected gains from foreign-only adoption is actually negative. In line with the arguments above, this turns out to be the case for countries whose exports are concentrated in highly AI-exposed sectors (GBR: Finance; ISR: ICT Services) or a highly substitutable across exporters (SAU, RUS, NOR, AUS; commodity exporters), as shown on Figure 10 .

4.3 Additional Channels and Robustness Tests

4.3.1 Correcting for unmeasured 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 multinational ones (MNEs) (Cernat, 2024).[36] To correct for these under-recorded services trade flows, we re-compute our results by taking into account the contribution of MNEs who are providing domestic services which may be foreign generated.[37]

[36]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.

[37]This is based on their intangible assets - the most likely input that is unrecorded between the local and foreign affiliate - and their importance in the value added they generate in the domestic economy. This varies widely across sectors: in services such as finance, ICT, and telecommunications, MNE's value added share accruing to intangible assets ranges between 11 and 17 % (Figure D.1). In some advanced manufacturing industries, pharmaceuticals, computer/electronic equipment and chemicals, this amounts to 13 and 17 %. For a full description see Section D.1 of the Appendix.

Adjusting for under-reported services trade affects the magnitude of the reported results only marginally. For the five countries most affected by the correction of under-reported service trade (Ireland, Luxembourg, Sweden, Switzerland and the United Kingdom), annual real welfare gains from AI in our experiment of relying only on international linkages to benefit from AI are only between 0.01 and 0.06 percentage points larger when taking the under-reported services trade into account (Figure D.2). Given that our correction of under-reported service trade is likely to represent an upper bound,[38] it suggests that the issue of under-reported services trade is unlikely to change the findings meaningfully.

4.3.2 Robustness Tests

In our baseline model, we use sector-specific capital and within-country mobile labour to capture the sector-specific nature of production. As a first robustness test, we relax this assumption by allowing both labour and capital to be mobile across sectors within each country. The green diamonds in Figure 12 show that our overall results are not materially affected by this choice, although sectoral patterns may differ.

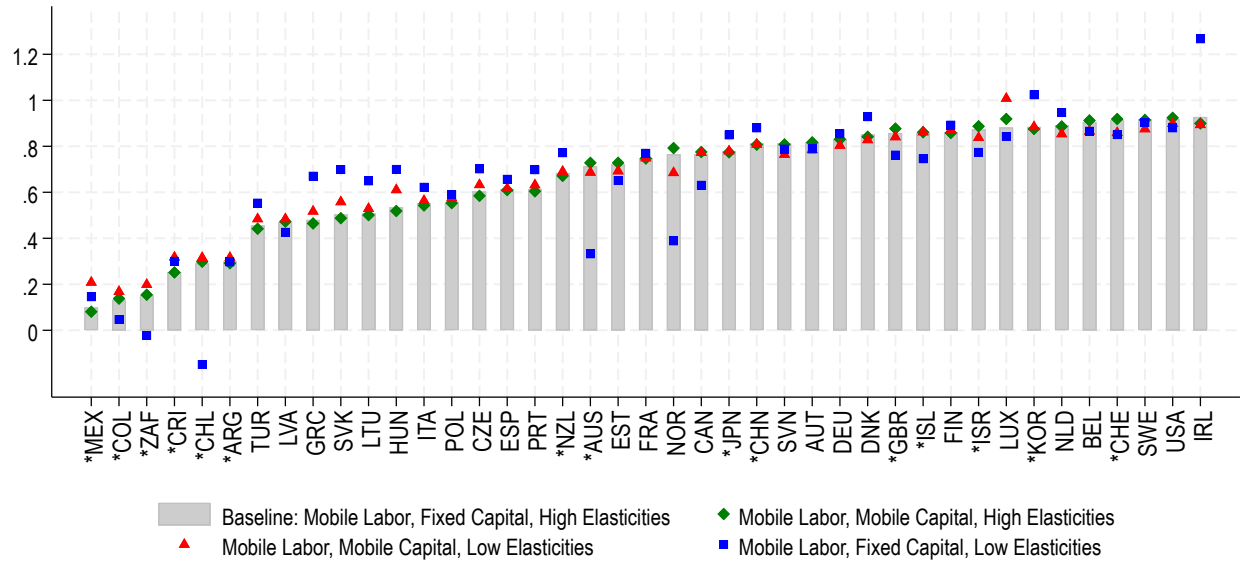
As a second robustness test, following Baqaee and Farhi (2019), we set lower elasticity of substitution values compared to the baseline levels than in the baseline reported in Table 1. In particular, we set the elasticity of substitution between the intermediate bundle and the value-added bundle (ϕ) to 0.01, the elasticity across factors (η) to 0.01, the elasticity among sectoral intermediate bundles (ε) to 0.01, and the Armington elasticities between country varieties (ξ_i and ξ_i^0) to 1.1, while keeping the sectoral consumption elasticity (σ) at 0.9.

Overall, the red triangles in Figure 12 show that our main results do not change drastically at the country level under this alternative parametrisation. However, a comparison of the red triangles (mobile factors, low elasticities) and green diamonds (mobile factors, high elasticities) is still informative. Welfare gains in low AI-adopting countries tend to be somewhat larger under low elasticities, while gains in high AI-adopting countries tend to be larger under high elasticities. Although these differences are modest, they are consistent with our key finding regarding the transmission of foreign productivity growth to domestic welfare gains: when substitution across inputs and foreign varieties is limited, then it is harder to substitute away from the output of low-adopting countries, allowing them to benefit more from foreign AI-driven productivity gains through stronger terms-of-trade improvements. By contrast, when elasticities are higher, it becomes easier to substitute away from varieties that become relatively expensive, which reduces the extent to which low AI adopting countries

[38] This is because all intangible flows of MNEs 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.

can "free-ride" on foreign productivity growth. Finally, when we combine low elasticities with sector-specific capital (blue squares), the country-level patterns become more varied, and we find that natural-resource-rich countries are strongly negatively affected, as the lower elasticity values make it difficult to reallocate production across sectors.

Figure 12. Robustness Tests for Mobile Factors and Elasticities



NOTES: Our baseline scenario assumes sector-specific capital and mobile labour, with elasticity values as reported in Table 1. Here, we relax both assumptions by considering alternative factor mobility configurations and lower elasticity values. Following Baqaee and Farhi (2019), we set $\phi = 0.01$, $\eta = 0.01$, $\varepsilon = 0.01$ and $\xi_i = 1.1$ for $\forall i$ in the low elasticity setting, while keeping $\sigma = 0.9$ (see Table 1 for definitions). The gray bar shows the baseline case. Green diamonds show welfare gains under mobile factors and high elasticities, red triangles under fixed capital and low elasticities, and blue squares under mobile factors and low elasticities. SOURCE: Authors' calculations.

As a final robustness test, we address two features of our baseline that rely on discretionary choices: the AI adoption estimates for countries where only a limited set of predictor variables is available, and the high-adoption scenario assumed for China and India. To assess whether these choices materially affect our results, we set productivity gains to the 10th percentile of the predicted distribution for all countries whose adoption estimates draw on the limited predictor set, and we revert China and India to their low-adoption scenario. We then re-solve the model under these more conservative assumptions. Figure A.9 shows that aggregate welfare gains remain qualitatively similar to the baseline for countries with a full set of predictors (all levels in the upper panel; blue triangles in the lower panel). For countries where adoption is imputed from limited predictors (upper panel: China; lower panel: red diamonds), the more conservative assumptions lead to smaller domestic effects and correspondingly reduced overall welfare gains, but the cross-country ranking and the

paper's main qualitative conclusions are preserved.

5 Conclusions

This paper has analysed the welfare implications of AI and their distribution across countries over the next decade using a multi-country, multi-sector general equilibrium framework covering 76 countries and 45 sectors. It finds sizeable but highly uneven gains from AI. Under medium-paced diffusion, AI raises real welfare by 0.1 to 0.95 percentage points across OECD economies over the next decade, with similarly large variation across the broader global sample. Countries with larger shares of AI-exposed knowledge-intensive services and more favourable conditions for adoption, including digital infrastructure, workforce skills, and innovation capacity, tend to gain the most.

We develop a novel decomposition of welfare gains to disentangle two main channels through which countries may benefit from AI in an international context: an import channel, capturing gains arising from foreign AI adoption transmitted through lower import prices, and an export channel, which reflects the competitiveness of domestic production in global markets. This distinction yields important insights: while countries can benefit unconditionally from cheaper imports driven by AI adoption abroad, staying competitive on global markets is conditional on adopting AI domestically. For countries specialising in highly AI-exposed or highly substitutable sectors such as commodities, the absence of, or limited, AI adoption can even lead to declining welfare.

The central policy implication is therefore that strengthening domestic adoption capacity, through investments in digital infrastructure, skills, innovation, and the ability of firms to reorganise production around AI, is likely to be the primary determinant of which countries capture the gains from AI. Counting on substantial benefits to arrive through trade is not a viable strategy.

Our analysis abstracts from several channels that merit further research. First, AI may itself lower trade costs in activities such as translation, communication, and regulatory compliance, thereby expanding or redirecting cross-border flows. Second, AI-driven automation may alter firms' location decisions, including through reshoring, changing the distribution of gains across countries. Third, our framework relies on pre-pandemic input-output structures and only partially captures cross-border flows linked to intangible assets and multinational firms. Finally, restrictive trade policies or elevated trade policy uncertainty may hamper the efficient specialisation and adjustment needed to absorb the asymmetric global productivity shock that AI generates. Future work should also refine the measurement of cross-border services

and intangible flows, allow for endogenous adoption and spillovers, and study distributional consequences within countries.

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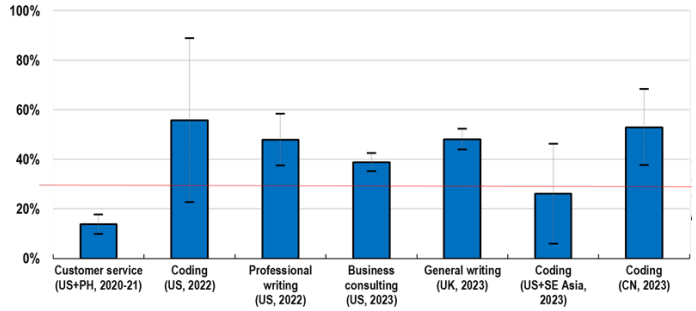
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A Appendix

