INTERNATIONAL MONETARY FUND

Unlocking AI-Led Productivity Growth in the United Kingdom

Matthieu Bellon, Pragyan Deb, Mahika Gandhi and Emma Rockall

SIP/2026/072

***IMF Selected Issues Papers* are prepared by IMF staff as background documentation for periodic consultations with member countries.** It is based on the information available at the time it was completed on June 24, 2026. This paper is also published separately as IMF Country Report No 26/173.

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July 2026

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ABSTRACT: AI offers a significant opportunity to lift the UK's lackluster productivity growth. The UK is well positioned, given its concentration in high-skill, knowledge-intensive services where AI shows the greatest potential. Realizing these gains hinges on five enabling conditions—infrastructure, financing, regulation, skills, and trade openness—with bottlenecks identified in each. Economy-wide reforms are a prerequisite but should be complemented by targeted interventions in regulation and skills. A model of endogenous technology adoption calibrated to the UK finds that halving regulatory constraints and expanding AI-related skills supply could jointly increase output gains by two thirds. Investment in sovereign AI capabilities carries substantial insurance value against supply-chain disruptions.

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UNLOCKING AI-LED PRODUCTIVITY GROWTH IN THE UNITED KINGDOM[1]

AI technologies offer a significant opportunity to lift the UK's lackluster productivity growth. The UK is well positioned to benefit, given its concentration in high-skill and knowledge-intensive services where AI is showing the greatest potential for productivity gains. However, the full realization of these gains hinges on a set of conditions—appropriate infrastructure, financing for innovation, enabling regulation, appropriate skills, and trade openness—and the paper identifies bottlenecks in each area. Although economy-wide reforms to planning, energy markets, and scale-up financing envisaged under the authorities' "growth mission" are a fundamental pre-requisite for the development and adoption of AI, they should be complemented by more targeted (AI-specific) interventions in regulation, skills, and supply-chain resilience to address market failures. Using a model of endogenous technology adoption calibrated to the UK, the paper finds that halving regulatory constraints and expanding the supply of AI-related skills could jointly increase the output gains from AI by two thirds over the baseline. The government's AI strategy encompasses the right areas, but greater priority could be given to clarifying the regulatory framework and expanding the supply of the skills necessary for effective AI adoption, which our analysis suggests are the most pressing constraints. Investment in the domestic AI ecosystem also carries substantial insurance value, as even moderate disruptions to foreign model access could generate large output losses.

A. Introduction

1. UK growth has decelerated markedly over the past two decades, with trend productivity weakening relative to peers. Production function decompositions suggest that the UK's slowdown has been driven primarily by weaker total factor productivity (TFP) growth, with subdued capital deepening also contributing (Indraccolo 2025; Goodridge and Haskel, 2022). Looking forward, additional headwinds (aging, migration slowdown, and a depreciated capital stock) may dampen the growth outlook.

2. Artificial intelligence (AI) is widely seen as a transformative opportunity to boost TFP growth in advanced economies. AI has the potential to boost TFP growth by automating tasks, improving process efficiency, accelerating innovation, and enabling new products and business models (Bailey, 2026). Like in past general-purpose technology revolutions—including the Information and Communication Technology (ICT) revolution—economy-wide productivity gains from the rise of AI are expected to be driven by effective AI adoption and to primarily come from AI-using sectors (see Annex I on the lessons from the past ICT revolution).

[1] Prepared by Matthieu Bellon, Pragyan Deb, Mahika Gandhi (EUR) and Emma Rockall (RES). Kristina Kostial, Luc Eyraud, Florence Jaumotte, Carlo Pizzinelli and participants in an HMT and DSIT seminar all provided helpful comments.

3. Against this background, the paper assesses the conditions under which the UK could realize AI's productivity potential. The analysis focuses on five enabling conditions—appropriate infrastructure (including but not limited to ICT and energy infrastructure), the financing of innovation, supportive regulation, skills, and resilience through trade openness—that have been highlighted as essential for technology diffusion in general, and for effective AI adoption in particular (Comin and Hobijn, 2010; Cazzaniga and others, 2024). The paper uses these as an organizing framework. It first establishes the rationale behind these factors and why they are considered most critical; then it identifies what constraints may exist in the UK in these areas; finally, it assesses whether public policies have a role in addressing them, and whether current ones are adequately designed.

4. The paper is organized in five main sections. It first reviews the literature quantifying the potential impact of AI on advanced economies' growth—with a focus on the main channels through which AI can raise TFP—and benchmarking the UK's potential relative to peers (Section B). Second, Section C draws from the literature and empirical findings to propose a framework to identify constraints to AI development and identify the main bottlenecks in the UK. Third, Section D discusses the role of economy-wide versus more targeted policies, and in particular the extent to which the UK authorities' AI strategy may address the bottlenecks identified in the previous section. Fourth, Section E conducts policy simulations to quantitatively assess the effects of targeted policies by leveraging a model of AI adoption calibrated to the UK economy. Section F concludes by highlighting areas where additional policy measures may be beneficial.

B. Potential of AI for UK Productivity and Growth

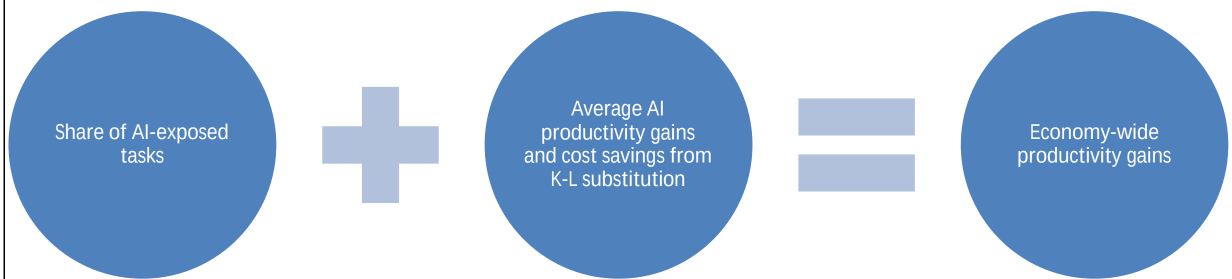
Estimates of aggregate TFP gains from AI vary widely across studies. Differences across estimates highlight that these gains depend on assumptions about the share of tasks that are exposed to AI, the average productivity gain per task, and cost-savings opportunities from AI adoption. The UK is well positioned to benefit from AI because (1) a large share of its workforce is in occupations exposed to AI, and (2) its most important sectors are those with the greatest potential for AI-driven productivity gains and cost savings from substituting hours of labor with AI services.

A Wide Range of Estimates in the Literature

5. The potential impact of AI on economic growth remains a highly debated topic and is marked by significant uncertainty. While empirical estimates are emerging at the micro level (see Misch and others, 2025, for a review), most studies of the macroeconomic effects on productivity remain essentially theoretical or focus on the labor market. Academic studies, private-sector analyses, and work by the Fund estimate a medium-term impact on aggregate TFP level ranging from below 1 to 35 percent over a decade (Briggs and others, 2023; Acemoglu 2024; Aghion and Bunel, 2024; IMF 2024; Filippucci and others, 2024; Filippucci and others, 2025; Cerutti and others, 2025; Misch and others, 2025; Bontadini and others, 2025).

6. Model estimates of aggregate AI gains typically rely on two determinants –the first one being the share of tasks that can legally or technically be automated and performed with AI (Figure 1). This share reflects both assumptions about the scope and capabilities of AI applications and the extent to which regulation can constrain AI use. A job is exposed to AI if the technology can be used for certain tasks and if regulation (licensing and training requirements, data privacy frameworks etc.) allows for its deployment.[2] Studies find that AI could support the performance of between 23 to 80 percent of tasks, illustrating the wide range of potential AI applications (Aghion and Bunel, 2024).[3]

Figure 1. Model Determinants of AI 's Potential Gains



Source: IMF Staff.

7. Then, the economic potential of automating tasks with AI depends on the average productivity gain and cost savings across AI-exposed tasks (second circle in Figure 1). Within the AI-exposed tasks, it is also important that tasks see their productivity increase through AI adoption. Micro-economic studies of AI task-level performance suggest that productivity could improve by between 15 and 55 percent (Brynjolfsson and others, 2023; Peng and others, 2023). Many factors affect these productivity gains. In particular, it depends on the extent of cost savings from capital-labor substitution as AI adoption implies the performance of tasks by AI models supported by capital –computers, data centers, and software—instead of workers. Therefore, countries with relatively high wages can benefit more from AI (Misch and others, 2025).

[2] There are licensing and training requirements for specific occupations, for example in sectors such as healthcare, law, and finance. Further, data privacy frameworks can constrain the information that AI systems may access and train on, limiting their applicability to tasks that depend on personal or sensitive data.

[3] In our framework, education and skills are a factor driving the *realization* of AI's potential, not the potential itself, and will therefore be covered in Section D. Nevertheless, while this section does not explicitly include education and skills as determinants of AI's potential, they are indirectly associated because AI-exposed tasks tend to be performed by high-skilled workers.

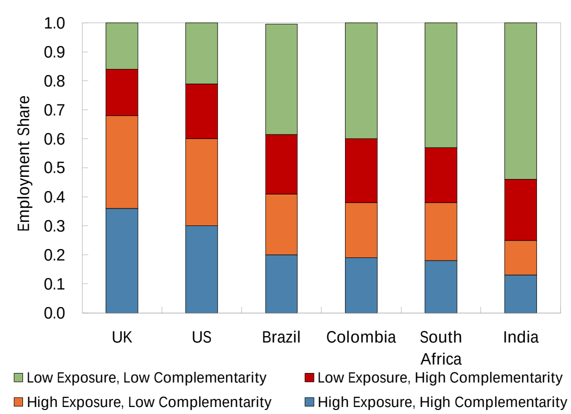
8. On both counts, current estimates of AI's economic potential could prove conservative as AI could accelerate the innovation process. AI capabilities and the associated productivity gains are still evolving, as the underlying innovation process remains rapid and dynamic. Continued innovation –both in fundamental models and in the complementary layers that support deployment (software, work organization)—will be crucial to expanding AI's potential. Furthermore, AI adoption can have positive feedback effects on the innovation process itself and accelerate innovation by automating the production of ideas and new technologies (see Aghion and Bunel, 2024 for examples; Bontadini and others, 2025).

Application to the United Kingdom

9. The UK economy compares favorably with peers across the two dimensions of Figure 1 and is therefore well positioned to benefit from AI. Misch and others (2025) estimates that the UK's TFP gains could range from 0.1 to 0.5 percent per year in the medium term, clearly above the average of European countries and on par with estimated US gains. These above-average gains stem from the UK's sectoral and labor characteristics which have positive implications for the two determinants of AI potential.

10. First, the UK's workforce is employed in tasks that are both highly exposed and complementary to AI. With roughly 36 percent of the workforce holding a college degree and nearly two-thirds employed in AI-exposed occupations, the country is well placed to capture substantial growth gains (Pizzinelli and others, 2023; Bick and others, 2025). Furthermore, more than half of these workers are in high complementary occupations –where AI can improve the productivity of existing workers rather than replace them—which suggests that disruption risks are limited for many occupations (Figure 2).

Figure 2. Workforce AI Exposure



Source: Pizzinelli and others (2023). High Exposure, High Complementarity are jobs highly exposed to AI and can be enhanced by it such as professionals and managers. High Exposure, Low Complementarity are jobs exposed to AI where substitution risk is higher such as administrative and clerical roles.

11. Second, the UK's economic structure and past experience with technologies suggest it could benefit from large productivity gains and cost savings per exposed task on average. During the ICT revolution, the UK stood out among European countries as more capable of reaping productivity gains from the new technologies (Annex I). Furthermore, occupations that have been identified as those likely to experience the largest productivity gains from AI (in business services, finance, IT, pharma) happen to be prevalent in UK's key sectors (Filippucci and others, 2024). These

occupations are dominated by cognitive, knowledge-intensive, and analytical tasks — precisely the activities where current generative AI and LLMs demonstrate the largest micro-level performance gains. Furthermore, various measures of labor costs place the UK above the OECD average (OECD, 2025). As a result, UK businesses have relatively more to gain from using AI to reduce labor costs and/or to increase worker productivity.

C. Bottlenecks to AI Development and Diffusion

This section identifies bottlenecks that could impede the realization of potential AI gains on the basis of a simple stylized framework. We examine five AI-enabling conditions and investigate how the UK performs across these conditions, drawing from surveys and independent assessments. The analysis identifies a few bottlenecks— barriers to the construction of ICT and energy infrastructure, constraints on business scale-up, regulation uncertainty, shortages of AI-relevant skills, and more speculatively, trade and geo-fragmentation risks to the sourcing of critical inputs which could constrain AI diffusion in the future.

12. Delivering the AI-driven productivity gains depends on key enabling conditions—infrastructure, innovation, regulation, skills, and resilience through trade openness. This simplified framework leaves out other, less critical, conditions supporting AI development and adoption, but these five general "enablers" are generally seen as essential for productivity—enhancing technology diffusion in general (Comin and Hobijn, 2010), and for effective AI adoption in particular (see the AI preparedness index in Cazzaniga and others, 2024).

- *Infrastructure (both ICT and energy), skills, and trade openness* are important enabling conditions for AI adoption. Econometric analysis of cross-country adoption rates confirms that these enabling conditions are meaningful drivers of AI adoption (Box 1 and Annex II). According to a variance decomposition of adoption rates, *AI-relevant skills* are the most important driver, followed by *infrastructure* and *openness* (see third panel in Figure 3). Beyond ICT infrastructure, *energy prices* –and by extension energy infrastructure—also matter (Annex II). These findings are consistent with prior empirical work highlighting the importance of skills and both ICT and energy infrastructure (Haag 2025; Misch and others, 2025).

