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ABSTRACT: This paper examines the uneven global impact of AI, highlighting how its effects will be a function of (i) countries' sectoral exposure to AI, (ii) their preparedness to integrate these technologies into their economies, and (iii) their access to essential data and technologies. We feed these three aspects into a multi-sector dynamic general equilibrium model of the global economy and show that AI will exacerbate cross-country income inequality, disproportionately benefiting advanced economies. Indeed, the estimated growth impact in advanced economies could be more than double that in low-income countries. While improvements in AI preparedness and access can mitigate these disparities, they are unlikely to fully offset them. Moreover, the AI-driven productivity gains could reduce the traditional role of exchange rate adjustments due to AI's large impact in the non-tradable sector—a mechanism akin to an inverse Balassa-Samuelson effect.

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WORKING PAPERS

The Global Impact of AI: Mind the Gap

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1. Introduction

Artificial Intelligence (AI) holds the promise of raising productivity, stimulating innovation, and altering the nature of work across the globe.[1] Nevertheless, its adoption so far is uneven, largely reflecting deep-rooted structural differences among advanced economies (AEs), emerging markets (EMs), and low-income countries (LICs). Looking forward, countries with advanced technological infrastructure and skilled workforces are likely to be more exposed to AI and able to harness it more effectively, potentially boosting economic growth. In contrast, some EMs and most LICs may struggle to keep pace, exacerbating existing income disparities and widening the income gap between countries.

Such cross-country differences are driven to a large extent by variations in industrial structures and occupational composition that create distinct patterns of "*exposure*" to AI automation and/or augmentation. While certain economies boast a higher share of high-exposure occupations and industrial sectors primed for AI integration, others remain concentrated in less digitally intensive activities—potentially lowering both their immediate risks and potential gains.

Secondly, in addition to exposure, AI "*preparedness*" also plays a pivotal role. Factors such as strong institutions, a sophisticated digital infrastructure, and a skilled workforce can significantly influence how effectively AI is adopted and integrated. Even when highly exposed to AI in principle, countries lacking strong foundations may struggle to realize meaningful productivity gains, underscoring how institutional and policy readiness can determine whether AI supports sustained growth or exacerbates existing inequalities.

Thirdly, persistent disparities in AI "*access*"—spanning advanced hardware, data centers, and global partnerships—can further widen the divide between AI frontrunners and underperformers. Insofar as geopolitical and national security considerations may influence technology-sharing practices, these constraints could weigh heaviest on EMs and LICs with the fewest alternative channels for AI-intensive investment and innovation.

This paper aims at estimating the domestic and global impact of AI-induced productivity gains, adopting a modeling approach that accounts for countries' different production sectors and transmission channels. The analysis takes a two-pronged strategy. First, it links AI exposure, preparedness, and access to total factor productivity (TFP) growth driven by AI adoption. For this purpose, microdata on task- and sectoral-level jobs' exposures to AI are combined with country-specific measures of AI preparedness and assumptions on AI access to gauge their impact on TFP for each country in the sample, covering AEs, EMs and LICs.

Second, the AI exposure-, preparedness- and access-driven productivity differences are used as inputs into the IMF's Global Integrated Monetary and Fiscal model (GIMF),[2] a multi-sector, multi-region dynamic general equilibrium model to evaluate their global and regional impact on growth and other macroeconomic outcomes.

[1] AI represents a wide spectrum of technologies designed to enable machines to perceive, interpret, act, and learn with the intent to emulate human cognitive abilities. Across this spectrum, generative AI (GenAI) includes systems such as sophisticated large language models that can create new content, ranging from text to images, by learning from extensive training data. Other AI models, in contrast, are more specialized, focusing on discrete tasks such as pattern identification. Meanwhile, automation is characterized by its focus on optimizing repetitive tasks to boost productivity, rather than producing new content. The field of AI is experiencing a swift evolution, especially with the advent of GenAI, which has broadened AI's potential applications. This suggests that its impact will expand to reshape job functions and the division of labor.

[2] See Kumhof et al. (2010) and Anderson et al. (2013) for detailed expositions.

Specifically, each region’s economy is divided into three sectors—non-tradable, tradable, and AI-intensive—to capture cross-country and within-countries heterogeneities in AI adoption. AI-related productivity shocks enter the model through a TFP channel, scaled by the interaction of country level parameters capturing AI preparedness and access, and sector-specific parameters for AI exposure. In a nutshell, bridging micro-level insights with macro-level dynamics within a structural cross-country framework allows quantifying how varying institutional readiness, workforce configurations, and high-tech resources across AEs, EMs and LICs shape AI's impact on their economic outcomes.

The GIMF simulations show that the level of global GDP would expand by nearly 4 percent under a high TFP growth scenario and 1.3 percent under a low TFP growth scenario over the next decade, with underlying TFP gains of 0.8-2.4 percent over the same time horizon. However, these gains are unevenly distributed, with AEs benefiting disproportionately—potentially realizing up to twice the income gains of LICs. The United States (US) stands out, registering the largest projected output increases at 5.6 percent and 1.9 percent in the high and low TFP growth scenarios, respectively. Europe and other AEs also see notable gains, driven by their relatively high AI exposure and preparedness. China ranks near the middle in terms of growth outcomes, on account of high AI preparedness but relatively lower exposure, due to the greater relative importance of manufacturing compared to services vis-à-vis AEs.

Near-term inflation is projected to rise on account of higher investment and stronger aggregate demand, before stabilizing as TFP growth exert downward pressure on prices. Two alternative scenarios—“Limited AI Access” and “Enhanced AI Preparedness”—reveal that constraints on AI diffusion or policy-driven improvements in readiness can significantly shape regional outcomes. Indeed, in the scenario of Limited AI Access, disparities in growth between countries would increase, with the impact on U.S. growth exceeding that on LICs by more than threefold. Importantly, cross-country disparities persist even in the Enhanced AI Preparedness scenario, suggesting that policy interventions can mitigate but are unlikely to fully eliminate the uneven cross-country impact of AI adoption.

Other key international macroeconomic variables, such as exchange rates and current accounts, exhibit less obvious behavior. The economic literature frequently highlights how productivity gains in a country’s tradable sectors lead to an appreciation of its real exchange rate, known as the Balassa-Samuelson effect. However, our GIMF simulations indicate that AI-driven productivity shocks, particularly in non-tradable sectors, could be accompanied by a depreciation of AEs’ currencies relative to EMs and LICs due to downward pressure on non-tradable prices. For instance, AI-driven productivity gains in U.S. non-tradable sectors like education and healthcare, which benefit from advanced digital infrastructure and a highly skilled workforce, would lower the relative price of non-tradable services and the value of the U.S. dollar. The potential depreciation of AEs’ currencies would improve their current account, even with AEs' larger investments in AI.

Despite providing valuable insights into AI’s potential domestic and global macroeconomic impacts, the analysis makes simplifying assumptions, as is the case when using a model. First, GIMF’s representation of labor markets is stylized; for instance, it lacks explicit modeling of unemployment dynamics and shifts in labor force participation, which could be consequential when AI automates or augments certain occupations. Second, the productivity shocks used in the model rest on assumptions about AI adoption patterns, which may not fully capture how AI diffusion could vary in speed across different sectors, regions, and timeframes in the medium to long term. Third, by focusing on a few broad sectors, the model overlooks the wide range of differences within those sectors. Fourth, it does not consider the organizational and managerial complexities that often determine how AI is actually deployed. Finally, the paper does not address distributional effects within countries—such as wage inequality or wealth concentration—further underscoring that these findings, while suggestive, should be viewed as scenario-based estimates rather than definitive forecasts.

This work contributes to an expanding literature on the impact of AI on macroeconomic outcomes. Much of the literature focuses on the labor market implications of AI, often employing a task-based approach to identify how occupations and workers may be at risk of displacement or benefit from productivity gains (Acemoglu and Restrepo 2018, 2022; Felten, Raj, and Seamans 2021, 2023; Webb 2020; Eloundou et al. 2024; Cazzaniga et al. 2024). Empirical evidence remains largely concentrated on AEs, particularly the United States, although recent cross-country analyses by the OECD (2023), Albanesi et al. (2023), Briggs and Kodnani (2023), and Gmyrek, Berg, and Bescond (2023) underline the broad heterogeneity in AI's effects across regions. Pizzinelli et al. (2023) provides micro-level insights into how AI complements or substitutes labor in different occupations. Cazzaniga et al. (2024) examine AI's distributional consequences, emphasizing differential AI exposure across many diverse countries by demographic groups and the necessity for both social safety nets and enhanced AI preparedness. Rockall et al. (Forthcoming) studies the impact of AI adoption on income and wealth inequality in a model where AI adoption is endogenous. Alonso et al. (2022) show that technological advancements in robotics can widen economic gaps, benefiting advanced countries while potentially causing GDP declines in developing countries, especially when robots replace unskilled labor. Meanwhile, Brollo et al. (2024) and Berg et al. (2025) focus on the deployment of fiscal policies to make the impacts of the adoption of generative AI more inclusive, while acknowledging the substantial uncertainty around AI's speed and scope of adoption. Korinek and Juelfs (2023) explore the implications of transformative AI—where human labor might become redundant—highlighting the economic and societal challenges such an evolution could pose and examining strategies for effective preparedness.

Some researchers have also explored AI's expected macroeconomic effects more directly, albeit in single-country frameworks. Focusing on the U.S. economy, Acemoglu (2025) cautions that anticipated productivity gains may be modest once more challenging, context-dependent tasks are considered, and highlights potential inequality dynamics tied to AI-driven automation. Aghion and Bunel (2024) offer a more optimistic vision by identifying channels through which AI could substantially boost productivity growth, both at the task level and through idea generation. The novelty of our paper lies in integrating earlier insights related to AI exposure, preparedness and access within a multi-country, multisector model to offer scenarios on global impacts and regional differences for AEs, EMs, and LICs related to AI adoption.

