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Economic impact of AI in emerging market economies

Key takeaways

- *The productivity and growth effects of artificial intelligence (AI) vary widely across countries, reflecting differences in sectoral composition and in the capacity to adopt and deploy AI. While advanced economies (AEs) are generally better positioned to reap the benefits of AI in the near term, substantial heterogeneity exists within emerging market economies (EMEs).*
- *AI preparedness – covering digital infrastructure, skills and institutional capacity – is a key determinant of overall gains, amplifying productivity effects where it is strong and constraining them where gaps persist, particularly in many EMEs.*
- *Closing AI preparedness gaps can support long-term convergence, as stronger infrastructure, human capital and institutions would enable EMEs to harness AI more effectively, help mitigate labour market risks through reskilling and retraining policies, and narrow growth differences with AEs.*

Artificial intelligence (AI) is emerging as a transformative general purpose technology with far-reaching implications for real economic activity. While early evidence points to sizeable micro-level productivity gains and labour market effects, the magnitude of these effects at the aggregate level remains uncertain. Cross-country differences in sectoral composition and in preparedness to adopt and deploy AI technologies shape how strongly AI affects output and employment. As a result, the near- and medium-term growth effects of AI are likely to differ markedly between advanced economies (AEs) and emerging market economies (EMEs).

Productivity gains and labour market effects

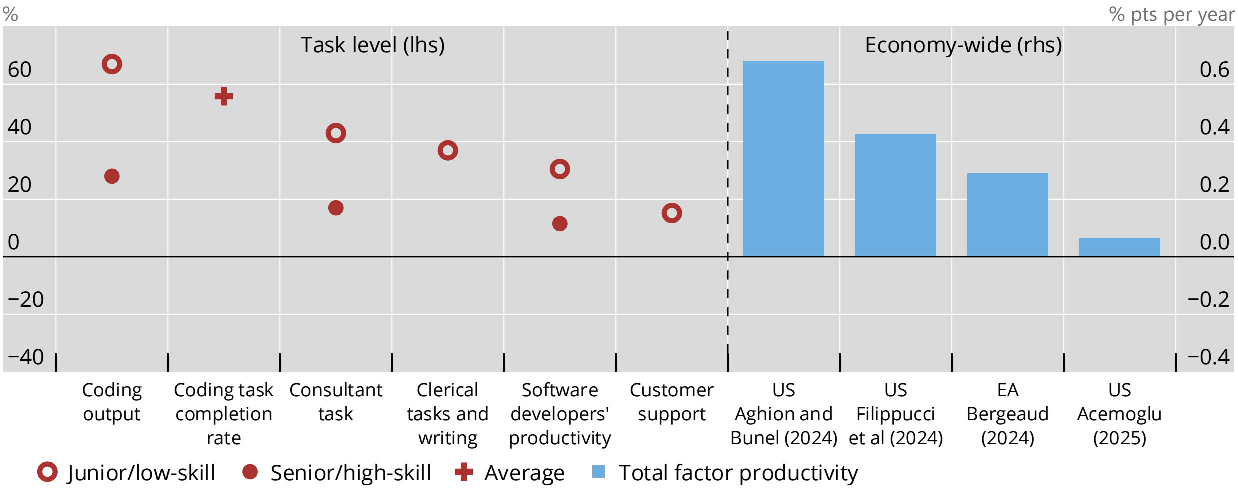
The effects of AI on real activity stem partly from its impact on productivity and labour markets. Early evidence from empirical studies using micro data suggests that generative AI (gen AI) could bring substantial productivity gains, especially by automating parts of non-routine cognitive tasks. Micro studies generally suggest large productivity gains of between 10 and 65%, with strong improvements in coding, consulting tasks and professional writing (Graph 1). Moreover, evidence suggests that AI tends to equalise workplace performance by raising the productivity of less experienced employees relative to those with greater seniority (Graph 1, filled vs empty dots). For example, in software development and coding, junior developers experienced productivity increases of 21–67%, while senior developers saw more modest gains of 7–26%. However, the equalisation effect refers to performance within narrowly defined tasks (eg coding). Across broader job roles, junior workers may remain more exposed to automation if their job involves a higher share of routine or AI-substitutable tasks, potentially reducing entry-level opportunities.

