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The Stabilisation Gap: Artificial Intelligence Exposure and Macroeconomic Policy Space in the World's Ten Largest Economies

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Abstract

The 2026 Prize in Economic Sciences recognised Robert E. Hall and Michael Woodford for the microeconomic foundations of macroeconomic stabilisation. This article asks what their framework implies for artificial intelligence (AI) in the ten largest economies by 2026 nominal GDP (IMF World Economic Outlook, October 2026): the United States, China, Germany, Japan, the United Kingdom, India, France, Russia, Italy and Brazil. I build a country index of occupational AI exposure from ILOSTAT employment by ISCO-08 major group and the AI Occupational Exposure scores of Felten, Raj and Seamans, and combine it with Stanford HAI capacity data, the IMF AI Preparedness Index, IMF fiscal data and BIS policy rates. Three findings emerge. First, AI capacity is far more concentrated than output: the United States and China produce 64% of the group's GDP but account for 90% of its AI private investment, and occupational exposure is unrelated to AI capacity (Spearman $\rho = 0.02$, exact permutation $p = 0.97$). Second, two pre-specified hypotheses are not supported: the most exposed economies do not have systematically less fiscal or monetary space ($\rho = 0.14$, $p = 0.71$), and lagged AI investment does not predict labour-productivity growth in 2018–2025 (randomisation $p = 0.86$). Third, a calibrated exercise based on the consumption Euler equation shows that, when the intertemporal elasticity of substitution is below one, an AI-driven rise in trend growth raises the interest–growth differential. With an elasticity of 0.5 and the mid-range OECD productivity scenario, the debt-stabilising primary balance rises by 1.1 percentage points of GDP in Japan and by 0.7–0.8 points in the United States, Italy and France. The gain would widen monetary room above the lower bound while narrowing fiscal room where public debt is highest.

JEL classification: E43, E52, E62, H63, J24, O33

1. Introduction

On 12 October 2026 the Royal Swedish Academy of Sciences awarded the Prize in Economic Sciences to Robert E. Hall and Michael Woodford for the microeconomic foundations of macroeconomic stabilisation (Royal Swedish Academy of Sciences, 2026). One year earlier the prize had gone to Joel Mokyr, Philippe Aghion and Peter Howitt for explaining innovation-driven growth, including the theory of growth through creative destruction (Aghion & Howitt, 1992). The two prizes speak to the same question from opposite ends. Creative destruction is about how new technologies raise the trend of output. Stabilisation is about how policy keeps output and inflation close to that trend when the economy is hit by shocks. Artificial intelligence (AI) is now widely treated as a candidate general-purpose technology, which makes it both a source of trend growth and a shock that stabilisation policy has to absorb.

This article brings the two strands together for the ten largest economies in the world by 2026 nominal GDP. These economies produce 66% of world output in 2026 and host most frontier AI development, yet they differ widely in how exposed their workforces are to AI, in how much AI they produce, and in how much fiscal and monetary room they have. The question is whether these differences line up in a way that matters for stabilisation. If AI raises trend growth, the natural rate of interest moves with it, and the

natural rate is the anchor of the neo-Wicksellian framework that Woodford (2003) developed. The same rate also governs the arithmetic of public debt through the interest–growth differential (Blanchard, 2019).

The literature has approached these links one at a time. Aldasoro et al. (2026) calibrate a multisector model and show that AI can be disinflationary in the short run when households and firms do not anticipate higher future productivity, which is an expectations channel in the spirit of Woodford's work, but they study a single model economy. Poloz (2021) discusses how technological progress complicates the conduct of monetary policy, with reference to Canada. Obstfeld (2025), Rachel (2025), Andrade (2025) and Baziki and Dupita (2025) discuss AI as one of several forces that could move the natural rate, without country-level measurement. Ageli (2026) relates AI and fintech indicators to economic performance in the G7 but does not measure labour-market exposure or policy space. A search of Scopus for studies combining AI with fiscal or policy space and with productivity or labour markets returned one record, which was not pertinent. To my knowledge no study compares AI exposure, AI capacity and stabilisation policy space across the largest economies, or quantifies what an AI-driven rise in the natural rate would mean for debt dynamics country by country.

The article makes three contributions. First, it builds a transparent country index of occupational AI exposure for the ten largest economies from public data, and validates it against three alternative constructions. Second, it tests three pre-specified hypotheses on concentration, policy space and productivity, using exact permutation inference that is valid for ten observations. Third, it links the exposure index to the consumption Euler equation that underlies Hall's (1978) work on consumption and the natural-rate framework of Woodford (2003), and computes the change in the debt-stabilising primary balance that an AI growth gain would require in each economy. The exercise is a calibrated scenario, not an estimate, and it is presented as such.

