

BIS chief says the AI boom is now funded by debt and circular deals, and warrants caution

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Artificial intelligence, growth and financial stability: challenges for central banks

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Let me begin by thanking the Reserve Bank of India (RBI) and the organisers for the invitation. ¹ It is a great pleasure to be at the world's largest fintech gathering. There are few places better suited to discuss the economics of new technology. India's digital public infrastructure is studied around the world as a model of inclusive innovation, and the gains achieved over the past decade are truly impressive. The RBI has been central to that transformation. It is also a valued stakeholder of the BIS and a partner with whom we have long enjoyed close and productive cooperation.

Within the broad field of digital innovation, advances in artificial intelligence (AI) are occurring at an unprecedented pace. AI is, understandably, at the top of everyone's mind. In my remarks today, I will focus on what AI means for the economy, in both advanced and emerging market and developing economies. I will organise my remarks around three questions. First, how is AI reshaping the global economy? Second, how do the macroeconomic effects of AI differ across sectors and economies? And third, what does this mean for central banks and the conduct of policy?

AI and the global economy

Let me start with the first question. In the few years since the launch of large language models, AI has already been reshaping global macro-financial conditions.

The demand side effects of AI are the most visible. AI has unleashed a broad investment boom – in data centres, specialised semiconductor manufacturing, cloud infrastructure and hardware. Optimism around AI has also helped global financial conditions to remain accommodative, supporting household consumption through wealth effects. The market capitalisation, capital expenditure and revenues of AI firms have reached macroeconomic significance in many economies (Frost et al (2026)). The five largest big tech companies alone are set to spend over a trillion dollars on AI-related capital expenditure between 2025 and 2026 (BIS (2026)). Industry participants expect global AI-related investment to grow further, from around \$500 billion today to between \$3 trillion and \$4 trillion by 2030 (Aldasoro et al (2026b)). Increasingly, the AI investment boom is financed not by earnings but through debt and, notably, through private credit. I will return to this point later.

At the same time, global trade is also being reshaped. Exports of goods with high AI content have grown rapidly. A large part of this reflects higher prices. Prices for goods relevant to AI have risen significantly over recent years,

while export prices of other goods have stayed flat or, in some cases, fallen. This means that the evolution of terms of trade has been uneven across economies. This evolution is driven by where an economy finds itself in the AI supply chain. For example, upstream exporters like Chinese Taipei, Korea, Malaysia and Singapore have gained as their export prices have risen more than import costs. Even in these economies, gains have been narrowly concentrated. In Korea, for example, five firms accounted for around 43% of export earnings in the first quarter of this year, up from 27% only two years earlier. On the other hand, economies investing heavily in their own digital infrastructure have faced higher costs for AI-related equipment and worsening terms of trade.

Let me now turn to the supply side.

AI has the potential to increase productivity significantly over the coming years. The recent empirical evidence is certainly compelling. Across a range of task-level studies, generative AI has been shown to deliver productivity gains of between 10 and 65%, and efficiency gains of roughly 20 to 50% in time savings. These gains are particularly evident in coding, consulting tasks and professional writing. Productivity gains are relatively larger for less experienced workers compared with their senior colleagues, at least within narrowly defined tasks (Brynjolfsson et al (2025a); Cui et al (2025); Dell'Acqua et al (2023); Gambacorta et al (2026a); Noy and Zhang (2023); Peng et al (2024)).

The open question before us is how much of these micro-level gains can translate into aggregate total factor productivity (TFP). Aggregate TFP outcomes depend on how labour and capital are reallocated in response to AI (Hsieh and Klenow (2009)) and on frictions in the AI adoption process (Brynjolfsson et al (2021)). Estimates in the literature span a wide range, and the median points to an increase of around half a percentage point per year in TFP growth. Preliminary cross-country evidence is encouraging: economies that were better prepared for AI in 2023 have, on average, recorded stronger labour productivity growth since then (Aldasoro et al (2026b)).

Beyond productivity, let me say a word about labour markets, since this is where public concern is most acute, and rightly so.

There are two simultaneous forces at play here. AI complements human labour, making workers more productive in tasks where human judgment continues to be crucial. But AI can also substitute for workers performing routine cognitive work. Which of these two forces dominates will vary across occupations, sectors and countries.

In economies with a large informal sector – and that includes much of the developing world – the balance between risks and benefits can be tenuous. AI can raise productivity and widen market access for micro-entrepreneurs. But at the same time, as AI is adopted in clerical and customer-facing service tasks in the informal sector, informal workers may face job displacement. These workers typically have the least social protection, the most limited access to training and the fewest alternatives if their tasks are automated.

