INTERNATIONAL MONETARY FUND

IMF Country Report No. 26/173

UNITED KINGDOM

SELECTED ISSUES

July 2026

This paper on the United Kingdom was prepared by a staff team of the International Monetary Fund as background documentation for the periodic consultation with the United Kingdom. It is based on the information available at the time it was completed on June 24, 2026.

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International Monetary Fund
Washington, D.C.

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June 24, 2026

Approved By
European Department

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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).

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[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

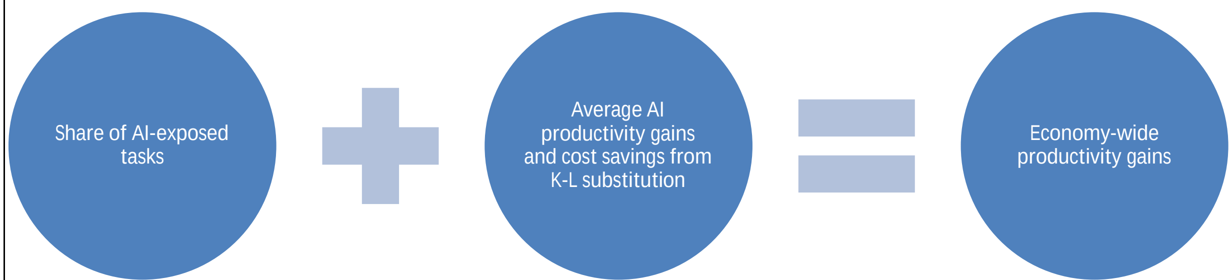
Estimates of aggregate TFP gains from AI vary widely across studies. Differences across estimates highlight that these gains depend on assumptions about the share of tasks that are exposed to AI, the average productivity gain per task, and cost-savings opportunities from AI adoption. The UK is well positioned 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.

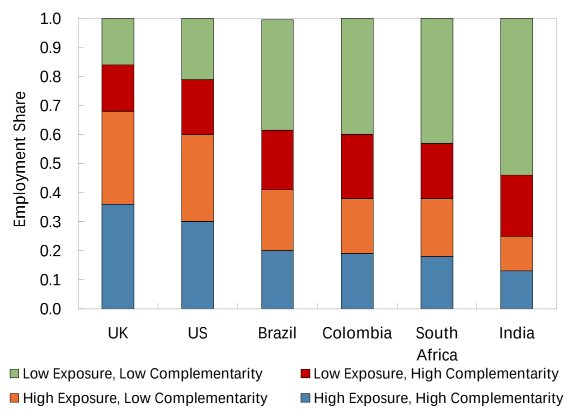
8. On both counts, current estimates of AI's economic potential could prove conservative as AI could accelerate the innovation process. AI capabilities and the associated productivity gains are still evolving, as the underlying innovation process remains rapid and dynamic. Continued innovation –both 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.

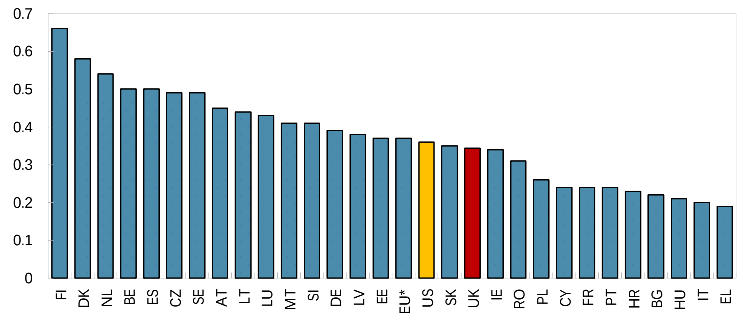
Box 1. United Kingdom: AI Adoption Over Time and Across Countries

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).

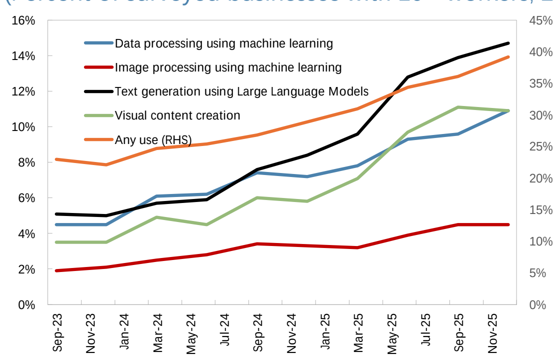
Figure 3. AI Adoption

Business Adoption Rates, mid-2025
(Percent)



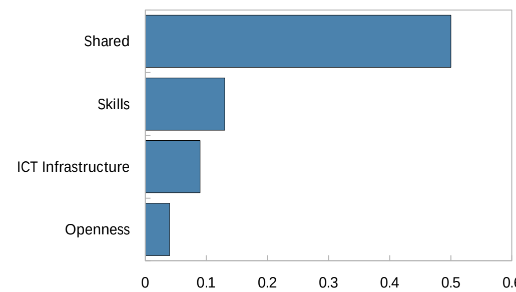
Source: 2025 ONS BICS (June 2025) and EIB-IS (2025).

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



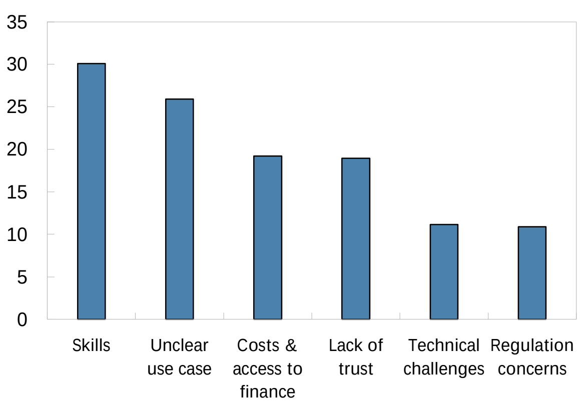
Source: ONS Business Insights and Conditions Survey, IMF staff calculation.
Notes: Includes all bunisesses with more than 9 employees.

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



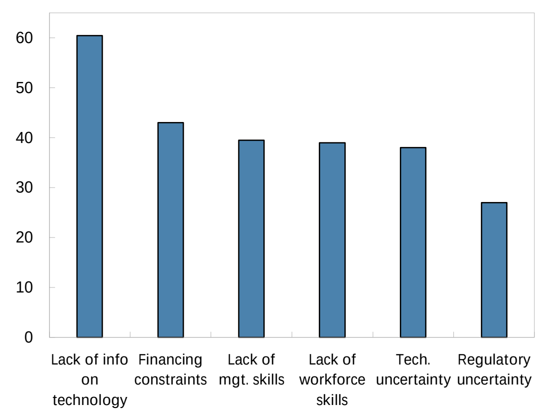
Source: EIB-IS survey, WB WDI, IMF AIPI and IMF Staff calculation.
Notes: Results from a regression with an R-square equal to 0.76. Each bar corresponds to the squared semi-partial R-square.

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).

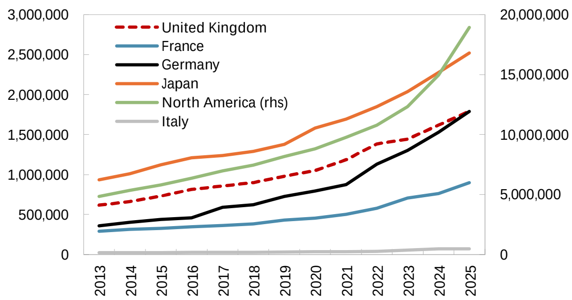
16. **High energy costs and cumbersome planning processes could slow future AI deployment.** Cross-country empirical analyses show that electricity prices are a significant determinant of AI adoption rates, suggesting that elevated UK prices are likely a headwind for AI development (Haag 2025) (fourth 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.

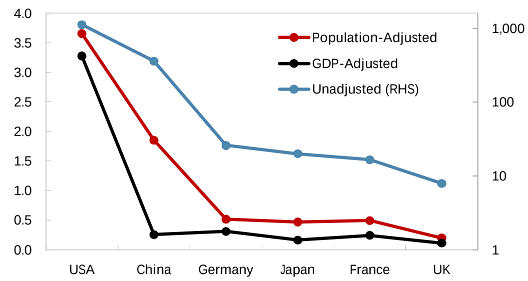
Figure 4. ICT and Energy Infrastructure

Datacenters (Net UPS Power)
(Gigawatts)



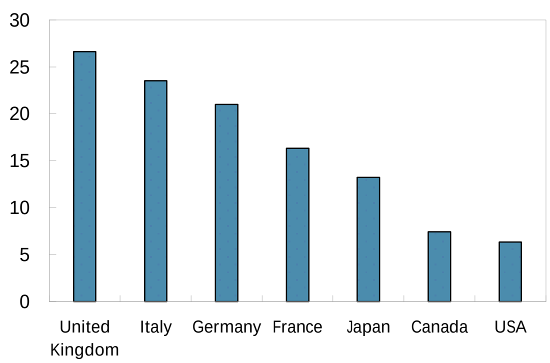
Source: The 451 Research Data Center Knowledge Base.

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



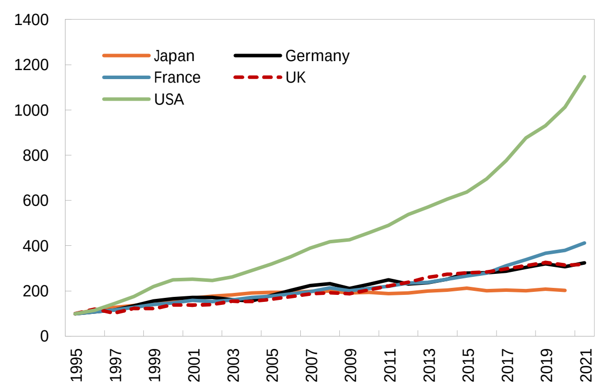
Source: Top500, World Bank, FRB Staff Calculations.
Note: Top500 data only represents the 500 most advanced commercial supercomputers. China stopped reporting around 2023, which may lead to overestimation of compute capacity of other economies in the future based on this data.

Electricity Prices
(In pence per kWh)



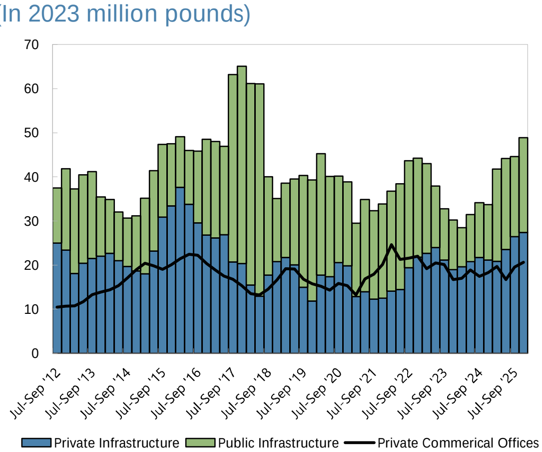
Source: ONS, derived from the International Energy Agency publication.

Real ICT Investment
(Base 1995=100)



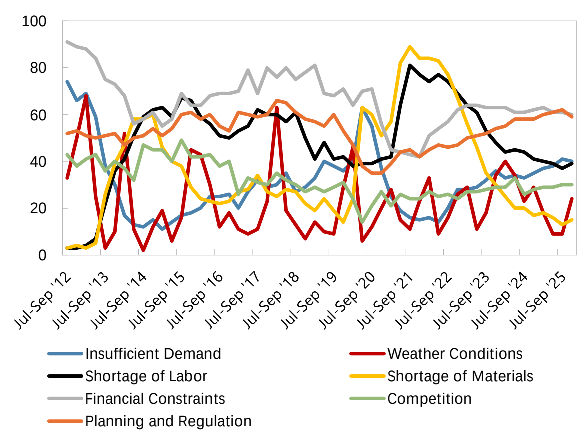
Source: EUKLEMS-INTANProd.

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

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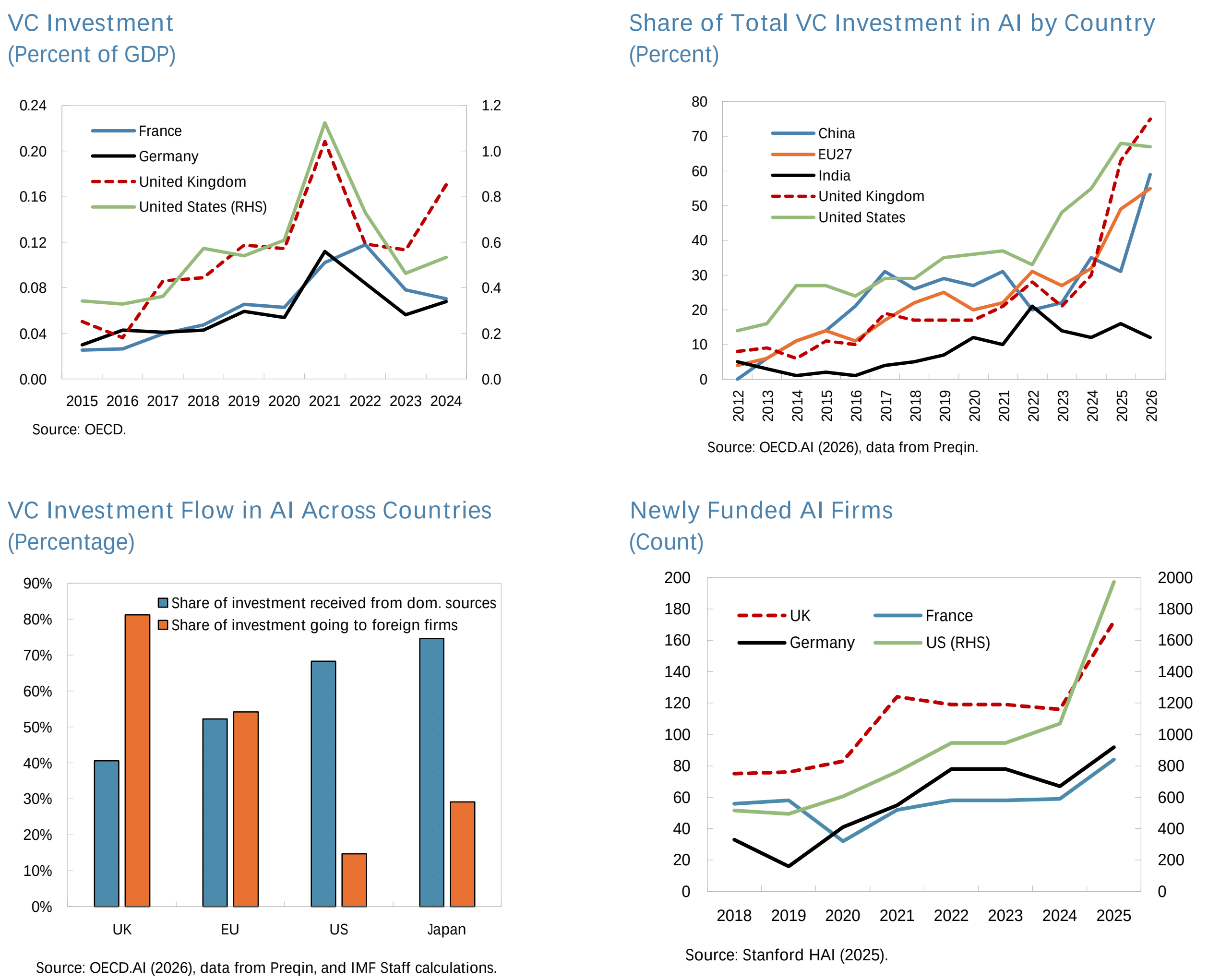
[6] The British Private Equity & Venture Capital Association's (BVCA) 'Venture Capital in the UK' 2025 report.

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

Figure 5. Financing of Innovation



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

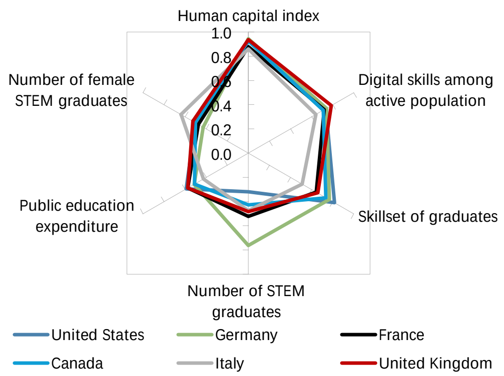
22. **The UK workforce is highly educated.** The UK scores highly on the human capital dimension of the IMF AI Preparedness Index, including among G7 peers (first panel of Figure 6). This reflects high average years of schooling and good digital skills among the active population (e.g., computer skills, 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.

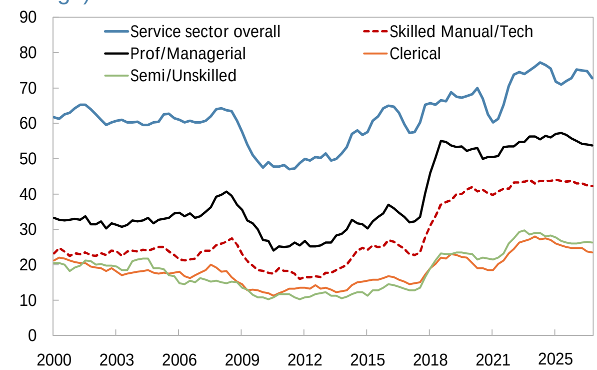
Figure 6. Skills

AI Preparedness Index: Human Capital Components
(Index)



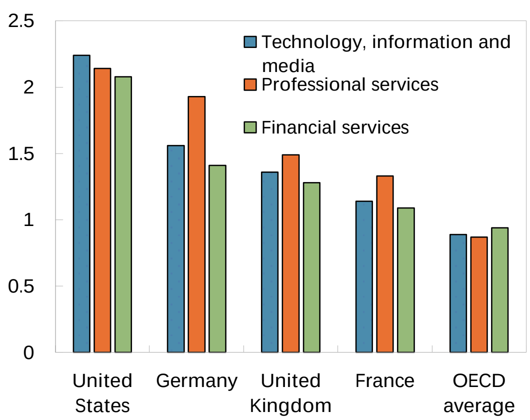
Source: IMF AI Preparedness Index.

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



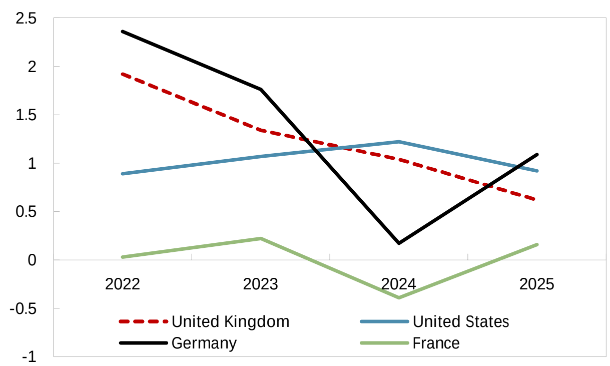
Source: The British Chamber of Commerce and Haver analytics.

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).

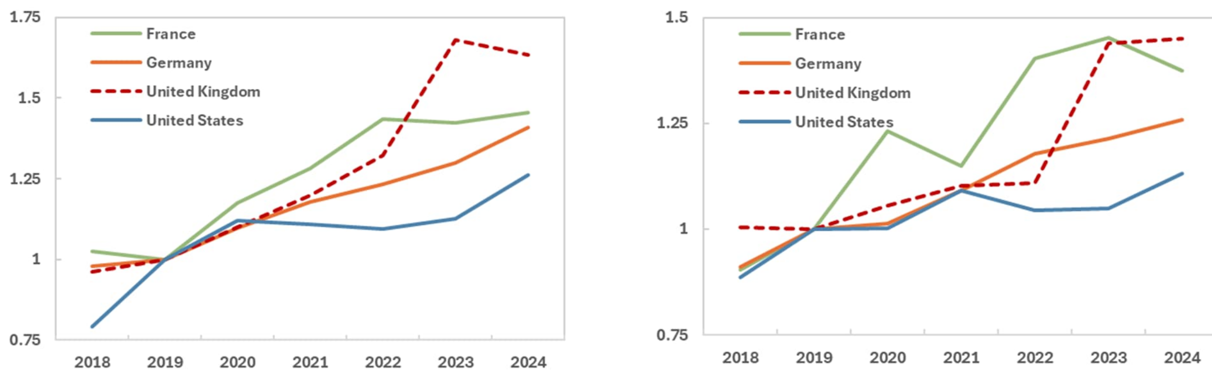
Trade Openness and Resilience

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.

