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by Leonardo Gambacorta, Enisse Kharroubi, Aaron Mehrotra and Tommaso Oliviero

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Artificial intelligence and growth in advanced and emerging economies: short-run impact

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Abstract

This paper investigates whether the positive effects of generative artificial intelligence (gen AI) on growth rate of value added differ across countries in the short run. Using an empirical strategy inspired by Rajan and Zingales (1998) and a dataset covering 56 economies and 16 industries, we find that the differential growth effects arise from variations in sectoral exposure to cognitive and knowledge-intensive activities, differences in production structures, and countries' AI preparedness. Our results suggest that, on average, gen AI is likely to benefit advanced economies more than emerging market economies, thereby widening global income disparities in the near term.

JEL classification: E24; O47; O57.

Keywords: generative artificial intelligence; emerging market economies; economic growth; productivity differentials; technological readiness, sectoral exposure to AI.

* Leonardo Gambacorta is with the Bank for International Settlements (BIS) and CEPR; Enisse Kharroubi and Aaron Mehrotra are with the BIS. Tommaso Oliviero is with the University of Naples Federico II, CSEF and Mofir. We thank Ralph De Haas for insightful comments and participants at the ASC – Institutions and Regional Development Conference, L'Aquila (2025). The views expressed are those of the authors and do not necessarily reflect those of the BIS.

1. Introduction

Over the last couple of years, the global adoption of generative artificial intelligence (gen AI) by individuals and organisations has surged dramatically, sparking an intense debate about its economic effects. The prevailing view is that this technological innovation will enhance worker productivity and spur firm growth and innovation (Brynjolfsson et al., 2023; Noy and Zhang, 2023; Babina et al., 2024). As aggregate productivity rises, gen AI could have a significant positive impact on the global economy (Baily et al., 2023; Goldman Sachs, 2023).

Although gen AI represents a general-purpose technology that is transforming cognitive capabilities, its impact is not expected to be uniform across individuals, occupations, and industries. First, gen AI mainly enhances cognitive and knowledge-intensive activities (e.g. professional services such as finance and IT, see Aldasoro et al., 2024b), while tasks with substantial physical components (e.g. construction) are expected to be less affected. Second, AI adoption may not be practical or beneficial for all firms and workers. Adoption rates and usage intensity remain low among less-educated and older population groups (Aldasoro et al., 2024c; Gambacorta et al., 2025), and their future trajectory is uncertain.

Productivity gains from AI at the firm or sector level may also fail to translate into equivalent macroeconomic gains. Broader economic factors—including frictions in adoption, potential disruptions to production networks, and regulation—mean that gen AI-driven improvements may not simply aggregate into a sum of sectoral effects.

Moreover, the benefits of gen AI are unlikely to be distributed evenly across countries. The aggregate growth impact of gen AI is likely to depend critically on national production structures, particularly the relative size of sectors exposed to the new technology. Advanced economies (AEs), which tend to have a greater share of value added from early-adopting sectors such as finance, healthcare, and advanced manufacturing, are expected to benefit more than emerging and developing economies (EMDEs). In many EMDEs, knowledge-intensive sectors are smaller, and low-skill, labour-intensive manufacturing is more prominent than in AEs. This suggests that EMDEs may be less affected by the productivity boost brought about by AI (Korinek and Stiglitz, 2021). In other words, the accessibility and adoption of this general purpose technology may reinforce existing socio-economic disparities by disproportionately benefiting certain sectors and countries.

In this paper, we examine whether the short-run growth effects of gen AI differ between AEs and EMDEs. Our key hypothesis, which we test empirically, is that the growth impact of gen AI is driven by sectoral differences in exposure to the technology and by country-level characteristics that influence its adoption and use. On the one hand, sectors with a higher incidence of skilled labour are more exposed to the productivity gains associated with gen AI. On the other hand, the heterogeneity in the impact of AI on growth may reflect countries' differing levels of readiness to adopt AI, from the quality of digital infrastructure to the regulatory environment. Our analysis focuses on short-term growth effects, abstracting from longer-run equilibrium dynamics.

Our empirical strategy closely follows the approach of Rajan and Zingales (1998). In their framework, the authors measure the extent of external finance dependence for each sector (using the US economy as a benchmark) and examine whether sectors more dependent on external finance grow disproportionately faster in countries with more developed financial markets. The parallel in our paper consists in using an industry-level measure of exposure to gen AI (benchmarking the US economy) and a country-specific measure of AI readiness capturing the potential gains from the adoption of the new technology.

We begin by identifying the exposure of each industry to gen AI. Building on Felten et al. (2021), we use an industry-level measure of AI exposure developed in Aldasoro et al. (2024), which is tailored to the US economy. As in Rajan and Zingales (1998), we treat the US distribution of sectoral exposures as a benchmark for all countries. This measure shows high exposure in service industries such as finance and education, and low exposure in sectors such as agriculture and transport.

To identify countries' readiness to use AI, we use the AI preparedness index (AIPI) from the IMF (Cazzaniga et al. (2024)). The measure captures four key dimensions relevant for AI adoption: digital infrastructure, human capital, technological innovation and legal frameworks. This measure reveals significant differences between AEs and EMDEs: the median value for the index is about one third higher in AEs than in EMDEs, although there is considerable heterogeneity within the latter group. Indeed, some EMDEs feature elevated AI preparedness that might provide important institutional and structural support for AI-driven growth.