So far, actual displacement has been limited. Many firms remain in a wait-and-see mode, experimenting with the technology while facing uncertainty about regulation, costs and the reliability of AI. But early signs of displacement are emerging in specific tasks and occupations, including customer support, programming and administrative work (Brynjolfsson et al (2025b); Hui et al (2023); Cuccio and Hennig (2025); Singh (2025)). Recent earnings calls suggest that firms are already preparing for this transition: nearly 80% of firms discuss plans to automate production processes and increase labour substitution (Aldasoro et al (2026b)). The lesson I draw here is not that we should resist the technology, but that we should prepare people for it. Reskilling and retraining the workforce to keep pace with AI will be key to ensure that it augments human labour rather than substitutes for it.

Differences across economies

This brings me to my second question. How are the effects of AI likely to differ across economies? Gains from AI differ across two broad dimensions: how well an economy can use AI and where it stands in the production of AI.

I will start with the use of AI. An economy's capacity to use AI is driven by two factors: its sectoral composition and its AI preparedness. So far, generative AI has delivered its strongest gains in finance, professional services and information services, activities that have a high share of cognitive and information-processing tasks. The size and economic weight of these sectors are greater in advanced economies. In many emerging market and developing economies, output is more concentrated in manufacturing and agriculture, where the productivity gains from generative AI have so far been more limited.

The second driver is preparedness: digital infrastructure, human capital, the innovation environment and the regulatory frameworks that determine how well an economy can absorb and deploy AI. The IMF's AI

Preparedness Index captures these dimensions and highlights that the gap between advanced and emerging market economies remains wide (Cazzaniga et al (2024)).

Putting these two factors together, a clear pattern of divergence emerges. Research by my colleagues at the BIS, using a cross-country data set covering 56 economies and 16 industries, finds that sectors more exposed to AI grow faster in economies where AI preparedness is higher (Gambacorta et al (2025)). Since advanced economies score higher on AI preparedness and have a larger share of high-exposure sectors, they are likely to benefit more from generative AI in the short term than emerging market economies, where production is often concentrated in low-exposure sectors.

But let me immediately add a qualification, and it is an important one. Emerging market economies are not a single bloc (Gambacorta et al (2026b)). The variation in AI preparedness within this group is enormous, and wider, in fact, than the average gap between advanced and emerging market economies. China and several economies in the Middle East are among the best prepared in the world to deploy generative AI. At the other end of the spectrum, many lower-income economies still face substantial gaps in digital infrastructure, human capital, innovation ecosystems and regulatory frameworks. India lies in between and, in my view, has a genuine opportunity to close the gap by building on the digital public infrastructure it has already created.

What about the second dimension, related to the production of AI? To answer this question, it is useful to think of AI not as a single product, but as a complex global supply chain. AI products and services are provided through a supply chain that can be classified into five broad layers: semiconductor chips, cloud infrastructure, training data, foundation models and, finally, AI applications that reach the end user (Gambacorta and Shreeti (2025)). Where an economy sits along this chain shapes its economic outcomes, particularly through effects on investment and capital formation.

Across most of the AI supply chain, two economic features stand out: high fixed costs and significant economies of scale and scope. That combination has a predictable consequence. It favours the emergence of a relatively small number of very large firms, the so-called global AI giants. These giants are concentrated in a handful of jurisdictions: the United States, China, Chinese Taipei, Korea and the Netherlands. The largest among them, especially those based in the United States and China, are also unusually broad. They operate across different layers of the supply chain, designing chips, operating cloud computing platforms, producing data, building foundation models and developing AI applications. They have also acquired real macroeconomic weight: the largest listed AI firms now account for a substantial share of total stock market capitalisation, capital expenditure and revenues in the economies where they are based (Rishabh and Shreeti (2026)).

These patterns raise important trade-offs for the rest of the world. The central one is the tension between building national capacity in order to strengthen resilience, and avoiding the wasteful duplication of the large fixed costs inherent in AI production, while focusing instead on areas of genuine comparative advantage. The key strategic question facing policymakers is therefore to determine where the greatest economic value lies for their economy along the AI supply chain. Beyond hosting full-stack AI giants, many smaller economies can still shape the AI ecosystem by building capacity in context-specific AI applications, developing models fine-tuned to local needs and languages, and providing domain-specific data.

AI and central banking

Let me now turn my attention to my third and final question. What do these developments in AI mean for central banking?