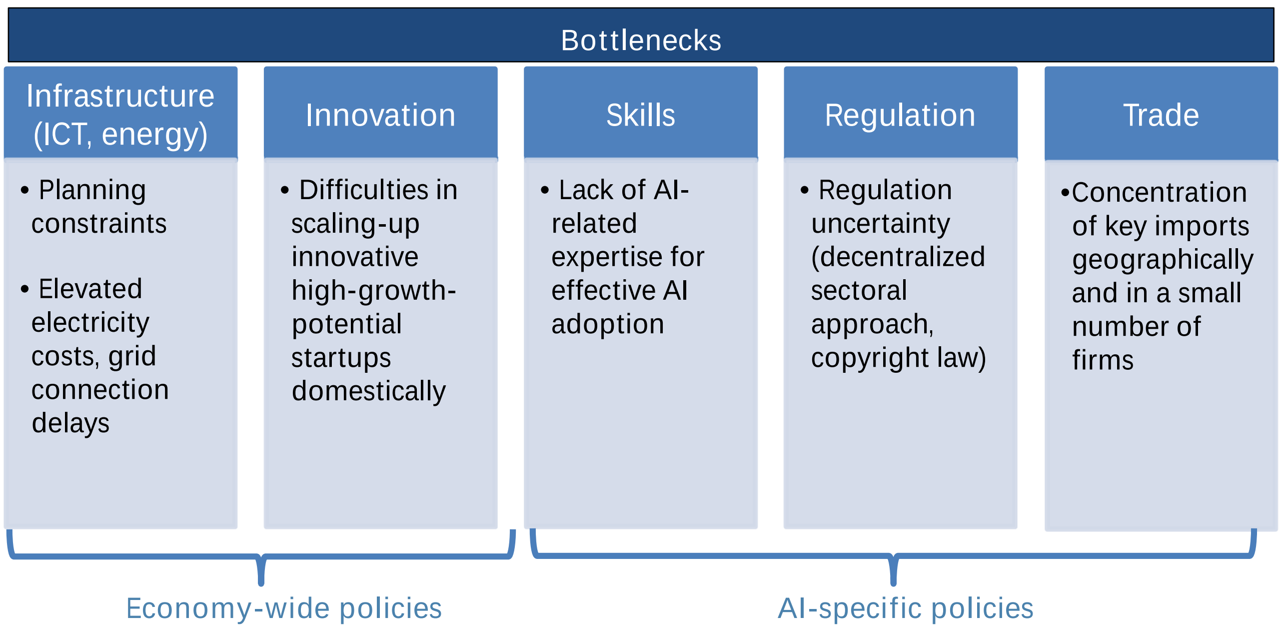
D. Policies for Lifting the Bottlenecks: Economy-Wide vs Targeted Policies

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.

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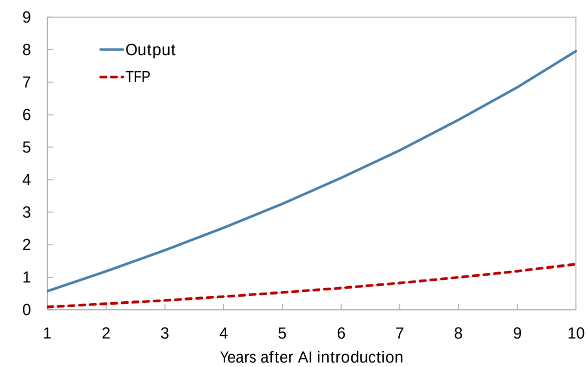
[8] Misch and others (2025) use a static framework without capital accumulation and report gains over the medium-term, which they take as 5 years. Our TFP measure strips out the contribution of capital deepening, making the two TFP estimates conceptually comparable in levels, but we take the medium-term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

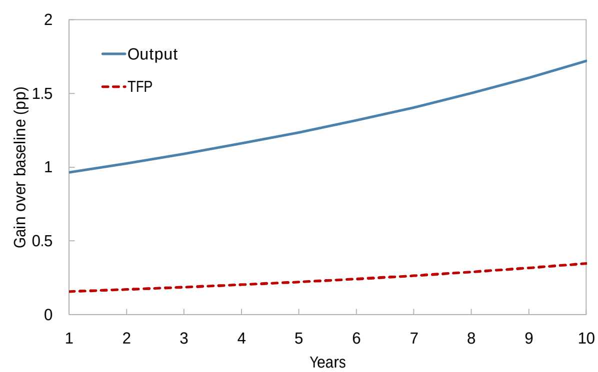
[9] To the extent that some of this investment takes the form of purchased services from foreign providers, the output gains may overstate the domestic value added, while the TFP gains—which capture efficiency improvements from task reallocation—are unaffected.

[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.

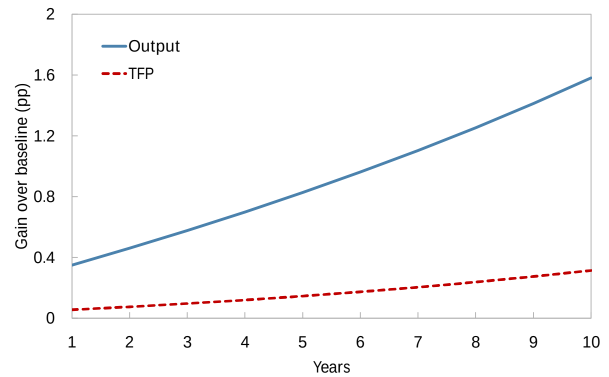
52. Halving the AI wage premium would deliver output gains of 0.83 percentage points within 5 years, growing to 1.58 percentage points by year 10 as the congestion externality compounds (Figure 11). TFP gains follow a similar profile, rising from 0.15 percentage

[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)



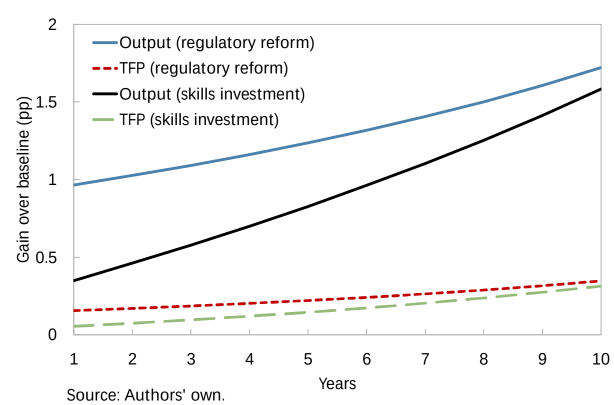
Source: Authors' own.

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

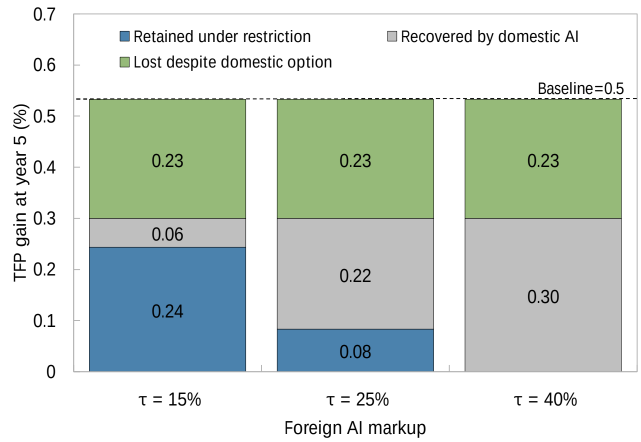
55. Finally, we assess the value of policies to support the UK's AI ecosystem and reduce exposure to the risk from a scenario where the costs of foreign AI technologies are significantly higher than in the baseline. Section C highlighted the UK's reliance on a small number of foreign suppliers for frontier 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

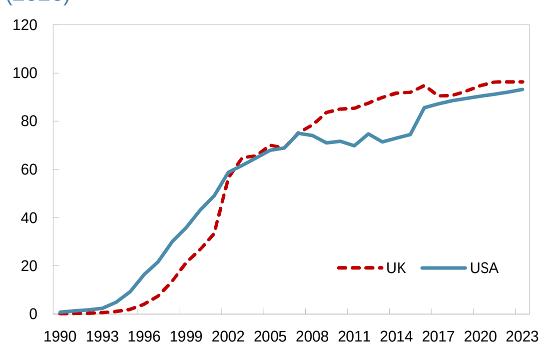
and others, 2008, Martin 2025). Nevertheless, other studies find that the UK's TFP growth fell somewhat short of the US in the earlier phase of the ICT revolution because of technology adoption lags and additional frictions undermining complementary investment in intangible capital (Basu and others,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

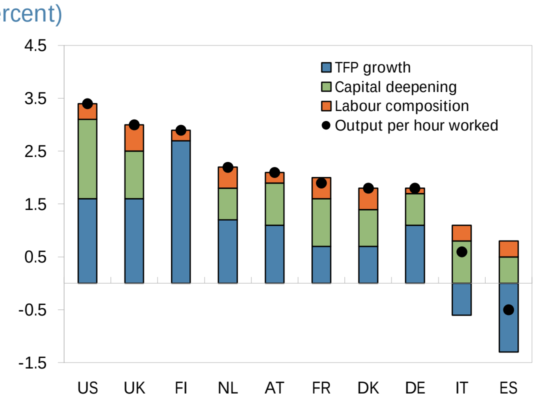
Share of the Population Using the Internet
(2026)



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:

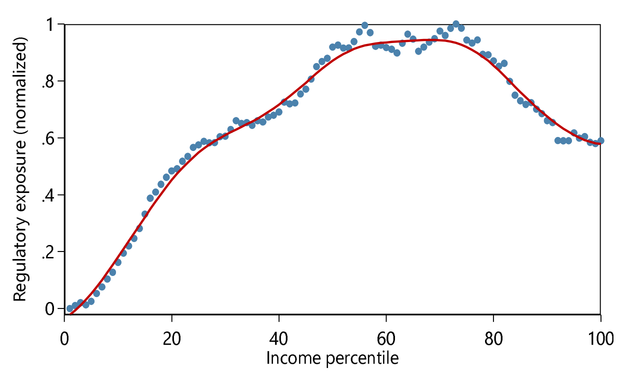
$$\beta_{potential(z)} = \frac{\beta_{baseline(z)}}{1 - \lambda \cdot \omega(z)}$$

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.

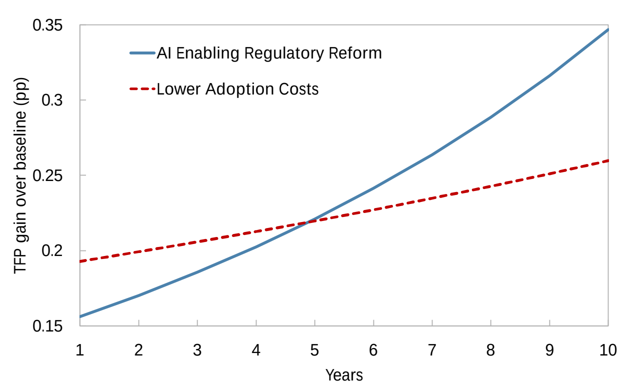
for others, a proxy for the likelihood that AI deployment in those roles faces regulatory scrutiny or legal liability constraints. The resulting index (Figure 1) peaks in middle-income occupations (including healthcare workers, educators, and public administrators) and is lower both at the bottom of 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).

References

Acemoglu, D., 2024. "The Simple Macroeconomics of AI." NBER Working Paper No. 32487. Published as Acemoglu, D., 2025. "The Simple Macroeconomics of AI." *Economic Policy*, 40(121), 13–58. https://www.nber.org/papers/w32487

Acemoglu, D., Aghion, P. and Zilibotti, F., 2006. "Distance to Frontier, Selection, and Economic Growth." *Journal of the European Economic Association*, 4(1), 37–74. https://doi.org/10.1162/jeea.2006.4.1.37

Adam, S., Advani, A., Miller, H. and Summers, A., 2024. "Capital Gains Tax Reform." In C. Emmerson, P. Johnson and B. Zaranko (eds), *The IFS Green Budget: October 2024*. Institute for Fiscal Studies. https://ifs.org.uk/publications/capital-gains-tax-reform

Aghion, P. and Bunel, S., 2024. "AI and Growth: Where Do We Stand?" Mimeo, Federal Reserve Bank of San Francisco. https://www.frbsf.org/wp-content/uploads/AI-and-Growth-Aghion-Bunel.pdf

Appenzeller, G., 2024. "Welcome to LLMflation — LLM Inference Cost Is Going Down Fast." Andreessen Horowitz (a16z), November 2024. https://a16z.com/llmflation-llm-inference-cost/

Artificial Analysis, 2026. Intelligence Index. https://artificialanalysis.ai/

Ash, E., Morelli, M. and Vannoni, M., 2025. "More Laws, More Growth? Evidence from US States." *Journal of Political Economy*, 133(7), 2139–2179. https://doi.org/10.1086/734009

Bank of England (BoE), 2025. "Unlocking Growth: What Can the Literature Tell Us about What's Holding Back High-Growth Firms?" https://www.bankofengland.co.uk/bank-overground/2025/unlocking-growth

Bank of England and Financial Conduct Authority (BoE and FCA), 2024. "Artificial Intelligence in UK Financial Services — 2024." https://www.bankofengland.co.uk/report/2024/ai-in-uk-financial-services

Basu, S., Fernald, J.G., Oulton, N. and Srinivasan, S., 2003. "The Case of the Missing Productivity Growth, or Does Information Technology Explain Why Productivity Accelerated in the United States but Not in the United Kingdom?" *NBER Macroeconomics Annual*, 18, 9–63. https://doi.org/10.1086/ma.18.3585249

Bailey, A. (2026) 'Can AI make cutlery?', speech at the 389th Cutlers' Feast, May 21st, 2026. https://www.bankofengland.co.uk/speech/2026/may/andrew-bailey-speech-at-cutlers-feast-sheffield

Bick, A., Blandin, A. and Deming, D., 2025. "The State of Generative AI Adoption in 2025." Federal Reserve Bank of St. Louis, On the Economy, November 13, 2025. https://www.stlouisfed.org/on-the-economy/2025/nov/state-generative-ai-adoption-2025

Bloom, N., Sadun, R. and Van Reenen, J., 2012. "Americans Do IT Better: US Multinationals and the Productivity Miracle." *American Economic Review*, 102(1), 167–201. https://doi.org/10.1257/aer.102.1.167

Bontadini, F., Corrado, C., Haskel, J. and Jona-Lasinio, C., 2025. "AI as an Innovation in the Method of Innovation: Implications for Productivity." Working Paper. https://spiral.imperial.ac.uk/server/api/core/bitstreams/aa4caa79-9ed3-4da2-b8f8-8281b022e249/content

Briggs, J., Kodnani, D., Hatzius, J. and Pierdomenico, G., 2023. "The Potentially Large Effects of Artificial Intelligence on Economic Growth." Goldman Sachs Global Investment Research, 27 March 2023. https://www.gspublishing.com/content/research/en/reports/2023/03/27/d64e052b-0f6e-45d7-967b-d7be35fabd16.html

Brynjolfsson, E., Li, D. and Raymond, L., 2023. "Generative AI at Work." NBER Working Paper No. 31161. Published as Brynjolfsson, E., Li, D. and Raymond, L., 2025. "Generative AI at Work." *Quarterly Journal of Economics*, 140(2), 889–942. https://www.nber.org/papers/w31161

Carella, A., Deb, P. and Haider, N., 2024. "Construction Planning Reforms for Growth and Investment" IMF Selected Issues Paper (SIP/2024/031). Washington, D.C.: International Monetary Fund https://www.imf.org/-/media/files/publications/selected-issues-papers/2024/english/sipea2024031.pdf

Cazzaniga, M., Jaumotte, F., Li, L., Melina, G., Panton, A.J., Pizzinelli, C., Rockall, E.J. and Tavares, M.M., 2024. "Gen-AI: Artificial Intelligence and the Future of Work." IMF Staff Discussion Note SDN/2024/001. https://doi.org/10.5089/9798400262548.006

Cerutti, E.M., Pascual, A.I.G., Kido, Y., Li, L., Melina, G., Tavares, M.M. and Wingender, P., 2025. "The Global Impact of AI: Mind the Gap." IMF Working Paper 2025/076. https://doi.org/10.5089/9798229008570.001

Comin, D. and Hobijn, B., 2004. "Cross-Country Technology Adoption: Making the Theories Face the Facts." *Journal of Monetary Economics*, 51(1), 39–83. https://doi.org/10.1016/j.jmoneco.2003.07.003

Comin, D. and Hobijn, B., 2010. "An Exploration of Technology Diffusion." *American Economic Review*, 100(5), 2031–2059. https://doi.org/10.1257/aer.100.5.2031

Confederation of British Industry (CBI), 2025. "AI Adoption among UK Firms." Unpublished CBI presentation.

Cottier, B., Rahman, R., Fattorini, L., Maslej, N. and Owen, D., 2024. "How Much Does It Cost to Train Frontier AI Models?" Epoch AI, June 2024 (updated January 2025). https://epoch.ai/blog/how-much-does-it-cost-to-train-frontier-ai-models

Council of Economic Advisers, 2025. "AI Talent Report." The White House, January 14, 2025. https://bidenwhitehouse.archives.gov/cea/written-materials/2025/01/14/ai-talent-report/

Department for Business and Trade and Department for Science, Innovation and Technology (DBT and DSIT), 2025. *Digital and Technologies Sector Plan*. Policy Paper. https://www.gov.uk/government/publications/digital-and-technologies-sector-plan

Department for Education (DfE), 2025. *Skills England: Sector Evidence on the Growth and Skills Offer*. https://assets.publishing.service.gov.uk/media/6863f18b3464d9c0ad609ddf/Skills_England_-_sector_evidence_on_the_growth_and_skills_offer.pdfhttps://www.gov.uk/government/publications/skills-england-sector-evidence-on-the-growth-and-skills-offer

Department for Science, Innovation and Technology (DSIT), 2025. *Artificial Intelligence Sector Study 2024*. https://www.gov.uk/government/publications/artificial-intelligence-sector-study-2024

Department for Science, Innovation and Technology (DSIT), 2026. *AI Opportunities Action Plan: One Year On*. Policy Paper. https://www.gov.uk/government/publications/ai-opportunities-action-plan-one-year-on

Department for Science, Innovation and Technology and UK Research and Innovation (DSIT and UKRI), 2025. *UK Compute Roadmap*. https://www.gov.uk/government/publications/uk-compute-roadmap/uk-compute-roadmap

Ministry of Housing, Communities & Local Government (MHCLG), 2025. *Local Authority Planning Capacity and Capability Survey 2025*. https://www.gov.uk/government/publications/local-authority-planning-capacity-and-capability-survey-2025/local-authority-planning-capacity-and-capability-survey-2025

Eaton, J. and Kortum, S., 2002. "Technology, Geography, and Trade." *Econometrica*, 70(5), 1741–1779. https://doi.org/10.1111/1468-0262.00352

European Commission, 2010. *A Digital Agenda for Europe*. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions, COM (2010) 245 final. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:52010DC0245

Felten, E., Raj, M. and Seamans, R., 2021. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses." *Strategic Management Journal*, 42(12), 2195–2217. https://doi.org/10.1002/smj.3286

Filippucci, F., Gal, P. and Schief, M., 2024. "Miracle or Myth? Assessing the Macroeconomic Productivity Gains from Artificial Intelligence." OECD Artificial Intelligence Papers No. 29. https://doi.org/10.1787/b524a072-en

Filippucci, F., Gal, P., Laengle, K. and Schief, M., 2025. "Macroeconomic Productivity Gains from Artificial Intelligence in G7 Economies." OECD Artificial Intelligence Papers No. 41. https://doi.org/10.1787/a5319ab5-en

Goodridge, P. and Haskel, J., 2022. "Accounting for the Slowdown in UK Innovation and Productivity." The Productivity Institute Working Paper No. 022. https://www.productivity.ac.uk/research/accounting-for-the-slowdown-in-uk-innovation-and-productivity/

González, J.L., Sorescu, S. and Del Giovane, C., 2024. "Making the Most Out of Digital Trade in the United Kingdom." OECD Trade Policy Papers. https://doi.org/10.1787/3f9c4a9a-en

Haag, A., 2025. "The State of AI Competition in Advanced Economies." FEDS Notes, Board of Governors of the Federal Reserve System, October 6, 2025. https://doi.org/10.17016/2380-7172.3930

Hilliard, A., Gulley, A., Kazim, E. and Koshiyama, A.S. (2026) 'Artificial intelligence policy worldwide: a comparative analysis', *Royal Society Open Science*, 13(2), 242234. https://doi.org/10.1098/rsos.242234

Indraccolo, L., 2025. "Bridging the Gap: Understanding the UK-US Productivity Decoupling." IMF Selected Issues Paper SIP/2025/112. https://doi.org/10.5089/9798229020985.018

International Monetary Fund (IMF), 2024. "Slowdown in Global Medium-Term Growth: What Will It Take to Turn the Tide?" Chapter 3 in *World Economic Outlook: Steady but Slow — Resilience amid Divergence*, April 2024. https://www.imf.org/en/Publications/WEO/Issues/2024/04/16/world-economic-outlook-april-2024

Jaumotte, F., Kim, J., Koll, D., Li, E., Li, L., Melina, G., Song, A. and Tavares, M.M., 2026. "Bridging Skill Gaps for the Future: New Jobs Creation in the AI Age." IMF Staff Discussion Note SDN/2026/001. https://doi.org/10.5089/9798229028196.006

Jorgenson, D.W., 2001. "Information Technology and the U.S. Economy." *American Economic Review*, 91(1), 1–32. https://doi.org/10.1257/aer.91.1.1