- Surveys emphasize the relevance of two additional enabling conditions. Many businesses cite *regulatory framework and access to financing* as key factors shaping the pace of AI adoption and innovation (fourth and fifth panels in Figure 3) (DSIT 2024; DBT and DSIT, 2025; TechNation 2025).

13. We use this simple framework to identify possible bottlenecks impeding the realization of AI productivity gains. We do so by examining trends, benchmarking the UK versus peers across indexes, studying responses from business surveys, and leveraging independent assessments. Specifically, we consider (1) whether appropriate infrastructure is in place to support AI deployment at scale; (2) whether financing is available for product and business-model innovation—especially for high-growth-potential firms; (3) whether regulation provides an enabling and predictable environment facilitating investment in organizational and process transformations while safeguarding trust; (4) whether a critical mass of skilled workers are available to drive adoption and innovation, ensuring effective use within firms; and (5) whether openness to trade supports access to frontier inputs (on the import side) and expands market opportunities for UK exporters of AI-enabled goods and services, thereby increasing expected returns to effective adoption.

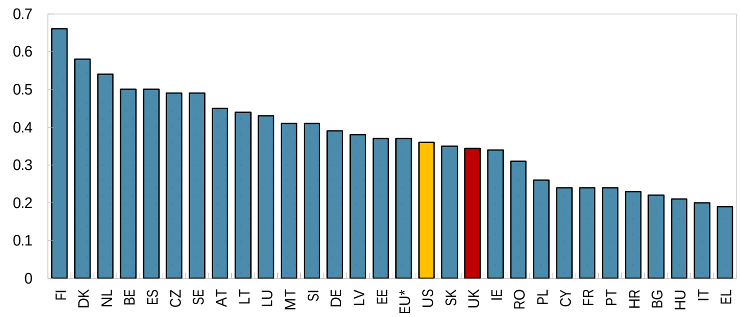
Box 1. United Kingdom: AI Adoption Over Time and Across Countries

AI adoption rates by businesses in the UK are high and growing fast. Surveys asking businesses whether they use AI to yield only rough proxies for the extent of *effective* AI adoption but are nevertheless informative of cross-country differences and trends. As of mid-2025, business surveys indicate that the AI adoption rate in the UK equaled 34 percent, close to the EU average of 37 percent and the US rate of 36 percent (first panel of Figure 3).[1] As elsewhere in the world, the UK's AI adoption rates are growing fast, having almost doubled from 2023 to 2025 (second panel of Figure 3). A cross-country survey also covering the US, Germany, and Australia offers some insight into the intensity of AI adoption by examining the purpose of AI usage: UK businesses report above-average adoption in data processing, image processing, and robotics, average rates in visual content creation and autonomous vehicles, and below-average rates in text generation using LLMs (Yotzov and others, 2026).

[1]There are several business surveys spanning multiple countries with overlap in coverage (e.g., a one-off survey in Yotzov and others, 2025; the EIB investment survey; the OECD ICT Access and Usage Database). Their results vary because of difference in the formulation of questions, the difference in timing, and difference in the sector and firm size coverage. However, results consistently show the UK adoption rates close to the US and the European average rates. Worker statistics and surveys yield similar results (Pierdomenico 2026; Bick and others, 2025).

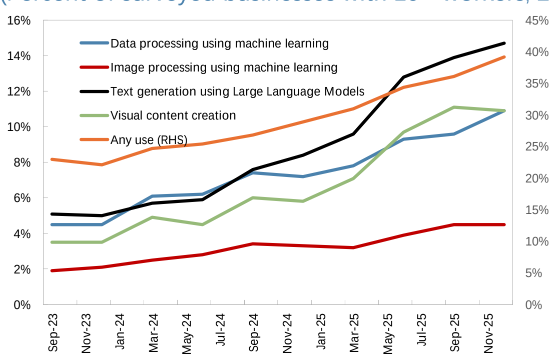
Figure 3. AI Adoption

Business Adoption Rates, mid-2025
(Percent)



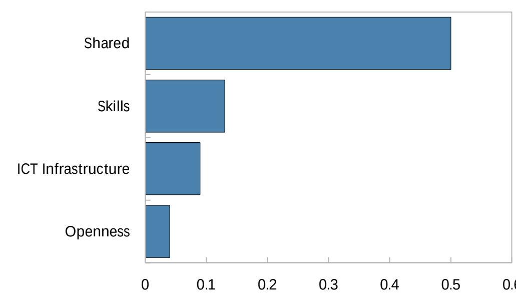
Source: 2025 ONS BICS (June 2025) and EIB-IS (2025).

Business Adoption Rates of AI Technologies
(Percent of surveyed businesses with 10+ workers, 2021–25)



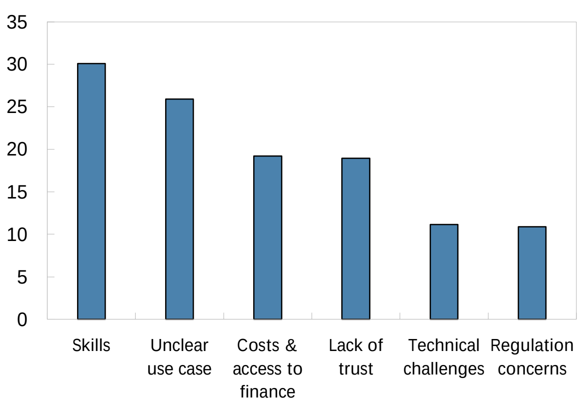
Source: ONS Business Insights and Conditions Survey, IMF staff calculation.
Notes: Includes all bunisesses with more than 9 employees.

Variance Decomposition of AI Adoption Rates
(Share of total variance)



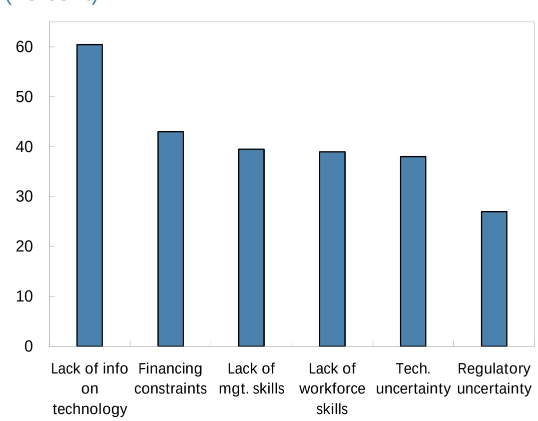
Source: EIB-IS survey, WB WDI, IMF AIPI and IMF Staff calculation.
Notes: Results from a regression with an R-square equal to 0.76. Each bar corresponds to the squared semi-partial R-square.

Obstacle to AI adoption in the UK, 2025 ONS Survey
(Percent of firms experiencing delays in AI adoption)



Source: ONS Business Insights and Conditions Survey, and IMF Staff calculations.

Obstacle to AI adoption in the UK, 2024 LSE-CBI Survey
(Percent)



Source: LSE and the Confederation of British Industry Survey.

ICT and Energy Infrastructure

14. The UK has a robust ICT infrastructure, although it lags the best performers. The UK ranks highly on the IMF global [AI Preparedness Index](#) for ICT infrastructure, sitting near the middle of the G7, somewhat held back by relatively high internet costs and lower secure-server density. Turning to AI-specific infrastructure, UK datacenter capacity is sizeable (first panel of Figure 4), ahead of comparably sized European peers. However, most existing facilities are designed for general-purpose enterprise workloads and lack the power density, energy integration, and technical specifications needed for AI training and inference (DSIT and UKRI, 2025). The UK also lags in terms of AI supercomputer capacity (second panel of Figure 4) and faces the highest electricity prices in the G7 (third panel of Figure 4).

15. UK investment in AI-related infrastructure is growing, but not as fast as in leader countries. Overall real investment in AI-related physical and digital infrastructure has grown at a slower pace than peers (fourth panel in Figure 4), and this is observed for both intangible and tangible investment. New orders for the construction of public and private infrastructure have been stagnant since the COVID-19 pandemic, although there have been signs of increased activity more recently (fifth panel in Figure 4), especially in the public sector. Focusing on datacenters, the rapid buildup in some peer countries could undermine the leadership position of the UK (sixth panel in Figure 4).

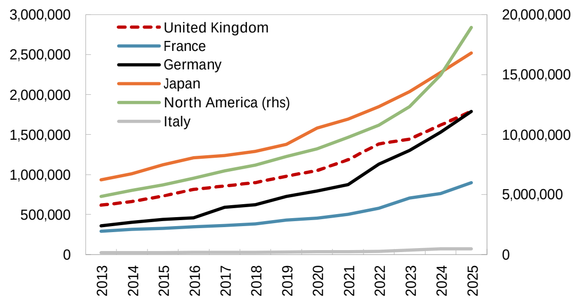
16. High energy costs and cumbersome planning processes could slow future AI deployment. Cross-country empirical analyses show that electricity prices are a significant determinant of AI adoption rates, suggesting that elevated UK prices are likely a headwind for AI development (Haag 2025) (fourth panel in Figure 3). Infrastructure building, including the construction of cheaper electricity generators, is hampered by restrictive planning and regulation, which are identified as key factors limiting construction activity (Carella and others, 2024). For datacenters specifically, the slow and outdated grid connection process is a bottleneck, with some sites facing waits of up to 5 years.[4,5] Independent assessments and some business surveys point to constraints on power availability and datacenter provision as factors weighing on AI growth in the UK, although these do not rank among the top barriers to adoption. Businesses can outsource some computing and datacenter services to circumvent these issues, and recent planning reforms have begun to address the most acute bottlenecks.

[4] Flint, April 16th, 2025. Four key policy and regulatory developments for the UK data centre market.

[5] Anecdotal evidence underscores these challenges: OpenAI launched its Stargate UK datacenter project in March 2024 to run its models on domestic compute infrastructure, but paused the project a month later citing the regulatory environment and energy costs.

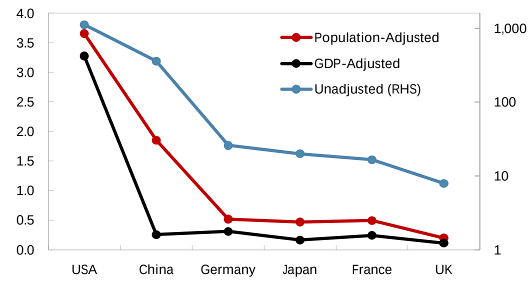
Figure 4. ICT and Energy Infrastructure

Datacenters (Net UPS Power)
(Gigawatts)



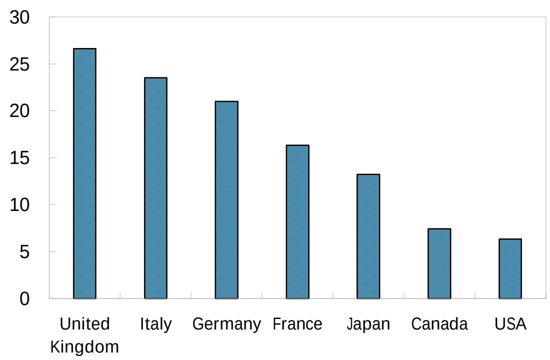
Source: The 451 Research Data Center Knowledge Base.

AI Supercomputer Capacity
(Cumulative 16-bit OP/s)



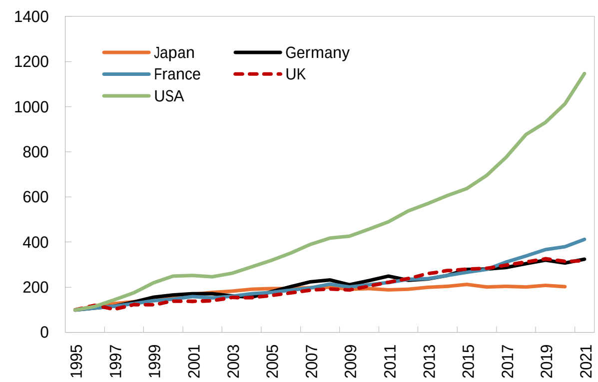
Source: Top500, World Bank, FRB Staff Calculations.
Note: Top500 data only represents the 500 most advanced commercial supercomputers. China stopped reporting around 2023, which may lead to overestimation of compute capacity of other economies in the future based on this data.

Electricity Prices
(In pence per kWh)



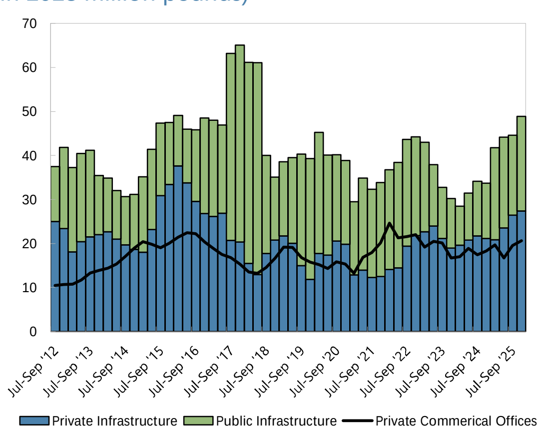
Source: ONS, derived from the International Energy Agency publication.