The main results are as follows. AI capacity is far more concentrated than output, and occupational exposure bears no relation to AI capacity. The two other pre-specified hypotheses are not supported: exposure does not predict policy space, and recent AI investment does not predict recent productivity growth. The calibrated exercise shows that the economies with the highest public debt, which are also among the most exposed, face the largest rise in the primary balance needed to stabilise debt if AI lifts growth and the intertemporal elasticity of substitution is below one. The same AI gain would widen the distance between policy rates and their lower bound. AI therefore eases the monetary side of stabilisation while tightening the fiscal side, and does so most where debt is highest. I call this asymmetry the stabilisation gap.

2. Background and hypotheses

2.1 From creative destruction to stabilisation

In the Schumpeterian growth model of Aghion and Howitt (1992), growth comes from innovations that make existing technologies obsolete. AI fits this description at the level of tasks: it can automate some tasks and raise productivity in others (Acemoglu & Restrepo, 2018). How large the aggregate effect will be is disputed. Acemoglu (2025) uses a task-based model and estimates that AI will raise total factor productivity by no more than 0.66% over ten years. Filippucci, Gal and Schief (2024) combine micro-level evidence with adoption scenarios and project gains of 0.25 to 0.6 percentage points per year in US total factor productivity, or 0.4 to 0.9 points in labour productivity. Briggs and Kodnani (2023) project about 1.5 points per year in US labour productivity after widespread adoption. The aggregate effect may also arrive with a lag, because general-purpose technologies require complementary intangible investment before they show up in measured productivity (Brynjolfsson et al., 2021).

The New Keynesian framework to which Hall and Woodford contributed describes how monetary policy should respond to such changes (Clarida et al., 1999; Woodford, 2003). A central object is the natural rate of interest, the real rate consistent with output at potential and stable inflation. Its empirical counterpart is the slowly moving real rate estimated by Laubach and Williams (2003) and Holston et al. (2017). In the simplest version, the natural rate follows from the consumption Euler equation, which links the real interest rate to expected consumption growth through households' time preference and their willingness to substitute consumption over time. Hall (1978) derived the testable implications of this equation for consumption, and Hall (1988) estimated the intertemporal elasticity of substitution and found it to be close to zero. That elasticity determines how strongly the natural rate responds to a change in trend growth.

2.2 Exposure, capacity and policy space

AI enters the economy through occupations. Felten et al. (2021) built the AI Occupational Exposure (AIOE) score by linking applications of AI to the abilities that each occupation uses, and Felten et al. (2023) extended it to language models. Eloundou et al. (2024) reach a similar conclusion with a different method: a large share of tasks in high-skill, non-routine occupations is exposed to large language models. Cazzaniga et al. (2024) used occupational exposure to show that about 60% of jobs in advanced economies are exposed, against about 40% in emerging markets, and introduced an AI Preparedness Index. Exposure, however, is not the same as capacity. Building and deploying AI requires private investment, compute and specialised talent, and these are concentrated in a few countries.

Stabilisation also depends on policy space. Monetary space is limited by the effective lower bound on nominal rates, and fiscal space by the level of debt and the cost of servicing it. The interaction between the two is a theme of Woodford's work on the fiscal requirements for price stability (Woodford, 2001), building on Leeper (1991). Blanchard (2019) showed that when the interest rate on public debt is below the growth rate of the economy, debt can be rolled over at low fiscal cost, and that this conclusion is sensitive to the gap between the two rates.

2.3 Hypotheses

Three hypotheses were specified before the data were analysed.

H1 (concentration and mismatch). AI capacity is more concentrated among the ten economies than output, and occupational exposure to AI is not aligned with AI capacity.

H2 (exposure and policy space). The economies most exposed to AI have less fiscal and monetary space to stabilise the shocks that AI may generate.

H3 (investment and productivity). Within countries, higher AI private investment relative to GDP is followed by faster growth of output per worker.

The calibrated exercise in Section 3.6 is not a hypothesis test. It traces the implications of a standard theoretical relation for each economy, under explicit parameter values taken from the literature.

3. Data and methods

3.1 Sample

The sample consists of the ten largest economies by 2026 nominal GDP in US dollars in the IMF World Economic Outlook of October 2026 (International Monetary Fund, 2026a), after removing regional aggregates. The ranking is United States, China, Germany, Japan, United Kingdom, India, France, Russia, Italy and Brazil. Canada ranks eleventh, with a GDP 6% lower than Brazil's, and is used only in robustness checks. The ranking is taken from the data rather than assumed: Russia enters and Canada leaves the top ten relative to rankings commonly cited for earlier years, partly because of exchange-rate movements. Table 1 reports the sample and the main indicators.