Using these measures of industry-level exposure to AI and country-level readiness to adopt the new technology, we estimate the impact of their interaction on the growth rate of real value added in each industry-country pair in 2022–23, after conditioning on country and industry fixed effects. A key contribution of our analysis is its global scope, which includes both advanced and emerging economies—an area of research that has received so far limited attention in the literature on gen AI's macroeconomic effects.

Our results show that for the same increase in AI preparedness of the economy, sectors with a high AI exposure experience greater growth in real value added than those with lower exposure. Comparing sectors at the 90th and 10th percentiles of AI exposure, a one standard deviation increase in AI preparedness is associated with a growth differential of approximately two percentage points.

We also show that this result is robust to the inclusion of several control variables. Among those, the stock of robots in use in the various sectors. This finding is important, as robots are another technological innovation that could affect the relative growth rates between sectors, but their implications for white- and blue-collar workers are likely to differ from those of gen AI.

Taking the estimates of industry-level AI exposures, and conditioning on the different distribution of industries across countries, we then estimate that the short-run growth impact of gen AI is greater in advanced economies than in emerging economies. In advanced economies, on average, the estimated increase in real value-added growth is 0.6 percentage points higher than in the country with the lowest increase in the global sample. The corresponding effect is on average around one third lower in EMDEs which also display considerable cross-country heterogeneity. Our estimates offer one of the first cross-country assessments of the near-term growth effects of gen AI adoption and their potential distributional implications.

The remainder of the paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the data and presents some initial descriptive evidence. Section 4 outlines the empirical model and reports the main results. Section 5 concludes.

2. Literature review

Our paper relates to various strands of literature on the implications of AI. These include evidence on productivity improvements at both the macro and micro levels, the implications of AI for income inequality across countries, and evidence on the diffusion of earlier technological innovations.

Several studies have examined the effects of AI on productivity at the macroeconomic level, given their importance for broader growth implications (Acemoglu and Restrepo, 2018; Aghion et al., 2018). That said, almost all existing research focuses on advanced economies, particularly the United States. One of the lowest estimated productivity gains from AI is reported in Acemoglu (2024)—an increase in total factor productivity (TFP) of 0.07% annually, albeit over a decade. Substantially larger gains in productivity growth are found in several other studies (e.g. Aghion and Bunel, 2024; Baily et al., 2023; Bergeaud, 2024; Filippucci et al., 2024).

To obtain macroeconomic productivity effects, the studies mentioned above draw on estimates of AI's productivity gains at the micro level. These gains are generally documented to be large. Noy and Zhang (2023) provide evidence for college-educated employees; Brynjolfsson et al. (2023) for customer support agents; and Peng et al. (2023) and Gambacorta et al. (2024) for software developers. The task-based productivity gains in these studies range from approximately 15% to over 50%.

Estimates of AI's macroeconomic productivity implications for countries other than the US - especially EMDEs - are notably limited. As a result, econometric analysis of the differential impacts on countries' growth trajectories arising from AI adoption tends to be scarce. There are a few exceptions, however. Cazzaniga et al. (2024) for instance estimate significantly lower AI exposures in emerging market and low-income countries compared to advanced economies, reflecting differences in economic structures. Based on three AI-related dimensions—exposure, preparedness, and access—and using a multi-sector global model, Cerutti et al. (2025) find that the growth impact of AI could be more than twice larger in advanced economies than in low-income countries. Focusing on Asia and the Pacific, Hennig and Khan (2025) argue that AI could increase inequality between countries, given that most jobs that can be complemented by AI are concentrated in advanced economies rather than in low-income countries. Our approach differs from these studies in terms of methodology, as we adopt a framework similar to Rajan and Zingales (1998) to examine how AI exposure and technological readiness interact to influence growth rates. The differences in sectoral composition, combined with varying degrees of technological readiness across countries, result in diverging short-run growth trajectories.

Historical evidence on technology diffusion can provide insight into how AI adoption rates may vary in the future, while suggesting that emerging and developing countries are likely to be at a disadvantage. Comin and Hobijn (2003), analysing the diffusion of innovations since the late 1700s, find that technological advances have generally trickled down from advanced to lower-income countries, with the speed of diffusion shaped by countries' human capital endowment and adoption of predecessor technologies. At the same time, both Comin and Hobijn (2010) and Comin and Mestieri (2018) find that adoption lags have declined for more recent innovations. Comin and Hobijn (2010) further document that variation in technology adoption accounts for at least one quarter of per capita income differences across countries. Relatedly, Ayerst (2024) develops a model in which firm-level distortions hinder technology adoption and have significant implications for aggregate productivity.