Jorgenson, D.W., Ho, M.S. and Stiroh, K.J., 2008. "A Retrospective Look at the U.S. Productivity Growth Resurgence." *Journal of Economic Perspectives*, 22(1), 3–24. https://doi.org/10.1257/jep.22.1.3

Martin, J., 2025. "The UK Productivity Slowdown: A Review of Timing, Magnitude, and Drivers." *International Productivity Monitor*, 48 (Spring), 29–62. https://www.csls.ca/ipm/48/Martin_Final.pdf

McLean, A. and Smith, D., 2025. *Technology Adoption Review 2025*. https://assets.publishing.service.gov.uk/media/6857e0995225e4ed0bf3ceb5/dsit_technology_adoption_review_web.pdf

Microsoft and Public First, 2025. *Unlocking the UK's AI Potential: Harnessing AI for Economic Growth*. https://microsoftuk.publicfirst.co.uk/uploads/Unlocking_the_UKs_AI_Potential.pdf

Misch, F., Park, B., Pizzinelli, C. and Sher, G., 2025. "AI and Productivity in Europe." IMF Working Paper 2025/067. https://doi.org/10.5089/9798229006057.001

Moll, B., Rachel, Ł. and Restrepo, P., 2022. "Uneven Growth: Automation's Impact on Income and Wealth Inequality." *Econometrica*, 90(6), 2645–2683. https://doi.org/10.3982/ECTA19417

NewMind AI, 2025. "AI Policy and Regulations of United Kingdom." NewMind AI Journal Country Report. https://www.newmind.ai/NewMind%20AI%20Journal%20Country%20Report-AI%20Policy%20and%20Regulations%20of%20United%20Kingdom.pdf

Nguyen, N. and Coyle, D., 2025. "Start-ups and Scale-ups in UK Technology Sectors." Bennett School for Public Policy, University of Cambridge. https://doi.org/10.17863/CAM.121131

Noy, S. and Zhang, W., 2023. "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence." *Science*, 381, 187–192. https://doi.org/10.1126/science.adh2586

OECD, 2025. *Taxing Wages 2025: Decomposition of Personal Income Taxes and the Role of Tax Reliefs*. https://doi.org/10.1787/b3a95829-en

OECD, 2026. "OECD Overall R&D Growth Stable; Government R&D Budgets Decline and Reorient towards Defence." OECD Statistical Release, March 2026. https://www.oecd.org/en/data/insights/statistical-releases/2026/03/oecd-overall-rd-growth-stable-government-rd-budgets-decline-and-reorient-towards-defence.html

Oliner, S.D., Sichel, D.E. and Stiroh, K.J., 2008. "Explaining a Productive Decade." *Brookings Papers on Economic Activity*, 2007(1), 81–152. https://doi.org/10.1353/eca.2007.0019

Oliveira-Cunha, J., Serra-Lorenzo, B. and Valero, A., 2024. "What an LSE-CBI Survey Found about AI Adoption in UK Firms." LSE Business Review Blog. https://blogs.lse.ac.uk/businessreview/2024/07/02/what-an-lse-cbi-survey-found-about-ai-adoption-in-uk-firms/

Parry, C., 2025. "Start-up Financing, Entry and Innovation", unpublished working paper. https://cparry96.github.io/website/parry_jmp.pdf

Peng, S., Kalliamvakou, E., Cihon, P. and Demirer, M., 2023. "The Impact of AI on Developer Productivity: Evidence from GitHub Copilot." arXiv preprint arXiv:2302.06590. https://arxiv.org/abs/2302.06590

Pierdomenico, G., 2026. "AI in Europe: Modest Near-Term Lift, Meaningful Long-Term Gain." Goldman Sachs European Economics Analyst, 21 January 2026.

Pizzinelli, C., Panton, A.J., Tavares, M.M., Cazzaniga, M. and Li, L., 2023. "Labor Market Exposure to AI: Cross-Country Differences and Distributional Implications." IMF Working Paper 2023/216. https://doi.org/10.5089/9798400254802.001

PwC, 2025. *Global Compliance Survey 2025*. https://www.pwc.com/gx/en/issues/risk-regulation/pwc-global-compliance-study-2025.pdf

Resolution Foundation, 2025. *Mountain Climbing: Making Progress on the UK's Growth Policy Challenge*. https://www.resolutionfoundation.org/publications/mountain-climbing/

Rockall, E.J., Tavares, M.M. and Pizzinelli, C., 2025. "AI Adoption and Inequality." IMF Working Paper 2025/068. https://doi.org/10.5089/9798229006828.001

Stanford Institute for Human-Centered Artificial Intelligence (HAI), 2025. *Artificial Intelligence Index Report 2025*. Stanford University. https://hai.stanford.edu/ai-index/2025-ai-index-report

TechNation, 2025. *Unlocking the UK's Growth Potential: The Tech Nation Report 2025*. https://2025.report.technation.io/

Tony Blair Institute (TBI) for Global Change, 2025. *From Startup to Scaleup: Turning UK Innovation into Prosperity and Power*. https://assets.ctfassets.net/75ila1cntaeh/10q8nKyiuKD4yWom2eM0rP/7fb039238ce5fc8d6880a60b04933cd5/50yltD2eFDmkz3vmFWVjHg--153208082025

van Ark, B., Inklaar, R. and McGuckin, R.H., 2003. "ICT and Productivity in Europe and the United States: Where Do the Differences Come From?" *CESifo Economic Studies*, 49(3), 295–318. https://doi.org/10.1093/cesifo/49.3.295

van Ark, B., O'Mahony, M. and Timmer, M.P., 2008. "The Productivity Gap between Europe and the United States: Trends and Causes." *Journal of Economic Perspectives*, 22(1), 25–44. https://doi.org/10.1257/jep.22.1.25

Vandenbussche, J., Aghion, P. and Meghir, C., 2006. "Growth, Distance to Frontier and Composition of Human Capital." *Journal of Economic Growth*, 11(2), 97–127. https://doi.org/10.1007/s10887-006-9002-y

Willemyns, J. ,2025. "Copyright & AI: the case for a pro-growth approach." Centre for British Progress. https://britishprogress.org/briefings/copyright-ai-the-case-for-a-pro-growth-approach

Yotzov, I., Barrero, J.M., Bloom, N., Davis, S.J. et al., 2026. "Firm Data on AI." NBER Working Paper No. 34836. https://www.nber.org/papers/w34836

WHY HAVE UK GILT YIELDS MOVED AHEAD OF G7 PEERS?

Since 2022, UK gilt yields—particularly at long maturities—have risen and moved above G7 peers. Elevated long-term yields increase sovereign borrowing costs and can transmit to financial conditions more broadly, with implications for fiscal sustainability and financial stability. This paper presents stylized facts and a range of complementary empirical analyses to identify the contribution of the UK term premium to higher yields, assess its drivers and derive policy-relevant insights.

The level of UK yields reflects both elevated expected short rates and the term premium. This paper focuses on the latter, which captures the time-varying risk compensation not explained by the expected path of short rates. Empirical evidence points to a coherent set of drivers behind the rise in the UK term premium across two dimensions: (1) a gradual long-term structural change in demand-supply conditions in the gilt market; and (2) a regime shift following the September 2022 gilt market turmoil, after which domestic risk factors have played a larger role and gilt markets have become more prone to volatility spikes.

Against this backdrop, policy should focus on three areas: managing the quantity and composition of bond supply, reinforcing policy credibility, and strengthening market resilience.

A. Introduction

1. While gilt yields had declined and remained broadly in the middle of the G7 range for much of the 2010s, they have risen and moved ahead of G7 peers in the past few years. This divergence is particularly pronounced at the long end of the curve, with 30-year gilt yield increasing more sharply relative to other G7 sovereigns (see Figure 1).[1] This shift began in 2022, coinciding with the gilt market turmoil following the September 2022 “mini budget” announcement, marking a clear break from previous dynamics.

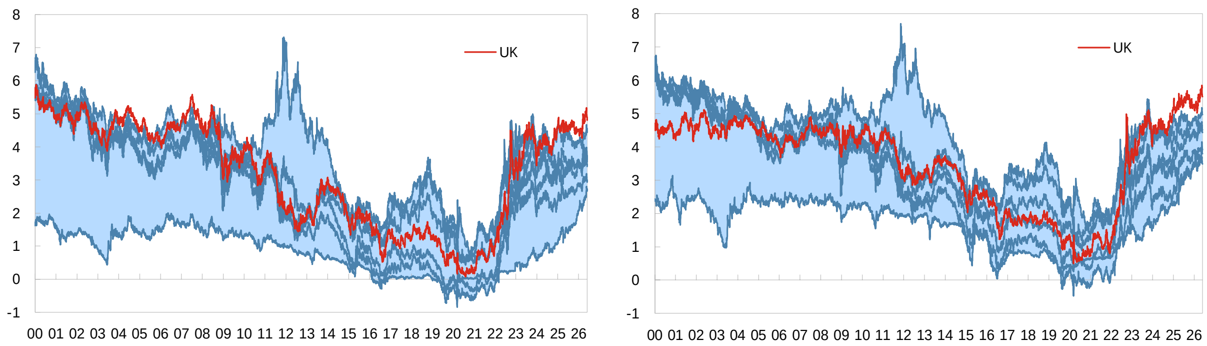
[1] This paper uses the G7 as the comparator group, reflecting their comparable credit quality and deep, liquid government bond markets. Including smaller or emerging economies would introduce structural differences that could obscure the patterns of interest.

Figure 1. G7 Long-Term Yields

UK Long-Term Yields Have Pulled Ahead of G7 Peers

G7 10-Year Sovereign Yields
(Percent)

G7 30-Year Sovereign Yields
(Percent)



Sources: Refinitiv Datastream, and IMF staff calculations. Blue area indicates range of yields of G7 peers.

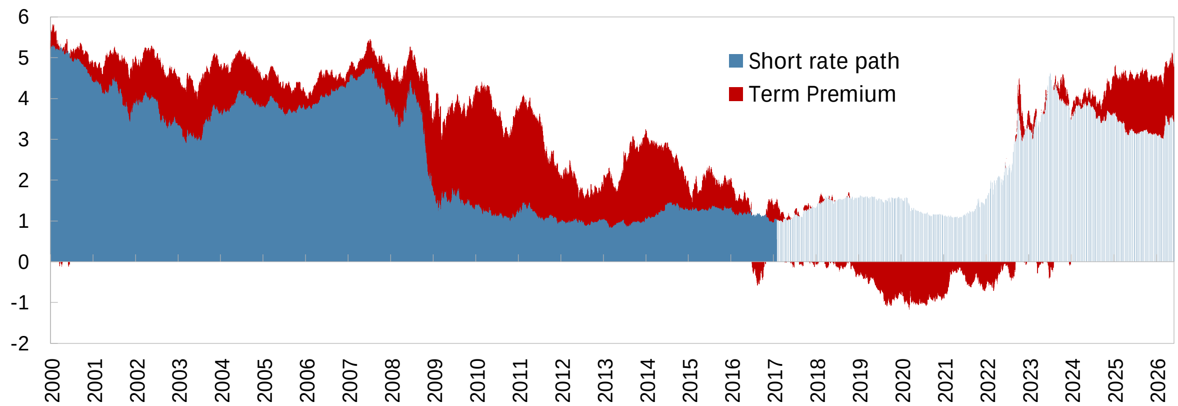
2. Over the past two years, increases in the UK term premium have more than offset declines in expected short rates, bringing long-term yields to their highest level since 2008.[2] Sovereign borrowing costs can move for different reasons. At longer maturities, yields can generally be decomposed into the expected path of future short-term interest rates and a term premium compensating investors for risk. In advanced economies, short rates are largely determined by the central bank's policy rate, which is set to achieve price stability. In the UK—similar to other economies—policy rates were raised sharply during the post-pandemic period of elevated inflation, driven by supply chain disruptions and pent-up demand, and further amplified by the energy price shock following Russia's invasion of Ukraine. While expected short rates have declined gradually since mid-2023, the UK term premium has increased, preventing longer-term yields from falling accordingly (see Figure 2). Decompositions based on the Bank of England's (BoE) term structure models similarly attribute 2025 movements in UK long-term yields primarily to changes in the (real) term premium (Panigrahi and Sidhu, 2026). These observations raise the question of what has driven long-term UK gilt yields—and the term premium in particular—to rise ahead of G7 peers, and what could be done to reverse this trend.

[2] See Annex 1.7 of the International Monetary Fund's October 2025 Global Financial Stability Report for background information on the term premium model used. Going forward we will use the terminology of "the term premium" to mean the 10-year sovereign bond term premium. Note that term premia are not observed directly—they reflect a latent variable that can be estimated with a model. This means that they are always model-dependent.

Figure 2. Term Premium Decomposition

The term premium has recently driven a wedge between gilt yields and the expected path of short rates

10-Year Term Premium and Expected Short Rate Path
(Percent)



Source: Bloomberg, IMF staff calculations. Latest data: 5/31/2026.

3. The expected path of short rates and the term premium are influenced by different policy channels. The expected path of short rates reflects monetary policy decisions in response to macroeconomic conditions, including exogenous shocks to inflation and growth, but is also shaped—albeit indirectly—by fiscal policy and underlying macroeconomic features of the economy. By contrast, the term premium captures risk compensation, uncertainty, and bond market structure factors, such as changes in the investor base. As a result, while short-rate expectations adjust in part to broader economic conditions, credible and predictable policies—particularly in fiscal policy, debt management, and efforts to enhance market functioning—can help contain the term premium by reducing uncertainty and improving the market's capacity to absorb shocks.

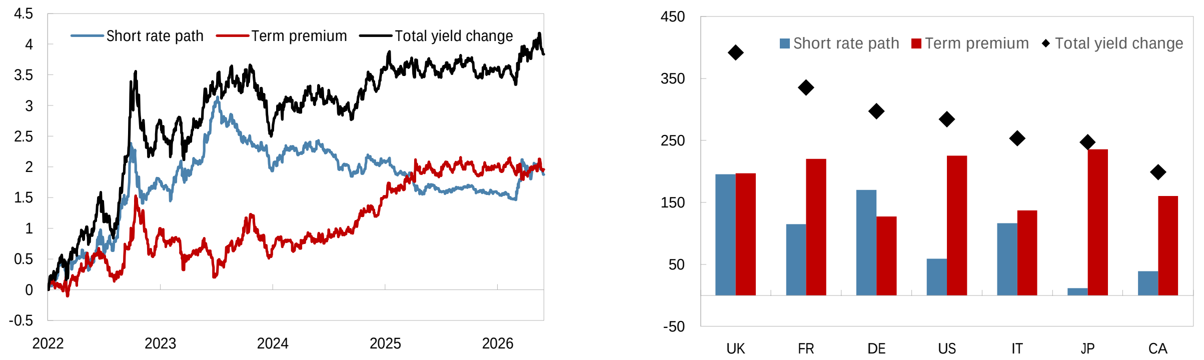
4. This paper focuses on the term premium, which can vary independently of monetary policy expectations and has been a key driver of higher long-term yields in recent years. Over 2022–26, both expected short rates and the term premium have contributed to increases in long-term gilt yields (see Figure 3). In March 2026, UK CPI inflation was highest among G7 peers—and had been on the higher end of the range since the mid of 2023 (Annex Figure 17). Commensurately, the UK policy rate was also on the upper end of the G7-range in recent years (Annex Figure 18). However, looking at the mid-2023 to early-2026 period, expected short rates declined (Figure 2), and an increase in the term premium (see Figures 2 and 3) was the primary force behind the rise in long-term yields to their highest levels since 2008. Most recently, the contribution of expected short-term rates to long-term yields jumped at the start of the 2026 conflict in the Middle East, as markets repriced for higher inflation expectations in response to the energy price shock—this illustrates how the short rate component reacts to exogenous shocks.

Figure 3. UK & G7 Yield Changes Since 2022

Both the expected path of short rates as well as the term premium have contributed to gilt yield increases

UK 10-Year Yield Component Change Since 2022
(Percentage point)

G7 10-Year Yield Component Change Since 2022
(Basis points)



Sources: Bloomberg, and IMF staff calculations.
Note: Yield and component changes since 1/1/2022 until 5/31/2026.

5. Term premia are shaped by a combination of financial, macroeconomic, policy, and structural supply–demand factors. A substantial body of literature examines the determinants of sovereign bond term premia. Foundational work focuses on the measurement of term premia using no-arbitrage term structure models, notably Kim and Wright (2005) and Adrian, Crump, and Moench (2013), which provide widely used decompositions of long-term yields into expected short rates and risk compensation. Building on these measures, the return-predictability literature demonstrates that term premia are time-varying and predictable using financial indicators such as forward rates (Cochrane and Piazzesi, 2005). Another important strand emphasizes the role of supply and demand factors within preferred-habitat or market segmentation frameworks. Vayanos and Vila (2009, published 2021) provide the theoretical foundation, while Greenwood and Vayanos (2014) show empirically that government bond supply of and investor demand for duration influence term premia. The impact of monetary policy and central bank balance sheets has also been extensively studied; Krishnamurthy and Vissing-Jorgensen (2011) and Hanson and Stein (2015) document how large-scale asset purchases affect long-term yields through duration removal and portfolio balance channels. Finally, a growing literature highlights the importance of global risk and policy uncertainty. Miranda-Agrippino and Rey (2020) emphasize the role of the global financial cycle, while Leippold and Mueller (2022) show that economic policy uncertainty can significantly affect the yield curve and term premia. Together, these strands underscore that term premia are shaped by a combination of financial, macroeconomic, policy, and structural supply–demand factors. The foundational literature is largely based on US data; UK-focused work is limited. For example, Kaminska and Mumtaz (2022) show that QE affects gilt yields through multiple channels—including signaling, policy uncertainty, and bond-supply effects—with the latter two operating through term premia. Stehn (2025) assesses drivers of the UK term premium and finds a positive relationship with unemployment, debt, inflation uncertainty and foreign term premia. Kadiric (2022) shows that the Brexit referendum materially affected sovereign risk premia (although not directly assessing the impact on the term premium).

Lengyel (2026) finds that higher-than-expected sovereign debt issuance raises yields by increasing both real term premia and inflation risk premia, with these effects becoming more pronounced during periods of market stress. This note adds a cross-country perspective combined with UK-focused analysis.

6. This Selected Issues Paper is structured as follows. Section B presents key stylized facts on the evolution of UK gilt yields in a G7 context, focusing on relevant long-term trends. Section C addresses the puzzle of why UK gilt yields have risen above G7 peers by combining multiple complementary empirical approaches, with a focus on the term premium and its drivers. Section D discusses policy implications.

B. Gilt Market Structure and Long-Term Trends

7. This section provides structural context for recent term premium dynamics by examining key features of the UK gilt market. It presents stylized facts on the investor base, market liquidity, and sovereign credit profile, with a focus on long-term trends and cross-country comparisons. These structural characteristics are difficult to capture in empirical models but are essential for interpreting recent developments in gilt yields and term premia.

Gilt Market's Investor Base

8. The UK's debt structure has historically reflected investors' strong demand for long-term bonds, which helped to contain the term premium despite a long average maturity. The UK debt's weighted average maturity is just under 14 years, compared to 6 to 9 years for other G7 countries (see Figure 4). This reflects the Debt Management Office's long-standing strategy of issuing a large share of long-dated bonds, alongside a relatively high proportion of inflation-linked securities and a limited reliance on short-term bills. A key factor underpinning this strategy has been strong demand from the UK's sizable defined benefit pension fund sector, which has a natural preference for long-term bonds and inflation-linked assets to match its liabilities (see Figure 5).[3] This stable demand at the long end of the curve has enabled the DMO to maintain a high average maturity, thereby reducing rollover risk at relatively modest cost.

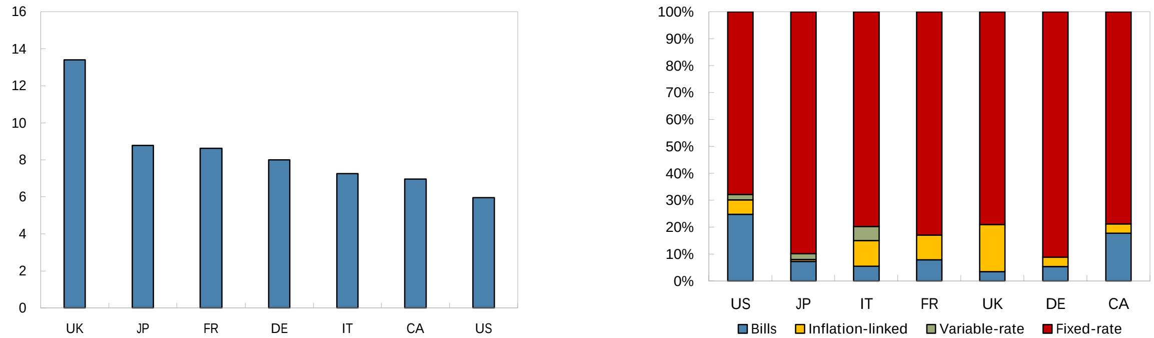
[3] See Greenwood and Vissing-Jorgensen (2018). Empirical evidence suggests that countries with larger insurance corporation and pension fund sectors have relatively lower long-term yields.