The rest of the paper proceeds as follows. Section 2 discusses the conceptual framework underlying AI exposure, preparedness, and access, as key drivers of AI adoption and productivity gains. Section 3 describes the global macro model, the calibration strategy, and the scenarios. Section 4 discusses the simulation results and key macroeconomic outcomes of the baseline scenarios. Section 5 evaluates the impact of two policy interventions on cross-country growth outcomes. Finally, Section 6 concludes.

2. Drivers of AI Adoption

The global effort to adopt AI technologies has brough to light striking disparities among AEs, EMs, and LICs. These differences stem from a wide array of structural, economic, and institutional factors—from availability of high-quality data to supportive regulatory regimes. While some countries are well-positioned to invest heavily in AI-driven innovation, others struggle to develop or incorporate even the most basic AI solutions. The resulting gaps in competitiveness, productivity, and human capital accumulation risk reinforcing existing cross-country inequalities and creating new ones. To understand and start creating a strategy to address these challenges, it is helpful to examine distinct dimensions of AI adoption. Three critical elements shape a country's capacity to benefit from AI: the degree of *AI exposure* (how extensively AI can affect its workforce and industries), *AI preparedness* (the readiness of a country's institutions, digital infrastructure, workforce, regulatory frameworks and governance structures), and *AI access* (the availability of AI-specific technologies, data, and infrastructure, along with global partnerships, necessary to fully harness AI).

Exposure

Jobs serve as the primary conduit through which AI effects manifest in industries and economies. Building on task-based analyses, Acemoglu and Restrepo (2022) and Felten, Raj, and Seamans (2021, 2023) conceptualize "exposure" by mapping the overlap between AI capabilities and the abilities required in each occupation. Pizzinelli et al. (2023) refine this approach by considering an occupation's "complementarity" potential—a measure incorporating broader occupational factors that influence the likelihood of benefiting from AI adoption. Because occupational structures differ across countries, the share of "high-exposure" jobs can vary substantially—up to 60 percent in AEs versus 42 percent in EMs and 26 percent in LICs (Cazzaniga et al. 2024). These disparities imply that entire industries and national economies face different extents of AI-related disruption and opportunity. In AEs, the high proportion of jobs with substantial exposure (whether complemented or replaced) suggests a larger and more immediate potential for productivity gains, alongside risks of labor displacement. By contrast, many EMs and LICs, which have fewer "high-exposure" jobs, may experience a much more subdued integration of AI, though this could still lead to sizable marginal benefits if the right digital infrastructure and skills training are in place.

Preparedness

Preparedness for AI adoption is essential for harnessing its potential while mitigating inherent risks. Historical episodes of technological change show that macroeconomic outcomes are shaped by structural and institutional frameworks (Cirera, Comin, and Cruz 2022), meaning that a country's ability to benefit from new technologies depends heavily on its readiness. Building on the technology diffusion (Keller, 2004) and adoption (Nicoletti, Rueden, and Andrews 2020) literature, the IMF has constructed an AI Preparedness Index (AIPI), comprising digital infrastructure, innovation and economic integration, human capital and labor market policies, and regulation and ethics (Cazzaniga et al. 2024).[3] Robust digital infrastructure sets the foundation for AI uptake (Nicoletti, Rueden, and Andrews 2020), while a digitally skilled workforce is necessary to leverage new technologies effectively (Bartel, Ichniowski, and Shaw 2007). A workforce equipped with strong digital skills, combined with robust infrastructure, underpins innovation and economic integration (Autor, Levy, and Murnane 2003). This combination not only drives domestic technological progress by fostering a dynamic R&D environment, but also supports international trade, attracts foreign investment, and encourages the inflow of new technologies (Bloom, Draca, and Van Reenen 2015). Finally, effective and adaptable regulatory frameworks maintain trust in AI through governance and cybersecurity measures (Carriere-Swallow and Haksar 2019; Haksar et al. 2021; Bank of America 2023; Jamilov, Rey, and Tahoun 2023). The IMF's AIPI shows that AEs and some EMs generally exhibit stronger digital infrastructure, skilled labor, ecosystems for

[3] The AIPI measures AI readiness across 174 countries based on digital infrastructure, human capital, technological innovation, and legal frameworks. It draws on official data and perception surveys compiled by several institutions (Fraser Institute, ILO, ITU, UN, UNCTAD, UPU, World Bank, and WEF). Each dimension is calculated by normalizing and averaging a set of sub-indicators (e.g., digital connectivity, labor policies, R&D investment, and regulatory adaptability).

innovation and economic integration, and governance framework, enabling them to harness productivity gains and limit risks. In contrast, many LICs, though less immediately exposed to AI-driven disruption, remain severely underprepared.

Access

A key determinant of cross-country AI adoption is the availability of the specialized technologies, data, and infrastructure that underpin AI development and deployment. At one end of the spectrum, the United States with its partners and China possess extensive semiconductor manufacturing capabilities, high-capacity data centers, and robust data ecosystems, enabling them to remain at the leading edge of AI research. Recent policy actions reflect the growing importance of these assets: the United States, citing national security considerations, is reportedly planning to restrict exports of advanced AI chips on a country and company basis (Bloomberg, 2025), and the European Commission has asked member states to review outbound investments in semiconductors, AI, and quantum technologies to address economic security concerns (European Commission, 2025). Meanwhile, Chinese AI advancements, such as DeepSeek and Alibaba, have demonstrated their ability to narrow the performance gap with U.S. peers despite geopolitical considerations and export controls. Their success is partly due to cost-effective training methods and the open-source release of some large language models, which can help circumvent the need for top-tier hardware (DeepSeek, 2025).

These developments also underscore a widening divide between the countries with ready access to advanced AI components and those without. Many EMs and LICs face limited availability of cutting-edge processors, large-scale computing clusters, or robust data repositories—deficits that constrain their capacity to innovate and compete in sectors exposed to AI. Uncertainties about future trade and technology restrictions add to these challenges, potentially limiting opportunities for technology transfers and collaboration. As a result, access to AI-specific resources—chips, data, and infrastructure—risks becoming a further source of global inequality, cementing the advantage of economies that can produce or readily acquire the critical inputs needed to harness AI’s transformative power.

3. Model, Calibration and Scenarios

Model

The analysis of the paper relies on the IMF’s Global Integrated Monetary and Fiscal Model (GIMF), a multi-region, multi-sector dynamic general equilibrium model. For a comprehensive survey of the model, see the foundational work by Kumhof et al. (2010) and Anderson et al. (2013). The model has been widely used for policy simulations, including Coenen et al. (2012) and Freedman et al. (2010). Recent and related applications of GIMF can be found in IMF (2023), Wingender et al. (2024) and Carton and Muir (Forthcoming).

These applications use GIMF-GVC—an extended version of the standard two-sector version of GIMF (tradable and non-tradable)—which adds a second tradable sector featuring global values chains. This is an important feature that allows from broader spillovers of shocks across countries, including supply-side and network effects, which are key considerations for analyzing the global impact of AI. This framework is used to simulate the domestic and global macroeconomic impacts of AI by evaluating changes in TFP across different scenarios and countries/regions.

GIMF focuses on the dynamic effects of shocks, with a distinction between the short term, during which nominal and real rigidities tend to amplify the effects of shocks on aggregate demand, and the medium to long term, during which the effects stem mainly from the permanent impact of productivity changes on the levels of key factors for production, that is, capital and labor. The model differs from detailed multi-country multi-sector static trade models by allowing for richer characterization of forward-looking decisions such as consumption, savings and investment. It also includes several macro policy levers like monetary and fiscal policies, which can impact both short and long run effects of shocks. The inclusion of the dynamic and policy dimensions, however, comes at the cost of a more stylized treatment of intra-temporal channels such as a higher degree of sectoral details as well as full input-output relationships across sectors.

The model is micro-founded and features two types of households in each region, each receiving labor income and lumpsum transfers from the government, and subject to consumption and labor income taxes. A first type is composed of finitely lived households in an overlapping generation structure (OLG) who make forward-looking consumption, savings, and labor supply decisions. In their budget constraint, OLG households also hold financial assets, including government and corporate bonds, and net foreign assets. A second group of households are liquidity-constrained, consume all their income every period and follow the labor supply decision set by the OLG households.

Production is determined by firms operating in monopolistically competitive markets, which set their profit-maximizing prices subject to nominal rigidities and a residual demand schedule.[4] As mentioned above, firms in the GIMF-GVC version produce non-tradable, tradable, and AI-intensive goods and services. This last category is a composite of tradable sectors that are most exposed to AI based on the exposure indicator calculated by Cazzaniga et al. (2024). The list of ISIC 2-digit sectors for the non-tradable, tradable and AI-intensive broad sectors is provided in Annex Table I. This broad sector is included in GIMF to capture some of the network externalities inherent to the development of AI technologies. Firms in the AI-intensive sector use some of the sector's composite output as intermediate consumption, which can be sourced either domestically or from foreign producers through AI-intensive global value chains. Finally, firms in the non-tradable and tradable sectors use a Cobb-Douglas technology to combine labor and capital. There is no foreign ownership in GIMF.

Investment is chosen by firms to maximize profits, subject to real adjustment costs. Investment requires inputs sourced both domestically and from foreign regions, which are not perfect substitutes. Investment also features a financial accelerator mechanism as in Bernanke, Gertler and Gilchrist (1999). Firms need to finance their investment, but their retained earnings are insufficient to provide full financing, so they must borrow from financial intermediaries. Corporate risk premia in the model are determined endogenously.

The long-term determination of the real global interest rate is ensured by balancing global savings and investment. The real exchange rate serves to adjust each country's saving position (its current account and associated stock of net foreign assets) relative to the global pool. Each region trades with the rest of the world and trade flows are tracked bilaterally in the model and separated into four types of flows. Two types of final goods (either for consumption or investment) and two types of intermediate goods and services (either tradable or AI-intensive goods and services). Trade flows react to demand, supply and pricing (i.e., the terms of trade and bilateral real exchange rates) conditions.