Real ICT Investment
(Base 1995=100)



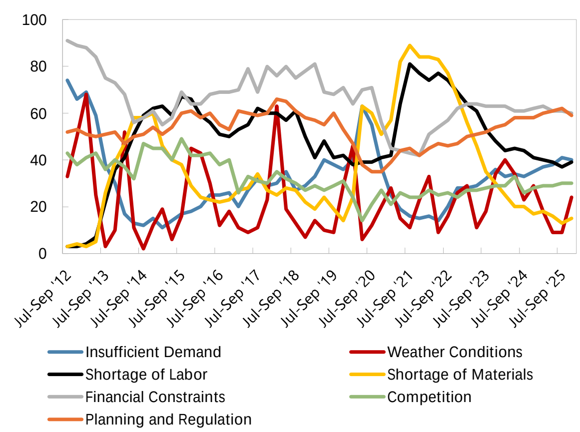
Source: EUKLEMS-INTANProd.

New Orders for Infrastructure Construction
(In 2023 million pounds)



Source: ONS and Barbour ABI.

Factors Limiting Construction Activity
(Percent responding “yes”)



Source: ONS and Barbour ABI.

Financing for Innovation

17. The UK's innovation financing base is solid, with robust R&D expenditure and a deep venture capital (VC) market. Gross domestic expenditure on R&D stood at 2.75 percent of GDP in 2022, marginally above the OECD average of 2.72 percent but well behind leading innovators such as Korea, the United States, Japan, and Germany (OECD 2026). On the supply side of venture capital, the UK is Europe's largest VC market by far, ranking third globally and growing rapidly (first panel in Figure 5). UK VC investment represented 0.17 percent of GDP in 2024, supporting more than 9,100 businesses.[6] Most of the VC funding in the last few years has been channeled into AI businesses, showing the large and growing role of AI in innovation (second panel in Figure 5). On the demand side, the number of newly funded AI startups and the total amount of private investment received for AI startups has increased rapidly (fourth panel in Figure 5).

18. However, a large share of UK VC investment flows abroad, and high-growth domestic firms frequently turn to foreign financing, increasing their likelihood of relocating. A structural weakness in the UK innovation ecosystem is that many high-growth innovation-intensive firms struggle to scale domestically, possibly reflecting difficulties in securing sufficient long-term risk capital. While early-stage finance is relatively accessible in the UK, a persistent "missing middle" opens at the scale-up phase (Parry, 2025). Seed-stage companies attract almost three-quarters of their funding domestically, a share that falls to less than one-third at the scale-up stage (TBI 2025), creating heavy reliance on US-based investors for growth rounds, and increasing the likelihood of these firms relocating to the US. In 2024 in the AI sector, UK recipients of VC financing raised only 40 percent of such financing domestically, while 80 percent of UK's VC financing was channeled abroad, mostly to US startups (second panel in Figure 5). Both US and EU startups' VC financing is more likely to come from domestic sources (70 and 50 percent respectively), while US and EU VC funds are much less likely to be invested abroad (15 and 55 percent respectively) (third panel in Figure 5).

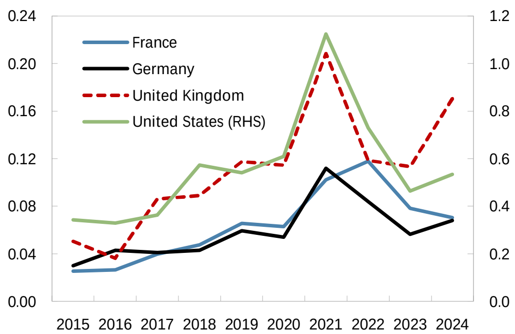
19. The lack of scale-up financing for high-growth, innovation-intensive firms is likely to constrain AI development in the UK. Multiple surveys of UK businesses converge in showing financing constraints as the first or second most-cited barrier to digital technology adoption (Oliveira-Cunha and others, 2024, CBI 2025, DSIT 2025, BoE 2025). Evidence suggests that financing constraints are most binding for SMEs, and particularly for young innovative firms in the ICT sector. In this sector, three in four founders identify access to growth capital as their primary obstacle (TechNation 2025). These startups tend to be intangible-intensive and lack the tangible capital that more easily serves as collateral in financing operations. Access to scale-up financing is also impeded by restrictive university spinouts rules and the lack of exit opportunities for investors, including via listing on the London Stock Exchange (Parry 2025, TBI 2025). UK firms also face restructuring costs (including notice periods, redundancy pay, consultation requirements) estimated at 19 months of salary per employee, compared with 7.4 months in the United States and under 3 months in

[6] The British Private Equity & Venture Capital Association's (BVCA) 'Venture Capital in the UK' 2025 report.

Denmark and Switzerland—a structural rigidity that compounds investor reluctance at the growth stage (Nguyen and Coyle, 2025).

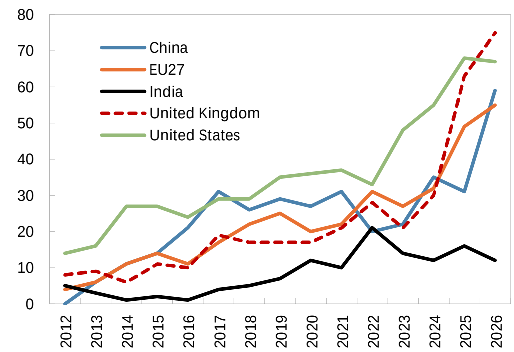
Figure 5. Financing of Innovation

VC Investment
(Percent of GDP)



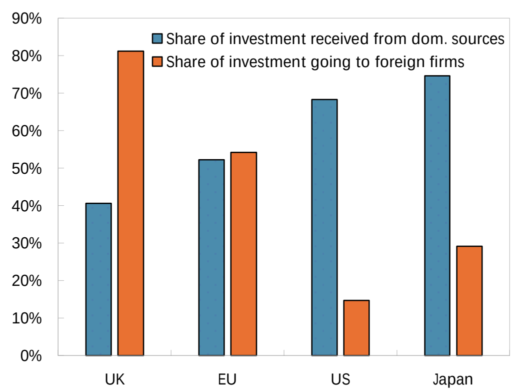
Source: OECD.

Share of Total VC Investment in AI by Country
(Percent)



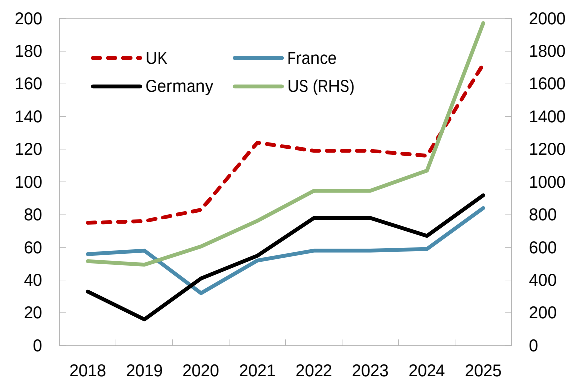
Source: OECD.AI (2026), data from Preqin.

VC Investment Flow in AI Across Countries
(Percentage)



Source: OECD.AI (2026), data from Preqin, and IMF Staff calculations.

Newly Funded AI Firms
(Count)



Source: Stanford HAI (2025).

Regulatory Framework

20. The UK's principles-based, sector-led approach to AI regulation has offered a broadly supportive environment for AI investment and adoption relative to peers. Rather than enacting AI-specific legislation, the government has relied since 2023 on existing laws and regulatory guidance based on five non-statutory cross-sector principles—safety, transparency, fairness, accountability, and contestability—implemented by existing regulators (FCA, ICO, CMA, Ofcom, and others) within their respective domains (NewMind AI, 2025). This architecture has avoided the compliance costs associated with the EU AI Act, whose tiered risk-classification system imposes conformity assessments, registration requirements, and transparency obligations on high-risk systems.

21. Nonetheless, regulation uncertainty can be a drag on effective AI adoption. While regulation never ranks as the main barrier to AI adoption for UK businesses overall, it always features prominently, especially for larger firms and in regulated sectors (BoE and FCA 2024, CBI 2025, DSIT 2025) (fourth panel in Figure 3). Nearly 60 percent of a government-commissioned survey respondents cited regulatory and policy obstacles as a barrier to AI adoption (McLean and Smith 2025). Evidence suggests that copyright rules are a salient issue, leaving firms unclear on the permissible use of data when training or deploying AI models. Firms in more heavily regulated sectors (including airports, rail transport, and financial institutions) also noted that regulators are not keeping pace with AI developments, increasing their own caution around AI deployment (CBI 2025). Taken together, the evidence suggests that the UK's approach has avoided compliance burden but that the lack of statutory clarity—on liability, intellectual property, and sectoral expectations—dampens adoption at scale.

Skills

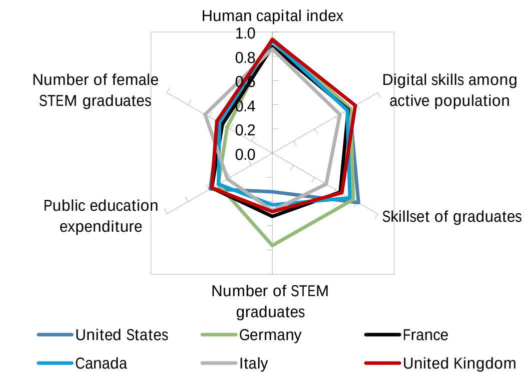
22. The UK workforce is highly educated. The UK scores highly on the human capital dimension of the IMF AI Preparedness Index, including among G7 peers (first panel of Figure 6). This reflects high average years of schooling and good digital skills among the active population (e.g., computer skills, basic coding). This strong general education base does not, however, fully translate into the specific technical, managerial, and implementation skills that AI adoption is likely to require. For example, the UK ranks below average on the perceived skillset of graduates (first panel of Figure 6). Focusing on selected sectors expected to benefit from AI—such as financial services, professional services, and ICT sectors—the prevalence of workers with AI engineering skills lags the US substantially (third panel in Figure 6). More broadly, this gap manifests in persistent shortages in intermediate and technical occupations—particularly in construction, and digital roles—suggesting that strong aggregate educational outcomes do not automatically translate into the more specialized capabilities required for effective technology adoption and diffusion.

23. The UK suffers from skill mismatches, with shortages being a persistent issue for businesses, especially in service sectors. As of 2025, more than 70 percent of UK companies surveyed by the British Chamber of Commerce report recruitment difficulties, with the ICT industry the second most affected. These difficulties partly reflect shortages—ICT were among the most elevated and fastest-growing (DfE 2025). Looking at occupations across the service sector, recruitment difficulties were most pronounced for professional and managerial positions such as engineers, lawyers, finance professionals, and HR managers (second panel in Figure 6). These roles combine technical knowledge with organizational and process management capabilities, typically involve planning, directing, and coordinating resources for the efficient functioning of businesses and are therefore essential to the governance and cultural change necessary for efficient AI adoption. One in three UK founders of Tech firms says that availability of talent is their biggest barrier to growth (TechNation 2025). Turning to AI specifically, a recent study found that the wage premium for AI-user skills is much higher in the UK than in the US, potentially signaling that these skills are in short supply (Jaumotte and others, 2026). Consistently, skill shortages are reported among the top barriers to AI adoption in the UK (Oliveira-Cunha and others, 2024; CBI 2025;

Microsoft and Public First, 2025) (see also the fourth panel in Figure 3). Taken together, this suggests that while the UK is well positioned in terms of general human capital, shortages in AI-specific and complementary skills could become a binding constraint as firms scale up adoption and organizational transformation accelerates.

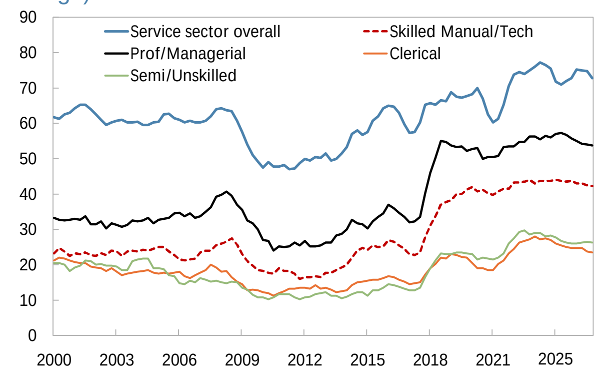
Figure 6. Skills

AI Preparedness Index: Human Capital Components
(Index)



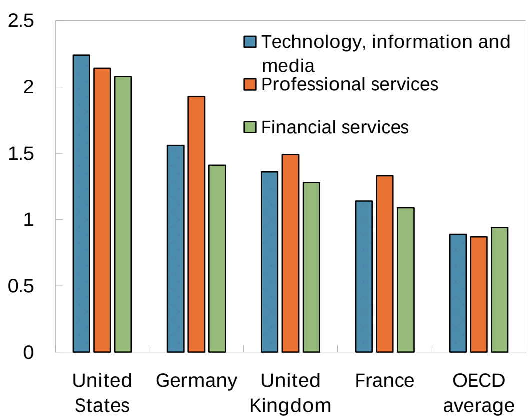
Source: IMF AI Preparedness Index.

UK Recruitment Difficulties in the Service Sector
(Percent of firms reporting difficulties, 4-quarter moving average)



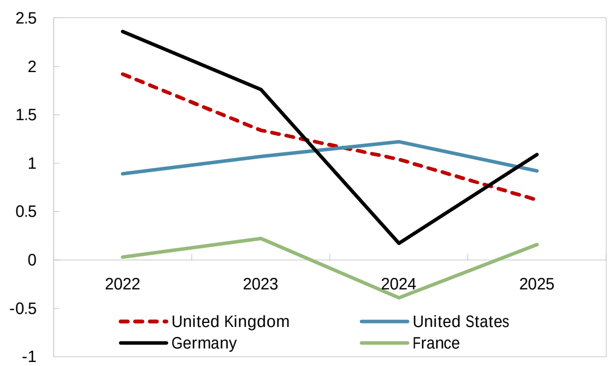
Source: The British Chamber of Commerce and Haver analytics.