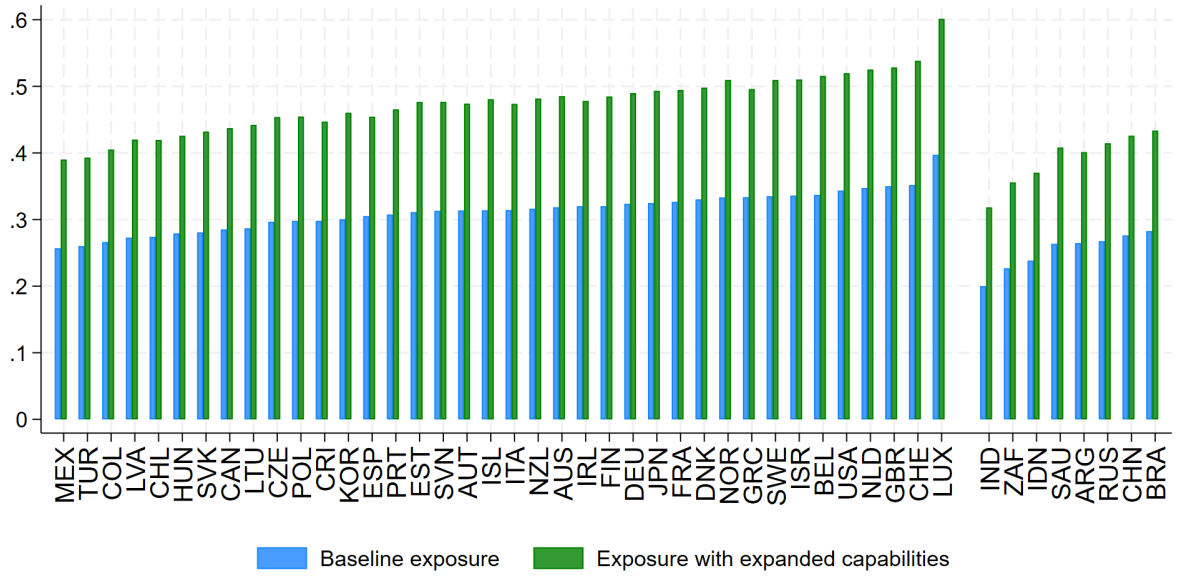
A.1 Additional Figures

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



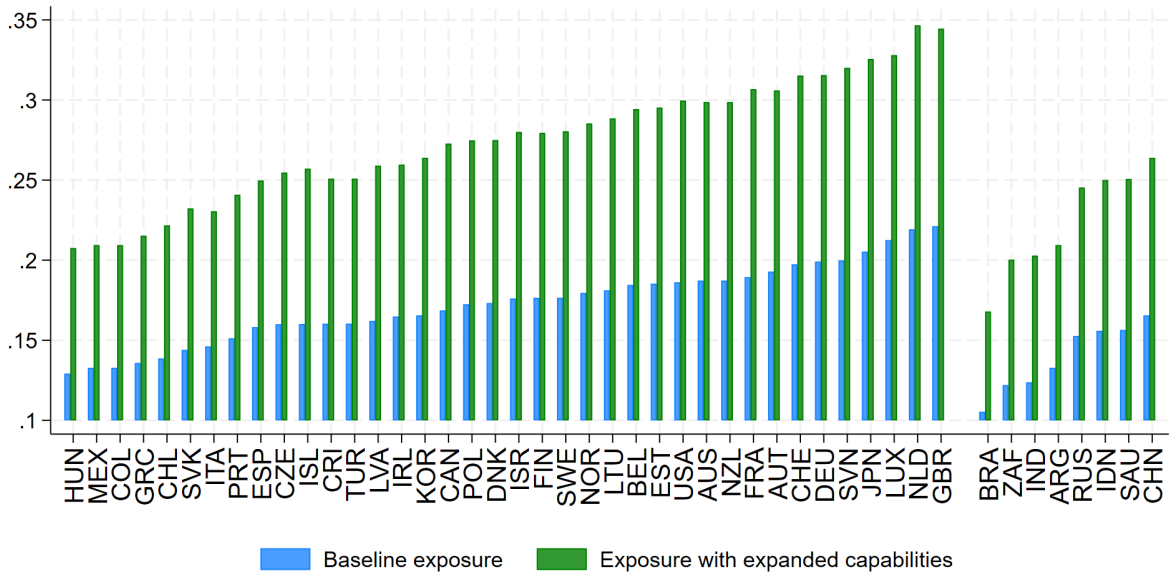
NOTES: The graph shows the worker-level productivity effects reported in different studies together with 95% confidence intervals. In parentheses, the reference country and year of the studies are shown.
SOURCE: Compilation from the literature by Filippucci et al. (2024a).

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



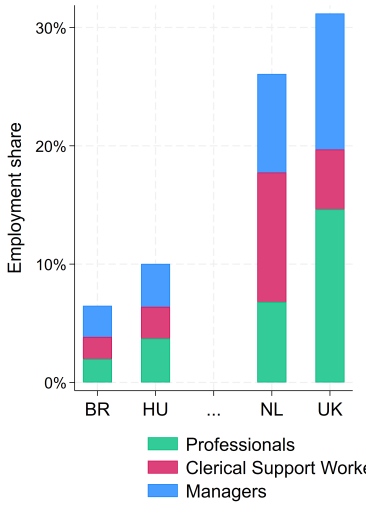
NOTES: This figure reports the average share of tasks exposed to AI across OECD economies plus the remaining of the G20. Country-level averages are obtained by mapping granular task-level exposure from Eloundou et al. (2024) to occupations within different sectors. This approach distinguishes the occupational composition of 43 sectors 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 and Eloundou et al. (2024).

Figure A.3. AI exposure in the *Construction* sector



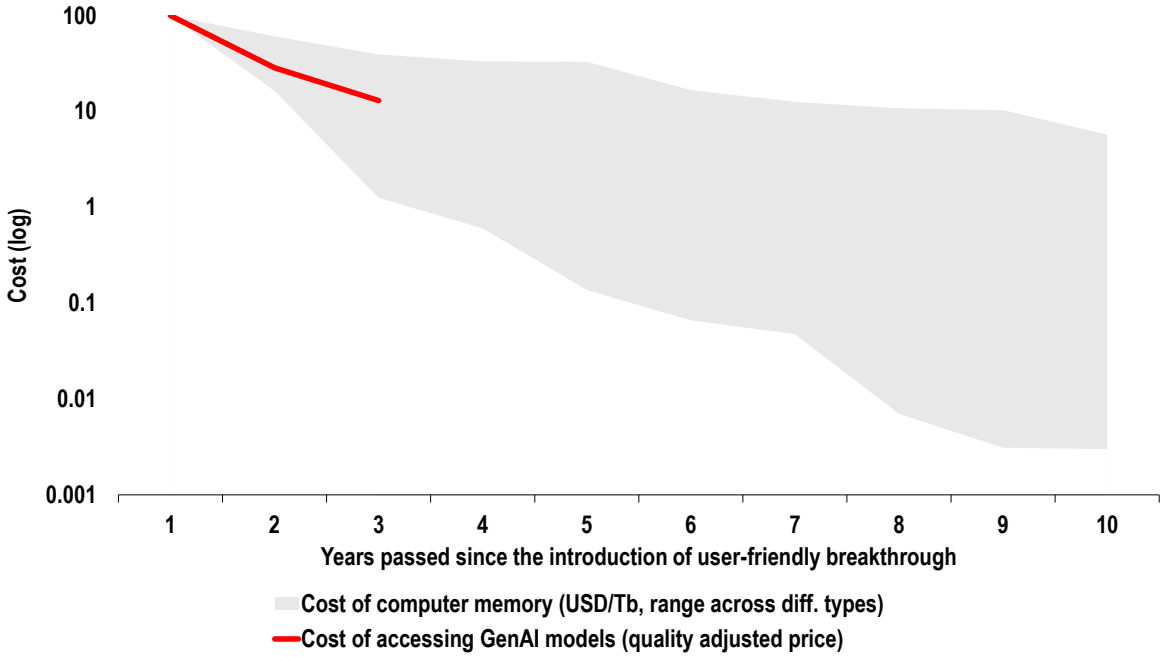
NOTES: This figure reports the average share of tasks exposed to AI in the Construction sector across selected countries. Country-level averages are obtained by mapping granular task-level exposure from Eloundou et al. (2024) to occupations within different sectors.
SOURCE: Authors' calculations based on national labour force statistics and Eloundou et al. (2024).

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



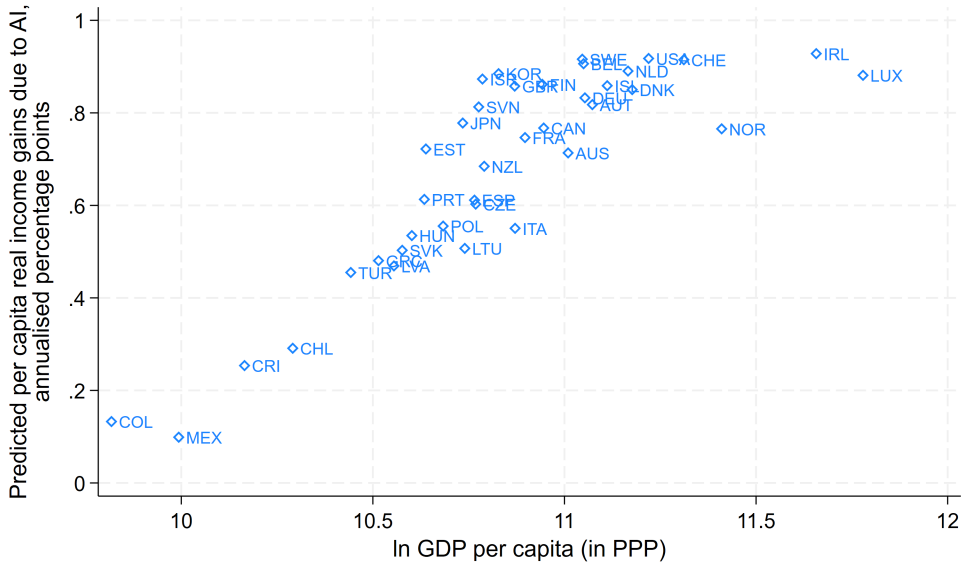
NOTES: The figure reports employment shares of occupations in the ISCO groups of Managers, Professionals and Clerical Support Workers (relatively high AI-exposure occupations) in the construction sector. Employment shares are shown for lowest vs. highest AI-exposed countries for which data on sectoral composition are available.
SOURCE: Authors' calculations based on national labour force statistics and Eloundou et al. (2024).

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



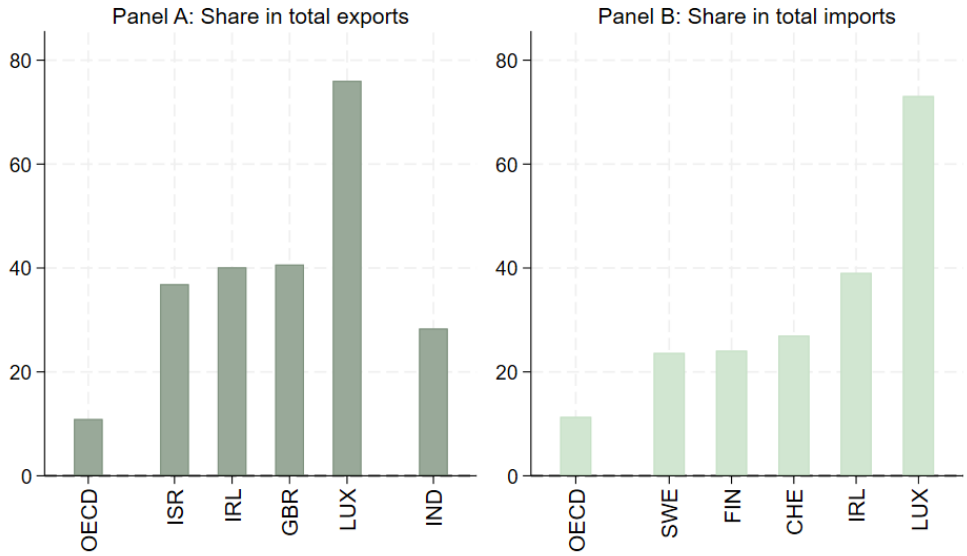
SOURCE: Cost of computation: Kurzweil (2024); Cost of computer memory: McCallum (2023). Cost of accessing GenAI models: Andre et al. (2025).