Figure 4. Sovereign Debt Structure

The UK stands out with its high average maturity and large share of inflation linked bonds

Sovereign Debt Weighted Average Maturity
(Years)

G7 Sovereign Debt Instrument Decomposition
(Percent)



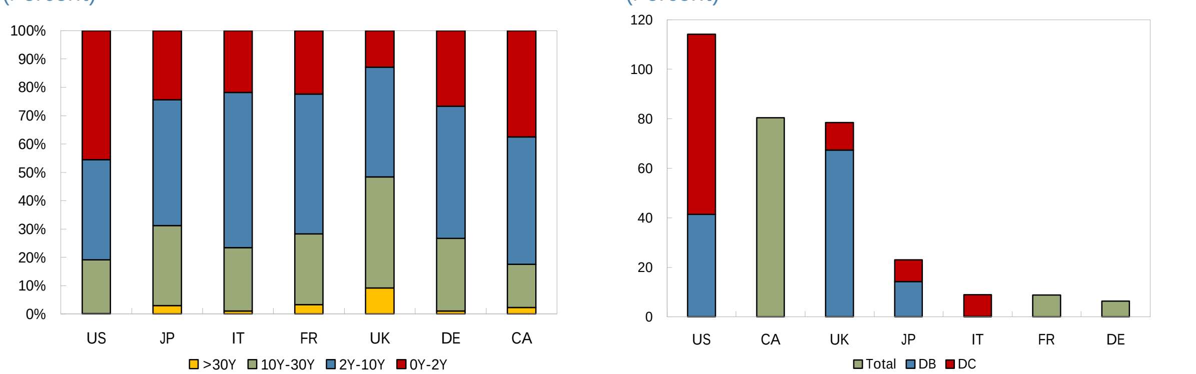
Source: Bloomberg, IMF staff calculations. Reference date: 2/12/2026.

Figure 5. Maturity Distribution and Pension Fund Size

Amongst G7 countries, the UK has the largest share of bonds with maturity >30 years. The UK has a large defined benefit pension fund sector, with long-term interest rate exposures on the liability side.

G7 Sovereign Debt Maturity Distribution
(Percent)

Pension Fund Assets as Percentage of GDP
(Percent)



Sources Bloomberg, and IMF staff calculations. Reference date: 2/12/2026.

Source: OECD. DB = defined benefit. DC=defined contribution. Note: breakdown between DB and DC is not available for all countries. 2024.

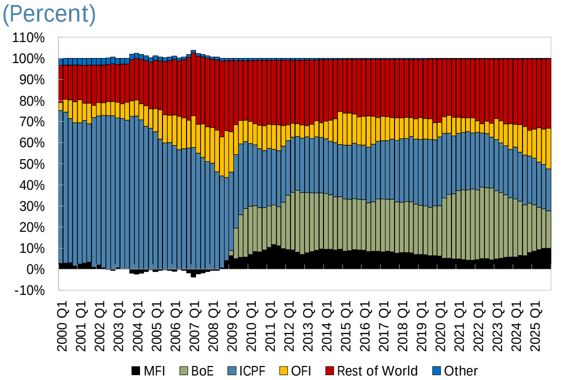
9. However, gilt demand is shifting, with weaker domestic institutional demand and greater foreign participation, resulting in a less stable investor base. UK pension funds are increasingly shifting from defined benefit to defined contribution schemes, and their holdings of gilts have declined both in absolute and relative terms. While insurance corporations and pension funds have reduced their share of gilt holdings over the past two decades, the BoE partly offset this by becoming a significant and stable holder through its asset purchase programs (Figure 6). With quantitative tightening now ongoing, however, the Bank is reducing its holdings. At the same time, foreign participation in the gilt market has increased, potentially bringing a larger share of more price-sensitive “fast money” investors and exposing the market to more volatile capital flows. The

trend of declining pension fund gilt holdings is expected to continue (Office for Budget Responsibility, 2025), in part due to a volume effect, but also due to the shift from defined benefit schemes to defined contribution schemes (see Annex Figure 21). The Office for Budget Responsibility estimates that the decline in the pensions sector's gilt holdings could push up interest rates on government debt by around 0.8 percentage points, assuming the stock of debt remains close to 100 per cent of GDP (Office for Budget Responsibility, 2025).

Figure 6. Gilt Holdings

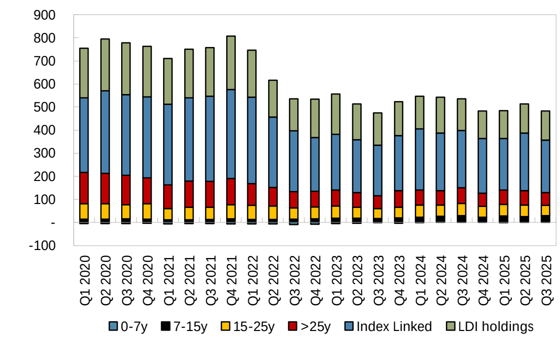
The share of gilts held by the insurance corporation and pension fund sector has declined, while foreign holdings have increased.

UK Gilt Market Holding Structure by Sector
(Percent)



Sources: HM Treasury, Office for National Statistics, and IMF staff calculations. MFI = monetary financial institutions. ICPF = insurance corporations and pension funds. OFI = other financial institutions. Sectoral holdings in the UK financial accounts are subject to limitations related to data granularity, coverage gaps, and the constraints of traditional survey-based methodologies.

Defined Benefit Pension Scheme Gilt Holdings
(GBP billion)



Sources: Office for National Statistics, and IMF staff calculations. LDI = liability-driven investment.

10. The shift in the investor base may have contributed to a higher term premium. A commonly cited explanation for the increase in long-term yields is a decline in structural demand for gilts, particularly at longer maturities. Empirically, however, the strength of this relationship is subject to uncertainty, as the relevant variables are slow-moving and observed at low frequency, making it challenging to distinguish genuine relationships from coinciding trends. To provide a high-level perspective, an index is constructed that captures the share of foreign holdings relative to more stable holders—namely the central bank, insurance corporations, and pension funds (see below). This indicator shows a positive correlation with the term premium (Figure 7), suggesting that a shift toward more price-sensitive investors may be associated with higher required compensation for holding gilts.

$$\text{Holders Vulnerability Index} = \frac{\text{Share of gilts held by foreign investors}}{\text{Share of gilts held by Central Bank, Insurance Corporations and Pension Funds}}$$

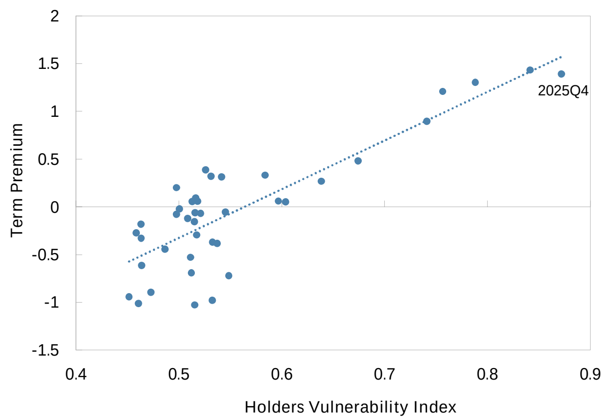
This relationship should be interpreted with caution: the UK does not necessarily stand out in terms of the share of foreign holdings.[4] The key observation is that there appears to be a gradual shift from stable investors with a long horizon towards more price-sensitive marginal investors (see Gies and others, 2023). For example, hedge funds account for 60 percent of the daily gilt market trading volume, versus 55 percent in the euro area and 30 percent in the US.[5] This is consistent with a broader narrative of a changing investor base and evolving supply–demand conditions in the gilt market, and suggests that a decline in stable long-term demand may have contributed to higher term premia. More broadly, an OECD survey amongst debt management offices shows that more than half of the respondents assess that hedge funds are marginal buyers in their markets, adding that these changes in the investor base towards more price-sensitive and leveraged investors could make markets more vulnerable to shocks (OECD 2026).

Figure 7. Term Premium and Investor Base

The term premium appears to be correlated with an indicator of investor base (in)stability

Term Premium and Holders Vulnerability Index

(Percent, index)



Sources: HM Treasury, Bloomberg, and IMF staff calculations

Size and Liquidity of the Market

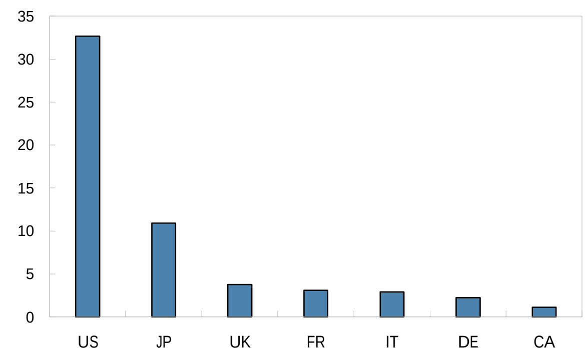
11. The UK gilt market is less deep and liquid than the largest benchmark markets, which may reduce its resilience to shocks. While similar in size to France and Italy, the UK market is smaller than the US and Japan (Figure 8). Absolute size is an important (but not the only determinant) of market liquidity (McCauley and Remolona, 2000), as there are economies of scale in market-making activities. Smaller, less liquid markets may therefore be more sensitivity to shifts in demand, particularly during periods of stress.

[4] In particular, France and Germany have a significantly higher share of foreign holders, 56 percent and 58 percent at the end of 2025 respectively.

[5] See Hedge fund dominance latest risk for febrile UK debt markets | Reuters.

Figure 8. Sovereign Bond Market Size

Market Size
(US dollar billion)



Sources: Bloomberg, and IMF staff calculations. Reference date: 3/6/2026.

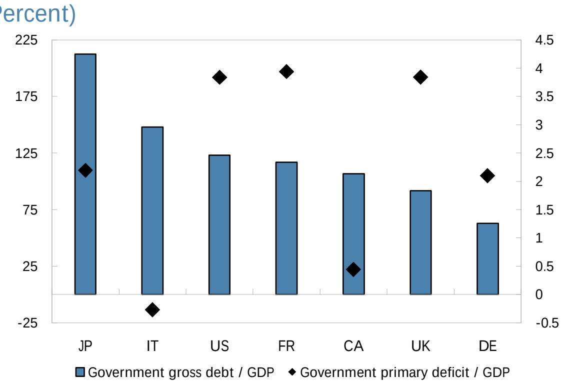
Sovereign Credit Risk

12. Among G7 countries, the UK's debt-to-GDP ratio is toward the lower end of the distribution, although it remains elevated in absolute terms. The debt-to-GDP ratio has risen from around 80 percent before the pandemic to just below 100 percent in recent years (see Figure 9). During and after the pandemic, the BoE absorbed a large share of outstanding government debt through asset purchases, but is currently unwinding these holdings under quantitative tightening.

Figure 9. Government Debt

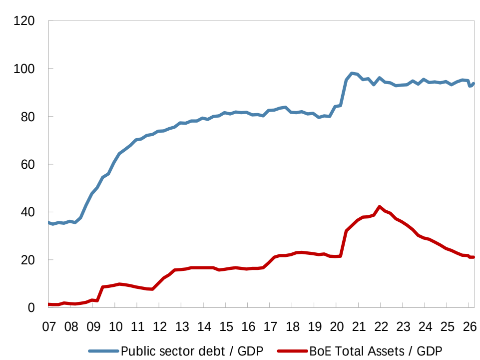
The UK has high deficit and debt ratios but these do not stand out among G7 countries.

2024 G7 Government Debt and Primary Deficit
(Percent)



Source: OECD (2024)

UK Public Sector Debt and Central Bank Assets
(Percent)



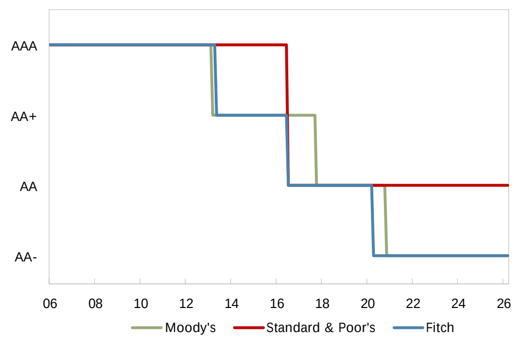
Source: Bloomberg

13. Over the past two decades, however, the UK's sovereign credit rating has declined from AAA to AA/AA (see Figure 10). Empirically, there is a correlation across advanced economies between sovereign credit ratings and yield curve steepness, as measured by the spread between 10- and 2-year yields. While this spread does not directly capture credit risk, it can be interpreted as a proxy for the term premium, and thus as a broader measure of country risk and uncertainty.

Figure 10. Credit Ratings

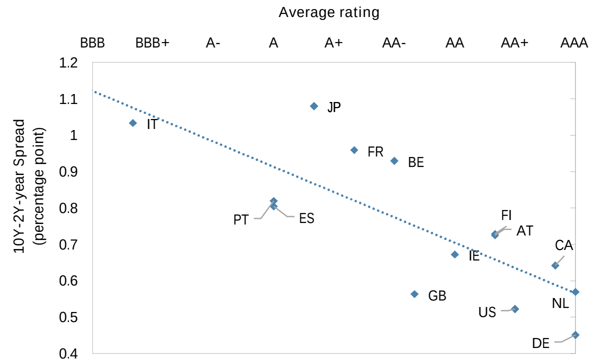
UK sovereign credit rating has declined over the past two decades.

UK Long Term Issuer Credit Rating
(Percent)



Sources: Bloomberg, and IMF staff calculations

Sovereign Credit Ratings and 10Y2Y Spreads
(Percent)



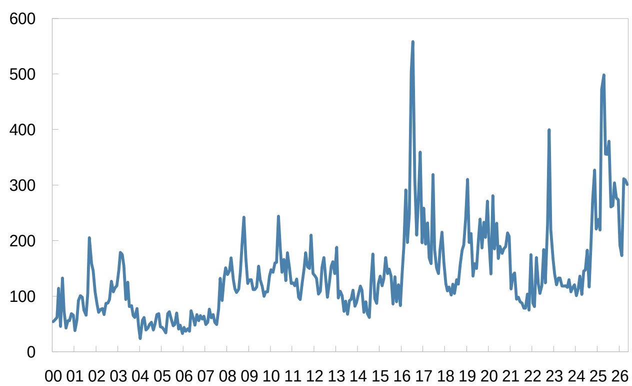
Sources: Bloomberg, and IMF staff calculations. Spreads taken on 4/24/2026.

Legacy of the 2022 Episode: Heightened Sensitivity to Policy Uncertainty?

14. Market feedback suggests that the September 2022 gilt market turmoil marked a structural shift in the fragility of the gilt market. The Economic Policy Uncertainty (EPU) index—capturing domestic policy-related uncertainty—spiked around both the Brexit referendum and the September 2022 gilt market turmoil episode (Figure 11).

Figure 11. Economic Policy Uncertainty

UK Economic Policy Uncertainty
(Index points)



Sources: Baker, Bloom, and Davis

C. Analysis of Term Premium Drivers and Dynamics

15. This section addresses the puzzle of why UK gilt yields have risen more than those of G7 peers, combining multiple complementary empirical approaches with a focus on the term premium. Understanding the drivers of yields and term premia is central to assessing sovereign

borrowing costs and financial stability risks. The analysis focuses on the term premium as the key object of interest. However, the term premium is a model-based measure and therefore subject to estimation uncertainty and noise. For empirical approaches that are sensitive to such noise—particularly high-frequency or variance-based analyses—observed yields are used instead, as they provide a more robust basis for inference.

16. We combine statistical, structural, and reduced-form approaches, each capturing different but complementary aspects of yield and term premium dynamics (see Table 1). A factor-based analysis extracts common patterns in yield changes and quantifies the relative importance of global and domestic drivers.[6] A structural Bayesian VAR provides decomposition of the UK term premium into contributions from global and UK-specific shocks based on identified shocks. A G7 panel regression examines cross-country relationships between changes in term premia and macro/credit fundamentals, risk factors, and structural supply-demand factors. A UK-specific time-series regression assesses whether the September 2022 Gilt market turmoil altered term premium dynamics. Finally, a volatility regression examines the relationship between key drivers and UK gilt yield volatility, testing whether market fragility increased after the September 2022 turmoil. While the statistical and reduced-form approaches do not establish causal relationships, taken together, these approaches provide a consistent picture across different methodologies.

Table 1. United Kingdom: Overview of Empirical Approaches

Approach	Objective	Variable of interest
Statistical: Factor-model (PCA)	Assess the time-varying importance of global and domestic factors	UK yield changes (daily and weekly)
Structural: Bayesian VAR (BVAR)	Decompose the UK term premium into contributions from identified global and UK-specific shocks	UK term premium
Reduced form: Panel regression of G7 term premia	Assess empirical relationships between changes in term premia and macroeconomic, risk, and supply–demand factors across G7 economies	G7 term premia changes (monthly, first differences)
Reduced form: Time series regression of UK term premium	Assess time-series relationships between the UK term premium and key drivers, and test whether sensitivities changed after September 2022	UK term premium changes (monthly, first differences)
Reduced form: Time series regression of gilt yield volatility	Assess the relationship between gilt yield volatility and global factors, and test whether sensitivities changed after September 2022	UK yield volatility (6-month standard deviation of yield changes)

Note: The BVAR, panel, and time-series regressions use the model-implied term premium as the dependent variable. This creates a potential tension, as a latent, model-based variable is related to observed drivers, implying that results may partly reflect properties of the underlying term structure model. By contrast, the PCA and volatility analysis use observed yields, as term premia estimates are too noisy at higher frequencies.

[6] Here yields are used instead of the term premium. The term premium is model-based, and therefore potentially noisy, to which PCA can be sensitive.

Global Versus Domestic Determinants of Yields

17. Global factors account for the majority of UK yield variation, but their importance varies over time. To assess the relative importance of global and domestic drivers, a principal component analysis (PCA) of G7 yield changes is used to extract the dominant patterns in yield dynamics. The analysis focuses on observed yield changes rather than model-based term premia, as the latter can be sensitive to estimation noise and model specification, which may distort the factor decomposition. The first principal component from a 12-month rolling PCA captures the co-movement in yields across countries and can be interpreted as a global factor. Yield changes are then decomposed into this global component and a residual domestic component, allowing for an assessment of the share of variance explained by global forces for each country.

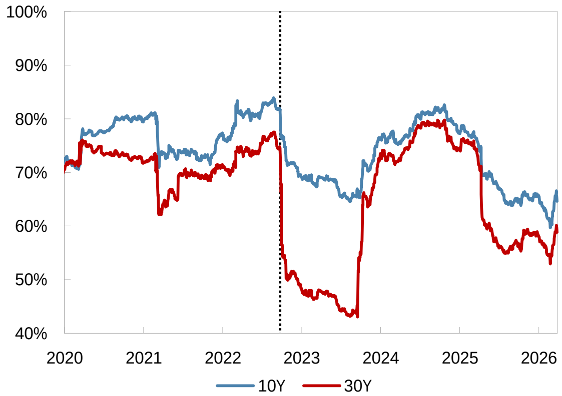
18. After the September 2022 episode, domestic factors have become more important. Over the period 2020–26, global factors explained between 60 and 90 percent of the variation in gilt yields (see Figure 12). This share declined markedly following the September 2022 episode, particularly for long maturities such as the 30-year yield, indicating a greater role for domestic factors during this period. The importance of the global factor subsequently increased again through 2024, before declining in 2025, when domestic factors regain prominence. Notably, this renewed importance of domestic factors coincided with a period of a widening UK term premium. Using weekly data—less sensitive to day-to-day noise—the impact of the September 2022 gilt market turmoil appears more pronounced, with the importance of global factors declining significantly relative to the pre-episode period.

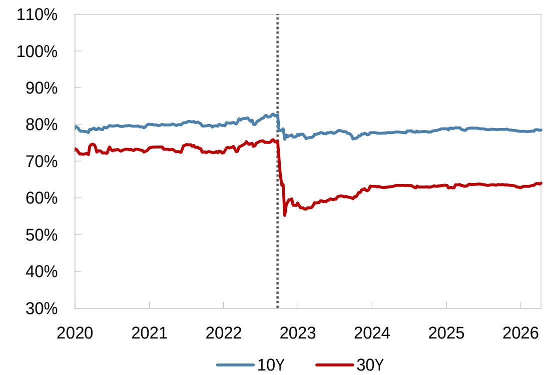
19. The post-2022 decline in the explanatory power of global factors points to a greater role for UK-specific shocks, with implications for the term premium. This shift is most pronounced at the long end and coincides with a widening in the UK term premium, suggesting that the increased importance of domestic factors is likely to reflect higher compensation for UK-specific risks and uncertainty. In this sense, the PCA results—while based on yields—are consistent with the broader evidence that recent upward pressure on long-term gilt yields has been driven in part by an increase in the term premium rather than by global factors alone.

20. This contrasts with high-frequency market dynamics: from a day-to-day trading perspective, gilt yields can appear relatively sensitive to global shocks, particularly during event-driven episodes. Market participants often describe this as a higher "beta" to global movements, especially since the September 2022 gilt market turmoil. This is most evident at high frequencies: during episodes such as the Middle East conflict, gilt yields exhibited some of the largest moves across G7 markets. However, this pattern is not born over longer horizons. The PCA, based on a 12-month rolling window, shows that the global factor explains only a limited share of variation, as periods of strong co-movement are offset by intervals in which idiosyncratic factors dominate. Over the full sample, there is therefore no clear evidence of a persistently higher sensitivity to global shocks.