Cross-country AI Skills Penetration by Industry
(Index)



Source: OECD.AI (2026), data from LinkedIn Economic Graph.

Net Migration Flows of AI Skills
(Index)



Source: OECD.AI (2026), data from LinkedIn Economic Graph.
Notes: This chart displays the net migration flows of LinkedIn members with AI skills from 2021 to 2025.

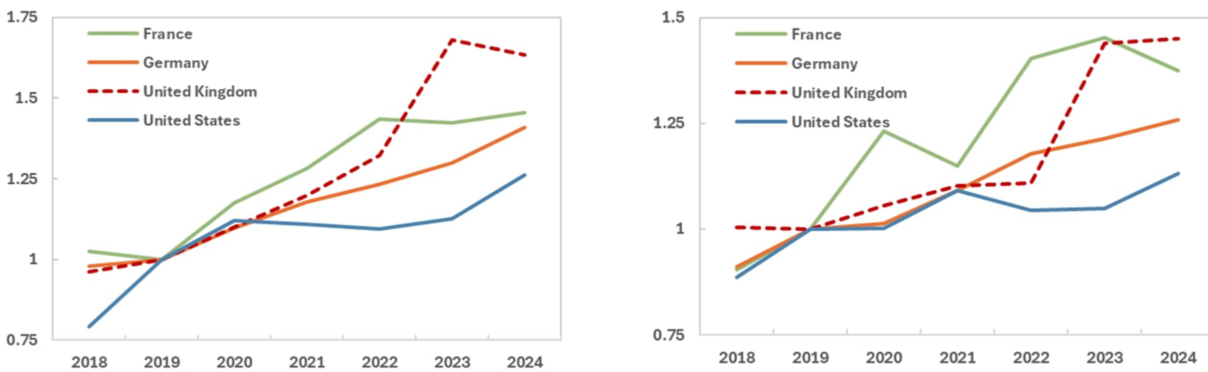
24. Furthermore, recent trends point to a risk of further deterioration in the supply of skills. High frequency indicators show that skill shortages have increased over the past decade and are at historically elevated levels (second panel of Figure 6). Expanding the supply of high skills, especially those needed for AI, takes time to expand through education and training, but can potentially be achieved faster through targeted immigration. While the UK experiences net migration inflows of cross-country workers with AI skills, these inflows have declined sharply in recent years (fourth panel in Figure 6).

Trade Openness and Resilience

25. **Strong UK services exports could be an asset for scaling AI-enabled services trade, while there are vulnerabilities to concentration risk on the import side.** Access to export markets is currently not a binding constraint. Digital trade represents more than half of the UK's exports, twice the OECD and EU averages, underpinned by strong comparative advantage in digitally deliverable services, particularly financial and professional services (González and others, 2024). Digital trade exports, including computer services, have grown at nearly three times the rate of other UK exports (Figure 7). On the import side, the UK sits in Tier 1 of the US AI Diffusion framework and therefore faces no procurement restrictions on advanced GPUs (hardware required for frontier AI training and inference). However, the UK's AI ecosystem depends heavily on US-headquartered hyperscalers for compute, cloud infrastructure, and foundation models, leaving it exposed to supply decisions and policy changes outside its direct control.

Figure 7. Trade

Exports of Computer Services (Percent of GDP, base 2019=1) | Imports of Computer Services (Percent of GDP, base 2019=1)



Source: UNCTAD and IMF Staff calculation. | Source: UNCTAD and IMF Staff calculation.

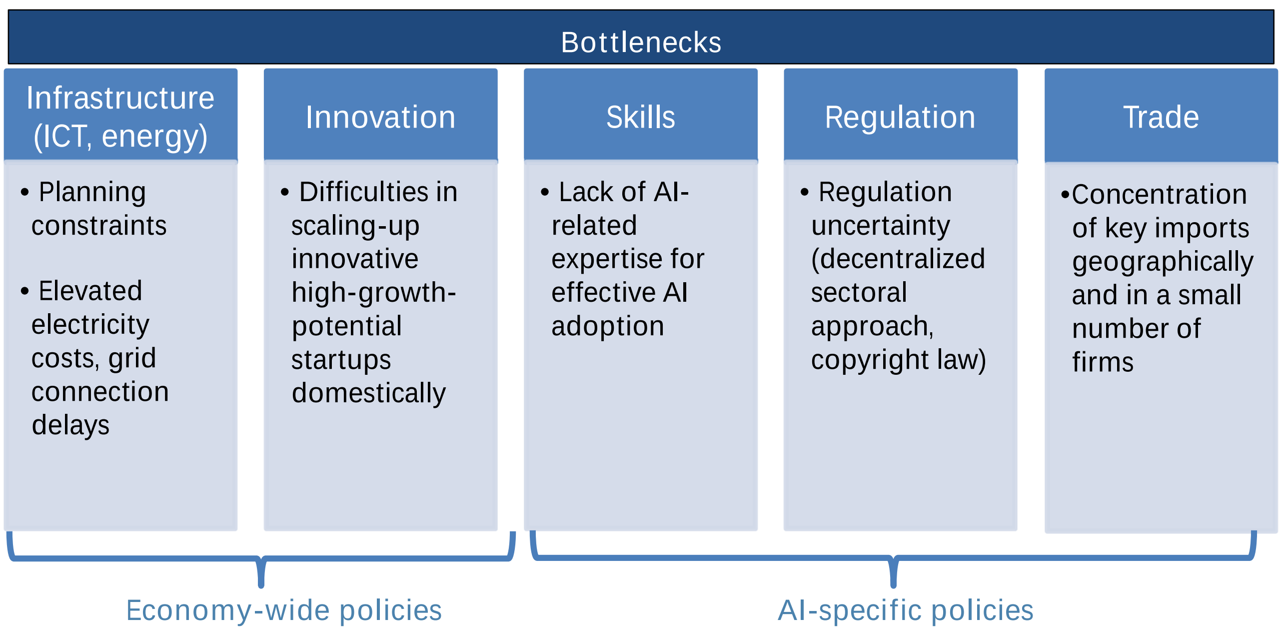
D. Policies for Lifting the Bottlenecks: Economy-Wide vs Targeted Policies

This section discusses possible policy responses to the identified bottlenecks. It shows that economy-wide reforms, as part of the authorities' broader "Growth Mission", are essential pre-requisites to address the bottlenecks that slow down the development and diffusion of new technologies, including AI. But specific market failures in AI development and diffusion mean that economy-wide policies alone may not be sufficient to unlock the full AI potential, calling for complementary targeted interventions.

26. **Both economy-wide policies as well as more targeted interventions for AI are needed to alleviate the identified bottlenecks.** Survey evidence, independent assessments, and cross-country comparisons summarized in the last section identify several obstacles for AI to thrive in the UK. Some of these, like the difficulties related to the slow development of AI-related infrastructure or high energy costs can be linked to *economy-wide* obstacles in the form of planning restrictions and elevated energy costs. These are best addressed as part of the wider structural reforms agenda,

some of which are already implemented as part of the authorities "Growth Mission". A similar argument can be made in the case of the UK's financing ecosystem which is adequate for generating startups and conducting early-stage research, but structurally undersized for the scale-up and diffusion phases that matter most for translating AI capabilities into economy-wide productivity gains. On the other hand, some obstacles and risks, such as the lack of AI-related expertise, a growing concentration risk from the UK's reliance on foreign frontier AI, and regulation uncertainty, may require more *AI-specific interventions*.

Figure 8. Economy-Wide vs Targeted Policies to Ease Bottlenecks



Economy-Wide Policies

Infrastructure: Planning Reform to Boost Construction

27. The government has taken important steps to ease constraints on investment in AI-enabling infrastructure through its planning reforms. The 2025 Planning and Infrastructure Act aims to speed up the delivery of nationally significant infrastructure, including digital and energy infrastructure. Datacenters were designated as critical national infrastructure by the UK government in September 2024, and the Planning and Infrastructure Act allows them to be opted into the Nationally Significant Infrastructure Projects regime. In parallel, AI Growth Zones, announced under the AI Opportunities Action Plan, layer a further fast-track pathway for designated sites with pre-cleared planning approval and access to clean power. Together these reforms are expected to address the most binding planning frictions affecting AI infrastructure, represent a meaningful improvement, and reflect the authorities' ambition to remove economy-wide barriers to investment. Because the same constraints that hold back data centers also hold back other types of

infrastructure, a successful planning reform would deliver gains well beyond AI—and also be a precondition for the AI buildout to materialize at scale.

28. The extent to which these reforms ease bottlenecks will depend critically on effective delivery and adequate scale. The payoff from announced reforms will materialize only gradually, and ensuring that reforms translate into materially shorter approval timelines, and predictable outcomes will be critical. A few areas may warrant particular attention. First, the capacity of the institutions that operationalize the reforms, such as local planning authorities, may need to be scaled up in tandem with the ambition of the reforms (MHCLG 2025). Second, stronger coordination between planning authorities, network operators, and investors could be warranted, for example, for proper sequencing of the consenting timelines for data centers and the grid infrastructure they require. And finally, systematic monitoring and regular reporting of approval times and project completions will help to demonstrate that reforms are being delivered, thereby giving businesses the confidence to undertake long-term investment. Given the general-purpose nature of AI, reducing planning frictions would raise investment and productivity not only in AI-related activities but across a wide range of infrastructure-dependent sectors.

Infrastructure: Accelerating Reforms to Lower Costs and Grid Connection Delays

29. The authorities have initiated a set of reforms aimed at addressing high electricity prices and grid connection delays. These challenges are economy-wide constraints that bear directly on AI competitiveness. Ofgem has reformed the grid connection regime in April 2025, replacing its “first-come-first-served approach” with a “first ready and needed, first connected” process, and the connections queue has been reduced substantially. On the supply side, the Clean Power 2030 Action Plan and the establishment of Great British Energy on a statutory footing are intended to accelerate the expansion of domestic clean generation, crowd in private investment, and improve long-term price predictability by lowering the instances where gas sets electricity prices. The government has also taken decisive steps to expand nuclear capacity, including final investment decision for Sizewell C. Together, these initiatives should, over time, ease capacity constraints and reduce risks faced by large electricity users.

30. The main challenge is the speed with which reforms can credibly relax energy-related constraints. Energy market reforms will take time to translate into lower and more stable prices, while AI-related demand for electricity is expanding rapidly. Continued attention to accelerating grid investment, expanding local network capacity in high-demand areas, and facilitating long-term power contracting for large users would help reduce uncertainty and operating cost volatility. Nuclear capacity additions will be helpful for the longer-term cost and reliability of the UK's clean grid, but their 2030s timeline means they cannot resolve the near-term cost pressure on data center investment decisions; the immediate burden therefore falls on accelerating permitting of new renewables, connections reform, network buildout, and electricity market design. Progress in these areas would benefit a broad range of sectors beyond AI, while directly easing one of the key input constraints identified for large-scale AI adoption.

Innovation: Mobilizing Financing

31. Recent reforms aim to address the persistent gaps in scale-up financing weighing on innovation-intensive firms and have been complemented by AI-specific financing initiatives. Pension fund consolidation under the Mansion House Accord aims to build the scale needed to invest domestically in riskier and more productive firms; listing and market reforms seek to lower frictions and improve exit opportunities; the British Business Bank's expanded Growth Guarantee Scheme and the National Wealth Fund are designed to crowd in private capital where coordination failures and information asymmetries are binding. While financing bottlenecks affect all sectors of the economy, these frictions are particularly consequential for AI, where large upfront investments in intangible capital are often required. On the AI-specific side, the £500m Sovereign AI Unit and the £100m advance market commitment for UK AI hardware startups (Box 2) layer targeted instruments on top of the broader scale-up financing architecture.

32. These reforms are appropriately oriented, but more is required given the scale of the gap. The British Business Bank's Growth Guarantee Scheme remains several times smaller, relative to GDP, than comparable schemes in the United States and major European economies. The National Wealth Fund's £27.8 billion capital over nine years is modest relative to peer policy banks; reaching the scale of institutions such as Bpifrance or KfW in France and Germany respectively would imply annual capital of roughly £21 billion (Resolution Foundation 2025). Some reforms could be considered including: (i) consolidating the fragmented landscape of public support schemes and improving coordination across them, without material disruption to their investment activity, so that they collectively cover the larger financing rounds where the missing middle is most binding (TBI 2025); (ii) scaling up the existing public-finance institutions over time—both the BBB and the NWF — to a footprint commensurate with peer economies, while preserving the discipline that comes from co-investment with private capital; and (iii)addressing the tax distortions that bear on innovation financing: making R&D tax credits payable in cash for loss-making startups (Adam and others, 2024), and reforming the capital gains tax treatment of capital losses and reinvestment to weaken the lock-in effects that discourage efficient capital reallocation.

Targeted AI Interventions

33. While high-quality economy-wide policies are a pre-requisite, targeted policies may also be needed, particularly given the rapid pace of AI technology development and adoption. Targeted interventions that address market failures that are specific to AI—such as those related to regulatory uncertainty about the permissible use of AI, AI specific skills shortages, and access to frontier models—may be needed to complement broader growth-enabling reforms. The case for such intervention is strengthened by the fact that competitor economies are investing heavily in AI infrastructure and skills (Figure 6), and the window during which policy intervention can shape the UK's competitive position is narrow. This suggests an important role for near-term temporary intervention, even where longer-term structural reforms are also underway but take time to deliver. The government's AI strategy (Box 2) recognizes these challenges and has committed significant resources.