[4] Nominal rigidities are modeled as menu costs following the Ireland (2001) version of Rotemberg (1982). In this specification, adjustment costs apply to changes in both the price level and the inflation rate.

Finally, GIMF also features a rich characterization of macroeconomic policies. Each region's fiscal policy pursues the twin objective of debt sustainability in the long run. i.e., ensuring a non-explosive government-debt-to-GDP path, and output stabilization in the short run. Monetary policy is similarly set to respond to shocks according to inflation forecast-based targeting. While monetary policy helps shape the economy's dynamics over the first five to ten years, it has no implications for the long-term outcomes in the real economy.

An AI shock is applied to the model with region- and sector-specific sizes, as described below. Unlike task-based models, this approach does not focus on worker replacement or augmentation, which are essential for studying the effects of AI on within-country inequality, an area that is not the focus of this paper.

Calibration

The GIMF calibration encompasses seven regions: China (CHN), Emerging Market Economies Asia, Central Asia, Russia, etc. (EMA); Emerging Market Economies Latin America, Middle East, Africa, etc. (EML); EU and Switzerland (EUS); Other advanced economies (OAD); the United States (USA); and a residual group, Rest of the World (ROW), which represents mainly LICs. More details about the grouping of countries can be found in Annex II. The OECD Inter-Country Input-Output database is used to calibrate input and trade shares, and value added by country and sector (Table 1).[5] Fiscal ratios are calculated from the IMF's Government Finance Statistics database.

GDP is produced in three sectors. Non-tradables are largely composed of construction and services, while tradables consist mainly of agriculture, mining, manufacturing and transportation activities. A third sector is composed of tradable goods and services that are particularly exposed to AI as measured by the sectoral index compiled using the approach by Cazzaniga et al. (2024). These include pharmaceuticals, computers, telecommunications and finance (see Annex Table I for the full list of sectors). This sector also features global value chains through roundabout production, meaning that firms in the sector use output from the sector, either domestic or foreign as an intermediate input.

Table 1 shows the importance of each sector for the different regions and Annex I contains the granular definition of each sector. Looking at value added by sector at the bottom of Table 1, the US stands out with 16.3 percent of GDP coming from the AI-intensive sector. However, it trades less in those goods and services as a share of GDP compared to the other regions, because the U.S. economy, more generally, trades much less overall with the rest of the world relative to other regions. Other advanced economies (OAD) and the EU-Switzerland region (EUS) also have a large share of total activity taking place in the AI-intensive sector, with 14.1 and 12.9 percent of GDP being produced in that sector, respectively. The AI-intensive sector in China represents 12.1 percent of GDP, ahead of other emerging and LIC regions. As a share of its exports (as opposed to share of GDP), AI-intensive exports are also largest, after the US, in the EU-Switzerland region and in other advanced economies.[6]

[5] Non-tradable and tradable goods are only produced using labor and capital. This requires a rebalancing of the input-output data by reassigning intermediate trade flows.

[6] It is important to highlight that these shares illustrate the relative size of the sector, encompassing industries that might be substantially impacted by AI. The actual adoption of AI is heavily influenced by the share of occupations exposed to AI in the sector, as well as AI preparedness, as discussed below.

Table 1. Region Size, by GDP Components and Sectors

	CHN	EMA	EML	EUS	LIC	OAD	USA	ROW
Share in World GDP (percent)								
	16.8	8.5	7.1	18.2	1.5	17.4	25.1	5.5
GDP by expenditure (percent of regional GDP)								
	CHN	EMA	EML	EUS	LIC	OAD	USA	ROW
Consumption	69.7	71.8	80.1	75.2	74.5	75.3	77.3	74.2
Investment	30.3	28.2	19.9	24.8	25.5	24.7	22.7	25.8
Exports	16.6	23.3	22.4	19.7	32.8	23.1	10.7	29.3
o/w AI-intensive	2.1	2.7	1.3	2.8	2.7	3.5	1.9	1.2
Imports	16.6	23.3	22.4	19.7	32.8	23.1	10.7	29.3
o/w AI-intensive	1.9	2.6	2.4	3.0	2.5	3.0	1.5	3.1
GDP by production (percent of regional GDP)								
	CHN	EMA	EML	EUS	LIC	OAD	USA	ROW
Non-tradable	60.0	55.7	61.3	64.2	51.6	66.1	68.0	56.3
Tradable	27.9	33.6	30.0	22.9	36.5	19.7	15.6	37.3
AI-intensive	12.1	10.7	8.7	12.9	11.9	14.1	16.3	6.4

Note: EMA = Emerging Market Economies Asia, Central, Asia, Russia, etc. EML = Emerging Market Economies Latin America, Middle East, Africa, etc. EUS = EU and Switzerland, LIC = Low-income countries, OAD = Other advanced economies and ROW = Rest of the World. The detailed composition of the countries in each group is presented in Annex II.

Elasticities in GIMF are calibrated broadly equally across regions, including for trade (reflecting the ease with which firms can substitute between producers from different countries) and the combination of various goods and factors to produce final goods. The elasticities of substitution for the AI-intensive sector are set at a slightly lower level than other types of goods. Similarly, substitutability between factors and intermediate inputs in the AI-intensive sector is set lower to reflect the importance of supplier-specific relations in the production process of new goods and services (Table 2).[7]

Table 2. Calibration of Key Production and Trade and Elasticities, All Regions

	Domestic / imported	Different regions	Capital-labor / intermediate inputs
Consumption	1.50	1.50	
Investment	1.50	1.50	
Tradable	1.50	1.50	
AI-intensive	0.60	0.60	0.60

Note: Elasticities are based on standard GIMF calibration. *Domestic / imported* refer to the elasticity of substitution between the different types of goods (*Consumption, Investment, Tradable and AI-intensive*) between domestic variety and a composite of foreign varieties. *Different regions* refer to the elasticity of substitution between different regions (trade elasticity). *Capital-labor / intermediate inputs* is the elasticity of substitution between a capital-labor bundle and an intermediate input bundle used in the production of the AI-intensive good.

Finally, markups are calibrated to reflect firms' market power by sector and region (Table 3). The parameter for domestic markups for AI-intensive firms is set at a higher level than the other sectors based on the assumption

[7] In contrast with final goods, intermediate goods depend on specific types of capital such as computing and skilled labor such as programmers that are more difficult to change in the short run.

of higher market power arising from potential network effects and winner-take-all dynamics.[8] LICs are assumed to have lower markups for imported goods than other regions, reflecting an assumption of lower market power for these countries on global markets.

Table 3. Calibration of Markups by Sector and Country Group

	Domestic	Imported	
		AE/EM	LIC
Consumption	1.10	1.05	1.01
Investment	1.05	1.05	1.01
Tradable	1.20	1.05	1.01
AI-intensive	1.25	1.05	1.01
Non-tradable	1.20		

Calibration of Productivity Shocks

To generate the simulations, growth in TFP is assumed to be delivered by Gen-AI adoption in each broad economic sector. The size of the shock at time *t* differs across regions, sectors and scenarios. First, a region-specific TFP shock is obtained by rescaling a benchmark TFP shock in country *b* proportionally to the product of a (region-specific, *i*) *AI preparedness* index and an *AI exposure* index, and multiplying it by a region-specific *AI-Access* index:

$$TFP\ shock_{i,t} = \frac{AI\ preparedness_i \times AI\ exposure_i}{AI\ preparedness_b \times AI\ exposure_b} \times AI\ Access_i \times TFP\ shock_{b,t} \quad (1)$$

Then, the region-specific TFP shock is apportioned to each sector *j* proportionally to the relative sectoral AI exposure in each region:

$$TFP\ shock_{i,j,t} = \frac{AI\ exposure_{i,j}}{AI\ exposure_i} \times TFP\ shock_{i,t} \quad (2)$$

Table 4 reports the AI exposure and preparedness levels by region and sector used to rescale the TFP shocks. Two possible benchmark TFP shocks (*high* and *low*) are utilized in the simulations. Details on the assumptions regarding all factors affecting the TFP shocks are explained below.

[8] Results are robust to alternative assumptions about markups for the AI-intensive sector.

Table 4. AI Exposure and Preparedness by Region and Sector

Country groups	Abbreviation	Sector	AI exposure	AI preparedness
China	CHN	Tradable	0.30	
		Non-tradable	0.43	0.64
		AI-intensive	0.58	
Emerging Market Economies Asia, Central Asia, Russia, etc.	EMA	Tradable	0.18	
		Non-tradable	0.41	0.50
		AI-intensive	0.72	
Emerging Market Economies Latin America, Middle East, Africa, etc.	EML	Tradable	0.24	
		Non-tradable	0.46	0.50
		AI-intensive	0.72	
EU and Switzerland	EUS	Tradable	0.40	
		Non-tradable	0.60	0.68
		AI-intensive	0.82	
Low-income countries	LIC	Tradable	0.17	
		Non-tradable	0.47	0.35
		AI-intensive	0.72	
Other advanced economies	OAD	Tradable	0.36	
		Non-tradable	0.56	0.73
		AI-intensive	0.77	
United States	USA	Tradable	0.43	
		Non-tradable	0.67	0.77
		AI-intensive	0.85	

Sources: Cazzaniga et al. (2024), and IMF staff calculations.

Note: The levels of AI preparedness are the same across the sectors within a country. EMA = Emerging Market Economies Asia, Central, Asia, Russia, etc. EML = Emerging Market Economies Latin America, Middle East, Africa, etc. EUS = EU and Switzerland, LIC = Low-income countries, and OAD = Other advanced economies. The detailed composition of the countries in each group is presented in Annex II. For ROW, the values of LIC are used.