Table 1
Sample and main indicators

Economy	Rank	GDP 2026 (US$ tn)	AI exposure (AIOE)	AI capacity (0–100)	AI Preparedness Index	Gross debt (% GDP)	Primary balance (% GDP)	Policy rate (%)
United States	1	32.64	0.13	72.3	0.77	126.8	−3.7	3.88
China	2	21.55	−0.61	45.4	0.64	104.4	−7.0	3.00
Germany	3	5.47	0.12	16.3	0.75	64.6	−2.8	2.50
Japan	4	4.34	0.00	17.9	0.73	199.4	−1.7	1.25
United Kingdom	5	4.27	0.23	17.1	0.73	102.0	−1.2	3.75
India	6	4.06	−0.67	26.7	0.49	83.1	−1.9	5.25
France	7	3.55	0.11	16.1	0.70	118.5	−2.7	2.50
Russia	8	2.86	0.01	11.6	0.56	19.3	−0.8	14.00
Italy	9	2.70	−0.05	10.5	0.62	137.9	0.8	2.50
Brazil	10	2.65	−0.24	14.9	0.50	97.0	−0.5	13.75

Note. Ranking by 2026 nominal GDP in US dollars, IMF World Economic Outlook (October 2026). AI exposure: employment-weighted AIOE index (Section 3.2); ILOSTAT survey shares for 2025, except China (ILO modelled estimates, 2025). AI capacity: Stanford HAI, 2024. AI Preparedness Index: IMF, 2023. Debt: 2026, World Economic Outlook; primary balance: 2026, Fiscal Monitor (April 2026). Policy rate: BIS, September 2026 (India: June 2026); Germany, France and Italy: European Central Bank. Canada (rank 11) is used only in robustness checks.

3.2 Occupational AI exposure

The exposure index follows the approach of Cazzaniga et al. (2024), using only public inputs. The AIOE scores of Felten et al. (2021) are defined for 774 occupations of the 2010 US Standard Occupational Classification (SOC) and are standardised across occupations. I map them to the International Standard Classification of Occupations (ISCO-08) with the official crosswalk of the US Bureau of Labor Statistics (U.S. Bureau of Labor Statistics, 2015); 99.6% of SOC codes are matched. Scores are averaged within each of 422 four-digit ISCO-08 occupations and then within each major group. Each country's index is the employment-weighted mean across major groups:

$$E_c = \Sigma_k s_{c,k} \cdot AIOE_k \quad (1)$$

where $s_{c,k}$ is the share of employment in major group *k* in country *c*, excluding the armed forces. Shares come from the latest ILOSTAT labour force survey data by ISCO-08 major group (International Labour Organization, 2026), which are available for 2025 for eight of the ten economies. China does not report ISCO-08 occupational data to ILOSTAT, so its shares come from the ILO modelled estimates for 2025,

which combine skilled agricultural and elementary occupations into one group; that group receives the mean of the two group scores, weighted by their pooled survey employment shares in the sample. The language-model version of the AIOE (Felten et al., 2023) gives a second index.

Three checks support the index. Using two-digit ISCO-08 shares instead of major groups gives a correlation of 0.99 across the thirteen economies with both. Using the ILO modelled estimates instead of survey data changes no country's index by more than 0.03. For China, an alternative index built from the occupational structure of the 2010 population census, with Chinese occupational groups mapped to ISCO-08, gives − 0.64, against − 0.61 from the modelled estimates. The index measures exposure, not displacement: high exposure can mean either substitution or complementarity, as Cazzaniga et al. (2024) stress.

3.3 AI capacity

AI capacity is measured with the Stanford HAI Global AI Vibrancy data released in September 2025, which refer to 2024 (Stanford Institute for Human-Centered Artificial Intelligence, 2025). The capacity score is the mean of the normalised (0–100) values of the absolute-scale indicators that Stanford uses for its ranking in the research and development, economy, infrastructure and talent pillars, including AI publications, citations, patents, notable models, private investment, newly funded companies, AI talent and supercomputing capacity. Seventeen indicators are available for all ten economies in 2024; semiconductor exports are missing for 2024 and drop out. The IMF AI Preparedness Index for 2023 is used as a second measure; it captures digital infrastructure, human capital, innovation and regulation rather than the production of AI.

3.4 Policy space

Fiscal space combines three 2026 indicators: general government gross debt (IMF World Economic Outlook, October 2026), the overall fiscal balance, and net interest payments as a share of revenue, computed as the difference between the primary and the overall balance divided by revenue (IMF Fiscal Monitor, April 2026; International Monetary Fund, 2026b). Each is standardised across the ten economies with the sign set so that higher values mean more space, and the fiscal index is their mean. Monetary space is the standardised policy rate from the BIS central bank policy rate database (Bank for International Settlements, 2026), measured in September 2026 (June 2026 for India, the latest available), as a measure of the room to cut before the lower bound. Germany, France and Italy share the European Central Bank's rate. The overall policy-space index is the mean of the fiscal and monetary indices. The effective interest rate on public debt used in Section 3.6 is interest paid in 2024 divided by the previous year's gross debt, from the IMF Public Finances in Modern History database (Mauro et al., 2015).

3.5 Hypothesis tests

With ten observations, asymptotic tests are unreliable. H1 and H2 are tested with Spearman rank correlations and exact two-sided permutation p-values computed over all 3,628,800 orderings of the ten economies. The concentration part of H1 is described with the shares of the United States and China

and the Herfindahl–Hirschman index of each measure within the group. Robustness samples replace Brazil with Canada, add Canada as an eleventh economy, and drop Russia; their p-values come from 20,000 random permutations.