The extent to which these micro-level gains translate into higher economy-wide total factor productivity (TFP) remains an open question. Aggregate outcomes depend on reallocations across firms and sectors, as well as on the degree of misallocation in labour and capital markets (Hsieh and Klenow (2009)). In addition, productivity gains in AI-exposed sectors may be partly offset by labour shifting towards lower-productivity activities with limited scope for automation, consistent with Baumol-type effects (Baumol (1967)). Finally, differences in adoption speed and complementarities with skills and organisational practices can further dampen measured aggregate productivity gains.

Consequently, the estimated magnitudes for economy-wide gains vary widely (Graph 1, bars). Acemoglu (2025) reports an annual increase in TFP of 0.07%, one of the lowest estimates of AI's benefits for macroeconomic productivity. By contrast, Aghion and Bunel (2024), Bergeaud (2024) and Filippucci et al (2024) estimate larger TFP gains, about one order of magnitude larger (0.3–0.9 percentage points per year), in part due to higher estimates of industries' AI exposure. Higher productivity gains are also reported in Baily et al (2023), especially in a scenario in which gen AI continuously triggers innovation.

AI's productivity gains are accompanied by important labour market implications. Two broad forces are at work: the complementarity of gen AI with tasks that benefit from human input, and its substitution for routine cognitive tasks that can be automated. Some projections suggest that by 2030, up to 60% of occupations could undergo substantial task reallocation, with 25–50% of workloads in AI-exposed jobs potentially replaceable by automation (McKinsey (2023)). In EMEs, widespread labour informality shapes AI's impact. While AI can raise productivity and market access for micro-entrepreneurs, informal workers face greater automation risks, weaker social protection and limited access to skills, making displacement more likely. In the short run, these risks may outweigh the gains.

Estimates of productivity gains from AI vary[1] Graph 1



[1] Data sources for task level productivity gains: coding output from Gambacorta et al (2024); coding task completion rate from Peng et al (2024); consultant tasks from Dell'Acqua et al (2023); clerical tasks and writing from Noy and Zhang (2023); software developers' productivity from Cui et al (2025); and customer support from Brynjolfsson et al (2025).

Sources of cross-country heterogeneity

Cross-country differences in the use and effectiveness of AI are likely to reflect two main factors. First, sectoral composition differs across countries, with AI-intensive industries (such as finance, education and information) more prevalent in AEs. Second, AI preparedness – encompassing digital infrastructure, skills and institutional capacity – shapes countries' ability to absorb, deploy and benefit from AI technologies.[1]