AI Access

In the remainder of the paper, most scenarios assume unrestricted access to AI-specific technologies in all regions ($AI\ Access_i = 1, \forall i$). Therefore, cross-country differences are driven exclusively by the different sector-region-level exposure and region-specific preparedness. In a *Limited AI Access Scenario* (see below), this variable is assumed to remain equal to one in AEs and China, while being reduced to 0.5 in other EMs and LICs.

AI Exposure

Building on the Occupational AI Exposure (AIOE) index developed by Felten, Raj, and Seamans (2021) and following Pizzinelli et al. (2023), jobs are classified as highly exposed to AI when their AIOE exceeds its median. This approach is used to construct a sectoral AI exposure measure, which is defined as the share of employment in each sector that falls in the highly AI-exposed category, following the following formula:

$$AI\ Exposure_{i,j} = \frac{\sum_o emp_{o,i,j} \cdot 1(AIOE_o > median(AIOE))}{\sum_o emp_{o,i,j}} \quad (3)$$

where $emp_{o,i,j}$ denotes employment in occupation o, sector j, and country i. ILO data is used to compute employment by occupation (ISCO-08) and economic activity (ISIC Rev. 4). This approach extends country-level estimates of AI exposure of Cazzaniga et al. (2024) to sectors and model regions. This approach implies that sectoral TFP gains are proportional to the employment exposure to AI in each given sector. It is important to note that the integration of AI technologies with robotics may result in greater benefits for robots and machines than what employment-based AI exposure might suggest. AEs are generally more exposed to AI than EMs and LICs. The US stands out as the country with the highest exposure to AI. Within countries and regions, a systematic pattern is found where the AI-intensive sector has the highest exposure to AI, the non-tradable sector has the second highest exposure, and the tradable sector has the lowest exposure to AI (Table 4).

AI Preparedness

Country-level estimates of AI preparedness are taken from Cazzaniga et al. (2024). This is known as the IMF AI Preparedness Index (AIPI) and is constructed as the simple average of its normalized components: digital infrastructure, human capital and labor market policies, digital innovation and economic integration, and regulation and ethics. The AIPI for each model region is obtained by taking averages of country values. In terms of AI preparedness, there is also a clear ranking with the US and other AEs at the top, followed by EMs and LICs (Table 4).

Benchmark TFP Growth

The magnitude of growth in TFP driven by GenAI remains a highly debated topic, marked by significant uncertainty. A prominent example is the 10-year output impact for the U.S. economy discussed by Acemoglu (2025) and Aghion and Bunel (2024). These authors, even when using the same conceptual framework, arrive at very different estimates of the share of tasks impacted by AI as well as different cost savings in these tasks, ultimately delivering very different TFP impacts.

Acemoglu (2025) concludes that AI will lead to TFP gains of around 0.7 percent over the next 10 years, translating into an annual TFP growth increase of about 0.07 percentage points. This estimate hinges on 4.6 percent of tasks being replaced profitably by AI, and a 27 percent increase in productivity due to labor cost savings.[9] [10]

In contrast, Aghion and Bunel (2024) arrive at a much higher TFP growth estimate. Their estimate is based on three key parameters: the share of tasks exposed to AI in developed countries estimated at 60 percent; (ii) the share of exposed tasks for which it will be profitable to use AI estimated at 50 percent (Besiroglu and Hobbhahn, 2022); and (iii) labor saving costs induced by AI of 40 percent (Peng et al., 2023; Noy and Zhang, 2023; Brynjolfsson et al., 2023), which taken together imply a cumulative median 6.8 percent TFP growth over 10 years, or 0.7 per year (their range of estimates is 0.7 to 12.4 percent cumulative TFP growth over a ten-year horizon).

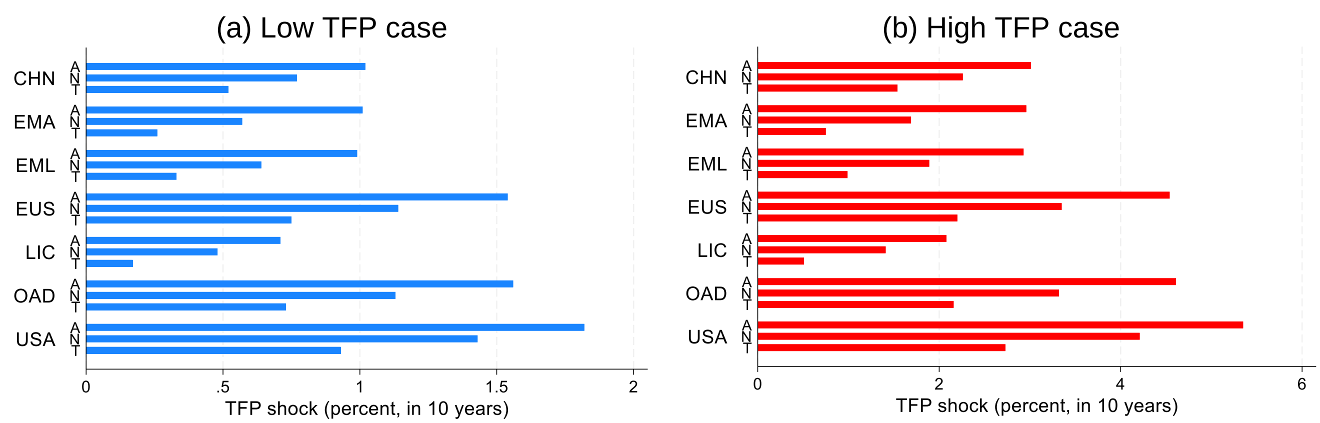
Considering this wide uncertainty, this paper uses two alternative benchmark assumptions regarding the AI-driven TFP impact, rooted in the simulations for the UK of Cazzaniga et al. (2024) and Rockall et al. (forthcoming), who find a TFP increase between 1.3 and 3.4 percent over a ten-year horizon. Rescaling these impacts by AI exposure and preparedness, using equation (1) delivers economy-wide values of 1.5 and 4.3

[9] Acemoglu's (2025) TFP gains are estimated using this intuitive equation: TFP gains over 10 years = GDP share impacted by AI over the next 10 years × average cost savings of impacted tasks. Drawing on Eloundou et al.'s (2024) findings, Acemoglu (2025) sets all tasks classified as having 50 percent or less of their activities impacted by AI and computer vision as not exposed, and the rest of tasks as "AI exposed tasks." He then calculates the wage bill of these occupations, and finds that they account for 20 percent of the aggregate wage bill. Following Svanberg et al. (2024) he assumes that only 23 percent of these tasks are profitable to automate leading to 0.23 X 0.20 = 0.046 tasks being exposed. Last, he assumes that the cost saving of the impacted tasks is equal to 27 percent.

[10] Relatedly, using Acemoglu's (2025) framework, Misch et al. (Forthcoming) estimate that cumulative productivity gains for Europe are about 0.8 percent over five years when the economic structure of Europe is considered, but the AI adoption rates and labor cost savings of Acemoglu (2025) are used. They also find that the cumulative productivity gains would be about 1.1 percent over five years when country-specific AI adoption rates and AO exposure measure from the baseline take-based estimates of Eloundou et al. (2024) are used.

percent for the US. While the *low* benchmark is about double the impact predicted by Acemoglu (2025), it still represents a very modest TFP effect driven by AI.[11] The *high* benchmark is closer to (but still significantly smaller than) the proposed median TFP gain of Aghion and Bunel (2024). Figure 1 contains the values of TFP shocks under the low and high TFP growth scenarios across model regions and sectors. Higher overall TFP shocks are observed in regions with greater exposure and preparedness to AI, notably in the US and other AEs. Similarly, higher sectoral TFP shocks within each region are associated with greater sectoral exposure to AI, with the AI-intensive sector experiencing the largest impacts, followed by non-tradables and tradables.

Figure 1. TFP Shocks under Baseline Scenarios (Low and High TFP Growth Scenarios)



Note: The left and right panel show TFP shocks under the low TFP growth baseline scenario and the high TFP growth baseline scenario, respectively. N, T and A stand for the non-tradable, tradable and AI-intensive sectors, respectively. EMA = Emerging Market Economies Asia, Central, Asia, Russia, etc. EML = Emerging Market Economies Latin America, Middle East, Africa, etc. EUS = EU and Switzerland, LIC = Low-income countries, and OAD = Other advanced economies. The detailed composition of the countries in each group is presented in Annex II. For ROW, the values of LIC are used.

Scenarios

All the factors affecting TFP discussed in the previous subsection contribute to building a number of scenarios meant to evaluate the macroeconomic consequences of AI diffusion across countries at different levels of development. The scenarios considered are three:

- *Baseline Scenario:* This scenario assumes no direct impediments to AI adoption, such that all regions have unrestricted access to AI-related technologies and data. Differences in AI preparedness and exposure remain, however, leading to heterogeneous productivity gains across regions and sectors $(AI\ Access_i = 1, \forall i)$.
- *Limited AI Access Scenario:* Here, EMs (except China) and LICs face constraints on the availability of AI-specific technologies, motivated by geopolitical considerations and potential export restrictions. The resulting shortage of advanced processors, data-sharing platforms, and supportive infrastructure halves TFP growth in these economies $(AI\ Access_i = 0.5, \forall i = EMA, EML, LIC)$.

[11] While it is difficult to directly compare the TFP impact estimated by Acemoglu (2025) and Rockall et al. (Forthcoming), as the latter is derived from a macroeconomic model, both studies assume similar productivity gains driven by labor cost savings from AI adoption. However, Acemoglu (2025) assumes that only 20 percent of tasks are exposed to AI, and of those, only 50 percent are profitable to automate. In contrast, Rockall et al. (Forthcoming) take a macroeconomic approach, assuming that the labor share will decline at the same rate as during the automation period, leading to task displacement at the aggregate level.