H3 uses a panel of the ten economies for 2017–2025. The outcome is the annual growth of GDP per person employed in constant 2021 PPP dollars (World Development Indicators; World Bank, 2026), and the regressor is AI private investment as a share of nominal GDP in the previous year (Stanford HAI and IMF). The regression includes country and year fixed effects:

$$\Delta \ln y_{c,t} = \beta \cdot AI_{c,t-1} + \alpha_c + \gamma_t + \varepsilon_{c,t} \quad (2)$$

Inference is by randomisation: the ten countries' AI-investment paths are permuted across countries 5,000 times, keeping each path intact, and the estimated β is compared with the distribution of permuted estimates. The panel has 79 observations because one Russian value is missing.

3.6 Calibrated exercise: AI, the natural rate and debt dynamics

The exercise links the exposure index to debt dynamics through two standard relations. In steady state, the consumption Euler equation gives the natural rate as

$$r^* = \rho + g / \theta \quad (3)$$

where ρ is the rate of time preference, *g* is trend growth of consumption per capita and θ is the intertemporal elasticity of substitution (IES). An AI-driven increase Δ*g* in trend growth therefore raises the natural rate by Δ*g*/θ and changes the interest–growth differential by

$$\Delta(r - g) = \Delta g \cdot (1/\theta - 1) \quad (4)$$

which is positive whenever θ < 1. The primary balance that keeps the debt ratio *b* constant is (r − g)*b*/(1 + g), so with full pass-through to the effective rate on public debt the required change in the primary balance is

$$\Delta pb^* \approx \Delta(r - g) \cdot b / (1 + g) \quad (5)$$

The AI growth gain for the United States is set at three values that span the literature on labour productivity over a ten-year horizon: 0.10 percentage points per year (low, consistent with Acemoglu, 2025), 0.65 points (central, the midpoint of the 0.4–0.9 range of Filippucci et al., 2024) and 1.50 points (high, Briggs & Kodnani, 2023). Each economy's gain scales the US value by its exposure relative to the United States, measured from the lowest major-group score (elementary occupations, − 1.19), so that an economy with all employment in the least exposed group would receive no gain. A variant also scales by the IMF AI Preparedness Index relative to the United States, as a proxy for adoption. The baseline IES is 0.5, a common calibration; 1.0 and 0.25 are reported as sensitivity values, the latter closer to Hall's

(1988) estimates. Nominal growth for 2026 is the sum of real growth and inflation in the World Economic Outlook.

The exercise is deliberately simple. It holds the rate of time preference, the term premium and fiscal policy rules constant, assumes that the AI gain is permanent over the horizon, and assumes full pass-through from the natural rate to the effective rate on debt, which in practice occurs only as debt is refinanced. Its purpose is to show the direction and the cross-country ranking of the effect, not to forecast fiscal outcomes.

4. Results

4.1 Concentration of AI capacity (H1)

Table 2 and Fig. 1 compare the distribution of output with that of two measures of AI capacity. The United States produces 39% of the group's 2026 GDP, but it accounted for 83% of the group's AI private investment in 2024 and for 68% of its supercomputing capacity. Together with China, it accounts for 64% of output and 90% of AI private investment. The Herfindahl–Hirschman index of AI private investment, 0.70, is three times that of GDP, 0.23. Stanford reports no AI private investment for Russia in 2024. The concentration part of H1 is supported.

Table 2
Concentration of output and AI capacity among the ten economies

Measure	United States (%)	United States + China (%)	Herfindahl–Hirschman index
Nominal GDP 2026	38.8	64.4	0.23
AI private investment 2024	83.2	90.3	0.70
Supercomputing capacity (Rmax) 2024	67.9	71.3	0.48

Note. Shares of the ten-economy total. The Herfindahl–Hirschman index is the sum of squared shares (1 = full concentration in one economy; 0.10 = equal shares). Sources: IMF World Economic Outlook (October 2026); Stanford HAI Global AI Vibrancy data.

4.2 Exposure and capacity (H1)

Exposure is highest in the United Kingdom (0.23), the United States (0.13), Germany (0.12) and France (0.11), close to zero in Japan, Russia and Italy, and lowest in Brazil (− 0.24), China (− 0.61) and India (− 0.67), where agricultural and elementary occupations still account for a large share of employment. Capacity follows a different order: the United States (72), China (45) and India (27) lead, and the European economies, Japan and Russia score between 11 and 18. Table 3 shows that the rank correlation between exposure and capacity is 0.02 (exact p = 0.97), and 0.08 for the language-model exposure index (p = 0.84). Panel (a) of Fig. 2 shows the pattern: the most exposed economies other than

the United States have little AI capacity, and the second-largest producer of AI, China, is among the least exposed.

Exposure is, however, strongly correlated with the IMF AI Preparedness Index ($\rho = 0.76$, $p = 0.015$). The two results are consistent: preparedness measures digital infrastructure, human capital and regulation, which rise with income, as does the share of employment in exposed occupations. Being prepared to adopt AI is different from producing it. The mismatch part of H1 is supported for capacity, and the results hold in all three robustness samples (Table 4).