Figure 12. Factor Analysis of Yield Dynamics

Domestic factors gained importance in gilt yield dynamics after the 2022 gilt market turmoil, and once again towards 2025.





Sources: Refinitiv Datastream, and IMF Staff Calculations. The global factor refers to the first principal component of a 12-month moving window principal component analysis. The dotted line indicates September 23, 2022, the date at which the "mini-budget" was presented.

Shocks Driving the UK Term Premium, Including Market Imbalances

21. The UK term premium receives contributions from distinct shocks—including global risk, country-specific risk, and demand-related factors—that can be separately identified. To complement the factor-based analysis, a Bayesian vector autoregression (BVAR) with sign restrictions is employed to identify these shocks and assess their cumulative impact on the UK term premium. Intuitively, the BVAR uses the co-movement of financial variables to infer the underlying shocks driving the term premium, allowing past movements to be decomposed into contributions from different sources. Identification is achieved using sign restrictions on the responses of key variables—imposing economically motivated patterns on how variables react to shocks—following an approach similar to Brandt and others (2023), using the BEAR toolbox developed by Dieppe, van Roye and Legrand (2016). The model is estimated using daily data and includes UK and US term premia, UK and US corporate credit spreads, the GBP/USD exchange rate, and the 10-year swap spread. Global risk shocks are characterized by widening corporate spreads and a strengthening of the US dollar, while global term premium shocks are associated with simultaneous increases in UK and US term premia (Table 2). UK- and US-specific risk shocks are identified by increases in the respective country's term premia and corporate spreads, with US risk shocks also leading to dollar appreciation. In addition, a structural shock is identified by an increase in the UK term premium combined with a decline in the UK swap spread,[7] interpreted as reflecting weaker demand for gilts and potential supply–demand imbalances.

[7] The swap spread is the spread between the interest rate swap and sovereign bond yields of the same maturity. It is indicative of demand conditions in the gilt market, with a decline in the swap spread suggesting weaker demand for government bonds relative to swaps and potential supply–demand imbalances. Annex Figure 19 shows the time-evolution of the 10-year swap-spread for the UK market.

Table 2. United Kingdom: BVAR Sign Restrictions

	Global Risk	Global Term Premium	UK Risk	US Risk	Structural demand/supply
UK term premium		+	+		+
US term premium		+		+	
US corporate spread	+			+	
UK corporate spread	+		+		
UK swap-spread					-
GBBUSD	-		-		

Note: corporate spreads are the Z-spreads to the sovereign curve taken from the US and UK Bloomberg investment grade corporate bond indices. The swap spread is the difference between the 10-year SONIA overnight-indexed swap rate and the 10-year UK gilt yield. The swap spread is indicative of demand conditions in the gilt market, with a decline in the swap spread suggesting weaker demand for government bonds relative to swaps and potential supply–demand imbalances. Under a global risk shock, the US dollar is assumed to strengthen, whilst corporate spreads widen. A global term premium shock reflects a common increase in term premia. A US/UK-specific risk shock drives up US/UK risk premia. The pound sterling weakens versus the US dollar under a UK risk shock. Lastly, structural demand/supply shocks are assumed to drive up the UK term premium, while reducing the swap-spread.

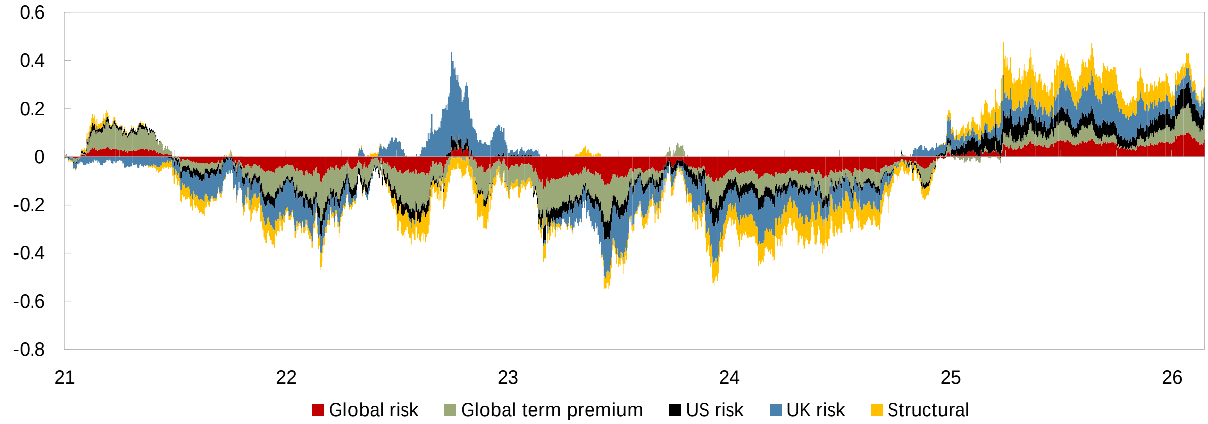
22. Structural supply–demand imbalances appear to have exerted more upward pressure on the UK term premium since 2024. The BVAR analysis shows how identified shocks contribute to movements in the term premium over time (see Figure 13).[8] To assess the economic plausibility of the decomposition, we examine key recent episodes. In early 2021, rising global inflationary pressures were reflected in a prominent contribution from global term premium shocks. Around the September 2022 episode, UK-specific risk shocks dominated, driving a sharp increase in the UK term premium. In the period from the beginning of 2024 to the end of 2025—when the term premium drove a wedge between long-term yields and the expected path of short rates—the decomposition points to a combination of shocks, with roughly equal contributions from global and UK-specific factors. Notably, the role of UK-specific risk shocks increased in late 2024, while spillovers from US risk shocks also contributed. Structural demand/supply shocks became more prominent from 2024 onwards (moving from negative to positive). This could reflect a range of mechanisms, including shifts in the investor base (e.g. from pension funds or central bank holdings toward more price-sensitive investors), increased net supply associated with issuance or quantitative tightening, or constraints in market intermediation and liquidity. These mechanisms, however, cannot be separately identified within the model.

[8] Annex Figure 22 shows the impulse response functions for the model.

Figure 13. Term Premium Shock Decomposition

The UK term premium increased in 2025 due to a combination of global and domestic shocks.

Term Premium Cumulative Contribution from Identified Shocks Since 2021
(Percentage point)



Source: Bloomberg, IMF staff calculations. Last data: 3/6/2026.

A Cross-Country Perspective on Supply-Demand Factors

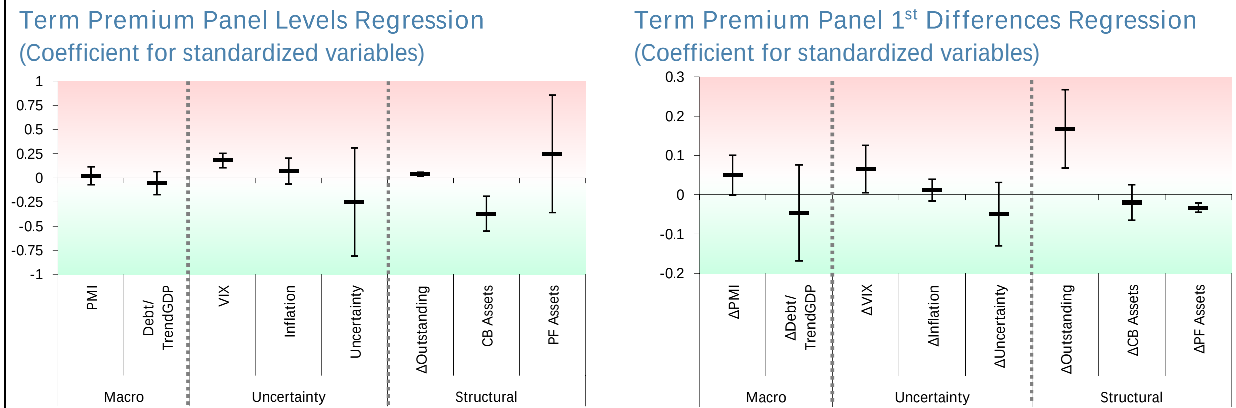
23. A cross-country panel regression is used to examine the relationship between term premia and macroeconomic, risk, and structural supply–demand factors across G7 countries. Variables are grouped into three categories: macro-credit factors, sources of uncertainty, and structural supply–demand conditions (Table 3). The analysis is subject to several limitations. Many candidate drivers co-move over time, making it difficult to disentangle their individual effects on term premia. Data availability and frequency differ across variables and jurisdictions, complicating the construction of a consistent panel dataset. In addition, the relatively small G7 sample limits statistical power; expanding the sample could increase observations, but the inclusion of smaller or emerging economies may introduce structural differences that obscure core patterns. Accordingly, the results are best interpreted as identifying correlations rather than causal relationships. Within this framework, a set of representative variables is selected for each category (Table 3). Macro-credit factors include purchasing managers' indices (PMIs), capturing forward-looking growth expectations, and debt-to-GDP ratios, adjusted by scaling debt to trend GDP to reduce cyclical distortions. Measures of uncertainty include the VIX as a proxy for global risk sentiment, inflation uncertainty (measured as the moving average deviation of CPI outcomes from expectations), and economic policy uncertainty based on the Baker-Bloom–Davis methodology. Structural supply and demand factors are proxied by net government debt issuance, central bank holdings relative to outstanding government debt, and pension fund assets relative to government bonds.

Table 3. United Kingdom: G7 Panel Regression	
$$\Delta Y_{i,t}^{n} = \alpha_i + \beta_t + \overbrace{\gamma^T \Delta X_{i,t}}^{\text{Macro/credit factors}} + \overbrace{\theta^T \Delta A_{i,t}}^{\text{Sources of Uncertainty}} + \overbrace{\beta^T \Delta Z_{i,t}}^{\text{Structural demand/supply}} + \varepsilon_{i.t}$$	
Macro/credit factors:	▪ Purchase Managers Index (lagged) ▪ Debt-to-trend-GDP ratio
Sources of Uncertainty:	▪ Equity Implied Volatility (VIX) ▪ Inflation uncertainty (average 6-month deviation of y/y CPI from survey expectation, lagged) ▪ Economic Policy Uncertainty (Baker-Bloom-Davis)
Structural demand/supply:	▪ Net issuance / percentage change in nominal amount of government debt outstanding ▪ Central bank assets: ratio of central bank assets over the amount of government debt outstanding ▪ Pension fund assets: ratio of pension fund assets over the amount of government debt outstanding
Quarterly and annual data are interpolated to a monthly frequency where needed. The dataset spans 2000–2025 at a monthly frequency. Regression results are reported in the Annex. α_i and β_t reflect country and time fixed effects, respectively.	

24. Overall, the results highlight the importance of supply-demand dynamics—particularly net issuance flows—in shaping term premia across advanced economies, while also pointing to a stabilizing role of long-term institutional investors. Regression results point to a consistent role of both global risk and supply factors. In a levels regression, interpreted with caution due to potential spurious trends, the VIX and net issuance are positively associated with term premia, while larger central bank balance sheets are associated with lower term premia (see Figure 14). A more informative first-differences specification confirms a robust positive relationship between net issuance and term premia, alongside a continued role for the VIX. There is also some evidence that stronger growth expectations (proxied by lagged PMIs) are associated with a higher term premium. In contrast, increases in pension fund assets are associated with lower term premia, consistent with their role as stable long-term investors, while the effect of central bank flows is not statistically significant at conventional levels. Annex Table 7 provides a sense of the economic significance of relevant drivers (confidence intervals indicated in the table). A percent increase (over 3 months) of the outstanding amount of debt through net issuance is associated with a 3.8 basis points increase of the term premium. A one percentage point increase in the pension fund holdings of gilts is associated with a 5.4 basis points decrease of the term premium.

Figure 14. Panel Regression Coefficients

Issuance flows and global risk sentiment appear to drive G7 term premia



Sources: Bloomberg, Refinitiv Datastream, OECD, Haver, and IMF staff calculations. Whiskers indicate 95 percent confidence intervals. Variables have been standardized (mean of zero, standard deviation of one) to assess the relative strength of the relationship between each variable and the term premium. Full regression tables can be found in the annex.

The Role of Domestic Uncertainty

25. The relationship between the UK term premium and domestic policy uncertainty is assessed using a UK-specific time-series regression. The analysis includes the key driver identified in the panel analysis—net issuance—and is augmented with a measure of policy uncertainty (Table 4). To test for changes in sensitivities, policy uncertainty is interacted with a post-2022-turmoil dummy.

26. The results indicate that, following the September 2022 episode, the UK term premium became significantly more sensitive to domestic policy uncertainty (see Figure 15). This supports market commentary suggesting that investors began to assign a higher risk premium to perceived policy uncertainty. Economically speaking, a one standard deviation change in the monthly EPU (80 index points) is associated with a 4.6 bps increase in the term premium, after the September 2022 gilt market turmoil.[9]

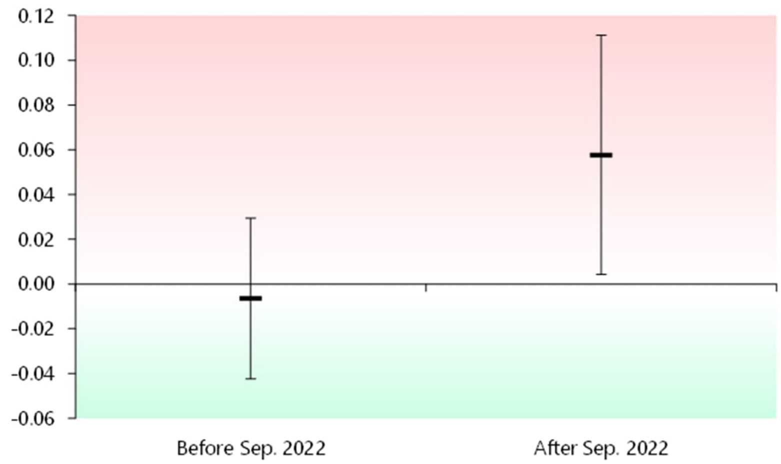
Table 4. United Kingdom: Term Premium Regression	
$\Delta\text{Term Premium} = \alpha + \beta \cdot \text{net issuance} + \gamma \cdot \Delta\text{EPU} + \delta \cdot \text{post}_{\text{Sep.2022}} + \theta \cdot \text{post}_{\text{Sep.2022}} \cdot \Delta\text{EPU}$	
Net issuance	3-month moving window change in nominal amount of government bonds outstanding, in percent
EPU = Economic Policy Uncertainty	UK specific index following Baker-Bloom-Davis
$\text{post}_{\text{Sep.2022}}$	Dummy, takes value 0 before September 2022, 1 during & afterwards

[9] Annex Table 8 shows the results of the time-series analysis. Note that the net issuance coefficient is similar in magnitude to the panel regression's net issuance coefficient (Annex Table 7).

Figure 15. UK Term Premium Sensitivity to Economic Policy Uncertainty

UK Term Premium appears to be more sensitive to domestic policy uncertainty after the September 2022

Term Premium Panel Sensitivity to UK EPU
(Basis point per UK EPU index point)



Sources: Refinitiv Datastream, Bloomberg, and IMF staff calculations.

Impact of the 2022 Episode on Gilt Yield Volatility

27. The September 2022 gilt market turmoil also appears to have increased the sensitivity of gilt yield volatility to global shocks. To assess this, UK gilt yield volatility—measured as a six-month moving standard deviation of yield changes—is regressed on US Treasury yield volatility and global risk (proxied by the VIX), with interaction terms capturing the period after September 2022 (Table 5). Similar to the PCA analysis, yields instead of term premia are used in this exercise, as model-based term premia introduce estimation noise that can distort high-frequency volatility measures. The results indicate that, following the episode, US yield volatility is more strongly associated with gilt volatility, and that gilt yields have become more responsive to global risk conditions (see Figure 16). While these relationships cannot be interpreted causally, they point to a more fragile market environment in which volatility is transmitted more readily across markets.

Table 5. United Kingdom: Volatility Regression

$$\sigma_t^{UK} = \alpha + \beta \cdot \sigma_t^{US} + \delta \cdot post_t + \gamma \cdot (post_t \cdot \sigma_t^{US}) + \theta \cdot VIX_t + \sigma \cdot (post_t \cdot VIX_t) + \varepsilon_t$$

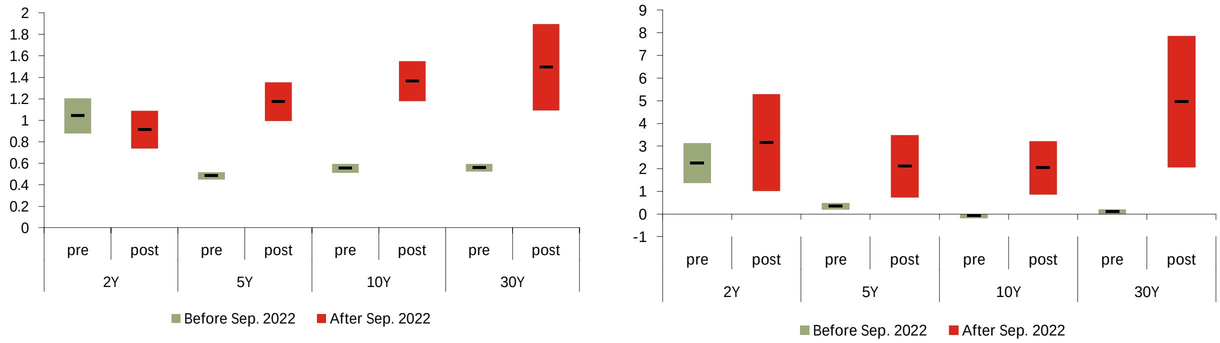
	Before Sep. 2022	After Sep. 2022
Relationship with US volatility:	β	$\beta + \gamma$
Relationship with global risk (VIX):	θ	$\theta + \sigma$

Figure 16. Gilt Yield Volatility

Gilt yield volatility might have become more sensitive to global drivers of volatility

Strength of the Relationship between Gilt and US Yield Volatility
(Regression coefficient)

Strength of the Relationship between Gilt Yield Volatility and VIX
(Regression coefficient)



Sources: Bloomberg, and IMF staff calculations.

Summary of Results

28. This section summarizes the main empirical findings and their consistency across approaches (see Table 6). Across complementary empirical methods, the evidence points to a coherent set of drivers behind the rise in the UK term premium across two dimensions: (1) a gradual *long-term structural change* in demand-supply conditions in the gilt market; and (2) a *regime shift* after the September 2022 gilt market turmoil, after which the UK domestic risk started to play a more important role as a driver of the term premium and gilt markets became more prone to volatility spikes.

29. One explanation for the rise in the UK term premium relates to structurally tighter supply–demand conditions in the market for longer-term bonds. Across all our empirical approaches, increases in net issuance are consistently associated with a higher term premium, while the higher term premium also appears to align with declining structural demand for long-term bonds, and a shift toward more price-sensitive investors. The footprint of long-term institutional investors—such as pension funds and central banks—which have historically exerted a stabilizing effect, has become much smaller.

30. Another explanation is that the September 2022 gilt market turmoil seems to mark a regime shift in how shocks are transmitted into gilt yields. The analysis points to two distinct changes in gilt market dynamics: first, a stronger role for domestic factors in determining the level of the term premium; and second, a greater propensity for the market to shift into high-volatility regimes.

- *Domestic factors—notably economic policy uncertainty—have become a more important driver of the term premium*. The PCA shows a clear decline in the share of gilt yield variation explained by the global factors after September 2022, indicating a greater role for domestic influences. In parallel, the time-series evidence shows that the term premium has become more sensitive to UK economic policy uncertainty.

- *Gilt markets also appear more prone to shifts into high-volatility regimes.* After the September 2022 episode, gilt market volatility shows a stronger association with US Treasury market volatility and the VIX index. A higher propensity to enter high-volatility regimes signals fragility because small shocks can trigger larger price moves, reflecting weak intermediation and limited shock absorption. These moves can become self-reinforcing through forced deleveraging, which amplifies and prolongs instability.

31. Evidence for other factors seems less robust or of limited policy relevance. In the G7 panel regression, the VIX is positively associated with the term premium, but it reflects exogenous global conditions and serves primarily as a control, offering limited policy insight. Other variables are not consistently significant across specifications, but in some cases this may reflect data limitations such as low frequency or measurement errors. For example, changes in central bank assets are not found to have a significant association with the term premium; however, more detailed data—such as outright government bond holdings—could be more informative for further analysis (if available). Our recommendations focus on policy actionable insights that find stronger support across multiple approaches.