Figure A.6. The projected AI-driven welfare gains are larger for initially more developed countries



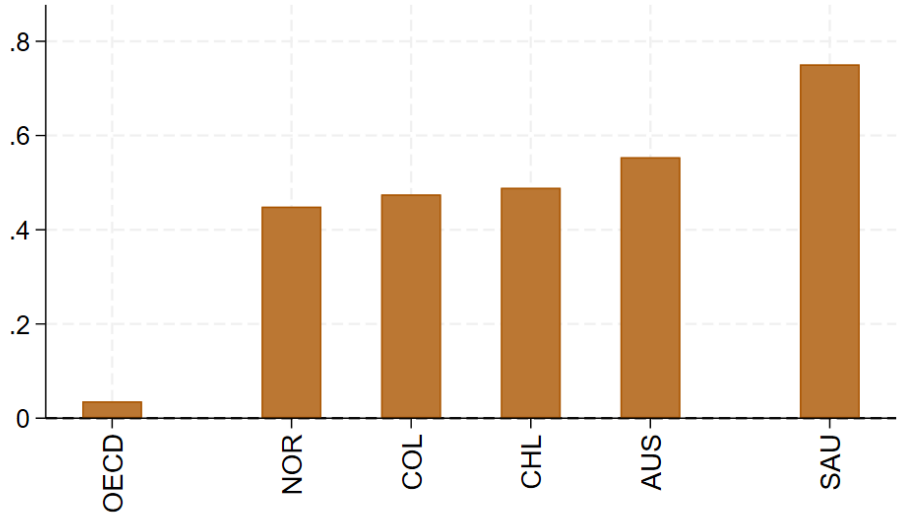
SOURCE: Authors' calculations and World Bank (2024).

Figure A.7. The most impacted countries by the AI shock in terms of exports and imports



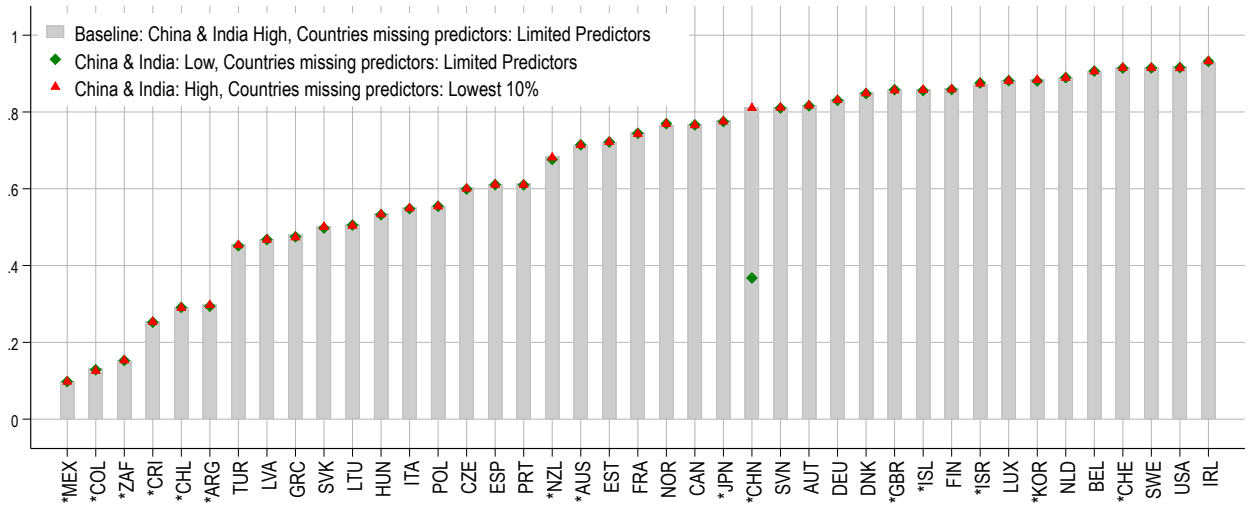
NOTES: This graph shows the export (Panel A) and import (Panel B) shares of countries in the five most AI exposed sectors, i.e., financial services, IT and information services, professional and technical services, publishing / AV and telecommunication services. Shares are shown for countries with the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

Figure A.8. Top 5 Oil and Mining Exporters by Share

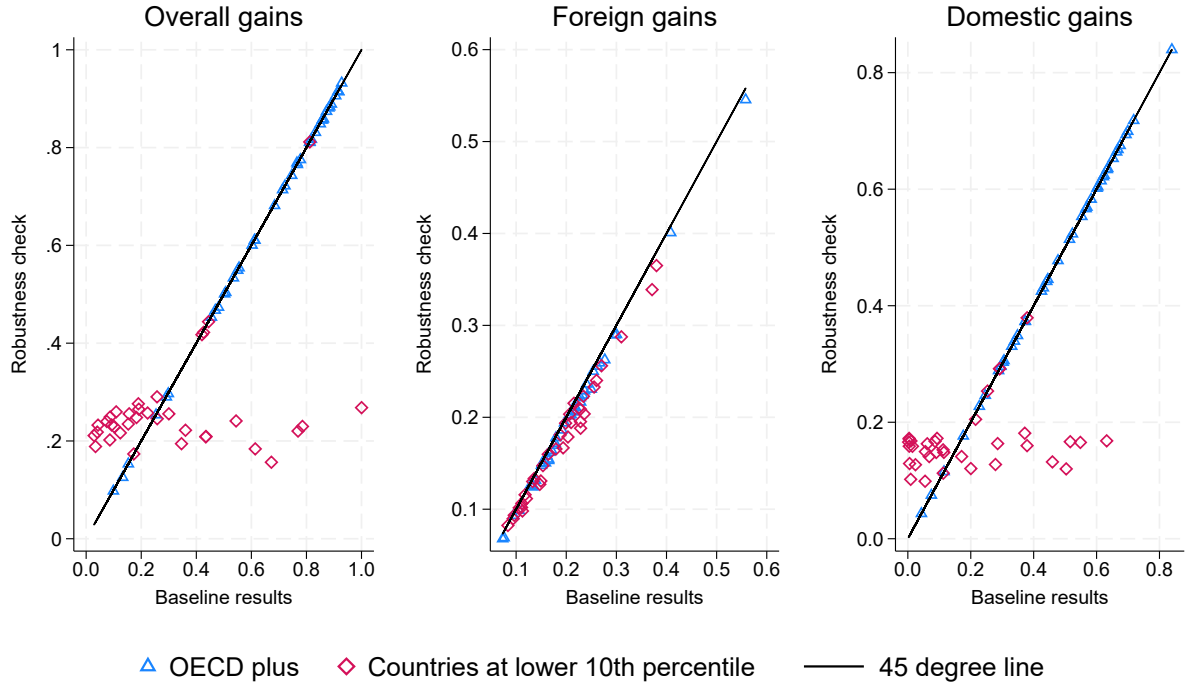


NOTES: This figure shows the top 5 countries with the highest export shares and OECD average in sectors with a high cross-elasticity of substitution, i.e., Mining and Coke/petroleum.
SOURCE: Authors' calculations from OECD ICIO (Yamano et al., 2023).

Figure A.9. Robustness check of predicted welfare gains due to AI



(a) Country Levels



(b) Domestic and foreign gains for all sample

NOTES: This figure compares the baseline decomposition results shown in Figure 7 with those from two robustness check scenarios: (i) where we set China and India's levels to low adoption rates predicted by their adoption covariates, (ii) where we set productivity gains to the 10th percentile for countries whose AI-based projections rely on a limited set of predictors. Aggregate welfare gains in the robustness check scenarios are qualitatively similar to those in the baseline for countries with a full set of predictors (upper panel and blue triangles in the lower panel). For countries with a limited set of AI adoption predictors (China in the upper panel and red diamonds in the lower panel), lower productivity gains in the robustness check lead to smaller domestic effects and correspondingly reduced overall welfare gains.

SOURCE: Authors' calculations.

B AI Adoption Calculations

B.1 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, occupation's 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, Côte d'Ivoire, Cameroon, Colombia, 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 3-D, 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*.

B.2 Details of AI adoption calculations

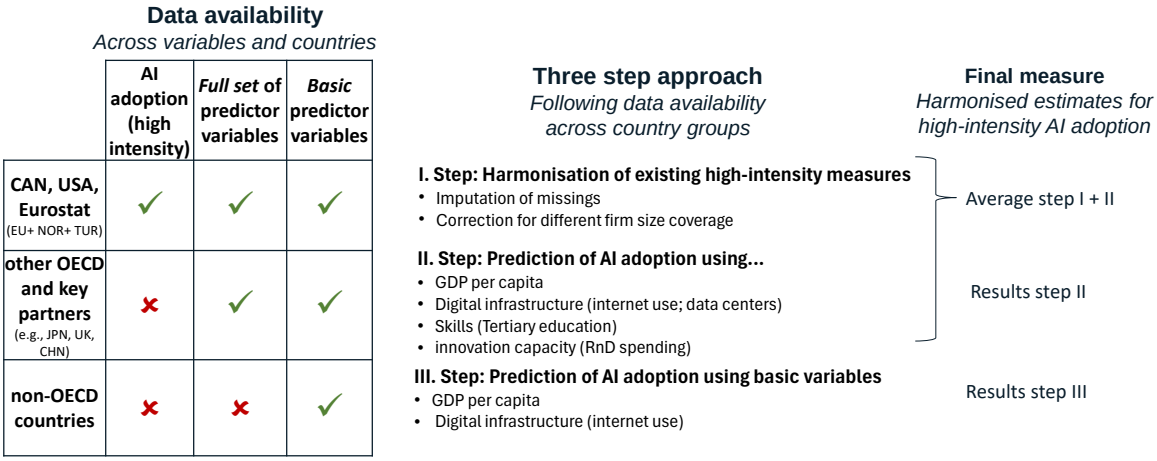
This paper defines AI adoption as the integration of AI in the production process of goods or services, which constitute core business functions. This definition goes beyond the occasional reliance on AI tools by employees in isolated tasks that are not directly related to core business activities. Given the landscape of heterogenous and often times 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 B.1.

B.2.1 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[39], the United States Census Bureau[40,41] and Central Bureau of Statistics of Israel.[42]

Figure B.1. Overview over most important steps in the calculation of harmonised AI adoption in core business functions



NOTES: 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' calculations.

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

[40]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.

[41]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).

[42]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 harmonize 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.

These surveys are harmonised in terms of their coverage of industries and firm sizes.[43] Data harmonisation consists in excluding micro firms (with less than 10 employees)[44] 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.[45] 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 B.1 provides an 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.

[43] For details on these harmonisation steps see Annex B of Filippucci et al. (2025).

[44] 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 Annex B of Filippucci et al. (2025) details on the methodology.

[45] 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 our efforts to identify comparable questions on AI use, differences remain in the level of detail provided to respondents regarding specific AI use cases.

Table B.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 (%popul.)	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 speeds (%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 broadb. subscr. (abs/per capita)	OECD Data Kitchen [**]	50	100
	Total mobile broadb. subscr. (abs/per capita)	OECD Data Kitchen [**]	50	100
	Use of mobiles (abs/%popul.)	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
	Gov. 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	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**

NOTES: [*] 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.