3. Data and stylised facts

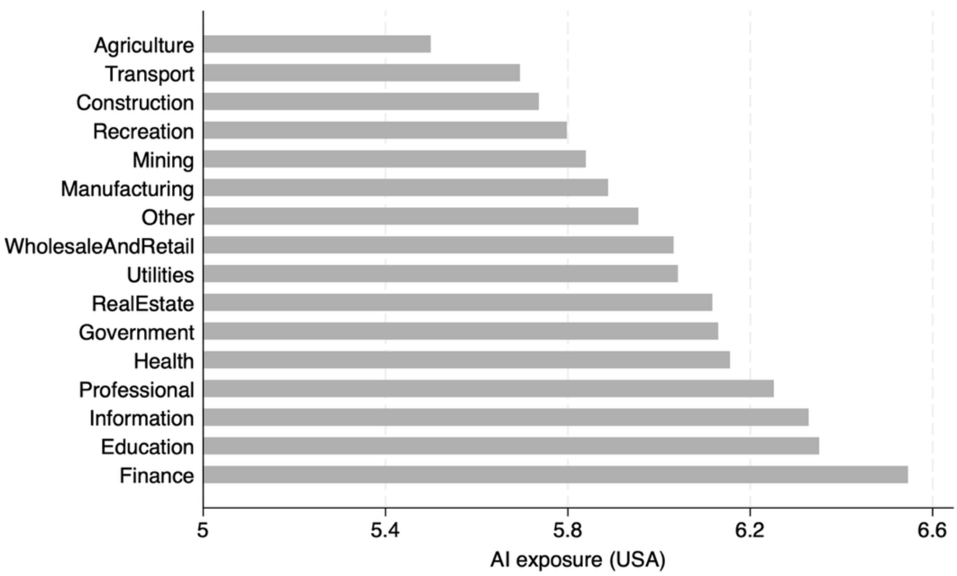
Our estimation sample comprises 56 economies, 29 of which are classified as advanced, and 16 industries, covering both manufacturing and services. We use three main sources of data.

First, we use data on industry-level exposure to AI ("AIIE") from Aldasoro et al. (2024). The authors construct this measure at the 2-digit level of the North American Industry Classification System (NAICS), building on the indicators developed by Felten et al. (2021). The measure draws on survey information regarding the extent to which gen AI can be used across various workplace abilities and occupations, and aggregates this information to the sectoral level.

As the data pertain to the United States, the implicit assumption in our study is that patterns of industry-level exposure to AI are the same in EMDEs and other AEs as in the United States. This assumption is analogous to that in Rajan and Zingales (1998) regarding external finance dependence across sectors.

Differently from Aldasoro et al. (2024), we aggregate the 20 sectors in the 1-digit NACE classification into 16 sectors. This ensures compatibility between the AI exposure data and other sources used in our analysis.[1] Using the 16-industry structure, Figure 1 shows that Finance, Education, and Information are the sectors with the highest AIIE scores, while Agriculture, Transport, and Construction have the lowest.

Figure 1. Industry-level exposure to AI



Second, we use data on real value added, by country and industry, from the Asian Development Bank (ADB). Specifically, we draw on sectoral data from the ADB's

[1] Specifically, we merge the following industries: (1) Wholesale and Retail; (2) Electricity, Gas, and Water Supply into the group "Utilities"; (3) Professional, Scientific and Technical Activities and Administrative and Support Service Activities into "Professional"; (4) Accommodation and Food Service Activities and Arts, Entertainment and Recreation into "Recreation"; (5) Other Service Activities and Activities of Households as Employers, as well as Undifferentiated Goods- and Services-Producing Activities of Households for Own Use into "Other".

multiregional input-output tables, which are available at constant 2010 prices for 62 economies plus an aggregated "Rest of the World".

Comparing sectoral shares in total value added between emerging and advanced economies reveals some differences in the potential for AI adoption (Figure 2). In particular, some typically labour-intensive sectors are larger in emerging economies—most notably Agriculture. Mining and Manufacturing also account for larger shares in EMDEs, with the latter comprising about one-fifth of total value added. In contrast, Health and Professional services are typically larger in advanced economies. Somewhat unexpectedly, the data suggest that the Wholesale and Retail sector is larger in emerging economies, while the share of Finance is similar between AEs and EMDEs. These patterns are influenced by production structures in countries such as China, Korea, and Singapore.

Figure 2. Share of industries in total real value added: AEs vs EMDEs

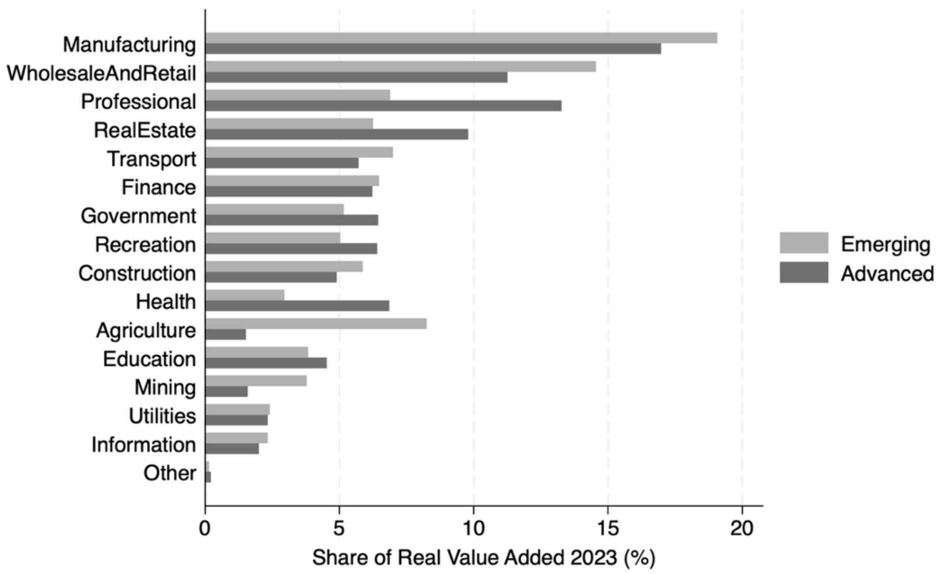


Figure 3 shows the growth rate of real value added by sector from 2022 to 2023, differentiated by AEs and EMDEs. Our analysis of AI's impact on growth focuses on this period, which saw a rapid acceleration in gen AI adoption. For example, according to a global survey conducted by McKinsey in April 2023, the year was regarded as a pivotal moment: despite the short time since many gen AI tools were launched, one-third of corporate respondents reported using gen AI regularly in at least one business function (McKinsey, 2023).