Table 6. United Kingdom: Summary of Findings

Approach	Key Result	Interpretation
Factor model (PCA)	Global factors explain most yield variation, but their importance declines after September 2022	September 2022 had a profound impact in what drives gilt yields
Structural: BVAR	Structural supply–demand shocks contribute notably to recent term premium increases	Changes in investor base and issuance conditions are relevant drivers
Panel regression (G7)	Term premia are positively associated with global risk (VIX) and net issuance; pension funds reduce premia	Global risk and supply dominate; long-term investors stabilize markets
UK time-series regression	Sensitivity of term premia to policy uncertainty increases after 2022	Greater role for domestic risk and policy credibility
Volatility regression	Gilt volatility becomes more sensitive to US volatility and global risk after 2022	Increased cross-market transmission and market fragility

D. Discussion and Recommendations

32. Policy responses should target the underlying economic drivers of elevated gilt yields. The analysis points to drivers across two dimensions: first, gradual long-term changes in structural demand-supply conditions in the gilt market, and second, a regime-shift after the September 2022 gilt market turmoil. Effective policy responses should therefore focus on mitigating these pressures and strengthening the market's capacity to absorb them.[10]

33. First, reducing the volume and adjusting the composition of gilt supply can help limit upward pressure on the term premium. The analysis shows that higher net gilt issuance is associated with a higher term premium, which may also be impacted by the weaker structural demand for long-dated gilts. Policymakers should therefore focus on three channels: reducing issuance needs through fiscal consolidation, adapting the maturity and instrument composition of issuance to market demand, and ensuring that quantitative tightening does not unnecessarily amplify bond-supply pressures.

- *Staying the course on planned fiscal consolidation is key to limiting the amount of net gilt issuance.* The fiscal adjustment that began last year aims to stabilize net debt over the medium term and is underpinned by the June 2025 Spending Review. With elevated debt and gilt market pressures, delivering the planned deficit reduction requires a cautious approach to new spending pressures, including further prioritization where needed without raising fiscal deficit targets, and the development of contingency plans on both the tax and revenue sides should the consolidation be pushed off course.

- *The issuance composition should continue to be calibrated to avoid concentrating supply in segments of the curve with limited absorption capacity.* The DMO is already taking steps in this direction: it has shortened the maturity of its issuance, reduced the share of index-linked gilts,[11] concluded a consultation on bill issuance,[12] and is considering switch auctions[13] that could support liquidity in the long end of the curve. Maturity shortening can increase rollover-risk, which can be limited by staying the course on the planned fiscal consolidation, however.

- *Balance sheet normalization should be conducted in a way that does not unnecessarily amplify supply-demand imbalances.* The BoE is reducing its gilt holdings under the Asset Purchase Facility (APF), but this has the effect of increasing the amount of gilts to be absorbed by the market. While frequent adjustment to quantitative tightening QT should be avoided as it risks

[10] While this paper focuses on the term premium, expectations of future short rates have also contributed to the rise in long-term gilt yields. Therefore, anchoring inflation expectations and maintaining credible monetary policy remain essential for overall yield dynamics.

[11] For example, see Debt Management Report 2026–27

[12] See Consultation on the UK Treasury bill market - GOV.UK, The UK Treasury bill market - Response document and Publication of the T-bill consultation response

[13] See DMO Financing Remit 2026–27

undermining the role of the Bank rate as the active tool of monetary policy, it should nevertheless be implemented in a manner that preserves market stability, including by following a predictable and pre-determined path.[14] In addition, given the changing investor base and reduced structural demand for long-term gilts, skewing the sales away from longer maturity gilts could be considered if market conditions warrant.

34. Second, policy credibility and predictability are key to strengthening market confidence and reversing the impact of the September 2022 episode. Clear communication and well-signaled policy changes can anchor expectations and reduce the risk of sharp repricing in sovereign yields. Recent reforms have strengthened the stability and credibility of fiscal policy. In line with past Article IV recommendations, the authorities did not announce any new measures in the spring, making the Fall budget the sole fiscal event, and the Office for Budget Responsibility now only assesses rule compliance at the time of the Fall budget. This has signifyingly reduced speculation about interim fiscal adjustments. In addition, the fiscal buffers have been increased. Managing the risks to the medium-term consolidation path in a more shock-prone world and a proactive approach to dealing with longer term spending pressures would help strengthen credibility and support market confidence. Beyond the fiscal strategy, the authorities should sustain the implementation of their structural reform agenda. The economic payoff from many structural reforms will materialize only gradually, and credibility will ultimately hinge on sustained delivery.

35. Finally, enhancing resilience in the broader core funding market ecosystem is critical to improving the gilt market's capacity to absorb shocks. Constraints in intermediation—reflecting repo market functioning, dealer balance sheet capacity, and the broader institutional framework—affect how smoothly gilt flows are absorbed and how strongly shocks are reflected in yields. Evidence from the System Wide Exploratory Scenario (SWES) shows that individual actions can collectively amplify shocks through procyclical asset sales in combination with limited intermediation. While post-2022 reforms, particularly for LDI funds, have improved resilience, these gains may not be sufficient. The exercise also underscores the central role of repo markets, whose capacity to absorb stress is critical. The FPC has received feedback on its discussion paper on gilt repo market resilience,[15] and the BoE intends to publish a comprehensive update, including potential policy proposals, in early 2027.

[14] Note: the Bank of England amended its auction schedule in April 2025 in light of market volatility. See Asset Purchase Facility: Gilt Sales Amendment - Market Notice 10 April 2025 | Bank of England.

[15] See Enhancing the resilience of the gilt repo market – discussion paper feedback statement | Bank of England

Annex I. Supplementary Data and Empirical Results

A. Data Set

Table I.1 United Kingdom: Data Set				
Variable	Start date	End date	Frequency	Source
Term premium	Feb-99	Nov-25	Daily	Bloomberg, IMF staff calculations
Debt/GDP	Mar-00	Dec-25	Quarterly	Refinitiv
Central bank assets	Jan-00	Nov-25	Monthly	Haver
Pension fund assets	Dec-06	Dec-24	Annual	OECD
Inflation uncertainty	Dec-03	Dec-25	Monthly	Bloomberg, IMF staff calculations
GDP (nominal)	Mar-00	Dec-25	Quarterly	Haver
Economic policy uncertainty	Jan-00	Dec-25	Monthly	www.policyuncertainty.com
Government bonds outstanding	Mar-00	Sep-25	Quarterly	Haver
PMI	Aug-01	Dec-25	Monthly	Bloomberg
VIX	Jan-00	Dec-25	Monthly	Bloomberg

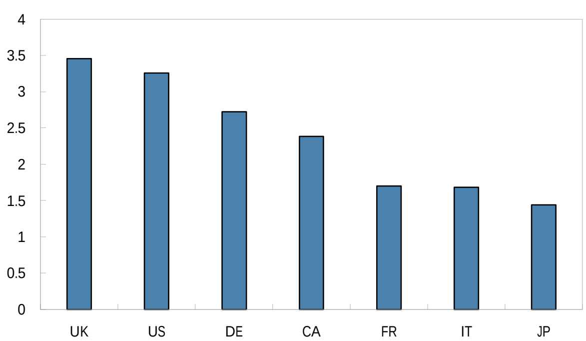
36.

B. Additional Stylized Facts

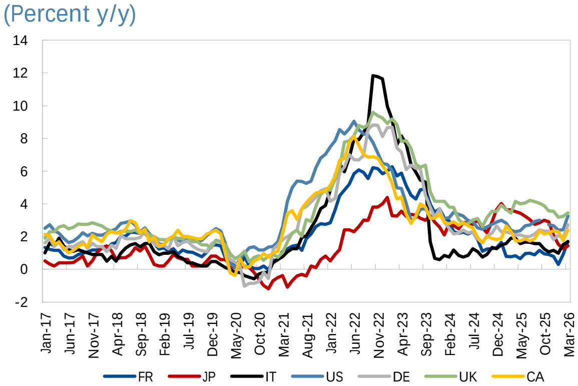
Figure I.1. Inflation

UK inflation has been higher than in G7 peers in recent years.

CPI Inflation March 2026
(Percent y/y)



CPI Inflation
(Percent y/y)

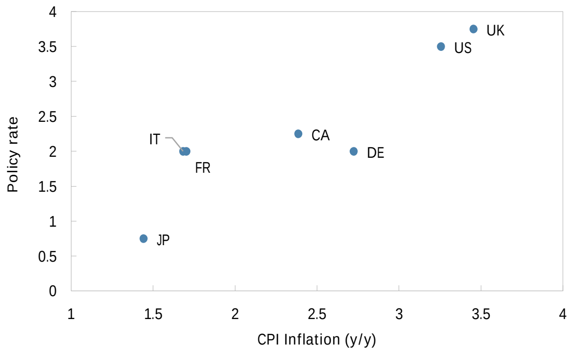


Source: IMF.

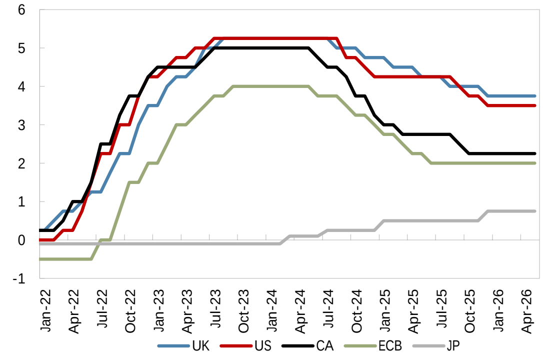
Figure I.2. Policy Rates

The UK's policy rate has also been on the upper end of the G7 range over the past years

Policy Rates & CPI Inflation March 2026
(Percent, percent)



Policy Rates
(Percent)

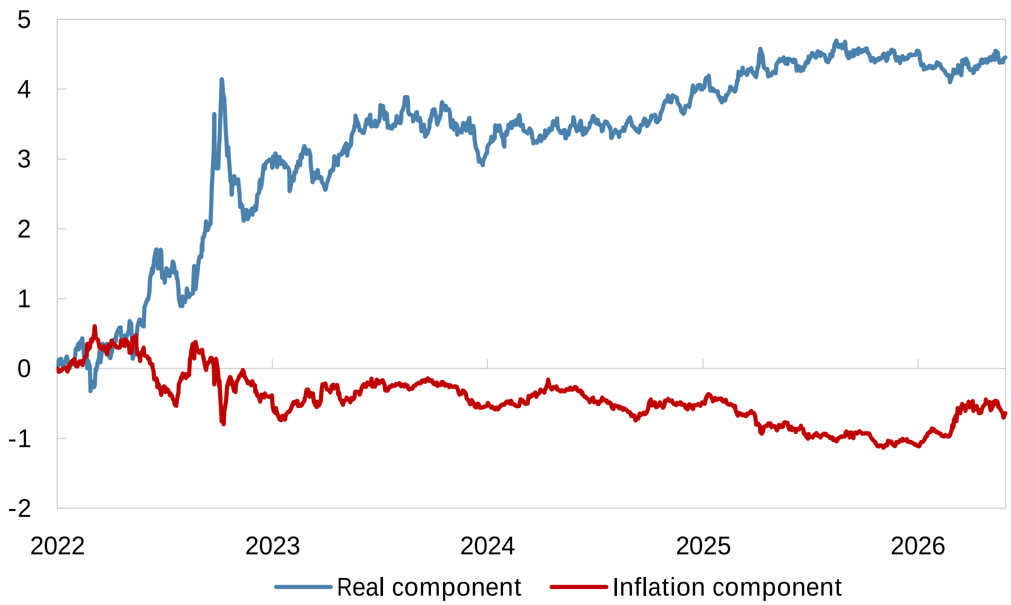


Sources: Bloomberg, and IMF.

Figure I.3. Real and Inflation Components of Gilt Yields

The real component of gilt yields has increased while the inflation component has been relatively stable since 2022.

UK 10-Year Gilt Yield Real and Inflation Components Change Since 2022
(Percentage points)

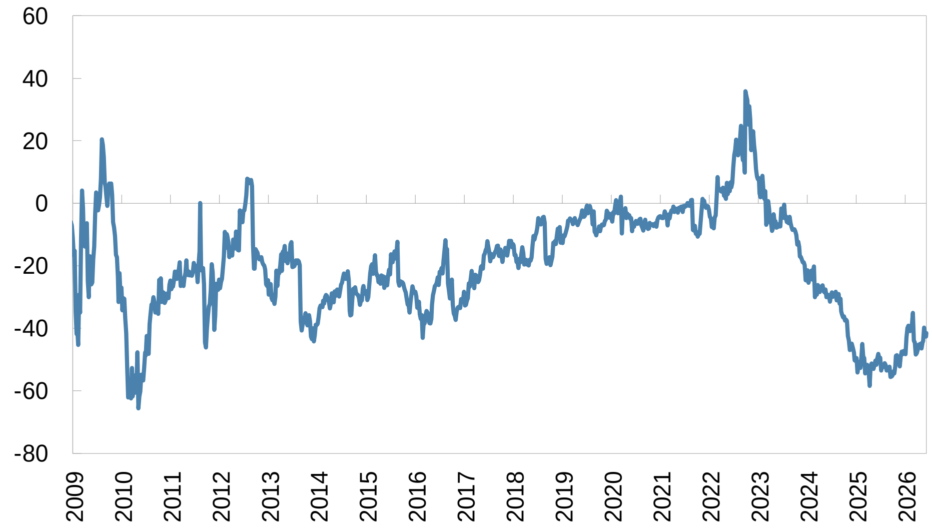


Sources: Bloomberg, and IMF staff calculations. Change from 1/1/2022 until 5/31/2026.

Figure I.4. Swap Spread

The swap spread has turned negative in recent years

UK 10-Year Swap Spread
(Basis points)

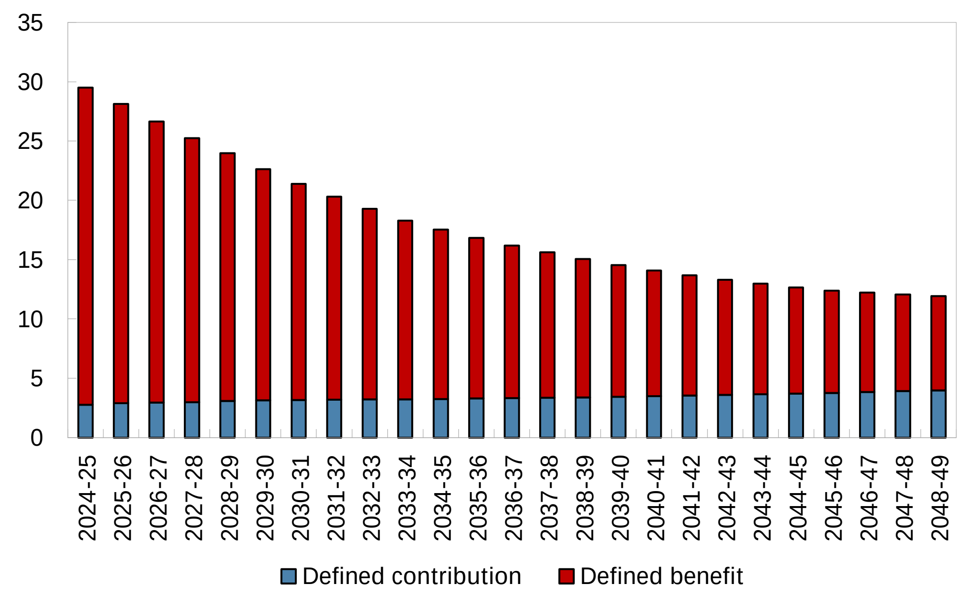


Sources: Bloomberg, and IMF staff calculations. The swap spread is computed as the difference between the 10-year SONIA swap rate and the 10-year gilt yield.

Figure I.5. Projected Gilt Holdings of the Pensions Sector

Pensions sector gilt holdings are expected to decline as defined benefit schemes shrink

Projected Pensions Sector Gilt Holdings
(Percent of GDP)



Source: Office for Budget Responsibility (2025).

C. Background on G7 Panel Regression

Table I.2. United Kingdom: G7 Panel Regression

Panel regression with dependent variable term premium. G7, monthly data			
	(1)	(2)	(3)
	Macro	Macro+Uncertainty	Macro+Uncertainty+Structural
ΔPMI_{t-1}	0.001	0.001	0.002*
	(0.001)	(0.001)	(0.001)
$\Delta\left(\frac{Debt_t}{GDP_t^{trend}}\right)$	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
ΔVIX_t		0.002*	0.002*
		(0.001)	(0.001)
$\Delta U_t^{inflation}$		0.040	0.053
		(0.069)	(0.063)
ΔU_t^{policy}		-0.000	-0.000
		(0.000)	(0.000)
Net issuance			3.763**
			(1.142)
$\Delta\left(\frac{CB\ Assets_t}{Gov.Bonds_t}\right)$			-0.108
			(0.128)
$\Delta\left(\frac{PF\ Assets_t}{Gov.Bonds_t}\right)$			-5.410***
			(0.995)
Constant	-0.003***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.000)
Observations	2138.000	1947.000	1802.000
R-squared	0.002	0.006	0.036

Notes: Standard errors in parentheses. Country FE included. SE clustered at country level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D. Background on UK Time Series Regression

Table I.3. United Kingdom: Term Premium Regression

Time series regression, UK, Monthly Data, Dependent Variable Term Premium

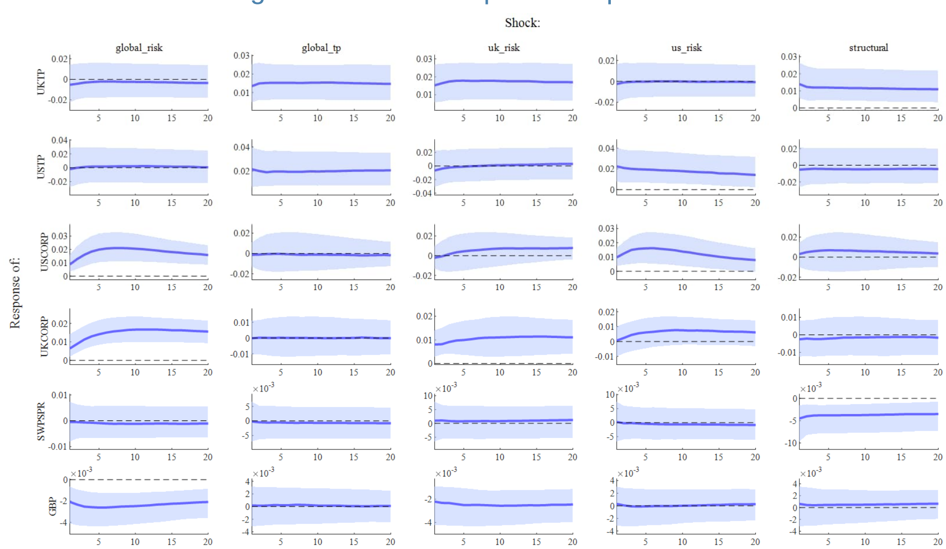
	(1)
	D.tp
Net issuance	4.068***
	(1.001)
ΔU_t^{policy}	-0.006
	(0.018)
$\text{post}_{\text{Sep.2022}}$	1.111
	(1.794)
$\text{post}_{\text{Sep.2022}}$ x ΔU_t^{policy}	0.064**
	(0.026)
Constant	0.090
	(0.788)
Observations	304.000

Notes: Standard errors in parentheses. Newey-West standard errors (lag 4). Includes issuance (3-month change) and policy uncertainty interaction with a dummy that takes the value of 1 during and after September 2022.
* p < 0.10, ** p < 0.05, *** p < 0.01

E. Background on UK BVAR Analysis

The BVAR sample consists of daily data spanning 2004-2026. Sign-restrictions (Table 2) are imposed on the first two periods of the impulse response functions (0-2). The analysis uses a standard Minnesota prior, and a 4-period lag-structure.

Figure I.6. BVAR Impulse Response Functions



Sources: Bloomberg, and IMF staff calculations using the BEAR Toolbox (Dieppe, van Roye and Legrand, 2016).

References

Adrian, Tobias, Richard K. Crump, and Emanuel Moench. 2013. Pricing the Term Structure with Linear Regressions. Journal of Financial Economics, 110(1), 110–138.

Baker, Scott R. & Nicholas Bloom & Steven J. Davis, 2015. "Measuring Economic Policy Uncertainty," CEP Discussion Papers dp1379, Centre for Economic Performance, LSE.

Brandt, Lennart & Saint Guilhem, Arthur & Schröder, Maximilian & Van Robays, Ine, 2021. "What drives euro area financial markets? The role of US spillovers and global risk," Working Paper Series 2560, European Central Bank.

Cochrane, John H., and Monika Piazzesi. 2005. Bond Risk Premia. American Economic Review, 95(1), 138–160.

Dieppe, Alistair & van Roye, Björn & Legrand, Romain, 2016. "The BEAR toolbox," Working Paper Series 1934, European Central Bank.

Don H. Kim & Jonathan H. Wright, 2005. "An arbitrage-free three-factor term structure model and the recent behavior of long-term yields and distant-horizon forward rates," Finance and Economics Discussion Series 2005-33, Board of Governors of the Federal Reserve System (U.S.).

Giese, Julia, Michael Joyce, Jack Meaning and Jack Worlidge (2023). “Preferred habitat investors in the UK government bond market”, Bank of England Staff Working Paper No. 939

Greenwood, R and Vissing-Jorgensen, A., “The Impact of Pensions and Insurance on Global Yield Curves”, Harvard Business School, Working Paper 18-109, 2018.