Box 2. United Kingdom: The Government's AI Strategy

The authorities have made AI development a strategic priority. AI features prominently in the UK's 10-year industrial strategy (DBT and DSIT, 2025) and was designated one of the three "Big Choices" by the Chancellor in her March 2026 Mais lecture. The strategic orientation is anchored by the January 2025 AI Opportunities Action Plan and supplemented by subsequent strategy documents, including the UK Compute Roadmap, the Digital & Technologies Sector Plan, the AI Growth zones program, and the AI for Science Strategy. The AI strategy complements ongoing reforms under the authorities' Growth Mission, which focuses on easing input constraints through higher public investment, planning reform, mobilizing patient capital, and expanding labor supply (IMF UK 2026 Staff report). As of early 2026, the government reports had met 38 of the 50 actions set out in the Action Plan, with progress tracked through an online dashboard (DSIT 2026).

Specific commitments span each of the enabling conditions identified in Section C:

- *Skills.* The authorities committed £200m to upskill the workforce through AI courses, expand the Growth and Skills Levy for employer-sponsored short AI and digital courses, develop new AI scholarship programs (including the £17.6m Spärck AI 100 scholarships), launch the £160m TechFirst program to support over 4,000 graduates and researchers, and establish a Global Talent Taskforce to attract top researchers.
- *Infrastructure and compute.* There are plans to invest £1.75bn to build public compute capacity through the AI Research Resource program, in partnership with the University of Edinburgh; develop AI Growth Zones (AIGZs) for accelerated data center buildout with streamlined planning approval and access to clean power; and an additional investment of £100m for a National Data Library to house high-value public sector datasets and make them AI-ready.
- *Innovation financing.* A £500m Sovereign AI Unit has been set up to allocate access to public compute, provide early-stage financing to startups alongside the British Business Bank, and finance the buildup of AI infrastructure. The authorities have also put in place an "advance market commitment" of £100m to act as a first customer for UK startups building AI hardware products.
- *Regulation and safety.* The text and data mining regime has been reformed, the Data Use and Access Act (DUAA) was passed in 2025, and there is increased funding for regulators to scale up their AI capabilities. The government has also provided £240m for the AI Security Institute to expand work on frontier model testing, foundational safety, and societal resilience.
- *Public sector adoption.* The government has committed to make the public sector a leader in AI adoption, supporting the diffusion of AI tools across central government and public services.

Regulation: Providing Clarity to Adress Information Asymmetry and Uncertainty

34. Uncertainty about the permissible use of AI in regulated sectors reflects an information friction. AI applications can cut across several existing regulatory boundaries. For example, a single AI system used in healthcare recruitment may fall under employment law, data protection, equality legislation, and sector-specific clinical governance rules simultaneously, with no single regulator responsible for clarifying whether its use is permissible. This fragmentation creates an information friction: even firms willing to invest in compliance cannot easily determine what compliance requires. The resulting uncertainty is self-reinforcing, as the absence of legal clarity discourages the early deployment that would generate the evidence base regulators need to develop informed rules.

35. Regulation uncertainty deters AI adoption, development, and large-scale investment decisions. The 2025 Data Use and Access Act (DUAA) is an important step forward, simplifying compliance and enabling responsible data sharing. But some important questions remain open. The application of UK copyright law to AI model training is the subject of ongoing review: the DUAA required the Secretary of State to publish an impact assessment and report on the issue by March 2026 (DUAA, ss135–137), and the government has indicated that it will not introduce reforms to copyright law until it is confident they will meet its objectives (DSIT, 2026). In the interim, the uncertainty may discourage firms from training AI models using UK-held data. The DUAA also introduces changes to the UK's data protection framework that diverge from EU norms, and while the EU renewed the UK's data adequacy status to 2031, the longer-term implications for firms serving EU clients will depend on how far the two regimes continue to differ. More broadly, there is significant industry demand for greater clarity on regulation (DSIT, 2024), and firms in regulated sectors report that regulators may lack the resources to keep pace with AI developments (CBI 2025), possibly slowing deployment even where no explicit prohibition exists.

36. There is scope to enhance regulatory clarity for AI in ways that could meaningfully support adoption and productivity gains. The government could give more cross-cutting and operational depth to its regulatory framework with assurance tools demonstrating compliance with AI governance principles and concrete guidance developed iteratively with industry and other stakeholders, along the lines of Singapore's model (Hilliard and others, 2026). It could also consider accelerating the resolution of outstanding legal questions, particularly on copyright, liability for AI-generated outputs, and the conditions under which AI-assisted decision-making is permissible in healthcare, financial services, and education (Willemyns, 2025). Academic research shows that well-crafted regulation can boost productivity (Ash and others, 2025). Moreover, the current decentralized regulatory model, in which each sector regulator interprets cross-cutting principles within its own remit, could benefit from clearer mechanisms for coordination and accountability, building on the government's existing requests for regulators to report on their strategic approach to AI (DSIT, 2024). Regulators may also need additional resources and technical capacity to ensure they can develop sector-specific guidance at the pace AI is evolving. Finally, the UK could consider maintaining compatibility with EU and US regulatory frameworks where possible, to avoid creating trade frictions that would raise costs for UK firms operating internationally and to preserve the data adequacy status that underpins digital services exports.

Skills: Rapid scaling to Remedy Congestion and Poaching Externalities

37. The market for AI-specific skills features two mutually reinforcing externalities. As more firms adopt AI, they compete for a limited pool of specialists, bidding up wages and raising effective adoption costs for all firms — including those yet to adopt. This congestion mechanism strengthens over time: deeper adoption raises demand for specialists, which raises the cost of adoption, which holds back further adoption. The poaching externality compounds the problem:

because trained workers can be hired away by competitors, individual firms have limited incentive to invest in AI training, which in turn means the aggregate supply of specialists grows more slowly than it would if firms could capture the full returns to their investment.

38. There is scope to better target the government's significant resources committed to AI skills to the most binding constraints (Box 2). As documented in Section C, shortages are most acute for professional and managerial roles—the AI engineers, data scientists, and implementation specialists that firms need to deploy AI effectively. The government's focus on short introductory courses aimed at the broad population is welcome, but may not be sufficient to build these capabilities at scale, and other programs to attract world-class researchers target only a narrow cohort of exceptional individuals. The recent reform of the Growth and Skills Levy is a positive step in expanding employer-sponsored training, but has simultaneously defunded Master's-level apprenticeships for learners aged 22 and over which might work against the acquisition of AI specific skills. There is a need for wider access to programs aimed at deepening specialist skills at levels where shortages are most binding. For example, the Growth and Skills Levy could be reformed to ensure that it supports the depth of training needed, including at the postgraduate level.

39. Two complementary approaches could help ease skill constraints: expanding access to global AI talent via immigration and accelerating the development of AI skills among domestic workers. In the near term, immigration is the fastest route to expanding the supply of AI specialists. The sharp recent decline in inflows of workers with AI-relevant skills (Section C) points to scope for streamlining visa pathways for AI-relevant occupations. Over the medium term, structured employer co-investment in AI training could help address poaching externalities by narrowing the gap between the private returns to the training firm and the broader social returns from AI-related skill investment.

Resilience: Addressing Imports Concentration Risk and Coordination Failures

40. The concentration of frontier AI development in a small number of foreign firms creates a vulnerability that the government has begun to address. Unlike the regulatory and skills bottlenecks, this constraint is not currently binding and is more speculative in nature. At present, UK firms enjoy access to foreign leading models and cloud infrastructure on broadly competitive terms. But if access were to be disrupted, whether through export restrictions in provider countries, other supply chain bottlenecks, or the exercise of market power, UK firms could face sharply higher costs or even lose access to frontier capabilities. A coordination failure may materialize in the sense that no individual firm has an incentive to invest in domestic alternatives that are commercially unprofitable today but would be collectively valuable if disruption materialized. To address this risk, the government has begun to invest in sovereign AI capacity (Box 2). Key commitments include the £1.75bn AI Research Resource for public compute and AI Growth Zones for accelerated data center buildout.

41. There are benefits to build the conditions under which a domestic AI ecosystem could scale rapidly if needed, rather than attempting to replicate frontier capabilities directly. This means continuing to invest in compute infrastructure and energy capacity, diversifying chip supply chains, ensuring access to high-quality training data through the National Data Library, and maintaining regulatory compatibility with like-minded partners to reduce the risk of fragmentation. The modelling in Section E shows that even modest investments in domestic resilience could recover a substantial share of the output lost under disruption scenarios, and that the insurance value of such investments significantly exceeds the government's current AI commitment of over £2 billion.

E. Quantifying the Benefits of Targeted AI Policy Interventions

This section quantifies the productivity implications of these targeted measures using a model of endogenous technology adoption calibrated to the UK economy and assesses their relative benefits (Rockall and others, 2025). The first two scenarios suggest that regulatory uncertainty and skills shortages are of broadly comparable importance as constraints on AI adoption, and that addressing both would deliver complementary gains, boosting the output gains from AI by two thirds. The third scenario stress-tests the assumption that UK firms will continue to enjoy access to frontier AI models on competitive terms, and assess the insurance value of supporting the domestic AI ecosystem.

42. We use a model of endogenous technology adoption, calibrated to the UK economy (Rockall and others, 2025), to quantify potential productivity gains from policy intervention to address AI-specific bottlenecks. In the model, occupations consist of tasks with varying degrees of exposure to AI. Firms decide whether to adopt AI for each task by comparing the cost of AI capital with the wages of workers currently performing those tasks and the capability of AI at those tasks. Tasks where AI offers the largest cost savings relative to labor are automated first.[7] Given the model is calibrated to the current economic structure, it likely provides a conservative estimate of long-run gains, as it does not fully capture potential structural transformation induced by AI.

43. The model focuses on the AI-specific frictions identified in Section C, taking as given that broader constraints on productivity (planning bottlenecks, energy costs, and gaps in scaleup financing) have been addressed by the economy-wide reforms proposed above. Those constraints, and the policies required to address them, have effects that extend well beyond AI adoption and are better assessed through broader measures. The baseline can therefore be interpreted as a conditional scenario in which these constraints are effectively addressed, allowing the analysis to isolate the additional impact of AI-specific policies on adoption and productivity. The policy experiments that follow capture the additional payoff from targeted interventions that address market failures that exist in the adoption of AI that underpin these remaining frictions.

[7] The model builds on the task-based general equilibrium framework of Moll and others (2022), extended to study AI diffusion. Occupational exposure to AI is measured using the AI Occupational Exposure index of Felten and others (2021), mapped to UK household data from the Wealth and Assets Survey. Full model details are provided in the Annex.

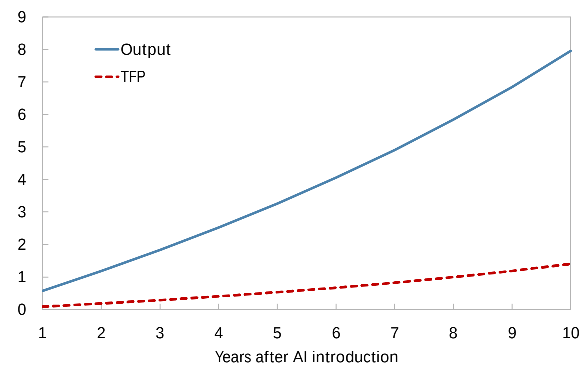
44. Two assumptions motivated by historical precedence and micro-estimates pin down the baseline— scale of adoption and the productivity benefits from adoption. The first anchors the long-run scale of adoption: we calibrate the model so that AI adoption raises the aggregate capital share by approximately 10 percentage points in the long run, in line with the increase observed in the UK over the previous wave of routine automation between 1980 and 2014. We assume AI reaches this long-run scale at twice the pace of routine automation, with the steady state reached in 17 years rather than 34, reflecting evidence that AI adoption is occurring much faster and that AI costs are declining more rapidly than earlier technologies (Appenzeller 2024). The second anchors the productivity benefits of adoption per automated task: we set the cost-saving gains from AI to 27 percent, the average of micro-empirical estimates from experimental studies of AI's impact on worker productivity (Brynjolfsson and others, 2023; Noy and Zhang, 2023; Peng and others, 2023), as used by Acemoglu (2024). Under these assumptions, the model's endogenous adoption path produces cumulative TFP gains of 1.4 percent at the 10-year horizon under the baseline, consistent with recent IMF estimates for the UK (Misch and others, 2025).[8] These estimates are broadly in line with the WEO baseline, which is produced independently and incorporates AI-driven productivity gains gradually as evidence of them materializes. The scenarios presented here should be read as illustrating the potential magnitude and relative importance of different policy levers, rather than as a forecast.

45. A central additional assumption underpinning the baseline is that the cost of AI technologies will continue to fall rapidly over the next decade. This trajectory of ‘commoditization’ reflects the fact that AI capabilities that are initially expensive and proprietary are likely to become widely available at low cost as the technology improves and competition between providers remains strong, much as earlier technologies such as computing hardware and internet services did. This assumption is well supported by recent data: the cost of using AI models has been falling by roughly 90 percent per year, faster than compute costs during the PC revolution or bandwidth during the dotcom boom, with a 99.7 percent decline in the cost efficiency frontier since March 2023 (Appenzeller 2024). Open-source models now perform within 2 percent of frontier models on key benchmarks (Stanford HAI 2025). However, the extent to which these cost reductions are passed through to end users remains uncertain. While falling inference costs suggest strong downward pressure on prices, evolving market structure, pricing strategies, and the need to recoup large upfront investments could slow pass-through. The baseline therefore assumes that competitive dynamics lead to a continued partial transmission of cost declines to users, an assumption that is relaxed in the final scenario below.