Regression results show that high-intensity AI adoption is positively correlated with real GDP per capita and digital infrastructure (Table B.2). Although these variables lose individual significance when additional regressors for innovation, skills and AI specific digital in-

frastructure 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 B.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 B.2. The econometric link between high-intensity AI adoption and its structural drivers

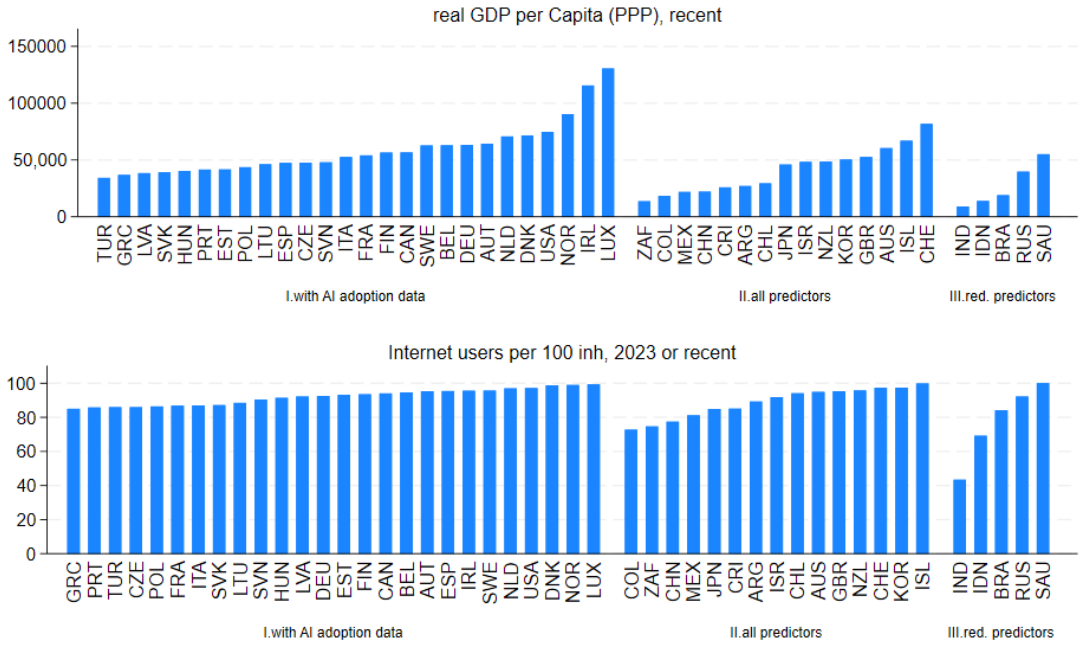
	(1)	(2)	(3)	(4)
	AI adoption	AI adoption	AI adoption	AI adoption
Real GDP p/capita (PPP), 2023	0.731***	0.270	0.093	0.071
	(0.1598)	(0.1942)	(0.1218)	(0.1647)
Internet users per 100 inh, 2023 or recent		3.574***	1.820	1.863
		(1.0367)	(1.2251)	(1.6600)
Business exp in R&D, %GDP 2023 or recent			0.284***	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	_	_	***	**

NOTES: Projected sector-level total factor productivity gains under different scenarios (cumulative over 10 years, in percent). 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.
SOURCE: Source: Authors' calculations based on World Bank (2024), International Telecommunication Union (ITU), Data Center Map (2025), OECD (2024a), OECD (2024b) and OECD (2023).

Descriptive statistics of selected variables are presented in Figures B.2 and B.3. Digital

infrastructure is measured by the share of individuals using the internet and the number of data centres per capita[46], 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 B.2. AI adoption predictor variables



NOTES: Descriptives statistics of *basic* predictor variables. "Red. Predictors" refer to the reduced set of predictors.

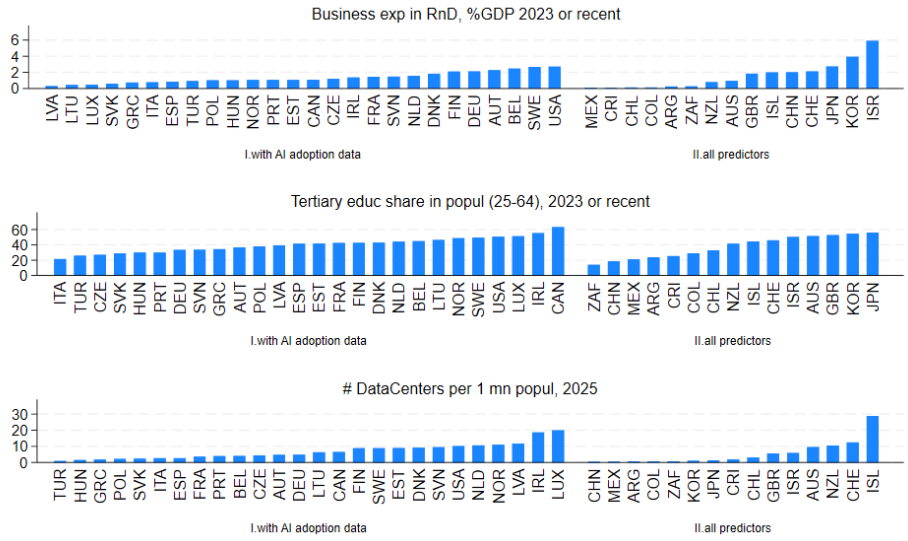
SOURCE: World Bank (2024), and International Telecommunication Union (ITU).

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 B.2, column 2). The resulting preferred adoption rate estimates are calculated as the average of the harmonised values (derived from observed data) and

[46] 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 (Lehdonvirta et al., 2025) 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.

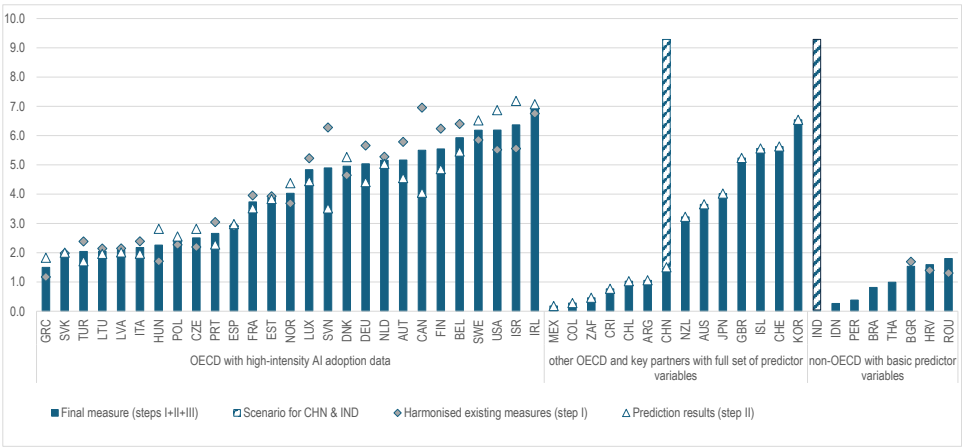
the imputed values (obtained from out-of-sample predictions based on fundamental drivers) (Figure B.4).

Figure B.3. AI adoption predictor variables



NOTES: Descriptives statistics of *additional* predictor variables.
SOURCE: Data Center Map (2025), OECD (2024a), and OECD (2024b).

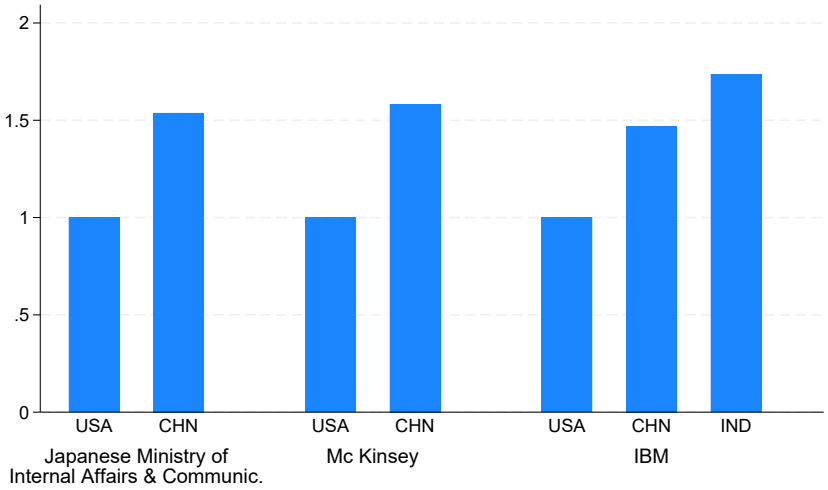
Figure B.4. Harmonised estimates for current AI use in core business functions, 2024



NOTES: AI adoption among firms, in % of firms. For China and India, the shaded areas represent the difference between low and high AI adoption scenarios.
SOURCES: Canada: Statistics Canada - Canadian Survey on Business Conditions (CSBC) (Statistics Canada, 2024); EU: Eurostat Community survey on ICT usage and e-commerce in enterprises (Eurostat, 2025); 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), Data Center Map (2025), OECD (2024a), and OECD (2024b).

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 B.5). 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 B.5. Cross-survey comparison of AI adoption in China and India relative to the US



NOTES: Country-level AI adoption relative to the US.

SOURCE: Japan Ministry of Internal Affairs and Communications (2024), McKinsey & Company (2023) and IBM (2023).

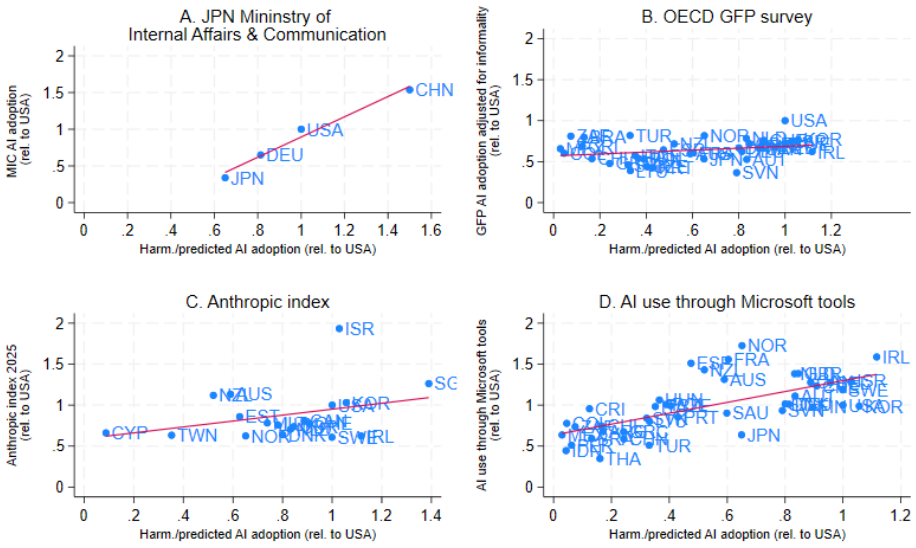
B.2.2 Cross validation of our preferred AI adoption estimate

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).[47] Although these

[47]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.

sources differ in purpose, sector coverage, and time reference, their findings on AI adoption show a positive correlation with our estimates (Figure B.6).[48]

Figure B.6. AI adoption relative to the US



NOTES: Comparing alternative data sources on AI adoption with our current calculations. This figure shows AI adoption values of different countries relative to the United States across different surveys. 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), OECD (2024c), Anthropic (2025) and Misra et al. (2025).