Third, we use data on AI preparedness from the IMF (Cazzaniga et al. (2024)).[2] The indicator measures a country's readiness to adopt AI along four dimensions: digital infrastructure, human capital and labour market policies, innovation and economic integration, and regulation and ethics. Each of the four dimensions is computed across a set of associated indicators. Finally, the headline AIPI index is obtained as the sum of the four dimensions.[3] It takes values between zero and one, with a higher value indicating greater AI preparedness. While the data used in our analysis pertain to the year 2023 due to data availability, the structural indicators used to compute the dimensions and thus the aggregate index are unlikely to change rapidly over time.

Figure 3. Growth rate of real value added, 2022–23: AEs vs EMDEs

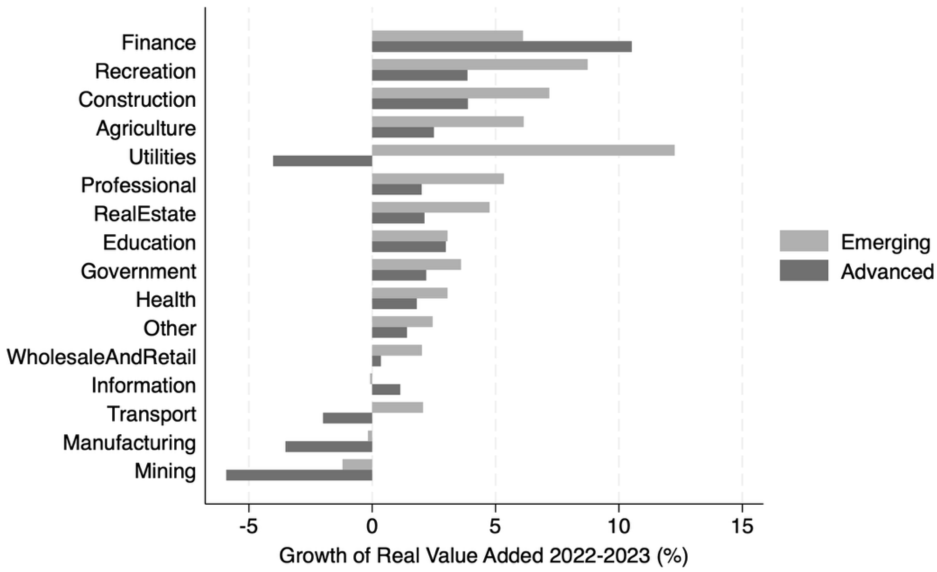


Figure 4 shows significant cross-country variation, as measured by the values for the headline indicator in 2023.[4] For our sample of countries, the median value of AIPI is 0.71 in AEs, ranging from 0.58 in Croatia and Greece, to 0.78 in Denmark. Within EMDEs, the median value is lower than in AEs, at 0.54. Moreover, the variation within EMDEs is much larger, ranging from 0.35 in Nepal to 0.80 in Singapore.

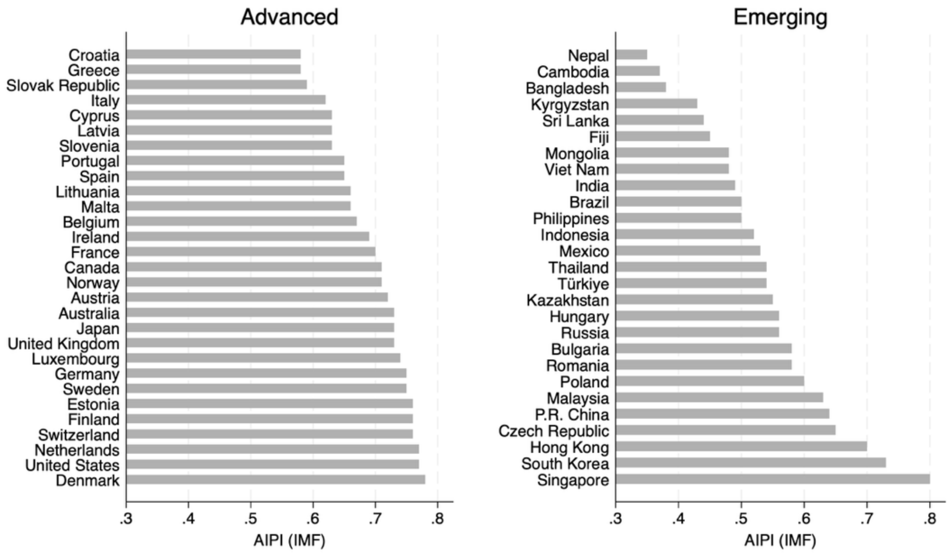
[2] The data were obtained from https://www.imf.org/external/datamapper/datasets/AIPI.

[3] For more details on the methodology and the list of the indicators used to compute the four dimensions of the AIPI index, see https://www.imf.org/external/datamapper/AIPINote.pdf.