Table 3
Rank correlations for H1 and H2

Hypothesis	Relation	n	Spearman ρ	Exact p
H1	Exposure vs AI capacity (Stanford HAI)	10	0.02	0.973
H1	Exposure vs AI preparedness (IMF AIPI)	10	0.76	0.015
H1	Generative-AI exposure vs AI capacity	10	0.08	0.838
H2	Exposure vs fiscal space	10	0.48	0.166
H2	Exposure vs monetary space	10	−0.15	0.657
H2	Exposure vs overall policy space	10	0.14	0.707
H2	Exposure vs gross public debt	10	0.04	0.918
H2	Generative-AI exposure vs overall policy space	10	0.05	0.892

Note. Two-sided p-values from the exact permutation distribution over all 3,628,800 orderings of the ten economies. Exposure: AIOE index; generative-AI exposure: language-model AIOE index. Policy-space indices are standardised so that higher values mean more space.

Table 4
Robustness of H1 and H2 to the composition of the sample

Sample	Relation	n	Spearman ρ	Permutation p
Top 10 with Canada for Brazil	Exposure vs AI capacity	10	0.03	0.945
Top 10 with Canada for Brazil	Exposure vs AI preparedness	10	0.71	0.027
Top 10 with Canada for Brazil	Exposure vs overall policy space	10	0.28	0.422
Top 11 (incl. Canada)	Exposure vs AI capacity	11	0.08	0.818
Top 11 (incl. Canada)	Exposure vs AI preparedness	11	0.75	0.010
Top 11 (incl. Canada)	Exposure vs overall policy space	11	0.14	0.693
Top 10 without Russia	Exposure vs AI capacity	9	0.02	0.982
Top 10 without Russia	Exposure vs AI preparedness	9	0.82	0.011
Top 10 without Russia	Exposure vs overall policy space	9	0.13	0.746

Note. Two-sided p-values from 20,000 random permutations (fixed seed).

4.3 Exposure and policy space (H2)

H2 is not supported. The rank correlation between exposure and the overall policy-space index is 0.14 ($p = 0.71$), with fiscal space 0.48 ($p = 0.17$), with monetary space − 0.15 ($p = 0.66$) and with gross debt 0.04 ($p = 0.92$). None of the robustness samples changes this conclusion. Panel (b) of Fig. 2 shows why: policy space is dominated by country circumstances unrelated to AI exposure. Russia and Brazil have the most monetary space because their policy rates of 14.0% and 13.75% respond to high inflation, and Russia has the most fiscal space because of its low debt. Among the most exposed economies, Germany has more fiscal space than the United States, and Japan has the least monetary space. With ten observations the test has little power to detect a moderate relation, so the result should be read as an absence of evidence for H2, not as evidence that exposure and policy space are unrelated.

4.4 AI investment and productivity (H3)

H3 is not supported either. The two-way fixed-effects estimate of β is − 2.11 (randomisation $p = 0.86$; Table 5): a lagged AI investment share one percentage point of GDP higher is associated, if anything, with slightly slower growth of output per worker, but the estimate is far from significant. The estimate is also unstable. Dropping the United States, the only economy with AI investment above 0.13% of GDP, changes the coefficient to 13.07. The data therefore show no measurable relation between AI investment and aggregate labour productivity in 2018–2025. This is consistent with the productivity J-curve of

Brynjolfsson et al. (2021), in which the gains of a general-purpose technology appear only after complementary investment, but the test cannot distinguish that explanation from a small or absent effect.

Table 5
AI private investment and growth of output per worker (H3)

Specification	β	Randomisation p	Observations	Countries	Years
Ten economies, country and year fixed effects	−2.11	0.855	79	10	2018–2025
Without the United States	13.07	–	–	9	2018–2025

Note. Dependent variable: annual growth of GDP per person employed (constant 2021 PPP dollars, %), World Bank WDI. Regressor: AI private investment in the previous year as a percentage of nominal GDP (Stanford HAI; IMF). Randomisation p from 5,000 permutations of whole AI-investment paths across countries (fixed seed).

4.5 AI growth, the natural rate and debt dynamics

Table 6 and Fig. 3 report the calibrated exercise. In the central scenario, the AI gain in trend growth ranges from 0.25 percentage points per year in India to 0.70 points in the United Kingdom, against 0.65 in the United States, because of the differences in exposure. With an IES of 0.5, the natural rate rises by twice those amounts, between 0.5 and 1.4 percentage points. For the economies whose policy rates are close to the lower bound, such as Japan at 1.25% and the euro area at 2.5%, this rise would widen the room for conventional monetary policy.

The fiscal side moves in the opposite direction. Because the natural rate rises by more than growth, the interest–growth differential widens by the same amount as growth, and the primary balance needed to stabilise debt rises with the debt ratio. In the central scenario the required increase is 1.14 percentage points of GDP in Japan, 0.78 in the United States, 0.74 in Italy and France and 0.68 in the United Kingdom, against 0.19 in India and 0.11 in Russia. In the high scenario the figures are 2.62 points for Japan and between 1.57 and 1.80 points for the United States, Italy, France and the United Kingdom. In the low scenario no economy needs more than 0.17 points. Scaling by preparedness as well as exposure changes the central figures by at most 0.14 points.