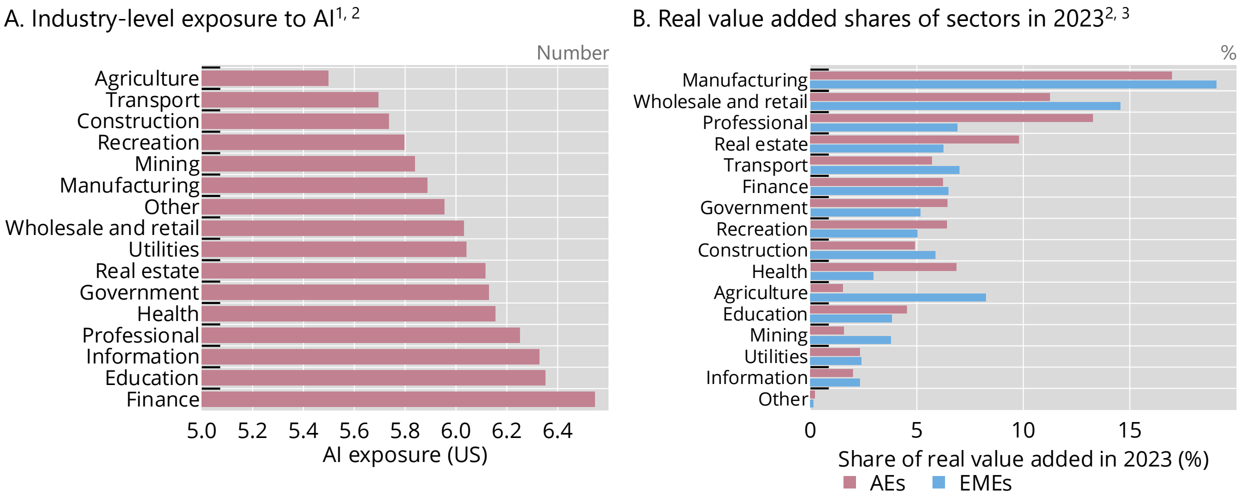
Sectoral composition

A country's sectoral production structure plays a key role in shaping AI deployment. Many EMEs are likely to see smaller near-term benefits than AEs, as their output is less concentrated in sectors with intensive cognitive and information-processing tasks enhanced by gen AI.

[1] The high concentration of the global AI supply chain, which gives a few jurisdictions a structural advantage in capacity development and income generation, is another source of cross-country heterogeneity (see Gambacorta and Shreeti (2025)).

Data on industry-level exposures to AI, coupled with information on countries' production structures, underscore this point. Agriculture, transport and construction show the lowest industry-level exposure to AI, as their core activities rely more heavily on physical and manual tasks that are primarily affected by robotics rather than gen AI (Graph 2.A). At the same time, the share of agriculture in total real value added is notably larger in EMEs than in AEs, while the share of professional services is smaller, which tends to be less conducive to the deployment and effective use of AI (Graph 2.B).

Production structure in many EMEs might not favour quick AI deployment — Graph 2



[1] Based on estimates of the extent that generative AI can be used across workplace abilities and occupations in the United States, aggregated to the sectoral level. Higher numbers indicate greater industry-level exposure to AI. [2] "Professional" includes professional, scientific and technical activities and administrative and support service activities. "Other" includes other service activities and activities of households as employers, as well as undifferentiated goods- and services-producing activities of households for their own use. [3] Based on data on real value added by country and industry at constant 2010 prices in 56 economies (29 AEs and 27 EMEs).

Sources: Felten et al (2021); Gambacorta et al (2025); Asian Development Bank.

AI preparedness

A country's capacity to adopt AI solutions and benefit from them also depends on the effective combination of several economy-wide factors regarding how well users can harness AI. AI readiness rests on strengths across several interrelated dimensions, which include: (i) reliable and scalable digital infrastructure; (ii) a digitally skilled and adaptable workforce; (iii) a vibrant environment for innovation and economic integration; and (iv) a sound regulatory and ethical framework. These key pillars are integrated in the International Monetary Fund's AI Preparedness Index (AIPI), which measures countries' structural readiness to adopt AI.

The AIPI shows that AEs are generally better positioned than EMEs and low-income countries to adopt AI, reflecting comparatively strong digital infrastructure, innovation capacity and regulatory frameworks (Graph 3.A). Countries that are higher on the AIPI have a larger employment share in high-exposure occupations. Within EMEs, there are differences across both regions and pillars. Some economies in Asia (eg Korea and Singapore) and the Middle East (eg Saudi Arabia and the United Arab Emirates) score highly on digital infrastructure (also favoured by renewable energy resources and power grids), but many EMEs exhibit an uneven profile – particularly in terms of human capital and regulatory preparedness (Graph 3.B). AEs generally have a higher share of AI-skilled workers and attract a net inflow of AI talent, reflecting stronger labour market opportunities and innovation ecosystems. By contrast, many EMEs exhibit lower domestic AI skills penetration and, in some cases, act as net exporters of AI talent (see Graph A.1 in the online annex). Governments' capacity to design, implement and oversee AI strategies is another key element shaping effective AI deployment; in this dimension, several EMEs – including China, Korea, Saudi