[4] Country classifications into advanced economies (AEs) and emerging and developing economies (EMDEs) follow the Bank for International Settlements (BIS) taxonomy.

The finding of significant cross-country variation also carries over to the sub-components of the index, as shown in Annex Figures A1-A4. For all the sub-components, the median values for EMDEs lag behind those of AEs. For digital infrastructure, the median for AEs stands at 0.18 and that for EMDEs at 0.14; for innovation and economic integration at 0.16 vs 0.12; for human capital and labour market policies at 0.17 vs 0.14; and for regulation and ethics at 0.20 vs 0.14, respectively.

Figure 4. AIPI index (IMF): AEs vs EMDEs



4. Empirical analysis

4.1 Baseline model

Our baseline model is specified as:

$$GR\_VA_{cj} = \beta AIPI_c * AIIE_j + \gamma Lagged\_Share_{cj} + \lambda_j + \tau_c + \varepsilon_{cj}. \quad (1)$$

In equation (1), the dependent variable is the growth rate of real value added, GR_VA_{cj}, in 2023 relative to 2022, in sector *j* and country *c*. As explanatory variables, we include $AIPI_c$, the measure for AI preparedness based on a set of macro-structural indicators for each country. We further normalise the variable by dividing it by the standard deviation, so that the coefficients can be interpreted as showing the effects of a one-standard deviation changes to AI preparedness. This (standardised) variable is then interacted with the industry-level exposure to AI (*AIIE*$_j$), using the US economy as the benchmark for sectoral differences in AI exposures (as discussed in Section 3).

The interaction between these two variables captures a potential mechanism through which gen AI could boost growth. In particular, for a given increase in a country's AI preparedness, sectors more exposed to AI are expected to grow faster, ceteris paribus (that is, after controlling for country and sector fixed effects, in the spirit of Rajan and Zingales (1998)). Thus, the combination of AI preparedness and sectoral AI exposure affects the relative growth rates across country-sector pairs.

As additional control variables, we include *Lagged_Share*$_{cj}$, which is the value added in 2022 of sector *j* in country *c*, measured as a share of total value added in country c in 2022. The covariates λ_j and τ_c are industry and country fixed effects, respectively, and ε_{cj} is the error term.

4.2 Results from baseline regressions

Table 1 reports the results from the baseline model.

Specification (I) shows that, controlling for country fixed effects, sectors with greater exposure to AI exhibit higher growth rates in real value added. This relationship is statistically significant at the 10% level. In addition, sectors that accounted for a lower share of total value added in the past tend to grow faster, a result that is statistically significant at the 5% level.

Specification (II) introduces the interaction between the sectoral AI exposure and the country-level AI preparedness (the variable is scaled by its standard deviation). While the coefficient on AI exposure alone turns negative, the coefficient on the interaction term is positive and statistically significant at the 5% level.

In order to interpret the estimated coefficient on the interaction variable, consider two sectors, one at the 10th percentile and one at the 90th percentile of the distribution of AI exposure. For the sector at the 10th percentile, a one standard deviation increase in AI preparedness is associated with an increase in the annual growth of value added of about 16.5 percentage point (ppt) (2.905 * 5.695 = 16.544). For the 90th percentile sector, the same increase in AI preparedness corresponds to increase in growth of about 18.5 ppt (2.905 * 6.351 = 18.450). Thus, the difference in sectoral growth rates amounts to around two ppts, for the same increase in a country's AI preparedness.

These results carry over to Specification (III), which includes both industry and country fixed effects. In this specification, the coefficient estimate on the interaction term between AI exposure and AI preparedness is almost identical to that in

Specification (II) and continues to be statistically significant at the 5% level. Note that the variable for the sector-level AI exposure is now absorbed by the industry fixed effects.

Table 1. Regression results, baseline model

Dependent variable: Growth rate of real value added over 2022-2023			
	(I)	(II)	(III)
AI exposure	2.519*	-13.170*	
	(1.457)	(7.652)	
AI exposure X AIPI		2.905**	3.043**
		(1.352)	(1.394)
Share of 2022 Total Value Added	-0.134**	-0.160**	-0.186*
	(0.066)	(0.070)	(0.099)
Observations	875	875	875
R-squared	0.157	0.160	0.195
Industry FE	N	N	Y
Country FE	Y	Y	Y

Notes: OLS estimation with standard errors clustered at country level in parentheses. Significance level: *p<0.1; ** p<0.05; *** p<0.01.

Table 2 considers the four sub-components of the AI preparedness index separately in the estimation. The objective is to evaluate which of the macro-structural characteristics of AI preparedness are particularly important in the interaction with sectoral AI exposures for near-term growth. Specifically, Specification (I) considers the quality of digital infrastructure, (II) innovation and economic integration, (III) human capital and labour market policies and (IV) regulation and ethics. All specifications include the lagged share of value added at the country-sector level, as well as both industry and country fixed effects. To enhance comparability across specifications, each index is also scaled by its standard deviation.

Table 2 suggests that all four sub-components of AI preparedness are relevant in stimulating near-term growth. Their interaction with sectoral AI exposure is always significant at a minimum of 10% level in the estimation, and there is little difference in the coefficient estimates between the sub-components. Statistical significance emerges as strongest for the sub-component of regulation and ethics (Specification (IV) in Table 2). Moreover, the finding that the interaction of the AIPI index (measured as the sum of the sub-components) with the sectoral AI exposure is statistically significant at the 5% level in Table 1 suggests that the interaction of the various macro-financial characteristics is important.