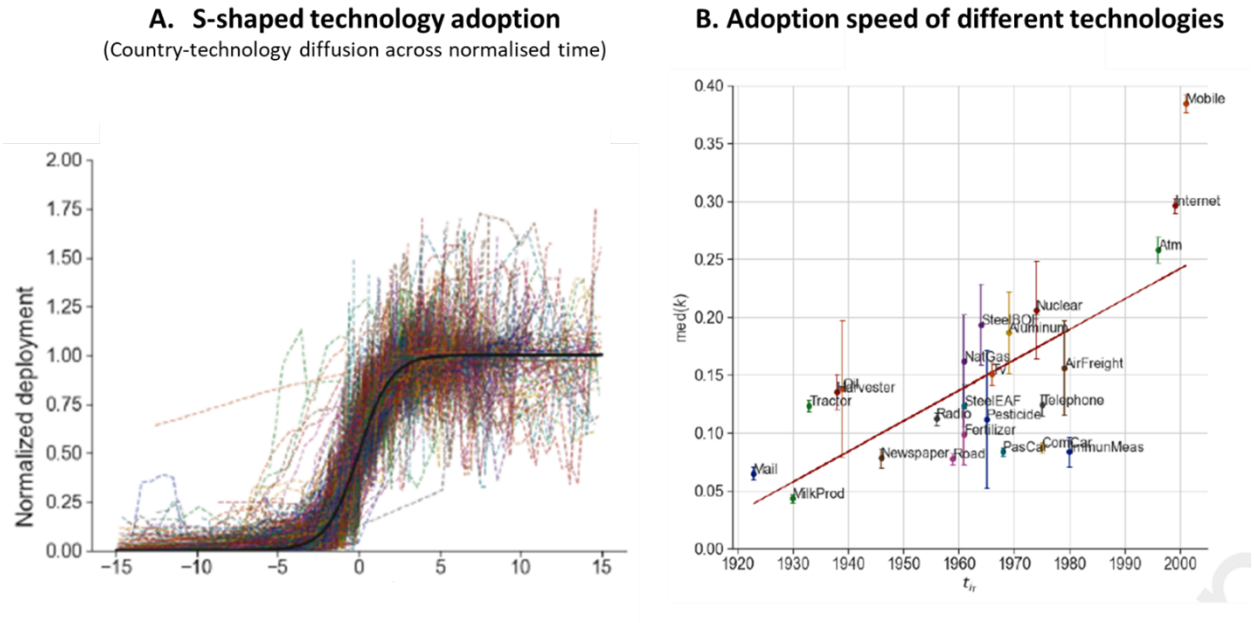
A few countries - particularly Latin American economies such as Mexico, Colombia, and Costa Rica - stand out in this pattern: in the GFP survey, their reported AI adoption rates are relatively closer to those of the United States than our estimates suggest. Relatively low AI predictions can be explained by the drivers of AI adoption, as depicted in Figures B.2,B.3 and Table B.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.

[48] 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.

B.2.3 Current AI adoption extrapolated over 10 years

As highlighted in 2.3, the future adoption path of AI is expected to follow an S-shaped curve as motivated by the diffusion of past technologies (B.9 and B.7).

Figure B.7. Diffusion path of past technologies



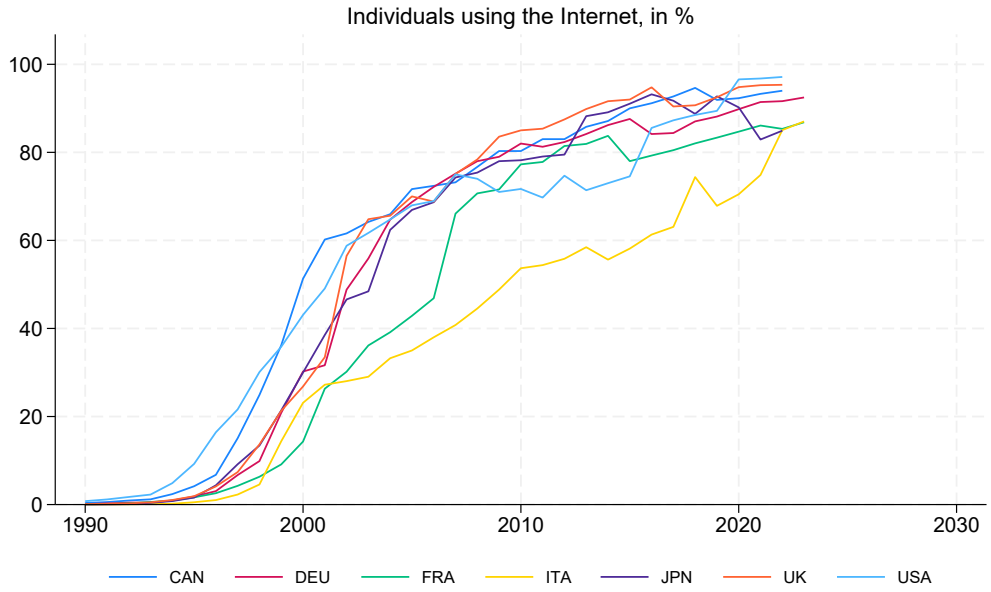
NOTES: Panel A shows the adoption path of 3015 country-technology pairs. The data are normalized and plotted using non-dimensional coordinates to allow to comparisons across country-technology pairs with different adoption speeds and saturation levels. The thick black line traces the idealized logistic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

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 B.7). 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 B.9 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.

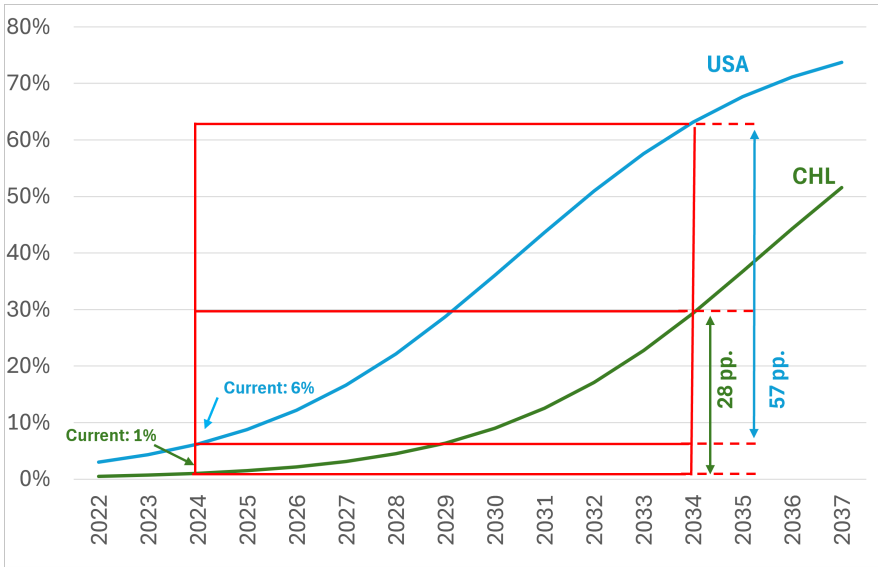
Assuming three scenarios - slow, medium, and fast adoption - the empirical strategy yields the estimates in Figure B.10 for the next 10 years.

Figure B.8. S-shaped adoption path of past technologies: the example of the internet



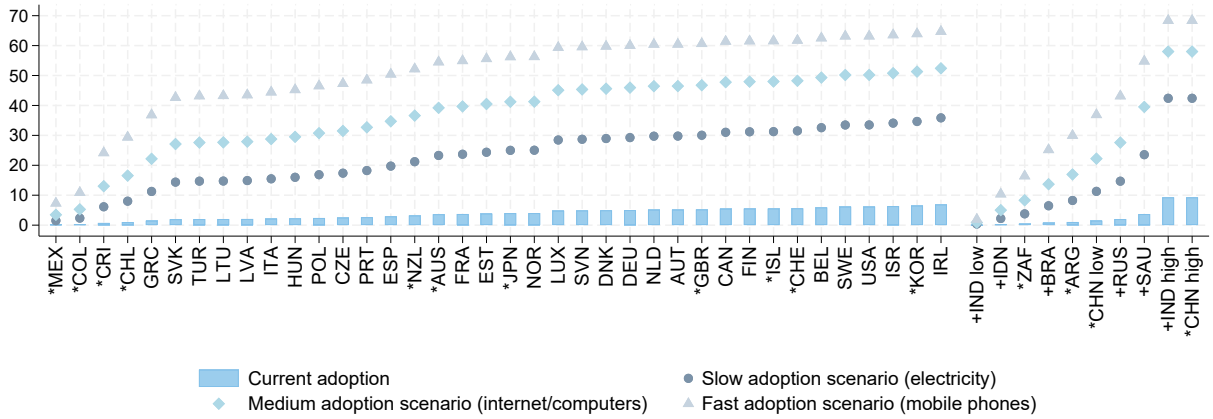
SOURCE: International Telecommunication Union (ITU).

Figure B.9. Current adoption rate differences across countries likely to drive adoption 10 years from now: United States versus Chile



NOTES: Future AI adoption path assumptions following the S-shape of previous GPTs under fast adoption speed scenario (following mobile phones), % of businesses.
SOURCE: Adoption speed is sourced from Tankwa et al. (2025). See Figure B.7.

Figure B.10. The expected increase in AI adoption varies a lot across countries



NOTES: Current and future adoption (in 10 years) based on the S-shaped adoption paths seen in previous GPTs, % of businesses. 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 Section B.2 of the Appendix 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 2.3).
SOURCE: Authors' calculations.

C Proofs

C.1 Proof of Proposition 1

The production function in sector ni is given in terms of all other sectors and factors by:

$$Y_{ic} = A_{ic} F_{ic} \left(\left\{ x_{jm}^{ic} \right\}_{jm \in \mathcal{CJ}}, \left\{ L_f^{ic} \right\}_{f \in \mathcal{F}} \right),$$

where F_{ic} represents the nested CES structure, $\mathcal{CJ}$ is the set of all country-sector pairs, x_{mj}^{ic} denotes the amount of output of country-sector jm used by ic and L_f^{ic} denotes the amount of factor f used by ic. With this, we can write the firm profit maximization problem as:

$$\pi_{ic} = p_{ic} y_{ic} - \sum_{jm \in \mathcal{CJ}} p_{jm} x_{jm}^{ic} - \sum_{f \in \mathcal{F}} w_f L_f^{ic}.$$

Using Shepard's Lemma, the change in prices are related to the price changes of all other sectors and factor price changes with:

$$\begin{aligned}\mathrm{d}\log p_{ic} &= -\mathrm{d}\log A_{ic} + \sum_{jm\in\mathcal{CJ}} \frac{p_{mj}x^{ic}_{jm}}{p_{ic}y_{ic}}\mathrm{d}\log p_{mj} + \sum_{f\in\mathcal{F}} \frac{w_f L^{ic}_f}{p_{ic}y_{ic}}\mathrm{d}\log w_f \\ &= -\mathrm{d}\log A_{ic} + \sum_{jm\in\mathcal{CJ}} \Omega^{ic}_{jm}\mathrm{d}\log p_{mj} + \sum_{f\in\mathcal{F}} \Omega^{ic}_{f}\mathrm{d}\log w_f.\end{aligned}$$

In vector and matrix notation, we can write:

$$\mathrm{d}\log p = -\mathrm{d}\log A + \Omega\,\mathrm{d}\log p + \Omega^F\,\mathrm{d}\log w.$$

$$\mathrm{d}\log p = -\Psi\,\mathrm{d}\log A + \Psi\,\Omega^F\,\mathrm{d}\log w, \tag{C.1}$$

where $\Psi = [I-\Omega]^{-1}$ is the Leontief inverse matrix. Assuming full employment and normalizing world GDP to 1 (i.e., $\mathrm{GDP}_W = 1$), $\mathrm{d}\log\Lambda_f = \mathrm{d}\log w$. Therefore:

$$\mathrm{d}\log p = -\Psi\,\mathrm{d}\log A + \Psi\,\Omega^F\,\mathrm{d}\log\Lambda.$$