Hanson, Samuel G. & Stein, Jeremy C., 2015. "Monetary policy and long-term real rates," Journal of Financial Economics, Elsevier, vol. 115(3), pages 429-448. https://doi.org/10.1016/j.jfineco.2014.11.001

International Monetary Fund (2025), October 2025 Global Financial Stability Report, Annex 1.7. https://www.imf.org/-/media/files/publications/gfsr/2025/october/english/ch1annex.pdf

Kadiric S, (2022). The determinants of sovereign risk premiums in the UK and the European government bond market: the impact of Brexit. Int Econ Econ Policy. 2022;19(2):267-298.

Kaminska, Iryna and Haroon Mumtaz (2022). Monetary policy transmission during QE times: role of expectations and term premia channels. Bank of England Staff Working Paper No. 978

Krishnamurthy, A., Vissing-Jorgensen, A., Gilchrist, S., & Philippon, T. (2011). The Effects of Quantitative Easing on Interest Rates: Channels and Implications for Policy [with Comments and Discussion]. Brookings Papers on Economic Activity, 215–287. http://www.jstor.org/stable/41473600

Leippold, Markus, Felix Matthys, Economic Policy Uncertainty and the Yield Curve, Review of Finance, Volume 26, Issue 4, July 2022, Pages 751–797, https://doi.org/10.1093/rof/rfac031

Lengyel, Andras (2026). Government bond issuance surprises and the term structure of interest rates in the UK, Journal of Banking & Finance, Volume 189, 2026, 107715

McCauley, Robert and Eli Remolona, 2000. "Size and liquidity of government bond markets," BIS Quarterly Review, Bank for International Settlements, November.

Office for Budget Responsibility (2025). "Fiscal risks and sustainability". CP 1343, July 2025

Organisation for Economic Co-operation and Development (2026). "Global Debt Report 2026". 4 March 2026

Panigrahi, Lisa and Amarjot Sidhu, 2026. "What were the drivers of UK long-term interest rates in 2025?", Bank of England. https://www.bankofengland.co.uk/bank-insights/2026/what-were-the-drivers-of-uk-long-term-interest-rates-in-2025

Robin Greenwood, Dimitri Vayanos, Bond Supply and Excess Bond Returns, *The Review of Financial Studies*, Volume 27, Issue 3, March 2014, Pages 663–713, https://doi.org/10.1093/rfs/hht133

Silvia Miranda-Agrippino, Hélène Rey, U.S. Monetary Policy and the Global Financial Cycle, The Review of Economic Studies, Volume 87, Issue 6, November 2020, Pages 2754–2776, https://doi.org/10.1093/restud/rdaa019

Stehn, Sven Jari (2025). "How Vulnerable are the UK's Public Finances?" Goldman Sachs Research, 26 September 2025

Vayanos, D. and Vila, J.-L. (2021), A Preferred-Habitat Model of the Term Structure of Interest Rates. Econometrica, 89: 77-112. https://doi.org/10.3982/ECTA17440

LABOR TAXATION IN THE UK

With labor tax revenues set to rise steadily over the medium term, the debate over how much additional revenue can be raised from labor taxes, while preserving work incentives and supporting growth, is likely to intensify. This annex seeks to contribute to the current policy debate. It uses a microsimulation model that combines household-level microdata with a detailed representation of the tax and benefit system to assess the revenue potential, labor-supply and distributional effects of alternative reforms. There are three main findings. First, the scope for new measures to raise significant revenue in the future through a uniform increase in labor taxes, without significantly weakening labor supply, is limited. Second, targeted increases in marginal tax rates toward the bottom of the earnings distribution could raise more revenue, with lower efficiency losses, but come with an equity trade-off. Third, more fundamental reforms that improve work incentives in line with optimal tax design could deliver higher revenues with a better efficiency-equity trade-off. These findings are robust to different modelling assumptions about the labor supply elasticities as well as the degree of social aversion towards inequality, although the key trade-offs can differ depending on the structural assumptions used.

A. Motivation

1. As one of the largest and most reliable sources of public revenues, labor taxation is likely to remain at the center of the UK fiscal debate. Labor taxes—income tax and national insurance contributions—account for just under half of all tax revenues in the UK, or around 16 percent of GDP. Labor income is, therefore, an obvious candidate for raising revenue to reduce the deficit and meet growing spending pressures. But the UK is already relying heavily on this channel: despite collecting somewhat less from labor taxes than many OECD peers, revenues have increased substantially in recent years and are projected to rise further as frozen thresholds broaden the tax base and push more income into higher bands. Taxing labor also creates disincentives to work and increase effort. This creates a tension between revenue needs and the growth agenda: additional increases may be *a priori* fiscally attractive, but their economic cost will depend critically on how they interact with the existing tax and benefit system, and how they affect people's decisions to work.

2. The extent to which higher labor taxation and the design of social benefits may be weighing on labor-market outcomes is already under discussion. Bank of England analysis suggests that the increase in employer NICs announced in the Fall 2024 budget, alongside rises in the National Living Wage, has added to labor costs and contributed to weaker employment growth. Recent work by the Institute for Fiscal Studies suggests these changes may have had particularly strong effects on job opportunities for young people. At the same time, Resolution Foundation analysis suggests that the design of health-related benefits may weaken incentives to work at the margin, particularly where support is more generous than standard unemployment benefits and conditionality is lighter.

3. This debate is likely to intensify in the coming years as spending pressures grow. Demands on public finances are set to increase, driven by defense spending commitments, the climate transition, and an ageing population. In this context, a key question is how much space there is to increase labor taxation under the current structure without exacerbating existing labor-market distortions and undermining the growth agenda. A related question is whether labor taxes should be increased uniformly across, or whether some rebalancing is needed across income brackets.

4. Modelling the tax system can help assess the trade-offs that tax and benefit reforms create between revenue potential, efficiency, and equity. Raising tax rates can increase revenue, but it may also reduce incentives to work, save, or earn more, lowering economic activity and limiting the revenue gain. At the same time, a more progressive system may improve equity by shifting the burden toward higher earners but can also create sharper distortions if it relies on very high marginal tax rates or abrupt benefit withdrawal. Conversely, depending on how they are designed, reforms that strengthen work incentives may improve efficiency and labor supply but may reduce redistribution or require offsetting measures elsewhere to preserve revenues. A model-based approach can help make these trade-offs more transparent by quantifying how alternative reforms affect labor decisions, earnings, and fiscal revenues across the earnings distribution.

B. Labor Taxes in the UK

5. The UK collects slightly less revenue from labor taxation than other OECD countries.[1] Indeed, many high-tax European economies collect substantially more revenue from labor taxes than the UK does (Figure 1.A). This reflects lower social security contributions in the UK compared to other countries and a greater reliance on progressive income taxes, although the distinction between these two types of labor income taxation is less clear-cut in the UK where national insurance contributions are more loosely linked to benefit entitlements.[2]

6. However, labor tax revenues have increased substantially in recent years and are set to rise further over the medium term. The UK's overall tax burden, measured by the tax-to-GDP ratio, has increased by about 5½ ppts since the mid-1960s and now stands at around 35 percent. Within this broader rise, labor-tax revenues—defined here as personal income tax plus employee and employer social security contributions—have also risen markedly. Having remained relatively low compared with other G7 economies for much of the post-war period, labor-tax revenues in the UK have risen by almost 4 percentage points of GDP since the mid-2010s. Under the current fiscal plans, revenues from labor taxes are projected to increase by a further 2 percentage points of GDP by the end of the decade, as the extension of the income tax threshold freezes beyond 2028 take effect (Figure 1.B). This implies that labor taxation will account for a large share of the projected increase in the overall tax burden over the coming years.

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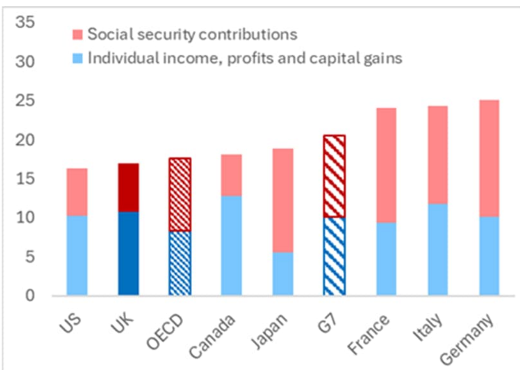
[1] Labor taxes are defined as personal income tax plus employee and employer social security contributions.

[2] For a discussion of the comparison of income tax and social security contributions across countries, see IFS "How do UK tax revenues compare internationally".

7. While average tax rates are low by international standards, marginal tax rates can be very high, particularly for high earners. The tax wedge—which measures the difference between labor costs to the employer and the corresponding net take-home pay of the employee—for an average earner in the UK is lower than the OECD and G7 averages (Figure 1.C). This reflects lower social security contributions than in many continental European economies. Marginal tax rates—the share of additional labor income that is either taxed away or lost due to the reduction in benefits—are also broadly in line with other advanced economies for average earners. However, the highly progressive labor tax system in the UK means that the marginal tax rates faced by high earners in the UK are significantly above those faced by workers in other G7 countries (Figure 1.D).

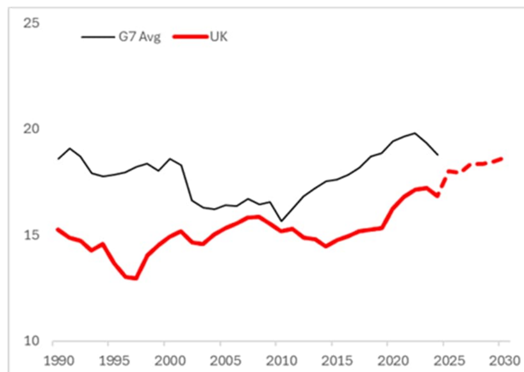
Figure 1. Labor Taxation Across Countries

A. Composition of Labor Taxes
(Percent of GDP; 2024)



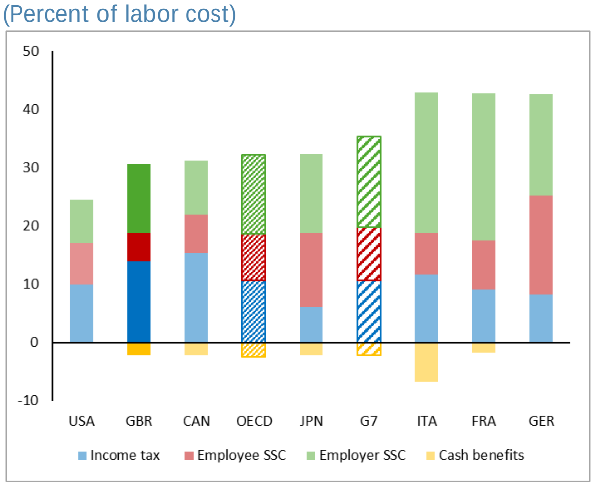
Sources: Global Revenue Statistics 2025 and staff calculations

B. Labor Tax Share
(Percent of GDP)



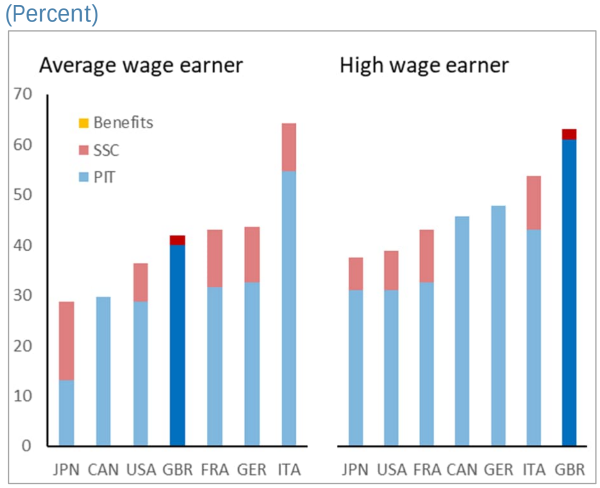
Sources: Global Revenue Statistics 2025 and staff calculations

C. Average Tax Wedge
(Percent of labor cost)



Sources: OECD Taxing Wages 2026 and staff calculations
Notes: The tax wedge is the share of income taxes and social security contributions, and cash benefits, in total labor costs. Household composition: 2 adult couple, with 2 kids, earning 100 percent and 67 percent of average wage.

D. Marginal Tax Rate
(Percent)

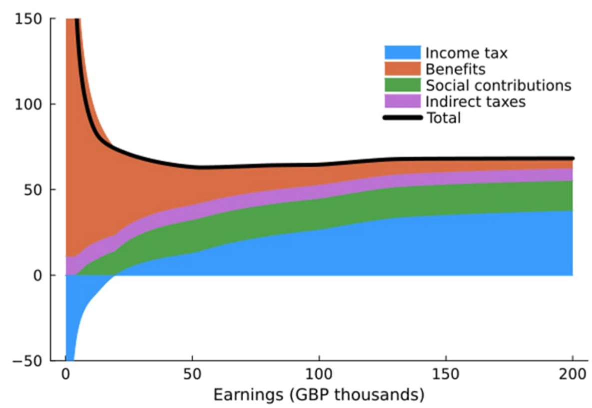


Sources: OECD Tax-Benefit model and staff calculations
Notes: The marginal tax rate is the percentage point increase in taxes paid for an additional 1 percent increase in labor income. Household composition: 1 adult, earning 100 percent of the average wage.

8. The UK tax system is marked by significant threshold effects. Threshold effects, or tax "cliff edges", here refer to sharp increases in marginal tax rates that can create either disincentives to enter the labor market or work more. Several important threshold effects in the UK tax system mean that marginal tax rates on labor earnings vary substantially depending on an individual's level of earnings. First, for low earners the withdrawal of Universal Credit (UC), the main means-tested benefit in the UK, can significantly reduce the financial gain from employment. This effectively creates a very high tax rate on participating in the labor market—the tax rate that someone pays on their earned income when they start working compared to what they would receive out-of-work (Figure 2.A). For those already in work, a second threshold exists when the basic income tax rate begins to apply, on earnings above the £12,570 personal allowance (PA). Third, there are a set of sharp threshold effects for higher earners that are driven by the combination of progressive income tax rates, withdrawal of child benefits (CB) at earnings above £60,000, and tapering of the personal allowance (PA) at earnings over £100,000. These can result in very high marginal tax rates as earnings rise, reducing the incentive to work more. Figure 2.B shows how the marginal effective tax rate—which takes into account both taxes and benefits—changes as earnings rise. These "tax cliffs" can result in the "bunching" of taxpayers just below the point at which high marginal tax rates take effect (Figure 2.C).

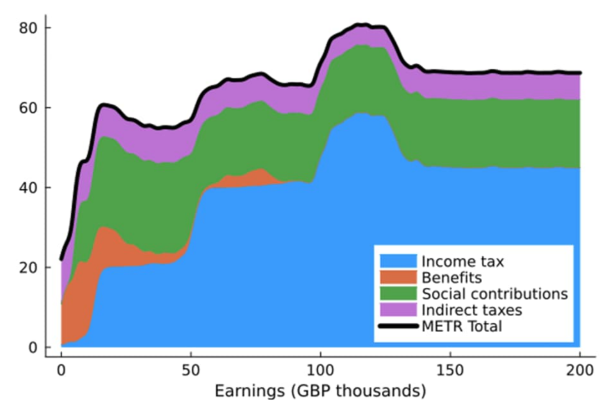
Figure 2. Structure of Labor Taxation in the UK

A. Participation Tax Rates
(Percent)



Sources: UKFRS 2023/24, UKMOD and staff calculations
Notes: The participation tax rate (PTR) is defined as the change in post-tax, post-transfer, income in work compared to out of work. Indirect taxes refer to VAT.

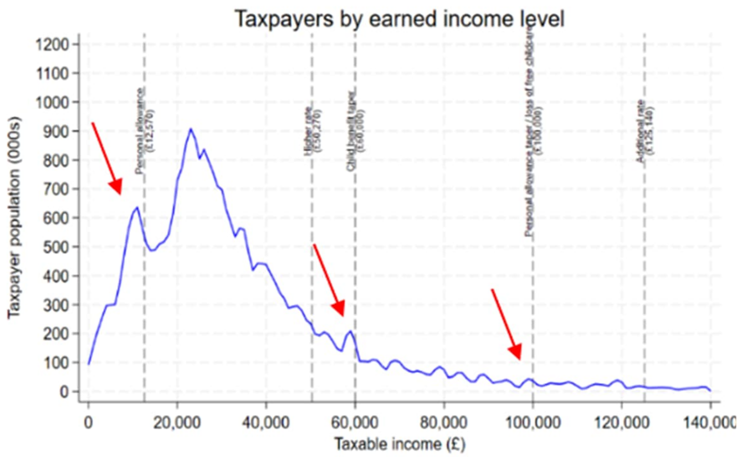
B. Marginal Effective Tax Rates
(Percent)



Sources: UKFRS 2023/24, UKMOD and staff calculations
Notes: The marginal effective tax rate (METR) is defined as the ratio of change in disposable income to change in pre-tax earnings. Indirect taxes refer to VAT.

Figure 2. Structure of Labor Taxation in the UK (Concluded)

C. Number of Taxpayers by Income Level
(Thousands)



Sources: UKFRS 2023/24, UKMOD and staff calculations
Notes: Single earner with no children. Average earner = 100% average wage; High earner = 200 percent of average wage.

C. Model and Data

9. The analysis presented here uses a microsimulation model based on the Mirrlees framework.[3] The model combines household-level microdata, a detailed representation of the current UK tax and benefit system, and a social welfare function to assess the revenue, labor-supply, and distributional effects of alternative labor income tax reforms. The framework assumes individuals differ in productivity and earnings, derive utility from consumption, and face disutility from work. They also respond to changes in after-tax income along two margins: whether to participate in the labor market, and, conditional on working, how much to work and earn. The government is assumed to choose a non-linear labor tax schedule subject to an exogenous revenue requirement, trading off revenue needs, efficiency costs from behavioral responses, and redistribution objectives. In this framework, the "optimal" marginal tax schedule depends on four sufficient-statistic objects: social marginal welfare weights (i.e. the value society places on an additional unit of consumption of an individual), the fiscal cost of participation responses, the local shape of the earnings distribution, and the intensive-margin elasticity of earnings with respect to the net-of-tax rate.

10. Household data for the UK are combined with a detailed description of the UK tax and benefit system. Data on earnings, employment status, and family structure come from the UK Family Resources Survey (FRS) 2023–24. UKMOD is then used to apply the main parameters of the

[3] See Brewer, Saez and Shephard (2010) and Piketty and Saez (2013) for an overview.

current UK tax and benefit system and to construct disposable income, participation tax rates, and marginal effective tax rates across the earnings distribution. The analysis focuses on the working-age population and maps the joint effect of taxes and transfers—including Personal Income Tax (PIT), National Insurance contributions (NICs), Universal Credit (UC), and non-means-tested benefits such as Child Benefit (CB)—into marginal effective tax rates (METR). These METRs capture the full incentive wedge created by both higher taxes and the withdrawal of benefits as earnings rise.

11. The calibration combines externally chosen parameters for labor-supply elasticities and social preferences inferred from the existing tax-benefit schedule. The baseline assumes an average intensive-margin elasticity of 0.15 and an average extensive-margin elasticity with respect to in-work income of 0.25 with a declining profile in income, with participation responses lowest for high-income workers (Table 1).[4] These values are taken from Adams and Phillips (2013) and are broadly within the range of estimates used in the empirical literature, albeit toward the lower end of that range.[5] In section E, we test the robustness of our results to these assumptions by increasing the elasticities used by 25 and 50 percent. Social marginal welfare weights are recovered using an inverse-tax approach: conditional on the assumed elasticities, the current UK schedule of marginal effective tax rates is inverted to infer the redistributive preferences that would have generated the same system (Bourguignon and Spadaro 2012; Jacobs, Jongen and Zoutman 2017). The non-linear reform scenarios then solve for alternative marginal tax schedules under different revenue targets, tracing the trade-offs between revenue, aggregate labor supply, and redistribution.

Table 1. United Kingdom: Participation Elasticities by Income Groups

	Adams and Phillips (2013)	Baseline calibration
Lowest 20 percent	0.50	0.49
Next 20 percent	0.31	0.37
Middle 20 percent	0.21	0.21
Next 20 percent	0.14	0.13
Highest 20 percent	0.06	0.08

Notes: Participation elasticities are defined as the percent change in the participation rate resulting from a percent change in in-work income. Adams and Phillips (2013) Table E.2.

[4] The simulations assume the participation elasticities are close to zero for the very lowest income earners. This is to ensure consistency with estimated labor force participation rates at very low incomes from the household survey data.

[5] This paper uses labor supply elasticities, which capture behavioral responses in employment, hours, and earnings to changes in the net-of-tax return to work. This is different from taxable income elasticities, which capture a broader set of responses, including tax planning, income shifting, incorporation, deductions, and timing effects. The latter may be particularly relevant for high earners, where observed taxable income responses can exceed labor-supply responses.