Table 6
Calibrated effect of an AI growth gain on the natural rate and the debt-stabilising primary balance

Economy	Gross debt (% GDP)	Relative exposure	Δg central (pp)	Δr* central (pp)	Δpb* low (pp GDP)	Δpb* central (pp GDP)	Δpb* high (pp GDP)
Japan	199.4	0.90	0.59	1.17	0.17	1.14	2.62
United States	126.8	1.00	0.65	1.30	0.12	0.78	1.80
Italy	137.9	0.86	0.56	1.12	0.11	0.74	1.71
France	118.5	0.98	0.64	1.28	0.11	0.74	1.70
United Kingdom	102.0	1.07	0.70	1.39	0.10	0.68	1.57
Brazil	97.0	0.72	0.47	0.93	0.07	0.42	0.98
Germany	64.6	0.99	0.64	1.28	0.06	0.40	0.92
China	104.4	0.44	0.29	0.57	0.04	0.28	0.65
India	83.1	0.39	0.25	0.51	0.03	0.19	0.44
Russia	19.3	0.91	0.59	1.18	0.02	0.11	0.24

Note. Intertemporal elasticity of substitution 0.5; full pass-through to the effective interest rate on public debt; equations (3)–(5). US gain in labour-productivity growth: 0.10 (low), 0.65 (central) and 1.50 (high) percentage points per year, scaled by exposure relative to the United States. Δg: change in trend growth; Δr*: change in the natural rate; Δpb*: change in the debt-stabilising primary balance. A calibrated scenario, not a forecast.

The result depends on the IES. With an IES of 1, the natural rate rises one for one with growth, the interest–growth differential does not change and the fiscal effect disappears. With an IES of 0.25, closer to Hall's (1988) estimates, the central-scenario increase rises to 3.41 points of GDP in Japan and to between 2.0 and 2.3 points in the United States, Italy, France and the United Kingdom. The effect is a fiscal cost for any IES below one, which is the range supported by most empirical estimates since Hall (1988). The ranking across countries is robust to the IES because it is driven by the product of debt and exposure.

5. Discussion

The three empirical results and the calibrated exercise fit together. AI capacity is concentrated in two economies, exposure is spread across the advanced economies, and the two are unrelated. Most of the ten largest economies will therefore experience AI mainly as adopters exposed to a technology developed elsewhere, not as producers. Their exposure is not matched by less policy space, which

means that the risk is not that the most exposed economies are already the most constrained. The risk lies in what AI does to the constraints themselves.

Here the work of the 2026 laureates is directly relevant. In Woodford's (2003) framework, the natural rate is the reference point for monetary policy, and a technology that raises trend growth raises that reference point. If the gain is anticipated, the natural rate rises before productivity does, because households want to consume part of their higher future income now; Aldasoro et al. (2026) show the mirror image, in which an unanticipated gain is disinflationary in the short run. Either way, central banks would need to recognise a moving natural rate in real time, which is difficult (Holston et al., 2017). The calibrated exercise adds a fiscal dimension. Through the consumption Euler equation whose implications Hall (1978) derived, the size of the response depends on the intertemporal elasticity of substitution, and Hall's (1988) estimates of that elasticity are small. A small elasticity means a large rise in the natural rate relative to growth, and therefore a wider interest–growth differential.

The resulting asymmetry is the stabilisation gap. The AI gain would lift the natural rate away from the lower bound, restoring room for monetary policy in the economies where it is scarcest, such as Japan and the euro area. At the same time it would raise the primary balance required to keep debt stable in the same economies, because they also have the highest debt. This links to Blanchard's (2019) argument that low interest rates relative to growth reduce the fiscal cost of debt: a technology that raises growth can reverse that condition if it raises interest rates by more. It also links to the fiscal–monetary interaction emphasised by Leeper (1991) and Woodford (2001): if fiscal authorities do not adjust, monetary policy alone cannot guarantee price stability.

Two features of the current data qualify the conclusion. First, Japan's effective interest rate on debt (0.68% in 2024) is far below its nominal growth, so Japan currently has a negative debt-stabilising primary balance and a cushion against a rise in rates; the AI effect would erode that cushion rather than create an immediate gap. Second, the pass-through from the natural rate to the effective rate on debt is gradual and depends on debt maturity, so the fiscal cost would build up over years. Policy makers in high-debt economies would have time to respond, but the arithmetic implies that the fiscal benefit of AI-driven growth should not be taken for granted when planning fiscal paths.

The null results are also informative. The absence of a relation between AI investment and productivity growth so far is a reminder that projections of large AI gains remain projections. For stabilisation policy this cuts both ways: the natural rate is unlikely to have moved much yet, but the expectations channel stressed by Woodford means that it can move as soon as markets come to believe in large gains.