Given these price changes, we can write the CPI change of country m as:

$$\begin{aligned}d\log p_m &= \Omega^0_m \mathrm{d}\log p \\ &= -\underbrace{\Omega^0_m\,\Psi}_{\lambda^m}\,\mathrm{d}\log A + \underbrace{\Omega^0_m\,\Psi\,\Omega^F}_{\Lambda^m}\,\mathrm{d}\log\Lambda \\ &= -\lambda^m\,\mathrm{d}\log A + \Lambda^m\,\mathrm{d}\log\Lambda\end{aligned}$$

Total income of country is can be written as:

$$\chi_m = \sum_{f\in\mathcal{F}_m}\Lambda_f \quad\Rightarrow\quad \chi_m\,\mathrm{d}\log\chi_m = \sum_{f\in\mathcal{F}_m}\Lambda_f\,d\log\Lambda_f.$$

We can write the welfare change of country m as:

$$\begin{aligned}\mathrm{d}\log W_m &= \mathrm{d}\log\chi_m - \mathrm{d}\log p_m \\ &= \underbrace{\sum_{i\in\mathcal{J}}\lambda^m_{im}\,\mathrm{d}\log A_{im}}_{\text{Direct domestic productivity gains}} + \underbrace{\sum_{i\in\mathcal{J}}\sum_{c\neq m\in\mathcal{C}}\lambda^m_{ic}\,\mathrm{d}\log A_{ic}}_{\text{Direct productivity gains from abroad}}\end{aligned}$$

$$\underbrace{-\underbrace{\sum_{f\in\mathcal{F}}\Lambda_f^m\,\mathrm{d}\log\Lambda_f}_{\text{Local-global mismatch}}+\underbrace{\frac{1}{\chi_m}\sum_{f\in\mathcal{F}_m}\Lambda_f\,\mathrm{d}\log\Lambda_f}_{\text{Local factor income change}}}_{\Delta\text{ allocation}}$$

Here, we separate out the domestic industries and foreign industries to elaborate the differences between domestic gains and foreign gains. □

C.2 Proof of Proposition 2

This section follows Çakmaklı et al. (forthcoming) closely. Instead of labor shocks and sectoral demand shocks, we will model the TFP shocks stemming from AI adoption. Our point of departure is the factor Domar weight identity:

$$\Lambda=\lambda\,\Omega^F=\chi\,\Omega^0\,\underbrace{\Psi\,\Omega^F}_{\equiv\Psi^F}=\chi\,\Omega^0\,\Psi^F.$$

Taking the total differential produces four distinct components:

$$\mathrm{d}\Lambda=\mathrm{d}\chi\,\Omega^0\,\Psi^F+\chi\,\mathrm{d}\Omega^0\,\Psi^F+\lambda\,\mathrm{d}\Omega\,\Psi^F+\lambda\,\mathrm{d}\Omega^F. \tag{C.2}$$

Our objective is to express every component in terms of $\mathrm{d}\log\Lambda$. Because factor endowments remain unchanged under TFP shocks, the log-change in factor Domar weights coincides with the log-change in factor prices:

$$\mathrm{d}\log\Lambda=\mathrm{d}\log w\Rightarrow\mathrm{d}\Lambda=\mathrm{d}\log w\hat{\Lambda}\Rightarrow\mathrm{d}\log w=\mathrm{d}\Lambda\hat{\Lambda}^{-1},$$

where $\hat{\Lambda}$ denotes the diagonal matrix formed from Λ. The generalized Shepard Lemma, expressed in row-vector form, links price movements to both productivity gains and factor cost changes:

$$\mathrm{d}\log p=-\mathrm{d}\log A\,\Psi'+\mathrm{d}\log w\;\Psi^{F'}=-\mathrm{d}\log A\,\Psi'+\mathrm{d}\log\Lambda\;\Psi^{F'}. \tag{C.3}$$

This relationship allows us to map all price-dependent expressions into functions of $\mathrm{d}\log\Lambda$ and the exogenous TFP shock $\mathrm{d}\log A$. Assembling the four components, we seek a representation of the form:

$$\mathrm{d}\log\Lambda=\mathrm{d}\log\Lambda\,D+B\quad\Rightarrow\quad\mathrm{d}\log\Lambda=B\,(I-D)^{-1}.$$

We now treat each of the four components in Equation (C.2) in turn, casting each into the $\mathrm{d}\log\Lambda\, D_i + B_i$ format before combining them.

Component 1: $\mathrm{d}\chi\,\Omega^0\,\Psi^F$

Country income shares move in proportion to factor Domar weight changes through the mapping Φ:

$$\mathrm{d}\chi = \mathrm{d}\Lambda\,\Phi = \mathrm{d}\log\Lambda\,\hat{\Lambda}\,\Phi.$$

Substituting back:

$$\mathrm{d}\chi\,\Omega^0\,\Psi^F = \mathrm{d}\log\Lambda\,\underbrace{\hat{\Lambda}\,\Phi\,\Omega^0\,\Psi^F}_{D_1}.$$

Component 2: $\chi\,\mathrm{d}\Omega^0\,\Psi^F$

To evaluate this component, we require the differential of the consumption expenditure shares. Expressing a generic element Ω^{0c}_{jm} through the nested CES price structure:

$$\Omega^{0c}_{jm} = \omega^{0c}_{jm}(\Delta^{0c}_{jm})^{\sigma}\,(p_{jm})^{1-\xi^0_i}\left(p^{0c}_j\right)^{\xi^0_i-\sigma}(p_{0c})^{\sigma-1},$$

where ω^{0c}_{jm} is the structural taste parameter, calibrated to match the observed share Ω^{0c}_{jm} in the pre-shock equilibrium. Log-differentiating (and noting that the taste parameters and demand shifters are held fixed under a pure TFP shock):

$$\mathrm{d}\log\Omega^{0c}_{jm} = (1-\xi^0_j)\mathrm{d}\log p_{jm} + (\xi^0_j-\sigma)\mathrm{d}\log p^{0c}_j + (\sigma-1)\mathrm{d}\log p_{0c}.$$

Applying the Shepard Lemma to the sectoral and aggregate consumption price indices:

$$\mathrm{d}\log p^{0c}_j = \sum_{n\in\mathcal{C}}\Xi^{0c}_{jn}d\log p_{jn}, \qquad \mathrm{d}\log p_{0c} = \sum_{in\in\mathcal{CN}}\Omega^{0c}_{in}\mathrm{d}\log p_{in},$$

and substituting these into the share differential yields:

$$\mathrm{d}\log\Omega^{0c}_{jm} = (1-\xi^0_j)d\log p_{jm} + (\xi^0_j-\sigma)\sum_{n\in\mathcal{C}}\Xi^{0c}_{jn}d\log p_{jn} + (\sigma-1)\sum_{in\in\mathcal{CN}}\Omega^{0c}_{in}d\log p_{in}.$$

Pre-multiplying by income-weighted shares and collecting terms, the jm^{th} entry of $\chi\,d\Omega^0$ decomposes into three lines:

$$\sum_c \chi_c\Omega^{0c}_{jm}\mathrm{d}\log\Omega^{0c}_{jm} = (1-\xi^0_j)\sum_c\chi_c\Omega^{0c}_{jm}d\log p_{jm} \qquad \mathrm{d}\log p\,\tilde{D}_{21}$$

$$+ (\xi_j^0 - \sigma) \sum_c \chi_c \Omega_{jm}^{0c} \sum_{n \in \mathcal{C}} \Xi_{jn}^{0c} d \log p_{jn} \qquad \mathrm{d} \log p \, \tilde{D}_{22}$$
$$+ (\sigma - 1) \sum_c \chi_c \Omega_{jm}^{0c} \sum_{in \in \mathcal{CN}} \Omega_{in}^{0c} d \log p_{in} \qquad \mathrm{d} \log p \, \tilde{D}_{23}$$

Each $\tilde{D}$ matrix acts on $\mathrm{d} \log p$. To re-express everything in terms of $\mathrm{d} \log \Lambda$, we substitute the generalized Shepard Lemma. For a generic sub-component indexed by k:

$$\mathrm{d} \log p \, \tilde{D}_k \, \Psi^F = \mathrm{d} \log \Lambda \, \underbrace{\Psi^{F'} \, \tilde{D}_k \, \Psi^F}_{D_k} \underbrace{- \mathrm{d} \log A \, \Psi' \, \tilde{D}_k \, \Psi^F}_{B_k}.$$

Right-multiplication by Ψ^F completes the mapping to factor space.

Line 1: The within-sector own-price response. In matrix form:

$$\tilde{D}_{21} = (1 - \widehat{\xi^0}) \, \widehat{\chi \Omega^0},$$

where $\widehat{\xi^0}$ assigns each sector's elasticity to the corresponding industry entries and $\widehat{\chi \Omega^0}$ is the diagonal matrix with entries $\chi \Omega^0$. Converting to factor space:

$$D_{21} = \Psi^{F'} \, (1 - \widehat{\xi^0}) \, \widehat{\chi \Omega^0} \, \Psi^F,$$
$$B_{21} = -d \log A \, \Psi' \, (1 - \widehat{\xi^0}) \, \widehat{\chi \Omega^0} \, \Psi^F.$$

Line 2: Cross-country substitution within the same sector. The matrix representation is:

$$\tilde{D}_{22} = (\widehat{\xi^0} - \sigma) \, \left[(1_{C \times C} \otimes I_N) \odot \left(\Xi^{0'} \, \hat{\chi} \, \Omega^0 \right) \right],$$

where the Kronecker structure $(1_{C \times C} \otimes I_N)$ isolates varieties belonging to the same sector across different origins. Converting:

$$D_{22} = \Psi^{F'} \, (\widehat{\xi^0} - \sigma) \, \left[(1_{C \times C} \otimes I_N) \odot \left(\Xi^{0'} \, \hat{\chi} \, \Omega^0 \right) \right] \, \Psi^F,$$
$$B_{22} = -d \log A \, \Psi' \, (\widehat{\xi^0} - \sigma) \, \left[(1_{C \times C} \otimes I_N) \odot \left(\Xi^{0'} \, \hat{\chi} \, \Omega^0 \right) \right] \, \Psi^F.$$

Line 3: Substitution across sectors through the aggregate consumption price index:

$$\tilde{D}_{23} = (\sigma - 1) \, \Omega^{0'} \, \hat{\chi} \, \Omega^0.$$

Converting:

$$D_{23} = (\sigma - 1)\, \Psi^{F'}\, \Omega^{0'}\, \hat{\chi}\, \Omega^{0}\, \Psi^{F},$$
$$B_{23} = -(\sigma - 1) \mathrm{d}\log A\, \Psi'\, \Omega^{0'}\, \hat{\chi}\, \Omega^{0}\, \Psi^{F}.$$