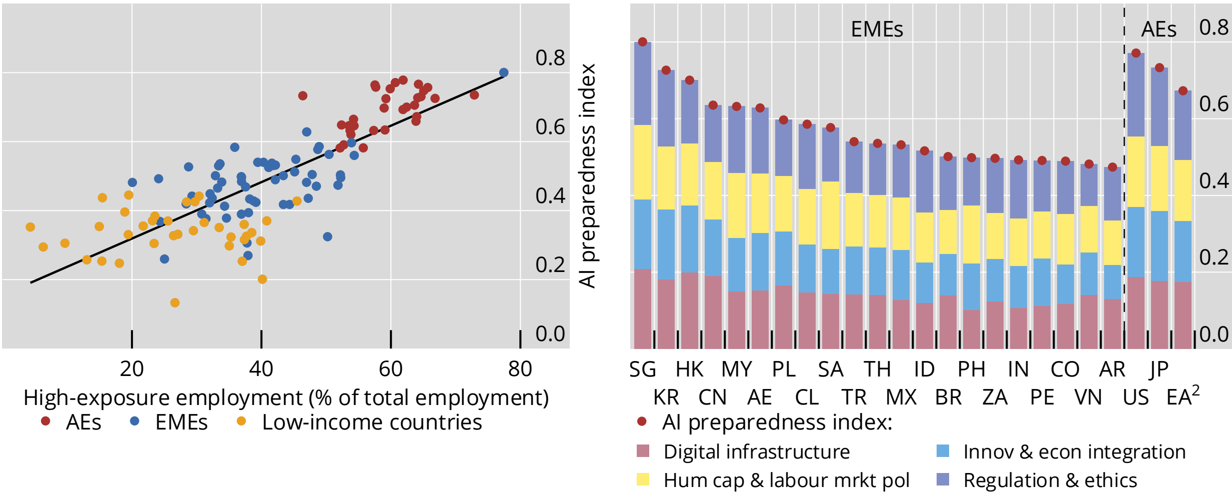
Arabia, Singapore and the United Arab Emirates – performed comparatively strongly in 2024 (Graph A.2 in the online annex).

AI preparedness differs across countries

Graph 3

A. AI Preparedness Index and employment share in high-exposure occupations[1]

B. AI Preparedness Index: dimensions



[1] The AIPI covers 174 countries as of 2023 and is computed as the sum of four equally weighted components: digital infrastructure, human capital and labour market policies, innovation and economic integration, and regulation and ethics. Each component is derived from multiple macro-structural indicators, sourced from different international institutions. The index ranges from 0 to 1, with higher values indicating greater AI preparedness. [2] For EA, simple average of all EA economies.

Sources: Cazzaniga et al (2024); BIS.

Quantification of the real effects across countries

Short-term effects

In the short run, the growth effects of gen AI in EMEs are generally expected to fall short of those in AEs. One reason is that ongoing AI investment – and its immediate boost to aggregate demand – tends to be particularly significant in AEs (Aldasoro et al (2026)). However, AI-related activities have also fuelled a recent surge in exports from several EMEs, particularly in semiconductors and computing equipment.

Another reason is the documented structural differences across countries and sectors. In the short term, gen AI adoption delivers larger gains in sectors with a high share of cognitive and information-processing tasks, providing AEs with larger professional and financial services sectors a stronger initial boost. Given these differences, a standardised increase in the AIPI would typically raise real value added growth by 0.6 percentage points on average in AEs relative to the global minimum (see Graph A.3.A in the online annex) but by only 0.45 percentage points on average in EMEs (Graph A.3.B) (see Gambacorta et al (2025)). This implies that, going forward, the convergence of EMEs' per capita income levels with AEs could proceed more slowly.

The short-term impact of gen AI on employment remains uncertain. EMEs have a larger share of workers in low-skill cognitive and clerical occupations that are susceptible to automation, raising the risk of initial job losses in specific tasks. Early evidence points to negative effects in call centres and business process outsourcing in India and the Philippines (Cucio and Hennig (2025); Singh (2025)). That said, labour market adjustments tend to unfold gradually, as firms often wait for clear productivity gains before reorganising work (Crafts (2021)).