[8] Misch and others (2025) use a static framework without capital accumulation and report gains over the medium-term, which they take as 5 years. Our TFP measure strips out the contribution of capital deepening, making the two TFP estimates conceptually comparable in levels, but we take the medium-term to be 10 years, consistent with the framework of Acemoglu (2024) on which their estimates are based.

46. Under this trajectory, adoption deepens and productivity gains compound over time (Figure 9). The model projects cumulative output gains of approximately 3 percent within the first 5 years, rising to around 8 percent over a decade—substantially larger than the 1.4 percent TFP gain at the 10-year horizon. The difference reflects capital deepening: as AI makes tasks cheaper to automate, firms invest in the infrastructure, compute services, and organizational capacity needed to deploy AI, raising the capital-labor ratio and boosting output beyond the pure efficiency gain.[9] However, the baseline does not represent the UK's full AI potential, as the analysis presented in Section C suggests regulatory constraints and skill shortages are currently an important constraint on AI adoption. We assess the scope for policy to address these frictions, before considering what happens if the commoditization assumption itself does not hold.

Figure 9. Baseline Productivity Impacts of AI
(Percent)



Source: Authors' own.

Regulatory Uncertainty

47. We first consider an exercise where policies reduce regulatory uncertainty. Section C made the case that such uncertainty is a significant constraint on AI adoption in the UK, particularly in sectors where AI has the greatest potential.[10] Well-designed regulation that addresses risks around privacy, security, and accountability can ease constraints by reducing potential legal liabilities and giving firms the confidence to invest.

48. Regulatory uncertainty constrains AI adoption not by raising costs but by limiting the range of tasks for which firms are willing to deploy AI. In the model, regulatory concerns reduce the number of tasks AI can effectively automate within different sectors below the theoretical potential. We calibrate this so that regulatory uncertainty holds back 20 percent of potential AI adoption on average, consistent with the share of executives reporting significant regulatory

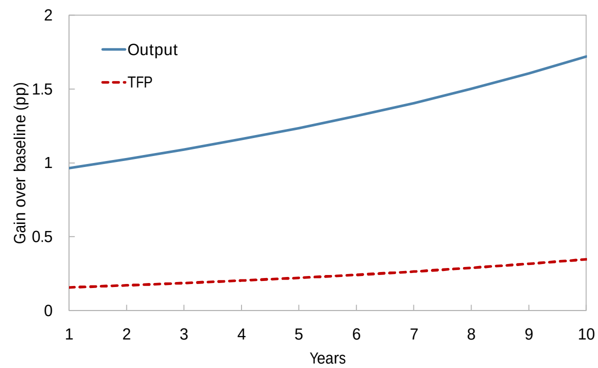
[9] To the extent that some of this investment takes the form of purchased services from foreign providers, the output gains may overstate the domestic value added, while the TFP gains—which capture efficiency improvements from task reallocation—are unaffected.

[10] Occupations with higher AI exposure also tend to face greater regulatory constraints, as measured by O*NET responsibility and criticality scales, suggesting that regulatory friction disproportionately affects sectors where AI has the greatest potential. Further analysis on this is presented in Annex III.

limitations (PwC Global Compliance Survey 2025). Within this, we also capture that some sectors are much more constrained by regulatory uncertainty than others. To do so, we construct an index of regulatory exposure from O*NET work context measures – including responsibility for outcomes, others' health and safety, consequences of error, and freedom and frequency of decisions—to capture which sectors face the greatest uncertainty about permissible AI deployment.[11] Many of the occupations with the greatest AI potential (such as managers, healthcare and education providers, legal practitioners and financial service providers) also face the greatest regulatory uncertainty (Figure III.1). We model regulatory reform as resolving half of this constraint, representing measures that clarify permissible uses and strengthening legal protections. The remaining half reflects substantive safety and accountability requirements, such as the need for a qualified professional to retain responsibility for clinical or legal decisions, that should remain even as AI capabilities improve.

Figure 10. Productivity Impacts of Regulatory Reforms

(Percentage point)



Source: Authors' own.

49. Under this scenario, providing regulatory clarity delivers gains that grow over time, as technology costs fall and regulatory uncertainty becomes a dominant constraint on adoption (Figure 10). Regulatory reform would boost output by 1.24 percentage points, and TFP by 0.22 percentage points within 5 years, growing to 1.72 and 0.35 percentage points respectively by year 10. This reflects the fact that as technology costs fall and adoption expands, regulatory uncertainty becomes the dominant barrier to adoption, leading the productivity gains from reform to grow over time. This highlights that targeted reforms which resolve this uncertainty preventing AI adoption are likely to be much more effective over the medium and long run than policies that aim to more generally lower adoption costs, such as adoption subsidies or tax breaks. To see this, we show in the annex that a policy to lower adoption costs through subsidies that delivered comparable productivity gains in the near term would deliver substantially smaller gains at longer horizons. This is because as AI becomes more mature and adoption costs fall, the value of cost-based interventions is eroded (Figure III.2).

[11] Details on the construction of the regulatory exposure index, and which sectors face the highest regulatory exposure, are in the annex.

Skill Shortages and Externalities for AI Talent

50. In a second exercise, we consider the impact of expanding the supply of workers and AI specialists with the skills necessary for effective AI adoption. For some firms, this means equipping existing employees to use off-the-shelf AI tools productively. But for firms seeking to deploy AI at-scale, adoption also requires more specialist capabilities: building bespoke applications on top of frontier models, developing the data and security infrastructure that AI systems depend on, and integrating AI into existing business workflows. These specialist skills are likely to be the binding constraint, because they require significant investment to develop and as shown in Section C are already in shortage. Section D identified two mutually reinforcing market failures in the market for AI specialists that broader skills reforms cannot resolve in the near term: a congestion externality and poaching externality. Without policy intervention, the pool of AI specialists is unlikely to expand fast enough to keep pace with demand, and the gap between what firms could achieve technologically and what the talent market allows them to realize grows over time.

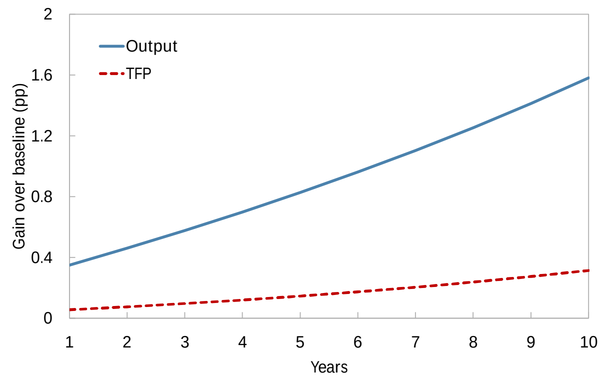
51. We decompose adoption costs into a technology component, which falls over time as AI matures, and a labor component, which rises over time as competition for a finite pool of specialists intensifies. The labor component captures the fact that deploying AI requires hiring or retaining specialist workers whose wages are bid up as more firms seek to adopt. The AI wage premium, currently estimated at 14 percent in the UK (PwC UK AI Jobs Barometer, 2024), enters adoption costs directly: a higher premium raises the effective cost of deploying AI for every firm, including those that have not yet adopted. We calibrate the AI labor share of adoption costs to 30 percent, consistent with the lower bound of estimates that 29–49 percent of frontier AI costs are attributable to labor (Cottier and others, 2024; Council of Economic Advisers 2025).[12] The poaching externality identified in Section D is reflected in the assumption that AI labor supply does not expand to meet rising demand absent policy intervention. As technology costs decline and adoption expands, the congestion markup on adoption costs grows from around 1.15× at year 5 to nearly 1.3× by year 10, with AI labor's share of total costs rising from around 39 percent to 46 percent over the same period. The result is that the faster AI technology improves, the more binding the talent bottleneck becomes. We model policy intervention as halving the AI wage premium through expanded training, vocational pathways, and immigration, for comparability with the regulatory scenario where reform also removes half of the estimated constraint. This lowers adoption costs for firms by reducing the labor component.

52. Halving the AI wage premium would deliver output gains of 0.83 percentage points within 5 years, growing to 1.58 percentage points by year 10 as the congestion externality compounds (Figure 11). TFP gains follow a similar profile, rising from 0.15 percentage

[12] Technical details of the decomposition are provided in the Annex.

points at the 5-year horizon to 0.31 percentage points in year 10. The implied increase in AI labor supply needed to achieve this premium reduction is approximately 27 percent at year 5, rising to 43 percent by year 10 as demand for AI talent grows with adoption. This underscores the value of early and sustained investment in AI skills through expanded university programs, sponsored vocational training, and immigration pathways.

Figure 11. Productivity Impacts of Increasing AI Skills
(Percentage point)

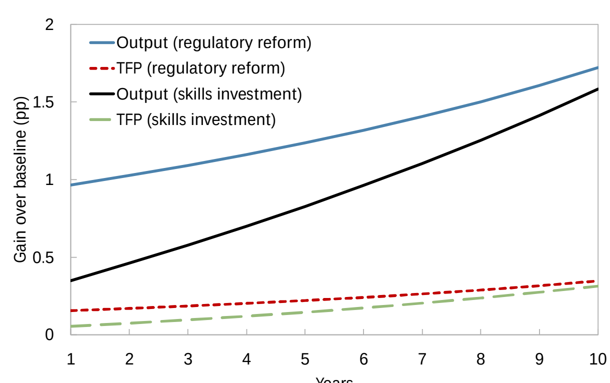


Source: Authors' own.

53. The analysis above does not capture the transitional labor market disruptions that may accompany AI adoption, including potential displacement effects during the adjustment period. However, work using the same model framework (Rockall and others, 2025) suggests that while higher output will lead to higher wages overall, many workers may see lower wages due to displacement. Wealth inequality is likely to increase through higher capital returns driving up risky asset prices, underscoring the importance of complementary redistributive policies alongside the supply-side interventions modelled here. How smoothly workers are able to reallocate to new tasks and roles will also matter for the aggregate productivity and output gains documented above.

54. Regulatory reform and skills investment deliver similar headline gains but operate through different channels and are therefore complementary (Figure 12). Regulatory reform expands the set of tasks for which firms are willing to deploy AI, unlocking productivity gains that cannot be achieved by making adoption cheaper. Skills investment tackles a self-reinforcing bottleneck that grows over time. Pursued together, the two policies ensure that neither regulation nor talent availability becomes the dominant constraint on adoption and could jointly increase the output gains from AI by two thirds over the baseline. Both, however, share an assumption embedded in the baseline: that UK firms will continue to enjoy access to frontier AI models on competitive terms. The remainder of the section examines what happens if

Figure 12. Comparison Between Regulatory Reform and Skills Investment
(Percentage point)



Source: Authors' own.

that assumption fails, and quantifies the insurance value of investing in domestic AI capacity against the risk of supply-side disruption.

Table 1. United Kingdom: AI Policy Reform: Summary of Productivity Impacts

	TFP (%)		Output (%)	
	Year 5	Year 10	Year 5	Year 10
Baseline	0.53	1.40	3.26	7.96
Policy gains over baseline (pp):				
Regulatory reform	+0.22	+0.35	+1.24	+1.72
Skills investment	+0.15	+0.31	+0.83	+1.58
Policy gains over baseline (%):				
Regulatory reform	+41%	+25%	+38%	+22%
Skills investment	+28%	+22%	+25%	+20%

Notes: Baseline row shows cumulative gains relative to year 0. All other rows show percentage point differences from the baseline. Policy gains are shown in percentage points (pp) and as a share of baseline gains (%). For example, regulatory reform adds 0.22pp of TFP at year 5; relative to the baseline gain of 0.53pp, this represents an increase of 41 percent (0.22/0.53). Regulatory reform removes 50 percent of estimated task-level regulatory constraints on AI use, calibrated so that regulation holds back 20 percent of potential AI adoption. Skills investment halves the AI wage premium through expanded training and immigration.