6. Limitations

The study has several limitations. First, ten observations limit statistical power; the exact permutation tests are valid, but they can detect only large relations, and the null results for H2 and H3 should be read accordingly. Second, the exposure index relies on US-based occupational scores applied to other economies, which assumes that the task content of an occupation is similar across countries; it also

measures exposure at the level of major groups, though the two-digit version gives almost identical results. Third, China's occupational structure comes from ILO modelled estimates rather than survey data, although the alternative based on the 2010 census gives a similar value. Fourth, Russia's position in the ranking depends on its exchange rate, and its AI investment data may be incomplete; the results without Russia are unchanged. Fifth, the calibrated exercise uses a steady-state relation with full pass-through and constant time preference, term premium and fiscal rules; it ignores the effects of AI on tax revenue, on public spending and on the composition of debt, any of which could offset or amplify the effect. Finally, the AI growth scenarios are taken from studies centred on the United States and scaled by exposure, which is a simplification of the adoption process.

7. Conclusion

Among the world's ten largest economies, AI capacity is concentrated in the United States and China, while occupational exposure to AI is spread across the advanced economies and unrelated to capacity. Exposure does not predict current policy space, and recent AI investment does not yet predict productivity growth. Read through the stabilisation framework recognised by the 2026 Prize in Economic Sciences, however, the possibility of AI-driven growth has a clear implication: when the intertemporal elasticity of substitution is below one, faster growth raises the natural rate by more than growth itself. That widens monetary room above the lower bound but raises the primary balance needed to stabilise public debt, most in Japan, the United States, Italy, France and the United Kingdom. Planning for AI therefore requires attention not only to its effects on jobs and productivity, but also to its effects on the interest rates that govern both monetary policy and public debt.

Declarations

Data availability. All data are public. The unmodified raw downloads, the processed country dataset, the output tables and the figures are deposited in Zenodo at https://doi.org/10.5281/zenodo.23350759. The sources are the IMF World Economic Outlook (October 2026), Fiscal Monitor (April 2026), Public Finances in Modern History database and AI Preparedness Index (IMF DataMapper); the World Bank World Development Indicators; the BIS central bank policy rate database; the Stanford HAI Global AI Vibrancy data (September 2025 release); ILOSTAT (employment by occupation, survey data and ILO modelled estimates); the AIOE data of Felten, Raj and Seamans; and the ISCO-08 to 2010 SOC crosswalk of the US Bureau of Labor Statistics. All were accessed on 13 October 2026.

Code availability. The Python scripts that download the data, build the dataset, run the tests and draw the figures are deposited with the data at https://doi.org/10.5281/zenodo.23350759, with a manifest of SHA-256 checksums of the raw files. All randomisation uses a fixed seed.

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Ethics approval. Not applicable. The study uses only public aggregate data and involves no human participants.

Author contributions. The author conceived the study, designed the analysis, interpreted the results and is solely responsible for the content.

Use of generative AI. Claude Opus 5.5 (Anthropic, 2026) was used to write and debug the data-processing and analysis code, to search for and check references, and to draft and edit the text. It was used to speed up implementation and drafting. The author specified the research question and hypotheses, reviewed every step of the analysis and all text, verified the references against their sources, and takes full responsibility for the content.