- *Enhanced AI Preparedness Scenario:* Under this scenario, domestic policy reforms and international support allow emerging markets and low-income countries to raise their AI preparedness to levels commensurate with the highest performers in their respective peer groups. This improvement in institutional readiness increases the scope for AI-driven productivity gains.

The baseline scenario is further examined under two alternative assumptions about TFP growth:

- A *low TFP growth simulation*—in the spirit of the more conservative projections of Acemoglu (2025)—which posit modest gains from AI, reflecting slower technology adoption and diffusion.
- A *high TFP growth simulation*—more akin to the optimistic outlook in Aghion and Bunel (2024)—which envisions substantial productivity advances.[12]

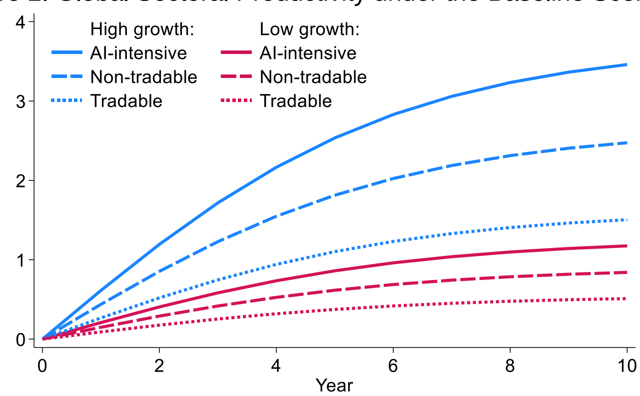
4. Baseline Results

This section presents the results of the high TFP and low TFP growth baseline scenarios discussed in Section 3, which assumes unrestricted access to AI technologies. The impact of AI shocks on productivity is discussed first, followed by the implications for output, inflation, exchange rates and current accounts.

Impact on Productivity

In the high-TFP growth baseline scenario, global TFP increases by 1.8 percent in five years, and 2.4 percent in ten years, with more productivity gains in the AI-intensive sector given its higher exposure to AI technologies, followed by the non-tradable and tradable sectors. The increase is much more modest in the low-productivity baseline scenario, with an increment of 0.6 percent in five years, and 0.8 percent in ten years, and reduced impacts on the respective sectors. Under both TFP assumptions, AI-intensive sectors worldwide see the largest increase, followed by non-tradables and, lastly by tradables (Figure 2).

Figure 2. Global Sectoral Productivity under the Baseline Scenarios



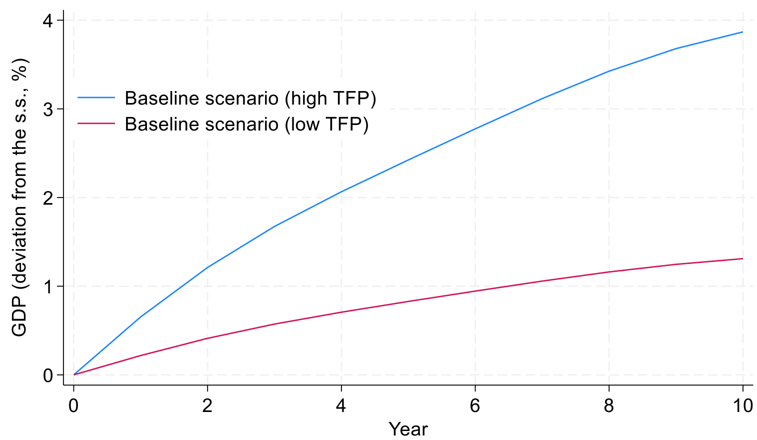
Note: The panel shows the global sectoral TFP under the high TFP growth baseline scenario (the blue lines) and the low TFP growth baseline scenario (the red lines), both as the deviations from the steady state.

[12] The limited AI access scenario and the enhanced AI preparedness scenario are examined based on high TFP growth assumption. While quantitatively different, the choice of TFP growth assumptions will not alter the qualitative implication of the scenarios.

Impact on GDP

With these productivity shock assumptions, world GDP is projected to rise by 2.4 percent in five years in the high TFP growth baseline scenario (Figure 3). As the productivity gains continue to materialize, the increase in the global output level reaches nearly 4 percent in ten years. This surge is driven both by the assumed productivity gains and the endogenous behavior of the variables in the model, notably the accumulation of capital stock and the evolution of aggregate demand. Policy variables, including monetary policy and fiscal policy, are assumed to adjust endogenously in response to macroeconomic conditions. In the low productivity baseline scenario, the increase in world GDP is more modest, amounting to 0.8 percent in five years, and 1.3 in ten years.

Figure 3. World GDP under the Baseline Scenarios



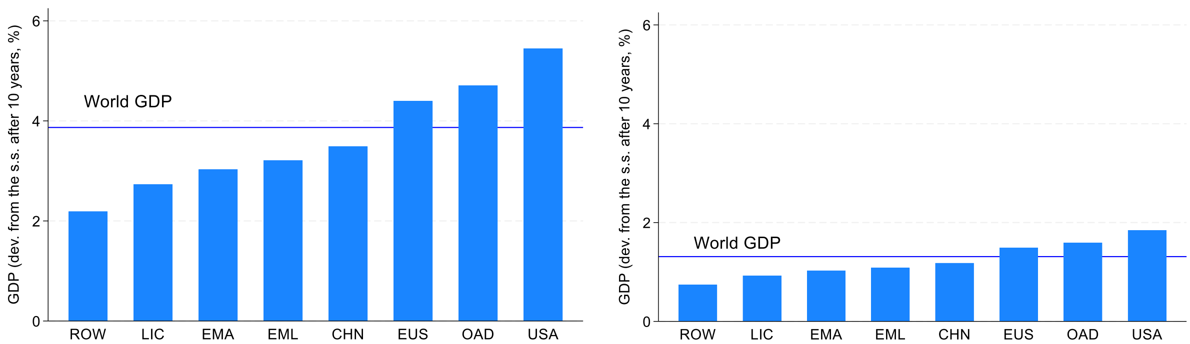
Note: The panel shows the world GDP under the low- and high-TFP growth baseline scenarios as the deviation from the steady state.

The global impact of the AI shock masks significantly uneven effects, with benefits disproportionally accruing to AEs. The U.S., Euro Area, and other AEs benefit the most under both productivity growth assumptions, with output increasing by 5.4 (1.8) percent in the U.S., 4.4 (1.5) percent in the EU and Switzerland, and 4.7 (1.6) percent in other AEs after 10 years in the high (low) productivity growth baseline scenario (Figure 4(a) and (b)). The particularly strong performance of the U.S. reflects both their strong AI preparedness, and their high occupational exposure to AI, which extends to dominant sectors in the economy.

Conversely, the impact on EMs and LICs is more modest, even though their access to AI technologies is not restricted in the baseline scenarios. The output increases by 3.2 (1.1) percent in EML, by 3.0 (1.0) percent in EMA, by 2.7 (0.9) percent in LIC, and by 2.2 (0.7) percent in the ROW after 10 years in the high (low) productivity growth baseline scenario. This reflects their weaker AI preparedness and a labor market and industrial structure less exposed to AI, particularly in LICs with a high share of employment in the agricultural sector and in manual occupations, which are much less exposed to AI. China is an interesting case: while the country is an innovation hub and is relatively well-prepared for smooth AI adoption, its high specialization in the manufacturing sector, as well as relatively lower share of AI-intensive occupations in the other sectors, make the economy overall relatively less exposed to AI, thereby reducing AI's macroeconomic impact relative to AEs, with output gains of 3.5 (1.2) percent after 10 years in the high (low) productivity growth baseline scenario.[13]

Figure 4. Cross-Country Differences of GDP in the Baseline Scenarios

(a) High TFP Growth Baseline Scenario (b) Low TFP Growth Baseline Scenario



Note: The left panel show the deviations of real GDP from the steady state for the high TFP growth baseline scenario after 10 years. The right panel show the deviations of real GDP from the steady state for the low TFP growth baseline scenario after 10 years. The global averages are shown as horizontal lines. EMA = Emerging Market Economies Asia, Central, Asia, Russia, etc. EML = Emerging Market Economies Latin America, Middle East, Africa, etc. EUS = EU and Switzerland, LIC = Low-income countries, OAD = Other advanced economies and ROW = Rest of the World. The detailed composition of the countries in each group is presented in Annex II.

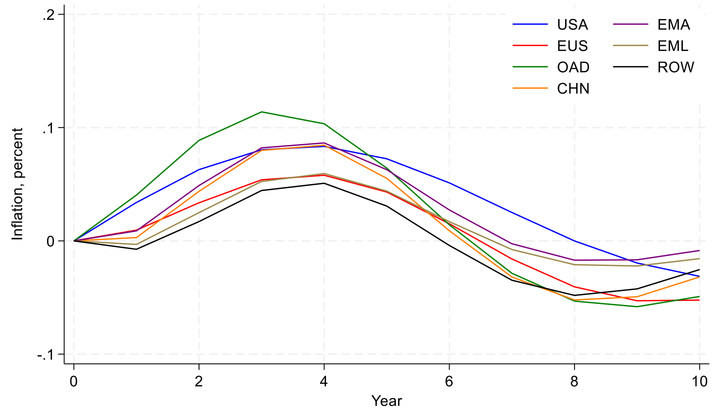
Impact on Inflation

The literature on the inflationary impact of technological shocks offers a variety of results. While positive productivity shocks tend to be disinflationary (e.g. Smets and Wouter, 2007), news shocks about future productivity trajectories can have inflationary effects (e.g. Jinnai 2013). In the GIMF simulations that embed nominal rigidities and monetary policy in an open-economy setting, inflation is estimated to increase modestly in the short term (Figure 5).[14] In response to the initial AI-related productivity shocks, aggregate demand increases, reflecting concurrent and expected income gains from higher productivity, which adds inflationary pressure. In the long term, increased supply capacity, driven by productivity gains and capital accumulation more than offset the demand-driven inflationary pressures, leading to a decline in inflation. In the model, the central banks also adjust policy rates, tightening them modestly in the short-term given the inflationary pressure. Although Figure 5 specifically presents the findings achieved under the high TFP growth assumption, the results are qualitatively similar, albeit reduced, when considering the low TFP growth assumption. This feature applies also to the effect on exchange rates and current accounts, which are presented below only under the high TFP growth assumption in the interest of brevity.