D. Simulation Results

12. Three parametric labor tax reform scenarios are constructed. The simulations are based on the current tax and benefit system (that is, before the extension of the income tax threshold freezes currently planned) and consider changes to the marginal effective tax rates (rather than changes to specific income tax or NIC rates) which better capture the joint effect of changes to taxes and benefits. Each scenario is designed to shed light on the implications of tax increases for revenue potential, labor market responses (as proxied by aggregate labor supply[6]), and equity considerations. The scenarios are as follows:

- Scenario 1: Uniform tax increase. Under this scenario, the marginal effective tax schedule is increased uniformly across the distribution of earnings. In practical terms, this entails an upward shift of the METR line in Figure 2.A.

- Scenario 2: Segmented tax increases. Instead of raising marginal tax rates uniformly for all taxpayers, this scenario increases the marginal rates only for a subset of earners, keeping the marginal tax rates unchanged for everyone else. This scenario is replicated for each of the following segments of the earnings distribution: (i) the bottom 25 percent; (ii) the middle 65 percent; and (iii) the top 10 percent.

- Scenario 3: Non-linear reform. Under this scenario, an "optimal" tax reform, which balances revenue and efficiency objectives using the Mirrlees approach, is simulated. While in the previous scenarios, the marginal tax rates were changed exogenously, here the shape of the "optimal" marginal tax schedule is determined endogenously by the revenue target, labor supply elasticities and welfare parameters of the model.[7] This means that marginal tax rates can increase or decrease at different points along the earnings distribution. Similar to the parametric reforms, marginal tax rates are calculated for a sequence of revenue target increases. The result is a series of optimal tax schedules ranging from revenue-neutral to revenue-maximizing reforms.

13. Under the first scenario, raising additional revenue by increasing the whole tax schedule would result in significant labor supply losses. The model suggests that a uniform increase in marginal tax rates could raise labor tax revenues by up to 6.5 percent—equivalent to around 1 percent of GDP—but that this would come at the cost of large labor supply responses, that increase with the size of the tax change.[8] Indeed, we find that labor supply could decline by as much as 13.5 percent. Figure 3.A shows the relationship between revenues and marginal tax rate, with

[6] The model is static in the sense that wages are fixed. This means that changes in labor supply can be captured through changes in aggregate earnings.

[7] Non-linear labor tax reforms following the Mirrlees-Diamond-Saez approach are modeled using the algorithm proposed by Jacquet, Lehmann and Van der Linden (2013) based on earnings distributions, calibrated elasticities and social welfare weights. See also Zoutman, Jacobs, and Jongen (2014) for a similar analysis for the Netherlands. Revenue targets are then increased sequentially to map out a revenue-earnings frontier.

[8] The tax increases envisioned under the government's current plans do not map directly into any one of the three scenarios modelled here.

revenues initially rising with tax rates, before declining as further increases in the rates reduce labor supply causing aggregate earnings to decline. Intuitively, these results reflect the fact that the current system already imposes distortions that weaken labor supply at both the extensive and intensive margins. The current system imposes high participation tax rates, especially for *low-income workers*. This is mainly due to the withdrawal of universal credit benefits which reduces the incentive to work. It also results in high marginal tax rates for *higher earners*, driven by the combination of rising statutory tax rates and thresholds, the tapering of the personal allowance, and the withdrawal of child benefit. These findings highlight the importance of balancing the need to raise revenues with protecting employment and minimizing economic distortions.

14. Under the second scenario, tax increases targeted toward the bottom of the earnings distribution could raise revenue with smaller efficiency costs. Table 2 shows the impact of increasing marginal effective tax rates by 5 percentage points across different parts of the tax schedule. Raising rates for the bottom 25 percent of earners generates the largest revenue gain, at 3 percent, with aggregate labor earnings falling by around 1.6 percent. This reflects the broad tax base affected by the reform: a higher marginal rate at the bottom applies not only to low earners, but also to the infra-marginal earnings of higher-income individuals. Raising rates for the middle 65 percent also increases revenue, by 1.9 percent, but with a somewhat larger decline in aggregate labor earnings of 1.9 percent. By contrast, raising rates only for the top 10 percent lowers revenue by 0.5 percent and reduces aggregate earnings by 0.9 percent, indicating that behavioral responses among high earners more than offset the mechanical revenue gain. A uniform 5 percentage-point increase raises more revenue than the targeted reforms, at 4.3 percent, but at the cost of a much larger decline in aggregate earnings of 4.4 percent. Figure 3.B shows similar effects for the full range of marginal tax rate increases, whereby increasing rates at low levels of earnings entails smaller labor supply distortions, while increasing rates at the top does not generate significant additional revenues. These results point to a clear revenue-efficiency trade-off: broader increases generate larger revenue gains, but also larger labor-supply losses, while increases at the top are more progressive but yield little additional fiscal space once behavioral responses are taken into account.

Table 2. United Kingdom: Targeted 5ppts Marginal Tax Increases Across Income Groups
(In percent relative to baseline)

	Change in tax revenue (%)	Change in labor earnings (%)	Change in average tax rate (%)			
			Bottom 25%	Middle 65%	Top 10%	All
Bottom 25%	3.0	-1.6	3.9	2.4	0.7	1.8
Middle 65%	1.9	-1.9		1.5	2.0	1.8
Top 10%	-0.5	-0.9			1.1	0.3
All	4.3	-4.4	3.9	3.9	3.9	3.9

Notes: The table shows changes in total labor tax revenues, total earnings and average tax rates in percentage points under a 5 percentage-point increase in marginal tax rates for (i) bottom 25% of earners, (ii) middle 65% of earners, (iii) top 10 % of earners, and (iv) all earners.

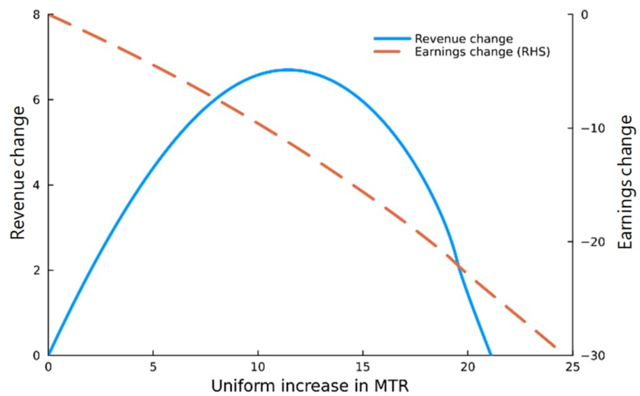
15. Larger revenue gains would require more fundamental structural reforms, which would improve the equity-efficiency tradeoff. A deeper redesign of the current system could strengthen labor supply by lowering participation tax rates for lower-income workers and smoothing some of the high marginal tax-rates higher up the earnings distribution. Figure 3.C shows the change in tax revenues and aggregate earnings under the optimally designed non-linear marginal tax increase in Scenario 3. In addition to the results for the non-linear marginal tax reform (shown by the solid lines) we also show the results from a £100 reduction in out-of-work benefits (shown by the dashed lines). Under the non-linear reform, higher marginal tax rates can raise more revenue than the previous scenarios, while also improving labor supply. This is illustrated by the blue region that lies above the zero horizontal line. An "optimal" revenue-neutral reform could raise aggregate labor supply by 3 percent, while non-linear reforms that raise up to 4.5 percent in additional revenues could result in still higher aggregate labor supply. In practice, this would involve a stronger role for in-work support at the bottom of the distribution by making transfers conditional on labor force participation more generous, combined with less reliance on abrupt withdrawal of benefits and tax allowances as earnings rise. Such a system would reduce some of the most distortionary features of the current schedule—notably weak incentives to enter work at low earnings and sharp cliff edges for higher earners—while preserving overall revenues.

16. While it may be possible to raise significantly more revenue under an ambitious reform package, this would involve sharper efficiency-equity tradeoffs. These can be seen in Figure 3.D which shows the optimal marginal tax schedules ranging from a revenue-neutral reform (blue line) to the revenue-maximizing reform (red line). From an efficiency perspective, the optimal schedules generally result in smaller labor market distortions than under the first two scenarios. From an equity perspective, however, the optimal reforms also imply lower marginal tax rates for earners above £100,000, but higher rates for low and middle-income earners, as can be seen from the profiles of the lines in Figure 3.D.

Figure 3. Labor Tax Reform Scenarios

A. Revenue and Earnings Change Under Uniform Tax Increases (Scenario 1)

(Y-axes: percent, x-axis: percentage points)

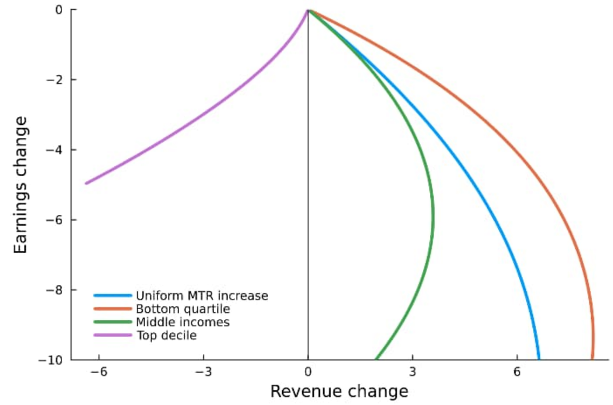


Source: IMF staff calculations.

Notes: The chart shows the percentage point change in tax revenues (blue line) and average earnings (orange line) against uniform increases in the marginal tax rate (horizontal axis).

B. Revenue and Earnings Change Under Targeted Tax Increases (Scenario 2)

(Percent)

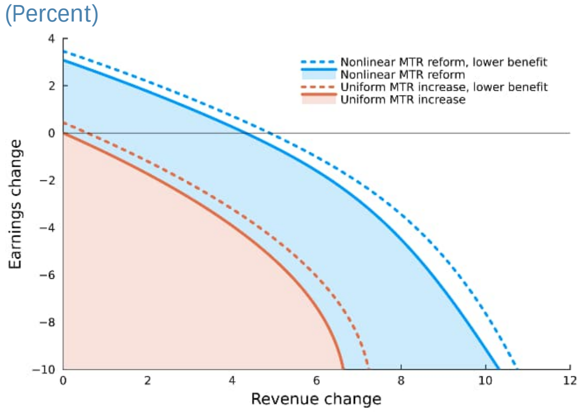


Source: IMF staff calculations

Notes: The chart shows changes to total earnings (vertical axis) and total revenue (horizontal axis) under different marginal rate increase scenarios. The blue line shows uniform increases applied to all workers. The orange line shows segmented increases only for the bottom 25 percent of earners. The green line shows increases for the middle-income earners between the 25th and 90th percentile. The purple line shows uniform increases for the top decile.

C. Revenue and Earnings Change Under Non-Linear Reform (Scenario 3)

(Percent)

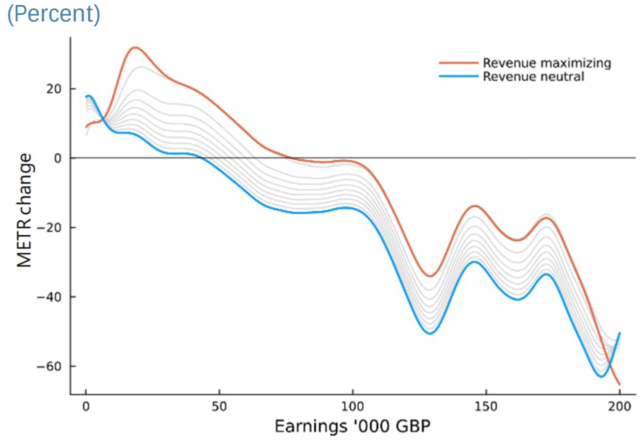


Source: IMF staff calculations

Notes: The chart shows changes to total earnings (vertical axis) and total revenue (horizontal axis) under the uniform marginal rate increase scenario (orange lines) and the non-linear reform scenario (blue lines). Dashed lines represent a supplementary reform that reduces the average out-of-work benefit by £100.

D. Marginal Tax Rate Change by Earnings Level Under Non-Linear Reforms (Scenario 3)

(Percent)



Source: IMF staff calculations

Notes: The chart shows the change in marginal effective tax rates (in ppts) under the revenue-neutral reform (blue line) and revenue-maximising reform scenario (orange line) across earnings levels.

E. Robustness

17. This section assesses the sensitivity of the baseline results to alternative assumptions on key structural parameters. In particular, we assess the impact of different assumptions regarding labor supply elasticities and the degree of inequality aversion. While the key findings are qualitatively robust, the analysis reveals strongly non-linear responses in both revenue and labor supply outcomes to these assumptions.

18. Assuming higher behavioral responses to tax changes reduces the revenue gains but increases the efficiency gains from reforms. We consider higher elasticities than the baseline for two reasons. First, the estimates from Adams and Phillips (2013) are at the low end of estimates for the UK, especially for the extensive margin elasticities of high-income earners, which have a disproportionate impact on aggregate results. Second, considering higher elasticities provides a more conservative estimate of the revenue potential of reform, which serves as a fiscal risk assessment. Increasing labor supply elasticities—such that people are more responsive to changes in post-tax earnings—leads to smaller revenue gains from higher marginal tax rates. At the same time, stronger behavioral responses mean that reducing distortions, as in the case of the non-linear reform scenario, leads to improvements in labor supply and greater efficiency gains. Quantitatively, increasing the average intensive and extensive elasticities from 0.15 and 0.25 to 0.19 and 0.31 (25 percent increase) respectively, imply materially lower revenue potential and larger labor supply losses. Increasing the elasticities by more, to 0.23 and 0.38 (50 percent increase from baseline) respectively, yield even smaller revenue increases. Using these higher elasticities, however, we find that more modest increases in marginal rates could *improve* aggregate labor supply. The green line in Figure 4.A shows that it could be possible to increase labor income taxes by up to 5 percent while still raising aggregate labor supply if behavioral responses were sufficiently strong.

19. The degree of inequality aversion also plays an important role in determining the optimal labor tax schedule. Higher inequality aversion implies a stronger preference for redistribution toward lower-income households, which implies higher marginal tax rates at the top of the distribution, all else equal. The reverse holds true when inequality aversion is lower. While the baseline simulations use an inequality aversion parameter of 1.0, we also show results when this parameter is set to 0.5 (lower redistributive motive) and 1.5 (higher redistributive motive).[9] Under the calibration with higher aversion to inequality, the earnings-revenue frontier pivots clockwise (Figure 4.B). This means that for lower revenue increases (below 5 percent), labor supply responds more negatively to the optimal schedule therefore shrinking the earnings-revenue frontier. For larger revenue increases, however, the labor supply losses are smaller than in the baseline case, which means the frontier is pushed out. With lower inequality aversion the frontier shifts to the right, implying more adverse earnings responses and lower revenue potential. This is a consequence of

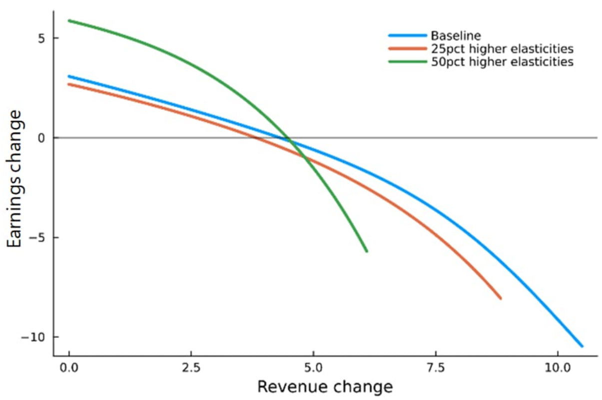
[9] The analysis assumes that social welfare function is isoelastic. This means the government or society values the marginal consumption of two individuals based only on their relative income levels. In the baseline if one individual earns 10 times less than another individual, society assigns 10 times as much value to an additional unit of consumption for the lower-income individual. With an inequality aversion parameter of 0.5, the ratio is 5; if inequality aversion is 1.5 the marginal consumption of the lower-income individual is valued 15 times more.

placing a greater weight on the efficiency costs borne by high earners. Figure 4.B shows that around 5 percent in additional revenue could be achieved with an associated 6.5 percent reduction in labor supply.

20. The effects of alternative assumptions are highly non-linear. This reflects the complex interactions between behavioral responses and the desired progressivity of the tax system. In particular, small changes in elasticities or inequality aversion can lead to disproportionately large changes in optimal tax schedules and associated revenue and aggregate earnings outcomes, especially at the top of the income distribution. As a result, while the qualitative conclusions of the baseline analysis remain robust—namely that there is scope to improve the efficiency-equity trade-off through tax reform—the quantitative results are sensitive to these assumptions. Higher labor elasticities and a lower inequality aversion both tend to reduce revenue potential (as shown in Figures 4 A and B), albeit through different channels, and with different implications for labor supply. This highlights the importance of carefully calibrating these parameters when considering reform options.

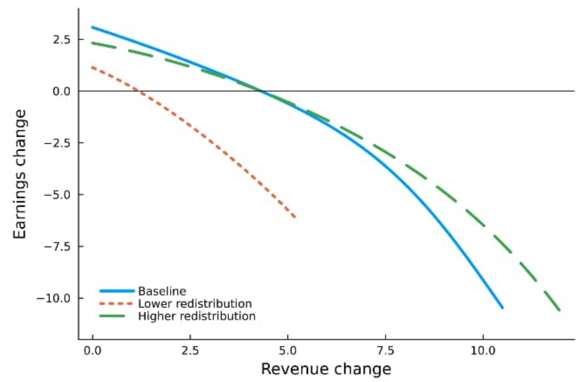
Figure 4. Robustness Scenarios

A. Revenue and Earnings Change of Non-linear Reforms Using Higher Labor Supply Elasticities
(Percent)



Source: IMF staff calculations
Notes: The chart shows changes to total earnings (vertical axis) and total revenue (horizontal axis) under non-linear reform scenarios.

B. Revenue and Earnings Change of Non-linear Reforms Using Alternative Inequality Aversion Parameters
(Percent)



Source: IMF staff calculations
Notes: The chart shows changes to total earnings (vertical axis) and total revenue (horizontal axis) under non-linear reform scenarios.

F. Policy Conclusions

21. There is limited scope for new measures to raise significant additional revenue through labor taxation without significantly weakening labor supply. The baseline model simulations in this paper suggest that a uniform increase in marginal effective tax rates could raise some additional revenue but would come with substantial labor supply losses. This is because increasing marginal tax rates across the whole schedule would exacerbate existing distortions, including weak incentives to enter the labor market at the bottom of the distribution and high marginal effective tax rates in upper parts of the earnings distribution.

22. More fundamental reforms could deliver higher revenue gains while strengthening work incentives across the earnings distribution. Targeted increases in marginal tax rates towards the bottom of the earnings distribution, accompanied by more generous in-work transfers, would be more efficient, reflecting the size of the tax base affected, but would come with equity trade-offs. More fundamental reforms that improve work incentives in line with optimal tax design could deliver higher revenues with a better efficiency-equity trade-off. The results point to the benefits of strengthening incentives to work at the bottom of the distribution while reducing very high marginal effective tax rates at the top. In practice, this would require a broader redesign of the tax-benefit schedule, including smoothing benefit withdrawal and other threshold effects, rather than simply increasing headline rates of income tax or National Insurance contributions.

23. Against the backdrop of rising spending pressures, designing labor taxation in a way that both raises revenue and is consistent with the UK's growth agenda will be central. This requires moving beyond a narrow focus on headline tax rates and placing greater weight on how the tax-benefit system affects people's incentives to work and firms' incentives to hire. Broad-based rate increases would risk adding to existing distortions and weaken labor supply, while better-designed reforms that strengthen incentives to enter and progress in work could support both fiscal sustainability and stronger medium-term growth.

References

Adam, S. and Phillips, D. (2013). "An ex-ante analysis of the effects of the UK Government's welfare reforms on labour supply in Wales" IFS Report No. R75.

Bourguignon, F., and Spadaro, E. (2012). "Tax-benefit revealed social preferences" *Journal of Economic Inequality*, 10: 75–108.

Brewer, M., Saez, E. and Shephard, A. (2010). "Means-testing and tax rates on earnings" in *Dimensions of Tax Design: the Mirrlees Review*, 1(4): 90-201.

Mirrlees, J. ed., 2011. *Tax by design: The Mirrlees review*. Oxford University Press (OUP) Oxford.

Piketty, T., and Saez, E. (2013). "Optimal labor income taxation" In *Handbook of Public Economics*, Volume 5, edited by Alan J. Auerbach, Raj Chetty, Martin Feldstein, and Emmanuel Saez, 391–474. Amsterdam: Elsevier.

Richiardi, M., Collado, D. and Popova, D., 2021. UKMOD–A new tax-benefit model for the four nations of the UK (No. CeMPA WP 7/21). *CeMPA Working Paper Series*.

Jacobs, B., Jongen, E.L., and Zoutman, F.T. (2017). "Revealed social preferences of Dutch political parties" *Journal of Public Economics*, 156, 81–100.

Jacquet, L, Lehmann, E. and Van der Linden, B. (2013) "Optimal redistributive taxation with both extensive and intensive responses" *Journal of Economic Theory*, 148 (5): 1770-1805.

Zoutman, F.T., Jacobs, B. and Jongen, E.L. (2013). "Optimal redistributive taxes and redistributive preferences in the Netherlands" *Erasmus University Rotterdam*.