Table 2. Baseline for each sub-component

Dependent variable: Growth rate real value added 2022-2023				
	(I)	(II)	(III)	(IV)
AI exposure X AIPI (digital infrastructure)	2.942*			
	(1.521)			
AI exposure X AIPI (innovation and integration)		2.541*		
		(1.366)		
AI exposure X AIPI (capital and labour market policies)			2.525*	
			(1.451)	
AI exposure X AIPI (regulation and ethics)				3.079**
				(1.283)
Share of 2022 Total Value Added	-0.181*	-0.174*	-0.168*	-0.182*
	(0.098)	(0.095)	(0.100)	(0.099)
Observations	875	875	875	875
R-squared	0.194	0.194	0.194	0.195
Industry FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y

Notes: OLS estimation with standard errors clustered at country level in parentheses. Significance level: * p<0.1; ** p<0.05; *** p<0.01.

4.3 Relevance of robots

Besides gen AI, another major technological innovation that could affect developments in sectoral value added is the increasing use of industrial robots. The implications of robotisation for growth are likely to differ from those of gen AI. In particular, industrial robots might boost growth through automation of blue-collar sector activity, while gen AI could have impacts mainly through the productivity of white-collar workers. [5]

To control for the impact of robot use on the growth in sectoral real value added, we use a dataset of robots per employee at the country-sector level. We have data on robots per employee for the following seven sectors: agriculture, mining, construction, professional services, health, manufacturing and utilities. For countries with missing

[5] In this paper, we examine the real effects of AI, with a focus on gen AI, which primarily automates or augments cognitive and information-processing tasks. This differs from robotics, which aims at automating physical and routine manual tasks. While the two technologies are largely treated as distinct at present, they may increasingly interact in the future as AI systems become embedded in autonomous machines and industrial robots (Ahn et al (2022); Sandini et al (2024)).

values, we predict the stock of robots by regressing the stock of robots (by sector) on the country's real GDP per capita and the number of internet users per capita, using data for countries where the sectoral robot stock is available. As we implement the regression at the sectoral level, we account for structural differences in robot use in the different industries. For sectors where data on robots are not available for any country, such as the government sector, we assign the (country-specific) minimum robot stock across industries for a particular country.[6] Finally, we normalise the stock of robots per employee by dividing the variable by the lagged sectoral real value added.

Table 3. Regression results, including robots

Dependent variable: Growth rate real value added 2022-2023			
	(I)	(II)	(III)
AI exposure	2.523*	-13.313*	
	(1.460)	(7.720)	
AI exposure X AIPI		2.934**	3.140**
		(1.368)	(1.405)
Share of Value Added	-0.135*	-0.165**	-0.203*
	(0.072)	(0.077)	(0.102)
Robot stock	0.025	0.080	0.304***
	(0.148)	(0.144)	(0.111)
Observations	875	875	875
R-squared	0.157	0.160	0.195
Industry FE	N	N	Y
Country FE	Y	Y	Y

Notes: OLS estimation with standard errors clustered at country level in parentheses. Significance level: * p<0.1; ** p<0.05; *** p<0.01.

Tables 3 and 4 report the results for the baseline measure of AI preparedness and its subcomponents, respectively, when controlling for the stock of robots. The coefficient on the interaction between the sectoral AI exposure and the country's AI preparedness remains positive and statistically significant across all specifications, and its magnitude is very similar to that of the baseline model. At the same time, the robot stock variable is positively associated with sectoral value-added growth, and its

6 Our key finding of a positive and statistically significant coefficient on the interaction between AI exposure and AI preparedness does not hinge on this assumption. In particular, the main result continues to hold if we instead assign a value of zero to the robot stock in those industries for which robot data are unavailable for all countries, such as the government sector.

coefficient is statistically significant at the 5% level or better in the specifications that include both industry and country fixed effects.

Table 4. Regression results, AIPI sub-components, including robots

Dependent variable: Growth rate real value added 2022-2023	(I)	(II)	(III)	(IV)
AI exposure X AIPI (digital infrastr.)	3.047*			
	(1.526)			
AI exposure X AIPI (innovation and integration)		2.640*		
		(1.379)		
AI exposure X AIPI (capital and labour market policies)			2.595*	
			(1.461)	
AI exposure X AIPI (regulation and ethics)				3.154**
				(1.291)
Robot stock	0.307***	0.298***	0.285**	0.294***
	(0.111)	(0.110)	(0.108)	(0.107)
Share of Value Added	-0.199*	-0.190*	-0.183*	-0.198*
	(0.101)	(0.097)	(0.103)	(0.101)
Observations	875	875	875	875
R-squared	0.195	0.194	0.194	0.195
Industry FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y