[13] As discussed in Section 3, we assume that TFP gains in the sectors are proportional to employment-based exposure of the sectors. to AI technologies. While the employment-based AI exposure in China's manufacturing sector is relatively low, it is possible that capital in the sector such as robots and machines will benefit from AI technologies more than the proportion suggested by the employment-based AI exposure.

[14] This finding relates to Aldasoro et al. (2024), which study the impact of AI on output, employment, and inflation in a closed-economy, multi-sector general equilibrium model. In that setting inflation depends crucially on households' and firms' expectation, and AI could have a disinflationary impact in the short term if they do not anticipate future productivity increase. In models with unemployment, insofar as AI adoption leads to some job displacement, the initial increase in inflation could be even more muted.

Figure 5. Inflation in the High TFP Growth baseline scenarios

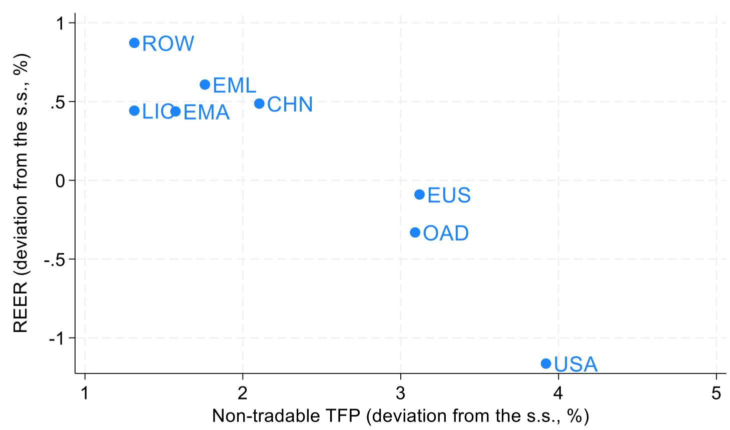


Note: The values are shown as deviations from the steady state. EMA = Emerging Market Economies Asia, Central, Asia, Russia, etc. EML = Emerging Market Economies Latin America, Middle East, Africa, etc. EUS = EU and Switzerland, LIC = Low-income countries, OAD = Other advanced economies and ROW = Rest of the World. The detailed composition of the countries in each group is presented in Annex II.

Impact on Exchange Rates and Current Accounts

The GIMF model results show that the broad sectoral reach and the characteristics of AI shocks across sectors and countries would trigger a modest real depreciation of AE currencies, notably the US Dollar. Specifically, the large increase in productivity in the US non-tradable sector relative to other countries' non-tradable sectors generates a real depreciation of the US Dollar relative to other currencies (conventional textbook channel shown in Figure 6).The US Dollar's depreciation would be most significant relative to LICs and EMs, while still evident but less pronounced compared to other AEs, reflecting larger US gains in non-tradable productivity.

Figure 6. Changes in Real Effective Exchange Rates and Non-tradable Sector TFP (10-year horizon)



Note: The values are shown as deviations of high TFP growth scenario outcomes from the steady state after 10 years. See Annex I for the list of ISIC sectors included in the Non-tradable sector. EMA = Emerging Market Economies Asia, Central, Asia, Russia, etc. EML = Emerging Market Economies Latin America, Middle East, Africa, etc. EUS = EU and Switzerland, LIC = Low-income countries, OAD = Other advanced economies and ROW = Rest of the World. The detailed composition of the countries in each group is presented in Annex II.

At first glance, this result may seem surprising because the economic literature has traditionally focused on how productivity gains in a country's tradable sectors often result in the real appreciation of its currency, a relationship known as the Balassa-Samuelson effect. This effect captures that the increase in the productivity of tradables leads to a positive impact on overall wages in the economy and therefore also increases the prices of non-tradables.[15] This makes prices higher in the country, leading to a real appreciation. In the case of AI shocks, the relatively higher increase in the productivity of non-tradables lowers the relative prices of non-tradables, and wages simultaneously rise and become equalized across sectors within each region, since there are no inter-sectoral labor market frictions in the model. Because the tradable sector must also pay these higher wages, the real exchange rate depreciates further to maintain international competitiveness for tradables. This is sometimes referred to in the literature as the "Inverse" Balassa-Samuelson effect, whereby productivity gains in non-tradables cause a real exchange rates depreciation, in the opposite direction of what is envisaged in the traditional textbook effect.[16]

In other words, these simulations of the global impact of AI highlights that real depreciation pressures for AE's would take place due to the substantial productivity gains in AEs' non-tradable sectors like education and healthcare, which are likely to benefit from AEs' advanced digital infrastructure and a workforce with a more AI-compatible skill set. This enhanced productivity would lead to a decrease in the relative price of AEs' non-tradable goods and services, culminating in a real depreciation of the US Dollar and other AE's currencies.[17]

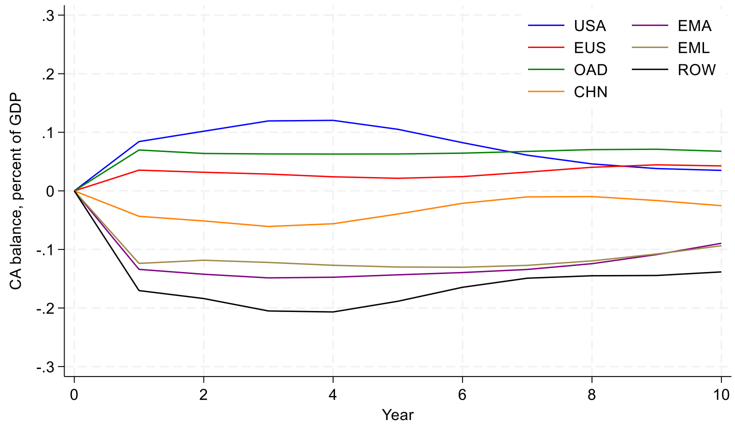
As a result of these exchange rate dynamics, the US and other AEs' current account would experience a moderate increase (Figure 7) stemming from two opposing forces that are at play in these results: (i) the depreciation of the US Dollar and other AEs' exchange rates relative to other currencies would increase U.S. net exports and the current account balance, and (ii) the higher investment driven by the AI shock would push AEs' current account into a further deficit. The former effect is quantitatively stronger than the latter.

[15] While empirical work finds that the relative productivity levels in tradable and non-tradable sectors has a role in the behavior of exchange rates (the so-called Balassa-Samuelson effect), other factors such as the impact of relative productivity and product market competition in the tradable/non-tradable sectors play a role on exchange rates. See Bordo et al. (2017) and MacDonald and Ricci (2007) for a review.

[16] Dadam et al. (2019) suggest that this inverse effect was present due to larger productivity gains in the service sector in the case of South Africa. In addition, Lopez-Marmolejo et al. (2023) analyze its recent potential presence in Mexico due to the declining productivity in the oil sector relative to the non-tradable sector.

[17] In our estimations, all countries/groups would experience larger productivity gains in the non-tradable sector than the weighted average of the tradable and AI-intensive sector (which is also a tradable sector). The larger relative dimension of the non-tradable sector in AEs, notably the US, implies that greater productivity gains in that sector also favor an appreciation of the exchange rate.

Figure 7. Current Accounts in the High TFP Growth Baseline Scenario



Note: The values are shown as deviations of baseline high TFP scenario outcomes from the steady state projection. EMA = Emerging Market Economies Asia, Central, Asia, Russia, etc. EML = Emerging Market Economies Latin America, Middle East, Africa, etc. EUS = EU and Switzerland, LIC = Low-income countries, OAD = Other advanced economies and ROW = Rest of the World. The detailed composition of the countries in each group is presented in Annex II.

Relation with Past Episodes of Technological Change

In the past, the world has often witnessed the invention of new technologies, including general-purpose technologies such as electricity and the Internet/Information and Communication Technology (ICT), as well as technologies with wide-reaching impacts such as shipping containers. The Internet revolution, originating from the Advanced Research Project Agency Network developed by the US Department of Defense in the late 1960s, marked a pivotal chapter in innovation history. The emergence of ICT, closely intertwined with the rise of the Internet, marked a transformative era in the way information is disseminated, and communications are conducted globally. Studies examining the macroeconomic impacts of ICT in advanced economies argue that ICT-related productivity gains and capital accumulation explained about 30-50 percent of aggregate labor productivity growth in the 1990s and early 2000s (e.g., Jorgenson, 2001; Jorgenson and Nomura, 2005; Jorgenson et al. 2008; van Ark et al., 2003; Oliner et al., 2008; and European Commission, 2010). For example, Jorgenson et al. (2008) argue that the contribution of the IT sector to TFP growth in the US is estimated to be about 0.47 percentage points per year in 1995-2006, which is of a similar magnitude to the TFP growth employed in the high TFP growth baseline scenario in this paper.

It is worth noting that these simulations do not incorporate explicitly potential challenges at the initial phases of new technology adoption. As discussed in Jovanovic and Rousseau (2005), it is possible that countries experience productivity slowdowns at first when an initially not user-friendly new technology is introduced, requiring the economy to adjust in the transition phase and potentially causing long-term productivity swings. For example, this was evident in the transition from steam power to electricity. While our simulations do not incorporate such initial productivity slowdown, they do embed countries' readiness for the adoption of AI technologies in TFP calculations.