Concentration Risk and Coordination Failures

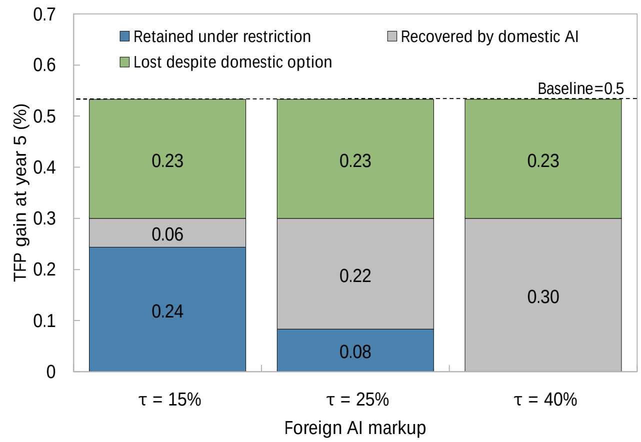
55. Finally, we assess the value of policies to support the UK's AI ecosystem and reduce exposure to the risk from a scenario where the costs of foreign AI technologies are significantly higher than in the baseline. Section C highlighted the UK's reliance on a small number of foreign suppliers for frontier AI capabilities, implying a risk if geopolitical or market developments restrict the access of UK firms to frontier AI inputs and technologies. We model restricted access as a markup on adoption costs when adopting foreign frontier AI technology, and consider a scenario with targeted investments in the UK AI ecosystem supporting the emergence of a domestic alternative. Firms then face a three-way choice: do not adopt, adopt a home-grown AI technology that is not subject to the disruption cost but is less effective, or adopt the foreign frontier model at higher cost. We assume that the domestic alternative delivers 90 percent of the benefits that the frontier model can deliver, conditional on adoption.[13] Figure 13 shows the

[13] The 90 percent figure is conservative. Open-source models now perform within 2 percent of frontier models on routine benchmarks (Stanford HAI, 2025) but score significantly lower on complex reasoning tasks—for example, DeepSeek scores approximately 74 percent of frontier on the Artificial Analysis Intelligence Index (2026). A 90 percent effectiveness ratio represents a well-funded domestic effort that closes much but not all of the gap.

decomposition of baseline productivity gains under three levels of disruption: a moderate markup of 15 percent, an intermediate markup of 25 percent, and a more severe disruption of 40 percent.[14]

56. Even moderate disruptions to AI access could impose significant costs on the UK economy, but the availability of a domestic alternative can substantially reduce this exposure (Figure 13). Under the central scenario of a 25 percent markup, restricted access reduces TFP gains at the five-year horizon from 0.53pp to 0.08pp and reduces the output gain from 3.26pp to 0.54pp—equivalent to approximately £82 billion per year in lost output relative to the baseline. A domestic alternative recovers roughly half of this loss, worth approximately £40 billion per year, by allowing firms to adopt a less capable but cheaper technology while foreign AI remains prohibitively expensive. Under severe disruptions (a 40 percent markup), the entire near-term productivity gain from AI is lost as UK firms are effectively shut out from the foreign technology, but the domestic option still recovers approximately £57 billion per year.

Figure 13. Productivity Impacts of Access Barriers and Domestic Alternative
(Percent)



Source: Authors' own.

57. These scenarios underscore that investment in the UK's domestic AI capacity can serve as valuable insurance against supply-side disruptions. The domestic alternative modelled here does not need to be the product of direct government intervention in AI development. Rather, it reflects an ecosystem in which UK-based firms and institutions have the infrastructure, skills, and incentives to develop and deploy AI independently if needed. Policies that strengthen this ecosystem, including investment in data center capacity and energy infrastructure, diversified chip supply chains, subsidized compute for the development of AI models, and facilitated access to training data, would reduce vulnerability to foreign supply disruptions while also supporting the application-layer AI technologies where the UK has a comparative advantage.

58. The government's current AI investment commitment of over £2 billion is modest relative to the potential benefits of such investments. Even under moderate disruption, the output recovered by greater domestic resilience substantially exceeds this figure. There is significant uncertainty over whether a disruption would materialize, how severe it might be, and how competitive a domestic alternative could become, particularly given winner-take-all dynamics in

[14] This is illustrative, but also consistent with recent examples. The US has, for example, has imposed revenue-sharing arrangements of 15–25 percent on AI chip exports to certain countries, which would be consistent with a 15–25 percent markup. With respect to monopoly margins, most of the large AI companies are currently loss-making, but looking elsewhere in the ecosystem NVIDIA reported gross margins of 75 percent in Q4 of fiscal year 2026, implying significant pricing power. More severe disruptions, such as full export restrictions, could imply significantly larger effective markups.

foundation model development. But these uncertainties cut both ways: the model does not capture potential positive spillovers from domestic AI investment, including to AI safety, domain-specific applications, and the broader innovation ecosystem, which would yield productivity benefits even absent disruption. On balance, the case for investing in the foundations of a resilient UK AI ecosystem is strong, provided that policy focuses on enabling conditions rather than attempting to replicate frontier capabilities.

F. Conclusion

59. The UK's growth performance has weakened markedly over the past two decades, but AI presents a transformative opportunity that could lift productivity. The slowdown has been driven primarily by sluggish total factor productivity growth. The UK is, however, well positioned to benefit from AI—its economy and workforce are concentrated in sectors and occupations where generative AI demonstrates the largest productivity gains and cost savings—but realizing this potential is far from automatic. The paper identifies binding bottlenecks across five enabling conditions—skills, financing for innovation, regulation, infrastructure and energy, and trade openness—that need to be addressed for the UK to capture the full gains from AI.

60. Although the effective adoption of AI will be fundamentally driven by the private sector, sound economy-wide structural policies are a prerequisite for accelerating gains. Economy-wide reforms under the authorities' Growth Mission are a necessary first line of action, as they address key bottlenecks—planning constraints, high energy costs, and gaps in scale-up financing. Going forward, priorities include ensuring that (1) recent planning reforms translate into materially shorter approval timelines for critical infrastructure; (2) renewables permitting, grid connection processes, and electricity market design continue to be reformed to narrow the UK's energy cost gap with peers; and (3) domestic capital for high-growth, innovation-intensive firms is further mobilized—including through better coordination and consolidation of public support schemes and fiscal incentives better tailored to financially constrained startups. Many of these reforms are already under way, and their effective delivery is a precondition for AI-related gains to materialize at scale.

61. While necessary, economy-wide reforms may not be sufficient, as AI development and diffusion are subject to specific market failures that warrant more targeted interventions. Regulatory frameworks lag technological change, creating uncertainty that could deter adoption even where no explicit prohibition exists. Poaching and congestion externalities discourage firm-level skill formation, leading to underinvestment in training. The concentration of frontier AI in a small number of foreign firms creates risks that geo-economic fragmentation aggravates. Illustrative modelling calibrated to the UK economy suggests that the gains from addressing these AI-specific bottlenecks are potentially large, compounding over time as technology diffuses through the economy. This calls for policies that expand the supply of AI-relevant skills –for instance by streamlining immigration pathways in the near term while ramping up education and training programs. On regulation, it is important to move ahead with plans to provide clarity on copyright issues and facilitate the use of AI in regulated sectors. The simulations also show that targeted investment in the UK's domestic AI ecosystem carries substantial insurance value against supply-side

disruptions. Beyond supply-side interventions, the government also has a role to play in ensuring that gains are broadly shared and that deployment proceeds responsibly. Across all areas, the central challenge is one of delivery, scale, and agile course-correction –translating a well-designed strategy into successful implementation with a pace and ambition commensurate with the opportunities brought by AI.

Annex I. Lessons from the ICT Revolution

Lessons from the ICT revolution show that general purpose technologies lift growth by diffusing across sectors in the economy and require complementary investment in intangible capital –including organizational change like new business processes and a reorganization of tasks and workers—if full advantage is to be taken of the new technology.

1. Past introductions of general-purpose technologies, like the Information and Communication Technology (ICT), have boosted economic growth, particularly in advanced economies. The emergence of ICT in the 1990s, 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 others, 2008; van Ark and others, 2003; Oliner and others, 2008; and European Commission, 2010) .

2. Evidence from past technological revolutions like the adoption of electricity and ICT suggests that productivity gains can materialize long after the original technological breakthrough. In the case of AI, its invention can arguably be traced back to the emergence of machine learning in the late 1990s. Drawing a parallel from previous innovation waves, this would imply that its effective use could start to be felt only now (Aghion and Bunel, 2024).

3. Most of the productivity gains from the ICT revolution came from effective ICT adoption in ICT-using sectors, rather than from the ICT sectors themselves. Decomposing growth drivers, the literature found that the majority of gains came from the adoption of ICT by market services (sectors like distribution services, financial and business services) while contributions from the rapid growth of ICT sectors themselves was less consequential given their small share in the overall economy (van Ark and others, 2003; Vandenbussche and others, 2006; van Ark and others, 2008).

4. ICT-led growth was more rapid in the US than in Europe, both because of larger ICT sectors and more effective adoption in ICT-using sectors. Growth differentials are not explained by investment rates. ICT sectors and investment in ICT goods by other sectors grew in Europe at about the same rate as in the US (van Ark and others, 2003). The two drivers of faster US growth are the larger initial size of the US ICT sectors and ICT capital stock—the absolute gap in ICT capital intensity kept widening—and more effective adoption of ICT technologies in ICT-using sectors.

5. The UK's growth gains differed from European peers and approached those in the US (Annex I Figure 1). Over the 1995–2006 period, the main difference in overall growth rates between the US and the UK is estimated to come from capital deepening (Martin 2025). Regarding TFP, comparisons between the UK and country peers reveal that the UK TFP grew almost as rapidly as in the US during the adoption phase of ICT, and faster than in most other European countries (Van Ark

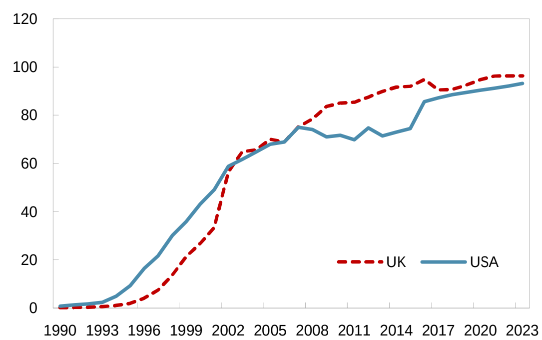
and others, 2008, Martin 2025). Nevertheless, other studies find that the UK's TFP growth fell somewhat short of the US in the earlier phase of the ICT revolution because of technology adoption lags and additional frictions undermining complementary investment in intangible capital (Basu and others, 2003).

6. Effective ICT adoption in the 1990s and 2000s was boosted by specific factors, including flexible markets, complementary investments in business practices, a high-skilled workforce, and openness to trade and ideas. US investment to adopt new business processes and organizational practices, also underpinned by more flexible labor markets and less restrictive product market regulations, enabled larger gains (van Ark and others, 2003; van Ark and others, 2008; Bloom and others, 2012). Other studies reflecting on technology revolutions in general highlight the importance of proximity to the innovation frontier for effective technology adoption (Comin and Hobijn, 2004; Eaton and Kortum, 2002; Acemoglu and others, 2006). At the country and sectoral level, the diffusion of a new technology and effective adoption thrives when trade and capital openness facilitates the flow of ideas embedded in inputs and direct investment, when there is a significant share of high-skilled workers who can learn and devise how to deploy the new technology, and when institutions are supportive of change.

Figure I.1. The ICT Revolution

ICT adoption took off with a small lag in the UK versus the US…

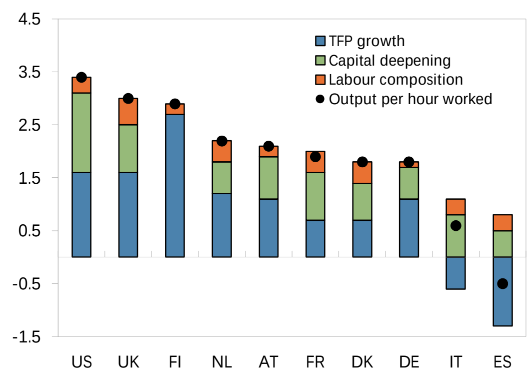
Share of the Population Using the Internet
(2026)



Source: Our World in Data from World Telecommunication/ICT Indicators Database - International Telecommunication Union (ITU), via World Bank.

…but led to rapid growth, sustained by TFP gains and capital deepening.

Decomposition of 1995–2006 Growth in Output Per Hour
(Percent)



Source: Martin (2025).

Annex II. Drivers of Business Adoption of AI Across Countries

This annex provides details on the cross-country regression analysis of AI adoption rates featured in Section C and the third panel of Figure 3. Infrastructure, skills, and trade openness are important enabling conditions for AI adoption. Simple econometric regressions of adoption rates on various factors show that these enabling conditions are meaningful drivers of AI adoption. According to a variance decomposition of adoption rates, AI-relevant skills are the most important driver, followed by infrastructure and openness. Further analysis shows that energy prices and uncertainty also matter.

1. We examine the structural drivers of AI adoption using the following cross-section regression:

$$y_i = x_i\beta + z_i\gamma + e_i \quad (1)$$

where y_i is the AI adoption rate mid-2025 in country i, and x_i are potential drivers of AI adoption including ICT infrastructure, human capital stock (both from the AI preparedness index in Cazzaniga and others, 2024), trade openness (as the ratio of exports plus imports over GDP from the World Bank WDI), and electricity prices (accessed from the UK Department for Energy Security & Net Zero and derived from the International Energy Agency publication, *Energy Prices and Taxes*). In some specifications, we also include controls z_i such as log GDP per capita and the country-level World Uncertainty Index.[1] By focusing on the drivers across countries in equation (1), we effectively focus on fundamental, structural drivers of AI adoption, as opposed to drivers that might temporarily raise or lower the rate of AI adoption relative to an underlying trend. To avoid capturing feedback effects of AI adoption on factors (for example, an increase in electricity prices from increasing datacenter demand), we use 2019 values for electricity variables, GDP per capita, openness, and the uncertainty index. The human capital and infrastructure index are based on year 2023 or before.

2. Appendix Table A1 shows the results of estimating equation (1). Column (1) suggests a strong and robust relationship between AI adoption and human capital, ICT infrastructure and trade openness, where countries scoring higher along these dimensions tend to have higher rates of AI adoption. Column (2) shows that these associations remain unchanged and mostly significant even after controlling for GDP per capita. Column (3) introduces industrial electricity prices and shows that AI adoption is significantly lower when electricity prices are more elevated. Column (4) introduces an index measuring the degree of economic and policy uncertainty at the country level, which is found to be significantly associated with lower adoption, consistent with the idea that uncertainty deters investment in new technology. Column (5) then includes all the above variables and confirms the result robustness.