Long-term effects

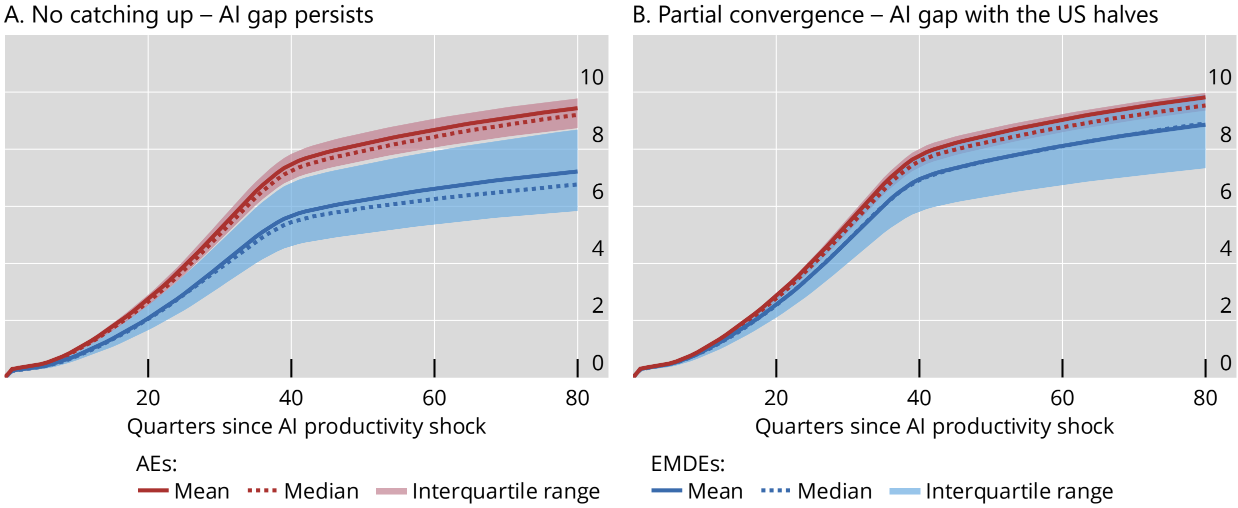
The heterogeneity in the effects of AI-driven productivity gains on real output is likely to widen further over the medium to long term if gaps in AI preparedness persist. Any assessment, however, remains tentative given the uncertainty around the diffusion and impact of AI technologies. Against this backdrop, differences in sectoral compositions and levels of preparedness for gen AI across AEs and EMEs imply that a sustained 0.5% yearly increase in TFP driven by AI over a decade would raise average real GDP in AEs by more than 2 percentage points relative to EMEs (Graph 4.A; see Cornelli et al (2026)).

A large part of this heterogeneity reflects differences in the AIPI. Under a scenario of partial convergence – where preparedness gaps relative to the United States shrink by half – real GDP in AEs rises by less than 1 percentage point relative to emerging market and developing economies (EMDEs) (Graph 4.B). This highlights the importance of policies that strengthen digital infrastructure, skills and institutional capacity.

The effects of an increase in productivity due to AI across countries[1]

In per cent, estimated change in the growth rate of real output

Graph 4



[1] The graph shows the effects of a perfectly anticipated positive supply shock to TFP arising from generative AI. The simulation covers 70 countries – 23 AEs and 47 EMDEs – and uses the AI industry exposure measure developed by Felten et al (2021) to assess the extent of the impact of AI adoption across industries. The calibration is set so that the aggregate impact on TFP growth amounts to 0.5% per year for the United States, as a benchmark, over a decade.

Source: Cornelli et al (2026).

In the long term, AI's impact on value added across industries suggests that general equilibrium effects dominate. Cornelli et al (2026) show that, in the steady state, output rises in all sectors, consistent with AI operating as a general purpose technology (Graph A.4.A in the online annex). Assuming total employment remains unchanged, labour mainly reallocates across sectors: construction and healthcare benefit the most, while mining and agriculture may experience larger employment reductions (Graph A.4.B). If AI adoption instead triggers significant labour market disruptions, employment effects could be more pronounced and uneven across sectors (Crafts (2021)).

Moreover, international trade and global linkages can significantly shape the cross-country distribution of AI-induced gains (Filippucci et al (2026)). EMEs importing AI-intensive goods and services may benefit from lower prices, while those integrated into the AI supply chain or specialising in AI-exposed sectors may experience stronger demand. As a result, trade openness can either amplify or mitigate domestic gains, depending on countries' position in global value chains. In this context, open digital trade, lower barriers to technology transfer and reskilling policies can support a more equitable distribution of AI gains. For EMEs, leveraging trade networks alongside continued investment in digital infrastructure, skills and institutions will be essential to harness the full potential of AI.

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