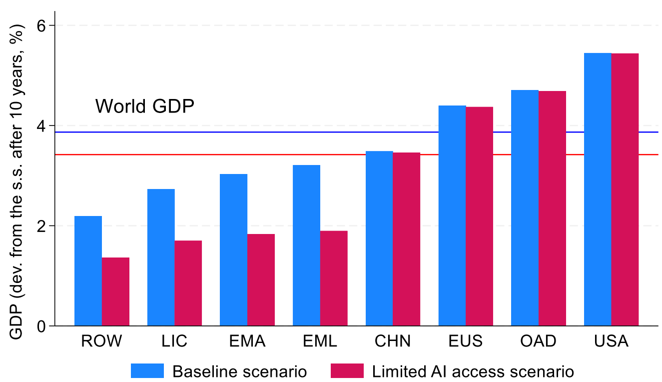
5. A Challenging Outlook for EMs and LICs

Limited AI Access Scenario

Many countries, mostly EMs and LICs, encounter significant limitations in access to advanced processors, extensive computing clusters, and comprehensive data repositories—shortcomings that hinder their ability to innovate and remain competitive in AI-driven sectors. Additionally, as discussed earlier, uncertainties surrounding future trade and technology restrictions can further exacerbate these challenges.

Against this backdrop, a plausible scenario (outlined in Section 3) assumes that EMs (excluding China) and LICs face constraints in the access to AI-specific technologies. Under such conditions, cross-country divergences that emerge from the AI shock would be exacerbated. The scenario analysis shows that, while there would only be slight changes to output growth in AEs and China, LICs and EMs would experience a significant deterioration vis-à-vis the global averages: the increase in real GDP in EMs and LICs would fall on average by around 1 percentage point relative to the baseline scenario (Figure 8). Among the EM and LIC groups, the output losses relative to the baseline scenario are more pronounced in EMs (EMA and EML) given higher AI exposure, as well as higher AI preparedness, which could be better utilized when AI technologies are fully accessible.

Figure 8. Regional Differences in the Limited AI Access Scenario



Note: The panel shows deviations of real GDP from the steady state for the high TFP growth baseline scenario after 10 years (blue bars), as well as the results in the limited AI access scenario (red bars). The global averages are shown as horizontal lines. EMA = Emerging Market Economies Asia, Central, Asia, Russia, etc. EML = Emerging Market Economies Latin America, Middle East, Africa, etc. EUS = EU and Switzerland, LIC = Low-income countries, OAD = Other advanced economies and ROW = Rest of the World. The detailed composition of the countries in each group is presented in Annex II.

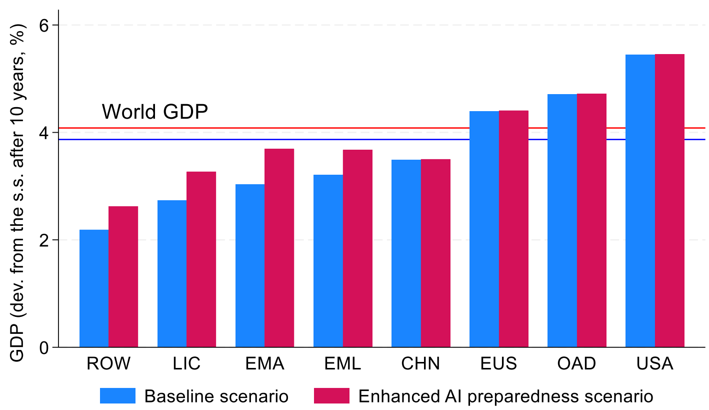
Enhanced AI Preparedness Scenario

As previously discussed, AI preparedness is a crucial determinant of AI adoption, which in turn enhances productivity and stimulates economic growth. According to Cazzaniga et. al (2024), the level of AI preparedness in AEs is more than double that observed in LICs, with EMs positioned between these two extremes.

AI preparedness is inherently multidimensional, encompassing a variety of factors that facilitate effective AI integration. Key elements include: the availability of robust digital infrastructure, continuous investment in human capital, inclusive STEM education, mobility of labor and capital, a dynamic research and development (R&D) ecosystem, and the flexibility of legal frameworks to accommodate digital business models. These key dimensions of AI preparedness are levers that countries can use to boost their AI preparedness. In particular, a large gap between the US and the LICs exists in terms of skills and digital infrastructure. While the gaps with the US are smaller for the EM groups, there is room for improvement in all areas, including the innovative ecosystem and legal framework.

To illustrate the role of improvements in AI preparedness, an "*enhanced AI-preparedness*" scenario assumes that, for countries in the EM and LIC groups, their preparedness index is lifted to a level equal to the best prepared country in their respective peer group.[18] The scenario also assumes no AI access restrictions, as in the baseline scenario. Model simulations show that, also in this scenario, significant cross-region inequality would persist. However, it would be partially offset vis-à-vis the baseline scenario, and the level of global GDP would marginally benefit (Figure 9). Additional output gains from the enhancement of AI preparedness are more pronounced in the AI intensive sector in the EM and LIC groups, as a sector with higher AI exposure benefit more from the enhancement of AI preparedness.

Figure 9. Regional Differences in the Enhanced AI Preparedness Scenario



Note: The panel shows the deviations of real GDP from the steady state for the high TFP growth baseline scenario after 10 years (blue bars), as well as the results in the enhanced AI preparedness scenario (red bars). The global averages are shown as horizontal lines. EMA = Emerging Market Economies Asia, Central, Asia, Russia, etc. EML = Emerging Market Economies Latin America, Middle East, Africa, etc. EUS = EU and Switzerland, LIC = Low-income countries, OAD = Other advanced economies and ROW = Rest of the World. The detailed composition of the countries in each group is presented in Annex II.

[18] Specifically, it is assumed that AI preparation index will increase to 0.63 from 0.50 in EMA, to 0.59 from 0.50 in EML, and to 0.48 from 0.38 in LIC and ROW.

Mind the AI gap: The Way Forward for EMs and LICs

Even if AI underperformers may not be able to fully close the AI gap, policy actions that improve AI preparedness and enhance adoption can help narrow it. For economies with strong foundational AI preparedness (most AEs and some EMs), emphasis may be needed on strengthening digital innovation capacity and adapting legal and ethical frameworks to govern and foster AI advances. Where foundational preparedness is weak (some EMs and most LICs), investment in digital infrastructure and human capital could be prioritized to reap early gains from AI while paving the way for second-generation preparedness. Public investment in AI should prioritize areas with positive externalities, as these are less likely to receive private sector investment—such as fundamental research, necessary infrastructure, particularly in EMDEs—and applications in the public sector where social returns are high—such as education, health care, and government administration.

Enhancing access to AI technologies, including hardware, software and, critically, relevant data, also has the potential to reduce the gap between AI frontrunners and underperformers. However, geopolitical and national security considerations may influence technology-sharing practices; these constraints often weigh heaviest on EMs and LICs with the fewest alternative channels for AI-intensive investment and innovation.

The recent development of an advanced LLM through the use of more efficient algorithms by DeepSeek, which reportedly requires less computing capacity and powerful chips than existing LLMs, provides a glimmer of optimism to AI underperformers. DeepSeek’s breakthrough in creating an advanced AI model at far lower expense disrupted the assumption that cutting-edge systems always demand large budgets and top-tier chips, resources that are only within reach of a few countries and companies. This breakthrough in the production of a more efficient LLM shows that technology leapfrogging cannot be dismissed, even under limited access to more advanced hardware components. Access to open-source code and relevant data could also help less-developed EMs and LICs narrow the AI gap and apply AI to address their own problems.

The example of Kenya’s advanced mobile banking and payment system, M-Pesa, is illustrative. Kenya managed to leapfrog over the limitations faced by traditional banking in AEs, leading to broader and quicker uptake of mobile financial services. M-Pesa allowed people to access financial services such as money transfers, savings, and loans through mobile phones without the need for a physical bank branch. In AEs, mobile payment systems like Apple Pay or Google Wallet rely on well-established banking systems, needing credit/debit cards, bank accounts, and sometimes complex infrastructure. In contrast, Kenya’s leapfrogging of traditional banking enabled financial inclusion to reach rural and underserved populations, where traditional banking infrastructure was non-existent. Importantly, the widespread adoption of M-Pesa also led to an improvement in Kenya's tech infrastructure, including mobile network coverage, internet access, data services, and e-commerce. This growth catalyzed the development of other tech startups, particularly in fintech, and created a vibrant digital economy.

6. Conclusions

This paper offers new insights into AI's impact on global growth and cross-country income differences, demonstrating that AI-induced productivity gains could lift global GDP by up to 4 percent in a high TFP growth scenario over the next decade. Nevertheless, these gains are far from being evenly distributed, with AEs benefiting disproportionately — reflecting their stronger AI preparedness and exposure, as well as greater access to high-tech infrastructure and data. Indeed, the estimated growth impact in AEs could be more than double than in LICs. Among AEs, the US emerges as a clear frontrunner, while other AEs and China also see notable boosts to output. Policy action can help reduce the cross-country AI gap. An enhanced AI preparedness scenario highlights the critical role that stronger institutions and digital infrastructures play in reaping the AI growth benefits. Improved access by EMs and LICs to AI data and technologies can also be a win-win, with positive spillbacks to AEs, through higher global growth.

Interestingly, the macroeconomic estimates in our global modeling approach suggest that AI's impacts could be different than textbook productivity shocks, because AI will affect the productivity in both non-tradable and tradable sectors. Traditional theory (e.g., Balassa-Samuelson effect) posits that productivity gains occur disproportionately in tradable sectors, leading to an appreciation of a country's real exchange rate. In contrast, the analysis shows that the significant AI-driven productivity increases in AE's non-tradable sectors—such as education and healthcare—could exert downward pressure on their non-tradable prices, leading to moderate currency depreciation relative to EMs and LICs. This real exchange rate movement can, in turn, bolster AEs external competitiveness beyond sectors benefited directly by AI, and generate spillovers globally.