3. We use the specification in column (1) to perform a variance decomposition. Specifically, we compute the squared semi-partial correlation for each predictor, which measures the unique contribution of each variable to the total explained variance (R^2)—that is, the share of overall

[1] Ahir, H, N Bloom, and D Furceri (2022), “World Uncertainty Index”, NBER Working Paper.

variance in AI adoption that each driver accounts for independently of the others. The residual between R^2 and the sum of these unique contributions reflects variance jointly explained by correlated predictors and cannot be attributed to any single driver. The results are illustrated in the third panel of Figure 3."

Table II.1. United Kingdom: Long-Run Determinants of AI Adoption Across Countries

	(1)	(2)	(3)	(4)	(5)
Human capital	5.69***	4.80**	5.25***	5.15***	5.16**
	(1.54)	(1.95)	(1.49)	(1.78)	(1.83)
ICT infrastructure	7.30***	6.59**	7.00***	8.69***	8.64***
	(2.35)	(2.54)	(2.25)	(2.46)	(2.56)
Openness	1.86**	1.49	2.05**	2.33**	2.31**
	(0.86)	(0.99)	(0.83)	(1.03)	(1.08)
Log GDP per capita		2.33		0.98	1.08
		(3.07)		(3.37)	(3.58)
Log electricity price			-2.77*		0.19
			(1.49)		(1.73)
Uncertainty				-2.01**	-2.06*
				(0.85)	(0.99)
Constant	32.64***	9.16	32.67***	24.15	23.16
	(1.23)	(30.98)	(1.18)	(33.83)	(35.85)
Observations	30	30	30	26	26
R-squared	0.759	0.764	0.788	0.869	0.869

Notes: All variables are standardized except for GDP per capita. Robust standard errors are shown in brackets, while significance levels are given by * p<0.10, ** p<0.05, *** p<0.01.

Annex III. Details on AI Policy Intervention Scenarios

This annex provides additional detail on the calibration and specification of the policy scenarios presented in Section E and presents supplementary results on the comparison between regulatory reform and cost-based interventions.

Model Overview

1. The analysis in Section E is based on a model of endogenous technology adoption calibrated to the UK economy (Rockall and others, 2025). The model economy consists of 100 sectors, ranked by their exposure to AI. Each sector produces output using labor and capital, with a sector-specific capital share $\alpha(z)$ that evolves endogenously as firms adopt AI. Within each sector, tasks are heterogeneous in how well AI can perform them relative to human workers: some tasks are straightforward to automate, while others require capabilities that AI lacks or that regulation restricts. Firms adopt AI for a given task when the cost saving from using AI capital exceeds the cost of adoption.

2. Two parameters govern the adoption decision. The first is the cost of adoption, b, which captures the expense of purchasing, integrating, and deploying AI within a firm's operations. This cost is assumed to decline over time as AI technology matures, reflecting the rapid fall in inference costs documented in the main text. The second is the effectiveness parameter, $\beta(z)$, which determines how many tasks in a sector can be productively automated by AI. A higher β means that a wider range of tasks can benefit from AI adoption, so the marginal task automated yields a larger cost saving. Together, b and β determine a sector's adoption threshold: as b falls, more tasks cross the cost-saving threshold, and the sector's capital share rises.

3. The source of productivity gains in the model is the reallocation of tasks from labor to more cost-effective AI capital. When a firm adopts AI for a task, it replaces wage costs with (lower) capital costs for that task, reducing unit costs and raising output per worker. Aggregated across tasks and sectors, this produces TFP gains, as the economy produces more output from the same inputs. In addition, the increase in the return to capital induces firms to invest more, raising the capital-labor ratio, which generates output gains beyond the TFP effect. This capital deepening channel accounts for the difference between the output gains and TFP gains reported in the main text.

Baseline Calibration

4. We calibrate the model so that its endogenous adoption path matches two key features of the data. First, the pace of adoption is set to replicate the increase in the aggregate capital share observed during the previous wave of routine automation in the UK, where the capital share rose by approximately 10 percentage points between 1980 and 2014. The adoption cost b declines linearly from its initial level to 20 percent of that level over a 17-year horizon—twice the pace of adoption cost decline for routine automation. This pace of cost decline is consistent with

evidence that inference costs for equivalent model performance have been falling at roughly 10× per year (Appenzeller 2024), substantially faster than cost declines during either the PC revolution or the dotcom boom.

5. Second, we calibrate the cost-saving gains from AI, which govern how much more productive AI is than labor at automated tasks, to 27 percent, the average of micro-empirical estimates from experimental studies of AI's impact on worker productivity (Brynjolfsson and others, 2023; Noy and Zhang, 2023; Peng and others, 2023), as used by Acemoglu (2024). Under these assumptions, the model's endogenous adoption path produces cumulative TFP gains of 1.4 percent at the 10-year horizon, consistent with recent IMF estimates for the UK (Misch and others, 2025), which apply Hulten's theorem to occupation-level measures of AI exposure to produce country-specific benchmarks.

Regulatory Reform

6. In the model, each sector's AI exposure is governed by a parameter $\boldsymbol{\beta}$ that determines how many tasks can be automated. We model regulation as a constraint on β that prevents AI from being deployed for certain tasks, even when adoption would otherwise be cost-effective. Specifically, the baseline β already incorporates current regulatory restrictions. We compute a potential β that would prevail without these task-level constraints:

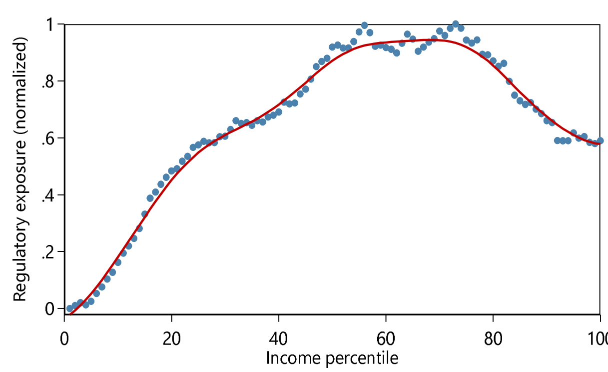
$$\beta_{potential(z)} = \frac{\beta_{baseline(z)}}{1 - \lambda \cdot \omega(z)}$$

where λ is a scalar calibrated to match the aggregate adoption gap, and $\omega(z)$ is a sector-level measure of regulatory exposure, normalized to have mean one. Regulatory reform is modelled as restoring 50 percent of the gap between baseline and potential β:

$$\beta_{reform(z)} = \beta_{baseline(z)} + 0.5 \cdot (\beta_{potential(z)} - \beta_{baseline(z)})$$

7. The aggregate calibration target, that regulation holds back 20 percent of potential AI adoption, is grounded in the PwC Global Compliance Survey (2025), in which over one in five executives globally reported that compliance requirements were limiting their organization’s adoption of AI to a great extent. To distribute this constraint across sectors, we use a regulatory exposure index constructed from five O*NET work context measures: responsibility for outcomes, responsibility for others' health and safety, consequence of error, freedom of decisions, and frequency of decisions. These measures capture the degree to which occupations involve decisions with significant consequences

Figure III.1. Regulatory Exposure by Income Percentile



Source: O*NET work context measures.

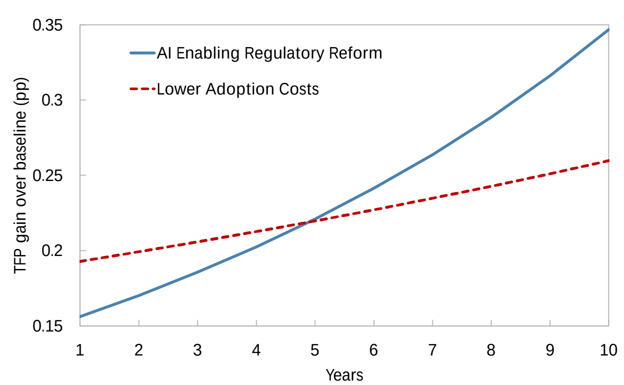
for others, a proxy for the likelihood that AI deployment in those roles faces regulatory scrutiny or legal liability constraints. The resulting index (Figure 1) peaks in middle-income occupations (including healthcare workers, educators, and public administrators) and is lower both at the bottom of the income distribution (where tasks tend to be manual and less regulated) and at the very top (where tasks are more autonomous and discretionary). This hump-shaped pattern implies that regulatory reform disproportionately benefits middle-income workers by unlocking AI adoption in the sectors where they are concentrated.

8. This measure is consistent with alternative approaches to identifying regulatory constraints on AI. In particular, the gap between theoretical AI exposure (as measured by the AIOE index of Felten and others, 2021) and observed AI deployment (as captured by Anthropic's economic index of actual AI use) is larger in sectors with high regulatory exposure — suggesting that regulation is a plausible explanation for why AI is not being deployed in tasks where it could technically be used.

9. To illustrate why the type of regulatory intervention matters, we compare our baseline reform—which expands the range of tasks for which AI can legally be deployed—with an equivalent reduction in adoption costs through subsidies or general deregulation that lowers the cost of deploying AI but does not change which tasks it can be used for. The subsidy is calibrated to deliver the same aggregate adoption gain as regulatory reform at the 5-year horizon: a 9.5 percent reduction in adoption costs, which could represent direct fiscal subsidies, tax incentives for AI investment, or reforms that reduce general compliance burdens without expanding the permissible scope of AI use.

10. While both policies produce identical TFP gains at the 5-year horizon (+0.2 percentage points), they diverge substantially thereafter (Figure 2). By year 10, regulatory reform delivers 0.35 percentage points of additional TFP compared with 0.26 for cost reduction. This divergence arises because cost-based interventions become less effective as technology costs fall—a 9.5 percent reduction in a small and declining number yields diminishing absolute gains—whereas removing task-level constraints has a persistent effect that is independent of the cost trajectory. As adoption costs approach zero, the only remaining barriers to full AI deployment are regulatory constraints on which tasks AI can perform; cost-based interventions are powerless against these barriers, while targeted regulatory reform addresses them directly.

Figure III.2. 15-Year Productivity Impacts of Regulatory Reform vs Lower Adoption Costs
(Percentage points)



Source: Authors' own.

11. This result has practical implications for policy design. Fiscal incentives such as R&D tax credits, AI adoption vouchers, or subsidized compute access can accelerate near-term uptake and may be particularly valuable for small and medium-sized enterprises facing liquidity constraints.

12. However, the model suggests that such interventions will deliver diminishing returns over the medium term as technology costs continue to fall. By contrast, reforms that clarify the permissible scope of AI in regulated sectors, such as updated guidance on AI-assisted medical diagnosis, algorithmic decision-making in financial services, or the use of AI in education, would unlock productivity gains that no amount of cost reduction can achieve.

Skills and Congestion

13. The skills scenario decomposes adoption costs into a technology component and an AI labor component, where the latter rises endogenously as firms compete for a limited talent pool. Specifically, the effective adoption cost is:

$$b(t) = b\_tech(t) \times (1 - c + c \times w\_AI(t))$$

where c is the structural AI labor share of adoption costs (calibrated to 30 percent, consistent with the lower bound of estimates that 29-49 percent of frontier AI costs are attributable to labor; Cottier and others, 2024; Council of Economic Advisers, 2025) and w_AI is the endogenous AI wage.

14. The congestion mechanism works as follows. As technology costs ($\boldsymbol{b\_tech}$) decline and adoption expands, demand for AI specialists rises. With a fixed supply of AI talent, this bids up the AI wage w_AI, which increases the labor component of adoption costs even as the technology component falls. The net effect is that total adoption costs decline more slowly than technology costs alone would imply. The congestion markup on adoption costs grows from approximately 1.15× at year 5 to over 1.3× by year 10, with AI labor's share of total costs rising from around 39 percent to 46 percent. The policy intervention reduces the AI wage premium by 50 percent, which can be interpreted as expanding AI talent supply through training programs, vocational pathways, and skilled immigration. The implied increase in AI labor supply needed to achieve this premium reduction is approximately 27 percent at year 5, rising to 43 percent by year 10 as demand for AI talent grows with adoption.

Access Barriers and Domestic Alternatives

15. The access barriers scenario considers the impact of restricted access to frontier AI technologies on UK productivity, and the extent to which a domestically developed alternative could mitigate this risk. We model restricted access as a markup τ on the adoption cost of foreign frontier AI. Firms in each sector then choose between two technologies: the foreign frontier model at cost $b(1 + \tau)$, with full effectiveness (baseline β), or a domestic alternative at cost b (no markup) but with lower effectiveness ($\beta\_domestic = 0.90 \times \beta\_frontier$). The 90 percent effectiveness ratio is in line with current evidence: open-source models now perform within 2 percent of frontier models on routine benchmarks (Stanford HAI 2025), but score significantly lower on complex

reasoning tasks, with DeepSeek achieving approximately 74 percent of frontier on the Artificial Analysis Intelligence Index (2026).

16. Each sector standardizes on one technology, choosing whichever generates greater adoption (higher $q*$) at equilibrium prices. Since wages and the return to capital depend on all sectors' technology choices through general equilibrium, the assignment is determined by fixed-point iteration: we guess an initial assignment, solve the full 103-equation system, check whether any sector would prefer to switch technologies at the resulting prices, and iterate until the assignment is stable.

17. In the main text, we report results for three markup levels (τ = 15 percent, 25 percent, and 40 percent) at the 5-year horizon. Under the central scenario (τ = 25 percent), all 100 sectors adopt the domestic technology at year 5, since the foreign markup pushes effective costs above the level at which frontier AI is cost-effective. This produces meaningful but reduced productivity gains: TFP of 0.30 percent compared with the baseline 1.53 percent, recovering nearly half the loss relative to the restricted scenario (TFP of 0.08 percent with no domestic option).

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