Component 3: $\lambda\, \mathrm{d}\Omega\, \Psi^{F}$

The intermediate input share differential follows a parallel logic. A representative element takes the form:

$$\Omega_{jm}^{kc} = \omega_{jm}^{kc} \left(p_{jm}\right)^{1-\xi_j} \left(p_{j}^{kc}\right)^{\xi_j - \varepsilon} \left(p_{M_{kc}}\right)^{\varepsilon - \phi} \left(p_{kc}\right)^{\phi - 1},$$

with the structural coefficient ω_{jm}^{kc} set equal to the observed share Ω_{jm}^{kc} at the initial equilibrium. Log-differentiating:

$$\begin{aligned} d\log \Omega_{jm}^{kc} = {} & (1-\xi_j) d\log p_{jm} + (\xi_j - \varepsilon) \sum_{n \in \mathcal{C}} \Xi_{jn}^{kc} d\log p_{jn} \\ & + (\varepsilon - \phi) \sum_{in \in \mathcal{CN}} \frac{\Omega_{in}^{kc}}{1-\alpha_{kc}} d\log p_{in} + (\phi - 1) d\log p_{kc}. \end{aligned}$$

Weighting by Domar-weighted input shares, the jm^{th} entry of $\lambda\, d\Omega$ splits into four lines:

$$\begin{aligned} \sum_{kc \in \mathcal{CN}} \lambda_{kc} \Omega_{jm}^{kc} \mathrm{d}\log \Omega_{jm}^{kc} = {} & \sum_{kc \in \mathcal{CN}} \lambda_{kc} \Omega_{jm}^{kc} (1-\xi_j) d\log p_{jm} && \mathrm{d}\log p\, \tilde{D}_{31} \\ & + (\xi_j - \varepsilon) \sum_{kc \in \mathcal{CN}} \lambda_{kc} \Omega_{jm}^{kc} \sum_{n \in \mathcal{C}} \Xi_{jn}^{kc} d\log p_{jn} && \mathrm{d}\log p\, \tilde{D}_{32} \\ & + (\varepsilon - \phi) \sum_{kc \in \mathcal{CN}} \lambda_{kc} \Omega_{jm}^{kc} \sum_{in \in \mathcal{CN}} \frac{\Omega_{in}^{kc}}{1-\alpha_{kc}} d\log p_{in} && \mathrm{d}\log p\, \tilde{D}_{33} \\ & + (\phi - 1) \sum_{kc \in \mathcal{CN}} \lambda_{kc} \Omega_{jm}^{kc} d\log p_{kc} && \mathrm{d}\log p\, \tilde{D}_{34}. \end{aligned}$$

Line 1: Own-price sensitivity of intermediate demand within each sector:

$$\tilde{D}_{31} = (1 - \hat{\xi})\, \widehat{\lambda\Omega},$$

where $\widehat{\lambda\Omega}$ has diagonal entries equal to the Domar-weighted column sums of Ω. Mapping to factor space:

$$D_{31} = \Psi^{F'}\, (1 - \hat{\xi})\, \widehat{\lambda\Omega}\, \Psi^{F},$$

$$B_{31} = -\mathrm{d}\log A\,\Psi'\,(1-\hat{\xi})\,\widehat{\lambda\Omega}\,\Psi^F.$$

Line 2: Reallocation of intermediate sourcing across origins within a sector:

$$\tilde{D}_{32} = (\hat{\xi}-\varepsilon)\,\left[(1_{C\times C}\otimes I_N)\odot\left(\Xi'\,\hat{\lambda}\,\Omega\right)\right].$$

Mapping to factor space:

$$D_{32} = \Psi^{F'}\,(\hat{\xi}-\varepsilon)\,\left[(1_{C\times C}\otimes I_N)\odot\left(\Xi'\,\hat{\lambda}\,\Omega\right)\right]\,\Psi^F,$$
$$B_{32} = -\mathrm{d}\log A\,\Psi'\,(\hat{\xi}-\varepsilon)\,\left[(1_{C\times C}\otimes I_N)\odot\left(\Xi'\,\hat{\lambda}\,\Omega\right)\right]\,\Psi^F.$$

Line 3: Reallocation across sectoral input bundles through the composite intermediate price index:

$$\tilde{D}_{33} = (\varepsilon-\phi)\,\Omega'\,\hat{\lambda}\,(1-\hat{\alpha})^{-1}\,\Omega,$$

with $\hat{\alpha}$ the diagonal matrix of value-added shares. Mapping to factor space:

$$D_{33} = (\varepsilon-\phi)\,\Psi^{F'}\,\Omega'\,\hat{\lambda}\,(1-\hat{\alpha})^{-1}\,\Omega\,\Psi^F,$$
$$B_{33} = -(\varepsilon-\phi)\,\mathrm{d}\log A\,\Psi'\,\Omega'\,\hat{\lambda}\,(1-\hat{\alpha})^{-1}\,\Omega\,\Psi^F.$$

Line 4: The response of intermediate demand to the industry's own output price:

$$\tilde{D}_{34} = (\phi-1)\hat{\lambda}\,\Omega.$$

Mapping to factor space:

$$D_{34} = (\phi-1)\,\Psi^{F'}\,\hat{\lambda}\,\Omega\,\Psi^F,$$
$$B_{34} = -(\phi-1)\,\mathrm{d}\log A\,\Psi'\,\hat{\lambda}\,\Omega\,\Psi^F.$$

Component 4: $\lambda\,\mathrm{d}\Omega^F$

Turning to the factor input shares, a representative element is:

$$\Omega_f^{kc} = \omega_f^{kc}\,(w_f)^{1-\eta}\left(p_{VA}^{kc}\right)^{\eta-\phi}(p_{kc})^{\phi-1},$$

with the structural coefficient ω_f^{kc} initialized at the observed share Ω_f^{kc}. The log-differential

is:

$$\mathrm{d}\log\Omega_f^{kc} = (1-\eta)d\log w_f + (\eta-\phi)\sum_{g\in\mathcal{F}}\frac{\Omega_g^{kc}}{\alpha_{kc}}\mathrm{d}\log w_g + (\phi-1)d\log p_{kc}.$$

Weighting by $\lambda_{kc}\Omega_f^{kc}$ and summing across industries, the f^{th} entry of $\lambda\, d\Omega^F$ separates into:

$$\begin{aligned}\sum_{kc\in\mathcal{CN}}\lambda_{kc}\Omega_f^{kc}\mathrm{d}\log\Omega_f^{kc} = (1-\eta)d\log w_f\sum_{kc\in\mathcal{CN}}\lambda_{kc}\Omega_f^{kc} &\qquad \mathrm{d}\log w\, D_{41}\\ +(\eta-\phi)\sum_{kc\in\mathcal{CN}}\lambda_{kc}\Omega_f^{kc}\sum_{g\in\mathcal{F}}\frac{\Omega_g^{kc}}{\alpha_{kc}}\mathrm{d}\log w_g &\qquad \mathrm{d}\log w\, D_{42}\\ +(\phi-1)\sum_{kc\in\mathcal{CN}}\lambda_{kc}\Omega_f^{kc}d\log p_{kc} &\qquad \mathrm{d}\log p\,\tilde{D}_{43}.\end{aligned}$$

Line 1: The own-wage elasticity of factor demand, aggregated across all hiring industries:

$$D_{41} = (1-\eta)\widehat{\lambda\Omega^F},$$

where $\widehat{\lambda\Omega^F}$ has diagonal entries equal to the Domar-weighted column sums of Ω^F.

Line 2: Within-industry reallocation across factor types:

$$D_{42} = (\eta-\phi)\,\Omega^{F\prime}\,\hat{\lambda}\,\hat{\alpha}^{-1}\,\Omega^F.$$

Line 3: The indirect effect of industry output prices on factor demand, operating through the substitution between value added and intermediates:

$$\tilde{D}_{43} = (\phi-1)\hat{\lambda}\,\Omega^F.$$

Applying the Shepard Lemma to convert from price space to factor space:

$$\begin{aligned}D_{43} &= (\phi-1)\,\Psi^{F\prime}\,\hat{\lambda}\,\Omega^F,\\ B_{43} &= -(\phi-1)\,\mathrm{d}\log A\,\Psi'\,\hat{\lambda}\,\Omega^F.\end{aligned}$$

Rank condition. Summing all components, the composite D matrix is singular by construction, reflecting the redundancy inherent in a system where all nominal magnitudes are determined only up to a common scalar. We resolve this by anchoring world nominal GDP:

$$\sum_f \Lambda_f\,\mathrm{d}\log\Lambda_f = 0.$$

Imposing this constraint on the first column of D:

$$D_{1,1} = 0, \quad D_{f>1,1} = -\Lambda_f.$$

With this normalization in place, the equilibrium response of factor Domar weights to the TFP shock is:

$$\mathrm{d}\log\Lambda = B\,\hat{\Lambda}^{-1}\,(I - D\,\hat{\Lambda}^{-1})^{-1} = B\,(\hat{\Lambda} - D)^{-1}.$$

□

D Additional Channels

D.1 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 multinational ones (MNEs) (Cernat, 2024). For instance, when a domestic sector buys ICT services from US companies (say, French companies by 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). 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[49] with the OECD-WTO Trade in Value Added (TIVA) dataset [50] - this so-called "mode 3" international service trade, which involves local subsidiaries, amounts to nearly *double* of the recorded - "mode 1" - service component.[51]

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 ac-

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

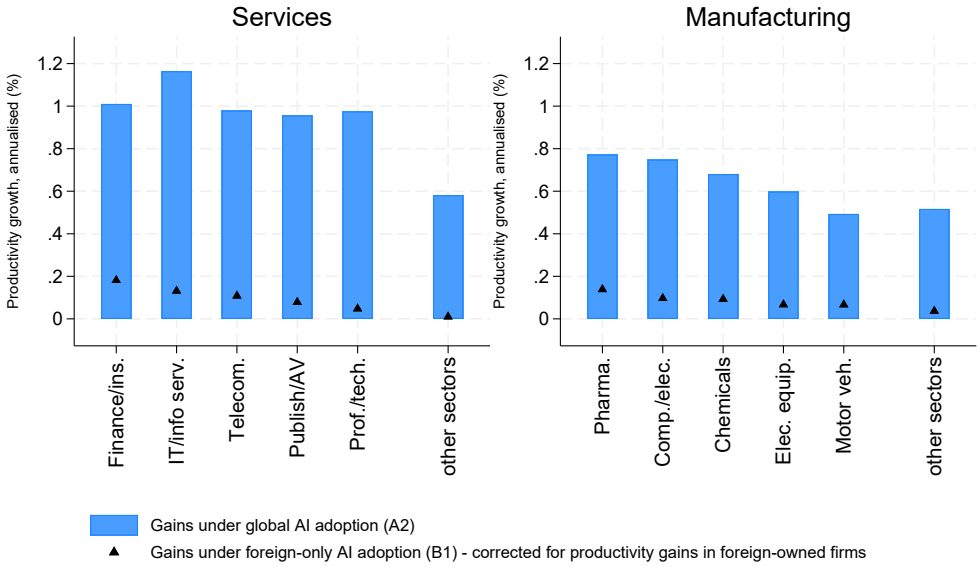
[50] https://www.oecd.org/en/topics/sub-issues/trade-in-value-added.html.

[51] 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.

crues 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 (AMNE) database (Cadestin et al., 2018)[52] 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.