Although these findings provide a valuable perspective on AI's macroeconomic effects, they should be read as suggestive scenarios rather than definitive estimates. Important avenues remain for future research. One priority is refining the representation of labor markets—including unemployment dynamics and skill mismatches—to capture more nuanced impacts of AI-driven structural change. Another is deepening the analysis of within-country distributional consequences, such as the channels through which different income groups are affected. Finally, further investigations could explore scenarios in which varying policy settings, such as infrastructure investments and fiscal policy alter the pace and breadth of AI adoption.

Annex I. Aggregation of Industries in GIMF

Sector	ISIC1 code	ISIC2 code	Description
AI-intensive	C	D21	Pharmaceuticals, medicinal chemical and botanical products
AI-intensive	C	D26	Computer, electronic and optical equipment
AI-intensive	H	D51	Air transport
AI-intensive	J	D58T60	Publishing, audiovisual and broadcasting activities
AI-intensive	J	D61	Telecommunications
AI-intensive	J	D62T63	IT and other information services
AI-intensive	K	D64T66	Financial and insurance activities
AI-intensive	M	D69T75	Professional, scientific and technical activities
Tradable	A	D01T02	Agriculture, hunting, forestry
Tradable	A	D03	Fishing and aquaculture
Tradable	B	D05T06	Mining and quarrying, energy producing products
Tradable	B	D07T08	Mining and quarrying, non-energy producing products
Tradable	B	D09	Mining support service activities
Tradable	C	D10T12	Food products, beverages and tobacco
Tradable	C	D13T15	Textiles, textile products, leather and footwear
Tradable	C	D16	Wood and products of wood and cork
Tradable	C	D17T18	Paper products and printing
Tradable	C	D19	Coke and refined petroleum products
Tradable	C	D20	Chemical and chemical products
Tradable	C	D22	Rubber and plastics products
Tradable	C	D23	Other non-metallic mineral products
Tradable	C	D24	Basic metals
Tradable	C	D25	Fabricated metal products
Tradable	C	D27	Electrical equipment
Tradable	C	D28	Machinery and equipment, nec
Tradable	C	D29	Motor vehicles, trailers and semi-trailers
Tradable	C	D30	Other transport equipment
Tradable	C	D31T33	Manufacturing nec; repair and installation of machinery and equipment
Tradable	H	D49	Land transport and transport via pipelines
Tradable	H	D50	Water transport
Tradable	H	D52	Warehousing and support activities for transportation
Tradable	I	D55T56	Accommodation and food service activities
Non-tradable	D	D35	Electricity, gas, steam and air conditioning supply
Non-tradable	E	D36T39	Water supply; sewerage, waste management and remediation activities
Non-tradable	F	D41T43	Construction
Non-tradable	G	D45T47	Wholesale and retail trade; repair of motor vehicles
Non-tradable	H	D53	Postal and courier activities
Non-tradable	L	D68	Real estate activities
Non-tradable	N	D77T82	Administrative and support services
Non-tradable	O	D84	Public administration and defence; compulsory social security
Non-tradable	P	D85	Education
Non-tradable	Q	D86T88	Human health and social work activities
Non-tradable	R	D90T93	Arts, entertainment and recreation
Non-tradable	S	D94T96	Other service activities
Non-tradable	T	D97T98	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use

Annex II. Country Groups and AI Preparedness

Group	Abbreviation	Country	AI Preparedness	Digitial Infrastructure	Innovation and Economic Integration	Human Capital and Labor Market Policies	Regulation and Ethics
CHN	CHN	China	0.64	0.19	0.15	0.15	0.15
EMA	BLR	Belarus	0.47	0.15	0.11	0.14	0.08
EMA	BRN	Brunei Darussalam	0.50	0.12	0.11	0.15	0.12
EMA	IDN	Indonesia	0.52	0.12	0.11	0.13	0.16
EMA	IND	India	0.49	0.11	0.11	0.12	0.15
EMA	KAZ	Kazakhstan	0.55	0.15	0.11	0.16	0.13
EMA	MYS	Malaysia	0.63	0.15	0.14	0.17	0.17
EMA	PAK	Pakistan	0.37	0.08	0.09	0.10	0.11
EMA	PHL	Philippines	0.50	0.10	0.12	0.15	0.12
EMA	RUS	Russia	0.56	0.16	0.12	0.16	0.12
EMA	THA	Thailand	0.54	0.14	0.12	0.14	0.13
EMA	VNM	Viet Nam	0.48	0.14	0.11	0.12	0.11
EML	ARG	Argentina	0.47	0.13	0.09	0.12	0.14
EML	BRA	Brazil	0.50	0.14	0.11	0.12	0.14
EML	CHL	Chile	0.59	0.15	0.12	0.14	0.17
EML	COL	Colombia	0.49	0.12	0.10	0.13	0.14
EML	CRI	Costa Rica	0.54	0.12	0.13	0.14	0.15
EML	EGY	Egypt	0.39	0.09	0.10	0.12	0.08
EML	JOR	Jordan	0.48	0.09	0.13	0.13	0.13
EML	MAR	Morocco	0.43	0.10	0.11	0.12	0.10
EML	MEX	Mexico	0.53	0.13	0.13	0.14	0.14
EML	PER	Peru	0.49	0.11	0.12	0.12	0.13
EML	TUN	Tunisia	0.47	0.11	0.10	0.13	0.12
EML	TUR	Türkiye	0.54	0.14	0.13	0.14	0.13
EML	UKR	Ukraine	0.51	0.14	0.10	0.15	0.12
EML	ZAF	South Africa	0.50	0.12	0.11	0.12	0.14
EUS	AUT	Austria	0.72	0.19	0.17	0.16	0.20
EUS	BEL	Belgium	0.67	0.17	0.17	0.16	0.16
EUS	BGR	Bulgaria	0.58	0.15	0.14	0.15	0.14
EUS	CHE	Switzerland	0.76	0.19	0.17	0.19	0.21
EUS	CYP	Cyprus	0.63	0.17	0.15	0.14	0.16
EUS	CZE	Czechia	0.65	0.17	0.16	0.16	0.16
EUS	DEU	Germany	0.75	0.19	0.18	0.18	0.20
EUS	DNK	Denmark	0.78	0.20	0.18	0.18	0.22
EUS	ESP	Spain	0.65	0.17	0.16	0.15	0.17
EUS	EST	Estonia	0.76	0.20	0.16	0.18	0.22
EUS	FIN	Finland	0.76	0.19	0.17	0.17	0.23
EUS	FRA	France	0.70	0.18	0.17	0.16	0.18
EUS	GRC	Greece	0.58	0.15	0.15	0.14	0.14
EUS	HRV	Croatia	0.58	0.17	0.14	0.13	0.14
EUS	HUN	Hungary	0.56	0.16	0.14	0.13	0.14
EUS	IRL	Ireland	0.69	0.17	0.16	0.17	0.19
EUS	ITA	Italy	0.62	0.17	0.16	0.13	0.15
EUS	LTU	Lithuania	0.66	0.18	0.15	0.17	0.17
EUS	LUX	Luxembourg	0.74	0.19	0.15	0.17	0.22
EUS	LVA	Latvia	0.63	0.16	0.15	0.16	0.16
EUS	MLT	Malta	0.66	0.17	0.15	0.15	0.19
EUS	NLD	Netherlands	0.77	0.19	0.18	0.17	0.22
EUS	POL	Poland	0.60	0.17	0.14	0.14	0.15
EUS	PRT	Portugal	0.65	0.16	0.16	0.15	0.18
EUS	ROU	Romania	0.58	0.15	0.15	0.13	0.15
EUS	SVK	Slovakia	0.59	0.17	0.14	0.15	0.14
EUS	SVN	Slovenia	0.63	0.16	0.14	0.15	0.18
EUS	SWE	Sweden	0.75	0.18	0.18	0.17	0.21
LIC	BGD	Bangladesh	0.38	0.09	0.11	0.09	0.10
LIC	CIV	Côte d'Ivoire	0.37	0.08	0.08	0.10	0.10
LIC	CMR	Cameroon	0.34	0.07	0.09	0.10	0.08
LIC	KHM	Cambodia	0.37	0.08	0.11	0.09	0.08
LIC	LAO	Lao	0.33	0.06	0.09	0.11	0.08
LIC	MMR	Myanmar	0.33	0.07	0.09	0.12	0.05
LIC	NGA	Nigeria	0.34	0.08	0.09	0.09	0.07
LIC	SEN	Senegal	0.40	0.08	0.09	0.10	0.12
OAD	AUS	Australia	0.73	0.18	0.16	0.17	0.21
OAD	CAN	Canada	0.71	0.17	0.16	0.17	0.21
OAD	GBR	United Kingdom	0.73	0.18	0.16	0.17	0.21
OAD	HKG	Hong Kong	0.70	0.20	0.17	0.16	0.17
OAD	ISL	Iceland	0.70	0.17	0.15	0.17	0.21
OAD	ISR	Israel	0.73	0.17	0.19	0.17	0.19
OAD	JPN	Japan	0.73	0.18	0.18	0.17	0.20
OAD	KOR	Korea	0.73	0.18	0.18	0.16	0.20
OAD	NOR	Norway	0.71	0.17	0.16	0.17	0.21
OAD	NZL	New Zealand	0.75	0.19	0.16	0.18	0.22
OAD	SAU	Saudi Arabia	0.58	0.14	0.12	0.18	0.14
OAD	SGP	Singapore	0.80	0.21	0.18	0.20	0.22
USA	USA	United States	0.77	0.19	0.18	0.18	0.22

Note. Countries not shown in the list are included in Rest of the World (RoW).

Source. Cazzaniga et al. (2024)

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