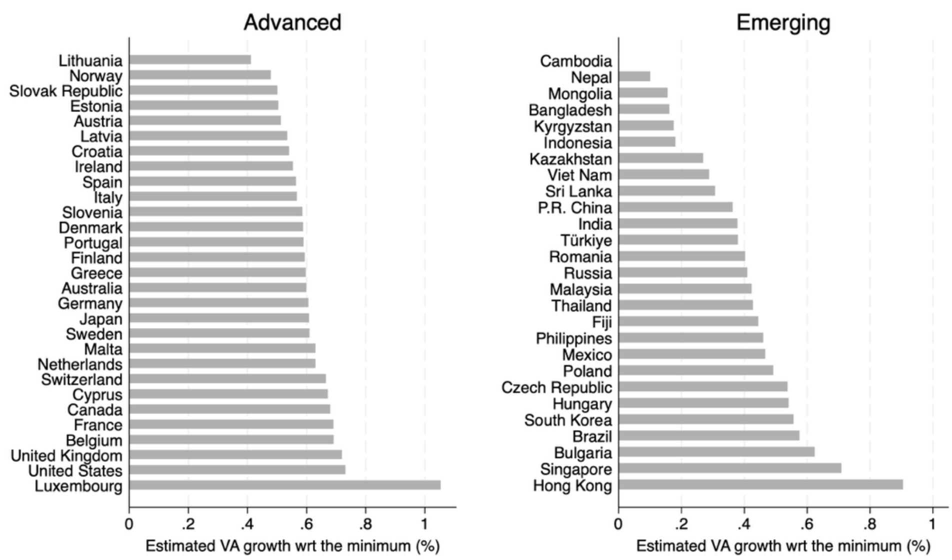
Notes: OLS estimation with standard errors clustered at country level in parentheses. Significance level: * p<0.1; ** p<0.05; *** p<0.01.

4.4 Country-level growth effects

What are the implications of the previous estimates for growth at the country level? To address this question, we simulate the impact of an increase in the AI preparedness index on the growth rate of value added. The simulation is based on the estimates of the baseline model in Table 3, specification (III). In particular, these estimates are obtained by predicting the growth rate of value added, for a given sectoral exposure to gen AI and a one standard deviation increase in AI preparedness. Then, we take the weighted average of the predicted sectoral components, where the weights are determined by the share of each industry in total aggregate value added. The results are presented in Figure 5. They are expressed as deviations from the country with the lowest estimated increase in predicted real value added growth in the global sample (Cambodia).

Figure 5 shows that, on average, generative AI is predicted to have a slightly larger short-run impact on aggregate value added in advanced economies (AEs). In these countries, on average, the increase in real value-added growth is about 0.6 percentage points higher than in the country with the lowest estimated increase in the global sample. In EMDEs, on average, the increase in value added growth is around 0.4 percentage points higher than in the country with the lowest impact. At the same time, there is substantial heterogeneity within each group.

Figure 5. Estimated impact of AI on value added: AEs vs EMDEs



Among AEs, Luxembourg stands out as the economy that is predicted to benefit the most from AI in the near term, in part due to the large role of the financial sector in the country. The United States and the United Kingdom are also among the AEs with some of the larger estimated growth impacts. Some countries in Central and Eastern Europe are estimated to experience smaller growth effects. Norway is also expected to experience a relatively small impact, largely due to the high share of the mining sector in its economy.

Among EMDEs, the largest predicted impacts are found in relatively high-income economies such as Hong Kong SAR and Singapore, where the share of the financial sector is also large. Notably, in the global sample, Hong Kong is surpassed only by

Luxembourg in the near-term growth impact. In contrast, EMDEs with a larger share of low-skilled, labour-intensive manufacturing are projected to experience smaller gains.

5. Conclusions

Most of the previous research on the growth and productivity benefits of gen AI has focused on the United States and, to a lesser extent, on other major advanced economies. There has been much less attention to cross-country differences in the growth impacts of AI, particularly between advanced and emerging economies. Our paper addresses this gap in the literature.

We document that differential growth impacts across countries stem from differences in sectoral exposures to gen AI, differences in countries' production structures and their level of technological readiness. The results suggest that, on average, gen AI is likely to benefit advanced economies more than their emerging market counterparts, thereby increasing global income disparities in the near term.

Our results pertain to growth impacts measured in terms of gross value added. To translate these estimates into TFP equivalents—and further into long-run cross-country projections—a structural model is needed that accounts for aggregate demand effects and intersectoral spillovers. We leave this extension to future research.

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Annex

Figure A1. AIPI sub-component: digital infrastructure.

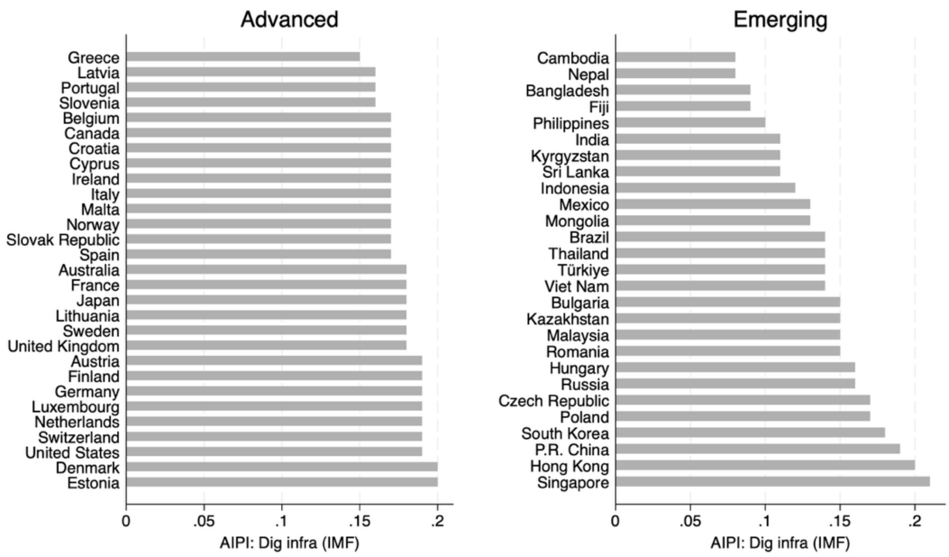


Figure A2. AIPI sub-component: innovation and economic integration.