As far as the objectives of monetary policy are concerned, they remain unchanged. What changes is the environment in which policy is conducted. AI is reshaping demand, supply and financial markets simultaneously, making the economy harder to read and increasing uncertainty around the transmission of monetary policy. That difficulty extends to the estimation of key unobservables. Potential output and the natural rate of interest are already measured with significant uncertainty. Structural change driven by AI can widen measurement errors, and discrepancies between actual and estimated output gaps may grow.

I want to dwell further on the longer-term direction of these effects. The 2026 BIS Annual Economic Report illustrates a range of possible scenarios. The first is a bounded productivity boost that shifts the overall growth trend permanently by a constant margin, akin to the shift that occurred during the Industrial Revolution. The second scenario is self-reinforcing explosive growth as AI autonomously improves itself. We call this the transformative AI scenario. The third scenario, which we call the demand bottleneck, lies somewhere in between.

In this last scenario, as automation advances, income is increasingly diverted away from labour towards further AI investment. As every displaced worker is also a lost consumer, the spending that supports innovation eventually shrinks. Over time, productivity gains and output stall – not for the want of technology, but for the want of demand.

These scenarios also have implications for the natural rate of interest, or r -star. Under the bounded productivity boost and transformative AI scenarios, higher productivity growth would increase the marginal product of capital and thus also increase the long-run r -star. But under the demand bottleneck scenario, r -star would increase initially as the supply side effects of higher productivity dominate, but would eventually fall below pre-AI levels as the demand bottleneck takes hold. The corresponding impact on inflation would move in the same direction as r -star, pushing prices up when stronger than expected productivity spurs demand and turning disinflationary in the demand bottleneck scenario. The takeaway from this analysis is that there is considerable uncertainty about the long-term effects of AI. Ultimately, these effects will be driven by how much AI progress relies on consumer demand, how competition shapes profit margins in the AI sector and how quickly AI products and infrastructure depreciate.

What about financial stability? One concern relates to cyber security. New AI models can aid both attackers and defenders, but the risks are asymmetric: attackers need to find only one vulnerability, while defenders need to protect the entire system. AI may therefore tilt the balance in favour of attackers (Aldasoro et al (2026a)).

Another concern relates to the AI investment boom. Equity valuations are elevated and increasingly concentrated among a small number of firms at the core of AI development, based on ambitious expectations of future earnings. At the same time, the capital expenditure of the largest firms is now outpacing their cash flows, prompting a growing reliance on debt and, increasingly, on private credit. Much of this financing is also opaque and interconnected. Under so-called circular financing, chip manufacturers and hyperscalers take equity stakes in AI firms, which in turn commit to purchasing their chips and compute, linking these players in ways that are difficult to observe and, at times, difficult to value.

The concern is straightforward. Should the returns to AI disappoint, a pullback in investment could turn today's capital expenditure boom into a bust. A key feature of the AI market that raises the risk of such a bust is the investment arms race between AI firms: driven by intense competition, these firms risk over-investing resources. History offers some instructive parallels here. The canal mania of the 1830s, the British railway mania of the 1840s, the electrification boom of the 1920s and the dotcom surge of the late 1990s were all based on important technological breakthroughs. All drew in more capital than eventual returns could justify. In each of these cases, the eventual correction that followed had economy-wide implications.

The consequences of such a correction could be larger than in the past. Households now hold more wealth in equities, so a sharp repricing could pass through more forcefully to consumption. With US stocks accounting for a large share of global equity markets, the effects could propagate globally. In some jurisdictions, windfall gains from rising AI-related exports may also contribute to domestic asset bubbles, further exacerbating financial stability concerns. I do not say that this is where the AI boom must lead. But the scale and speed of the current investment boom, and the weight of expected commercial returns, do warrant some caution.

Conclusion

Let me conclude.

The promise of AI is real. But its broader economic impact will be shaped by policy choices, not by the technology alone. The key question is not only how powerful this technology will become, but how widely its benefits will be shared across firms, workers and countries. Whether AI narrows or widens the gap between economies remains to be seen. That outcome will depend on investment in digital infrastructure and skills, on competition, on data governance and on sound institutions.

For central banks, AI does not change the mandate. But it can make the economy harder to understand and monitor. This raises the premium on measurement, judgment, policy agility and the international cooperation that allows us to learn from one another's experience.

India has shown that well governed digital technology can deliver real economic gains in an inclusive manner. That is the standard to which AI should be held. The future of AI will ultimately be determined not only by advances in technology, but by the quality of our policies and institutions.

Thank you.

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1 Footnote

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