Figure D.1. Correcting for unreported service trade introduces foreign generated gains from AI in intangible intensive services and manufacturing industries



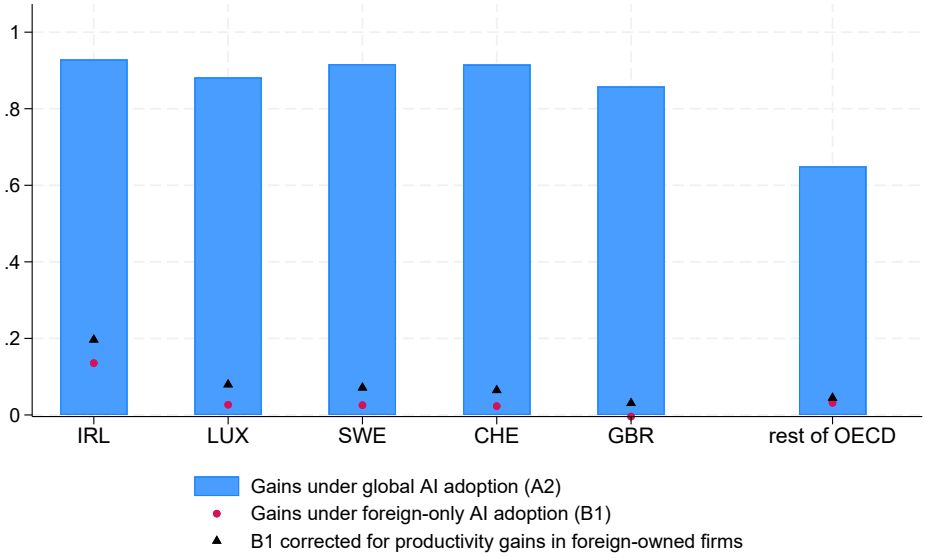
NOTES: This graph shows the average sector-level gains under global AI adoption and gains under foreign-only AI adoption which have been corrected for productivity gains in foreign-owned firms. The selected sectors are those with the largest corrected gains under foreign-only adoption.
SOURCE: Authors'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

The 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 % corresponding to about 0.1 percentage points of annual productivity growth (Figure D.1). Similarly, intangible capital in foreign-owned firms also plays an important role in some

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

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 % corresponding to about a little bit less than 0.1 percentage points of annual productivity growth.

Figure D.2. Correcting for unreported service trade lifts gains from foreign generated AI only moderately in a few countries



NOTES: Predicted real welfare gains due to AI over the next 10 years, percentage points (annualised). 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.

The extent to which the correction of unmeasured services trade leads to an upward adjustment of welfare 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 D.2 compares real welfare gains from AI through international linkages based on traditional input-output statistics with real welfare gains from AI through international linkages based on input-output statistics *corrected for gains in foreign-owned firms*. Corrected welfare gains from AI 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), welfare 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.[53]

[53]It should be noted that our correction of unmeasured service trade is likely to represent an upper bound.

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.

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

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

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 are sourced from the EU KLEMS IntanProd dataset.

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:

$$\text{ImputedServicesImports}_{ic} \doteq \frac{\widetilde{II}_{ic}}{\text{VA}_{ic}} = \underbrace{\frac{\text{VA}_{ic}^{subsMNE}}{\text{VA}_{ic}}}_{AMNE} \cdot \underbrace{\frac{CapServ_{ic}^{int}}{\text{VA}_{ic}}}_{IntanProd} \tag{D.4}$$

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 firmst that operate in the French ICT services sector, including US headquarters.

D.2 AI adoption spillovers across countries through trade

The integration of national economies into global production networks means that not only can welfare gains differ from productivity growth but also domestic productivity developments may be influenced by productivity developments abroad (Helpman and Trajtenberg, 1996; Carvalho and Voigtländer, 2014). An important source of productivity spillovers in

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.

our setting can arise through changes in AI adoption rates depending on global connections. The country-specific AI adoption projections presented in Section 2.3.2 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 learning from 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. Such patterns could be the outcome of downstream firms learning about AI solution 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 embedding them in downstream production interfaces).[54] In addition, multinational enteprises (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.[55]

D.2.1 Empirical Strategy for Spillovers

Below, we present the results from a separate scenario in which we consider the possibility that cross-country knowledge spillovers regarding technology use - AI adoption - are stronger than what we assume by imposing a uniform S-shape pattern on adoption for each country in Section 2.3. Instead, we explore the possibility that they are systematically related to trade patterns. Specifically, we augment the baseline AI adoption rates with an additional spillover term that depends on exposure to global AI adoption via intermediate input trade and foreign firm ownership as follows:

[54] 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).

[55] At a more fundamental level, the S-shape patterns that underpins the calculations in Section 2.3 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 B.9 in Section B.2.) of the Appendix. The calculations in this section boost the latter effect in a way that is linked to trade with more advanced adopters.

$$\Delta A_{ic} = \Delta \overline{A}_c + \beta \sum_{m \in \mathcal{C}} \sum_{j \in \mathcal{J}} \Omega_{jm}^{ic} \left(A_m - A_c \right) \mathbf{1}_{A_m > A_c} \tag{D.5}$$

In this expression, ΔA_{ic} is the projected increase in the AI adoption rate of sector i in country c over the next decade, accounting for international spillovers. It is the sum of the baseline increase in the AI adoption rate in country c without accounting for international spillovers – $\Delta \overline{A}_c$ (in percentage points, as computed in Section 2.3.2) – 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 $\mathcal{J}$ represent the set of countries and sectors, respectively, and the weight Ω_{jm}^{ic} in the spillover term captures the relative proportion of inputs sourced from upstream sector j in country m, expressed as a share of gross output of the downstream sector i in country c. The weights are multiplied by an indicator function $\mathbf{1}_{A_m > A_c}$ that equals 1 if the current AI adoption rate in country m 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. Finally, the parameter β governs the strength of international spillovers, which we calibrate in two ways as explained in Section D.2.2, and all weights Ω_{jm}^{ic} are computed based on input-output structures as observed in the OECD ICIO tables (for 2019) and corrected for unmeasured services trade (see Section D.2.3 of the Appendix).

Hence, the projected percentage point increase in the AI adoption rate in sector s of country c is given by the baseline adoption rate plus an average of the adoption rates in upstream sectors that have higher adoption rates, weighted by the focal sector's current exposure to these upstream sectors through intermediate input flows.[56]

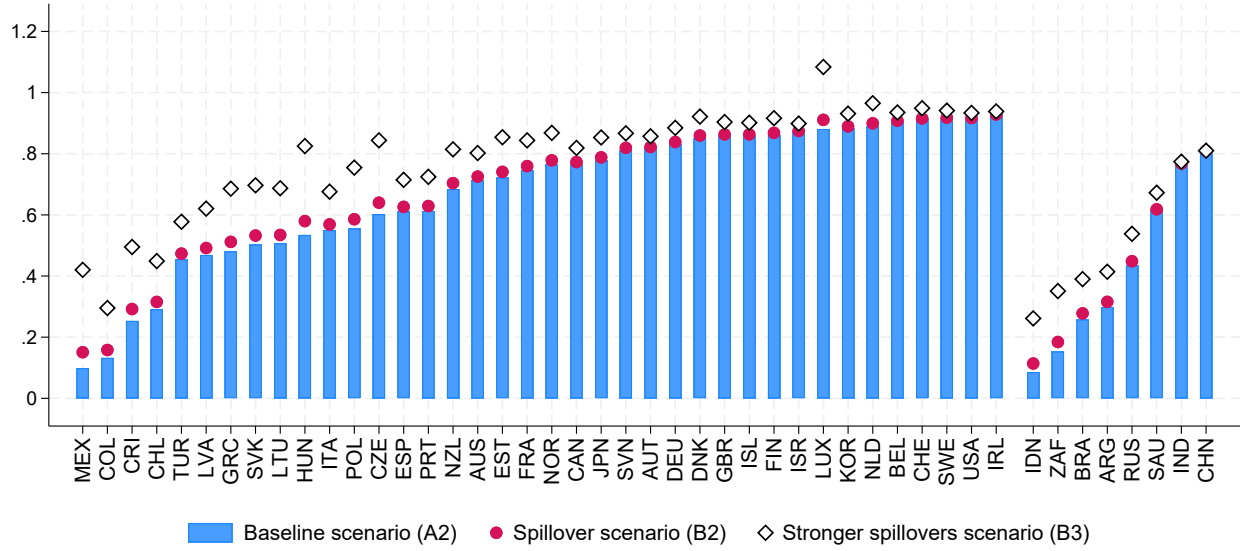
D.2.2 Spillover Results

To illustrate the extent to which trade-facilitated spillovers might change the results, we re-estimate the model under two alternative sets of AI-driven productivity shocks that allow for the international spillovers in AI adoption rates (Figure D.3). Both spillover scenarios are computed following the approach described above, but they differ in how the *strength* of international spillovers is calibrated.

[56] 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 flip-side of this phenomenon is missing intangible intermediate (service) trade between foreign and domestic affiliates of MNEs. Some of the results (Section 4.3.1) will attempt to correct for such missing trade and thus provide an assessment on the size of the likely impacts of knowledge spillovers through the presence of MNEs.

Spillover scenario 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 (D.5) to match that value.[57] 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 D.3), with the largest adoption gains observed in Mexico where AI adoption is currently relatively low and exposure to foreign AI adoption is high.

Figure D.3. Technology spillovers from leading AI-adopter trading partners can boost gains significantly in lagging AI adopter countries



NOTES: Predicted welfare gains due to AI over the next 10 years, percentage points (annualised). Spillover scenario adapts spillover estimates from previous literature on innovation (patents). Stronger spillover scenario uses an alternative illustrative experiment which leads to about six times as strong spillovers.
SOURCE: Authors' calculations.

This scenario may underestimate the strength of adoption spillovers in the context of AI, given that it could lead to faster learning from trading partners than what was observed in the context of patenting in previous literature. For instance, it may be reasonable to expect that 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.

[57] 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 et al. (2022).

However, the spillover scenario 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.

To assess the implications of stronger spillovers that tend to favour countries with higher trade exposure to the AI frontier, the second spillover scenario calibrates the parameter β in equation (D.5) so that the projected percentage point increase in AI adoption in the four Latin American OECD countries, i.e., Mexico, Colombia, Costa Rica and Chile, over the next 10 years 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).

The implied spillover dynamics in stronger scenario are about *six times* stronger. These amount to an almost threefold increase of the gains for Mexico and an increase of about 40% to 90% 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 such spillovers 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.

D.2.3 Adjusting AI-related knowledge spillover weights for under-reporting in international services trade

Let Ω^{ic}_{jm} denote the share of foreign intermediate inputs coming from country m and sector j to country c and sector i, as a share of gross output in country-sector c, i, as in equation (D.5), source from the OECD's inter-country input-output (ICIO) tables.[58]

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

$$\widetilde{\Omega}^{ic}_{jm} = \Omega^{ic}_{jm} \cdot z^{ic}_{jm}, \qquad z^{ic}_{jm} := \frac{II^{ic}_{jm} + \widetilde{II}^{ic}_{jm}}{II^{ic}_{jm}}, \tag{D.6}$$

where z^{ic}_{jm} is a correction factor that adjust for the relative difference between total intermediate imports and reported intermediate inports, in proportional terms, and $\widetilde{II}^{ic}_{jm}$ is the flow unrecorded imported intermediate services inputs, II^{ic}_{jm} 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-

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

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 *cs* (aggregated over all sources), as follows:

$$z_{jm}^{ic} = z_{ic} := \frac{II_{ic} + \widetilde{II}_{ic}}{II_{ic}} \tag{D.7}$$

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 D.4:

$$\widetilde{II}_{ic} = \text{VA}_{ic}^{\text{ICIO}} \cdot \text{ImputedServicesImports}_{ic}, \tag{D.8}$$

where $\text{VA}_{ic}^{\text{ICIO}}$ is sourced from the ICIO dataset to ensure internal consistency and avoid any issues from different value added measurement in ICIO from AMNE.