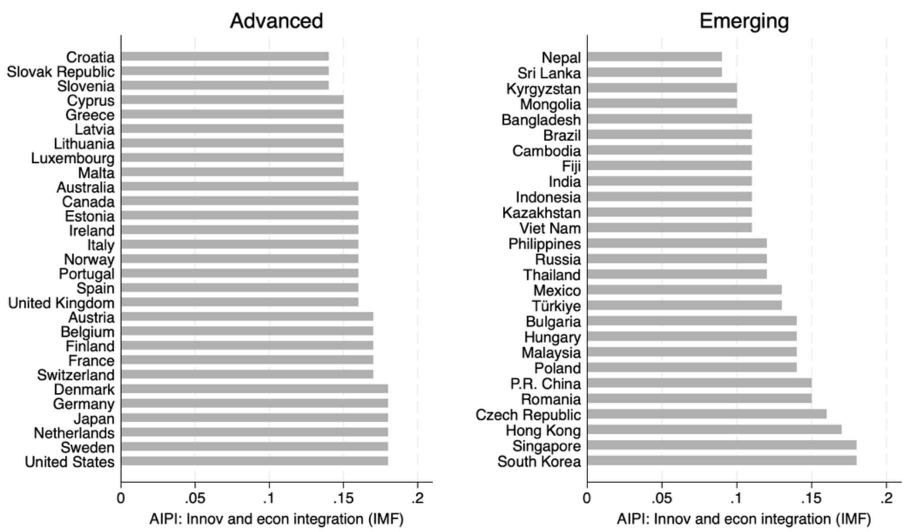


Figure A3. AIPI sub-component: human capital and labour market policies.

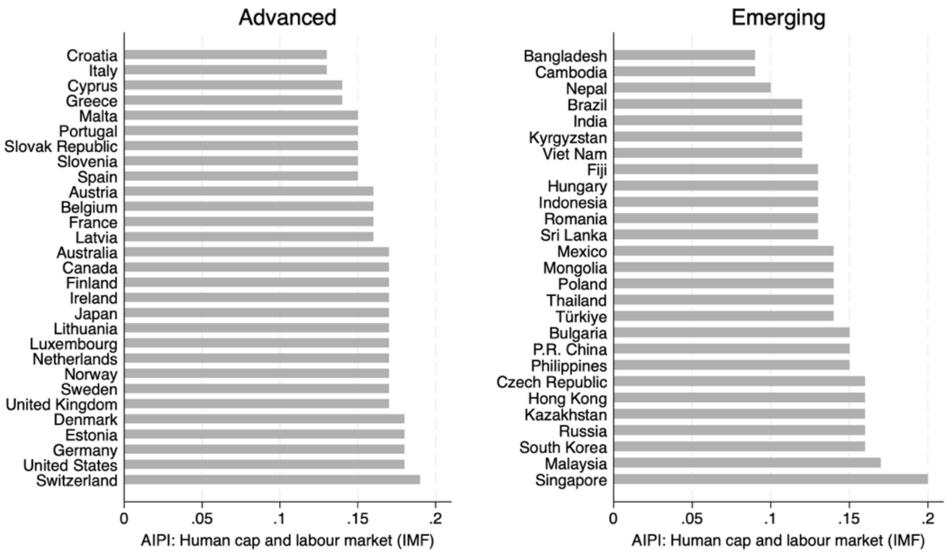
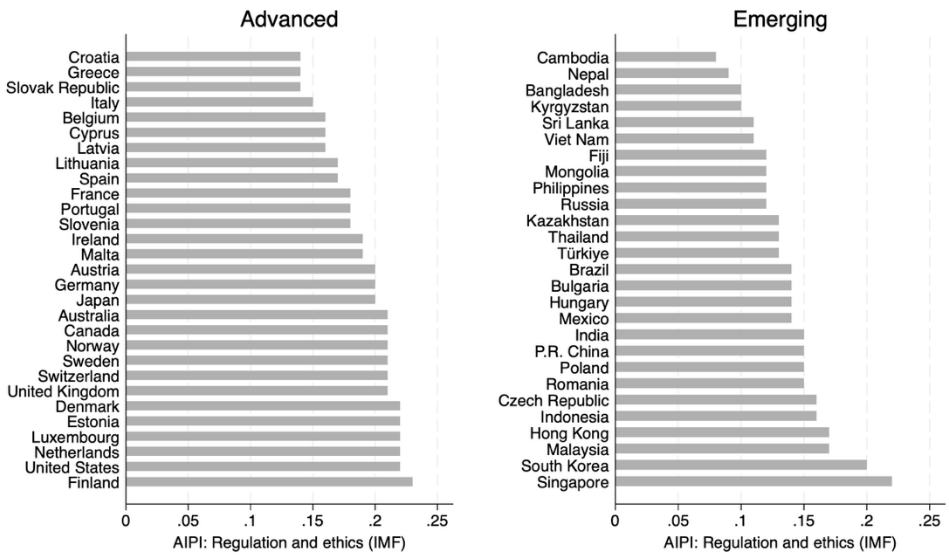


Figure A4. AIPI sub-component: regulation and ethics.



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