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Figures

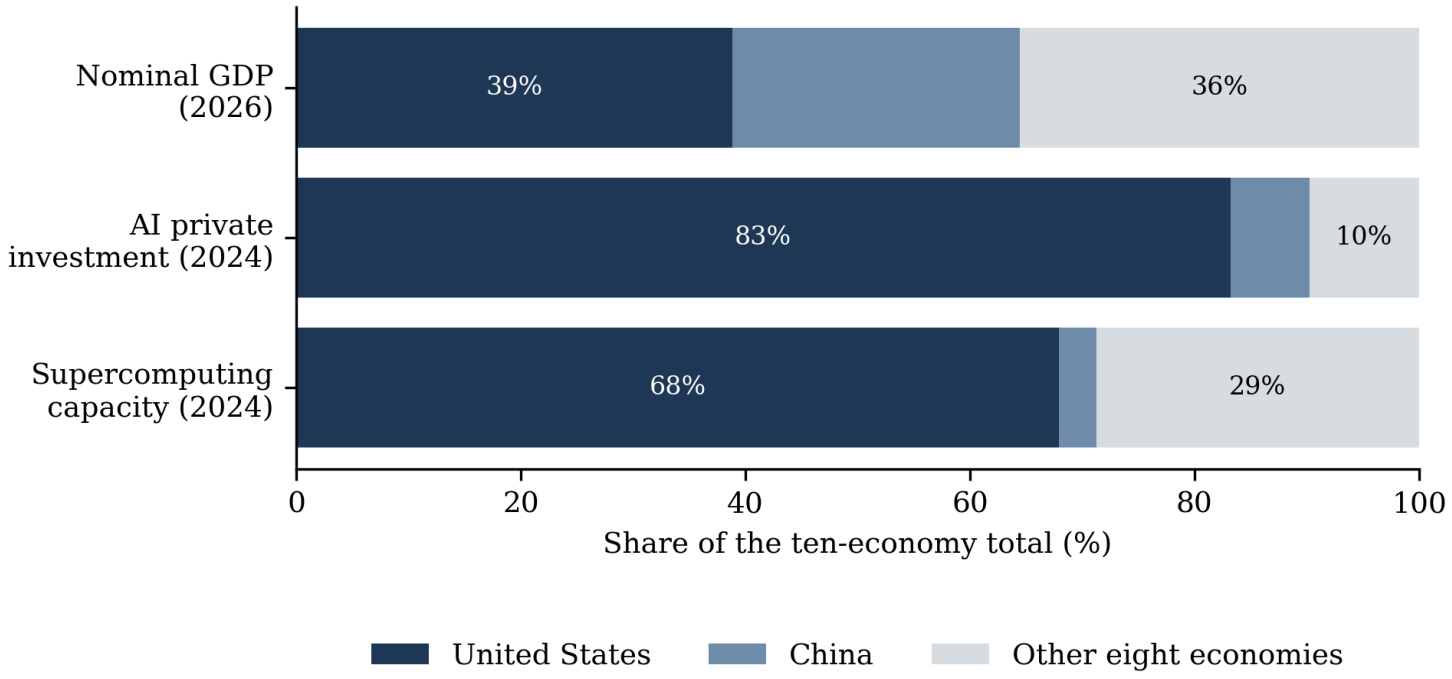

Figure 1

Shares of the United States, China and the other eight economies in the ten-economy totals of nominal GDP (2026), AI private investment (2024) and supercomputing capacity (Rmax, 2024). Sources: IMF World Economic Outlook (October 2026); Stanford HAI Global AI Vibrancy data (September 2025 release).

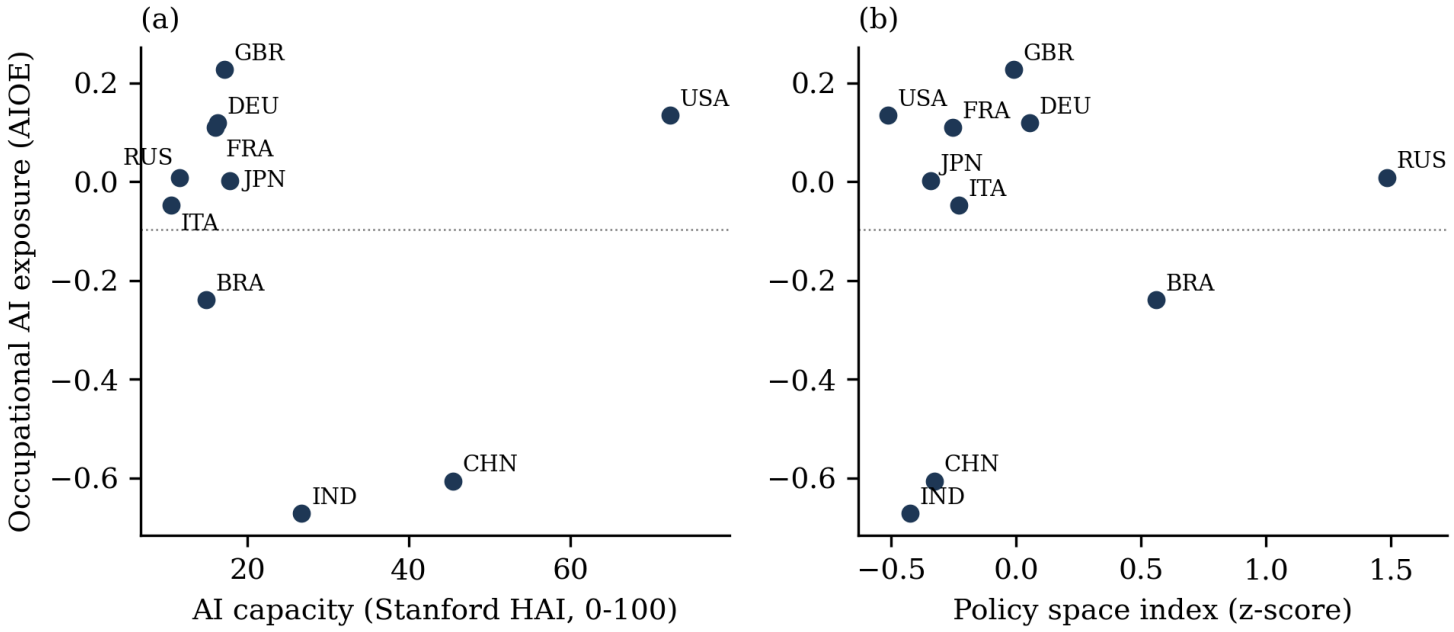

Figure 2

Occupational AI exposure (AIOE index) against (a) AI capacity (Stanford HAI, mean of 17 normalised indicators, 2024) and (b) the policy-space index (mean of standardised fiscal and monetary space, 2026). The dotted line marks the mean exposure of the ten economies.

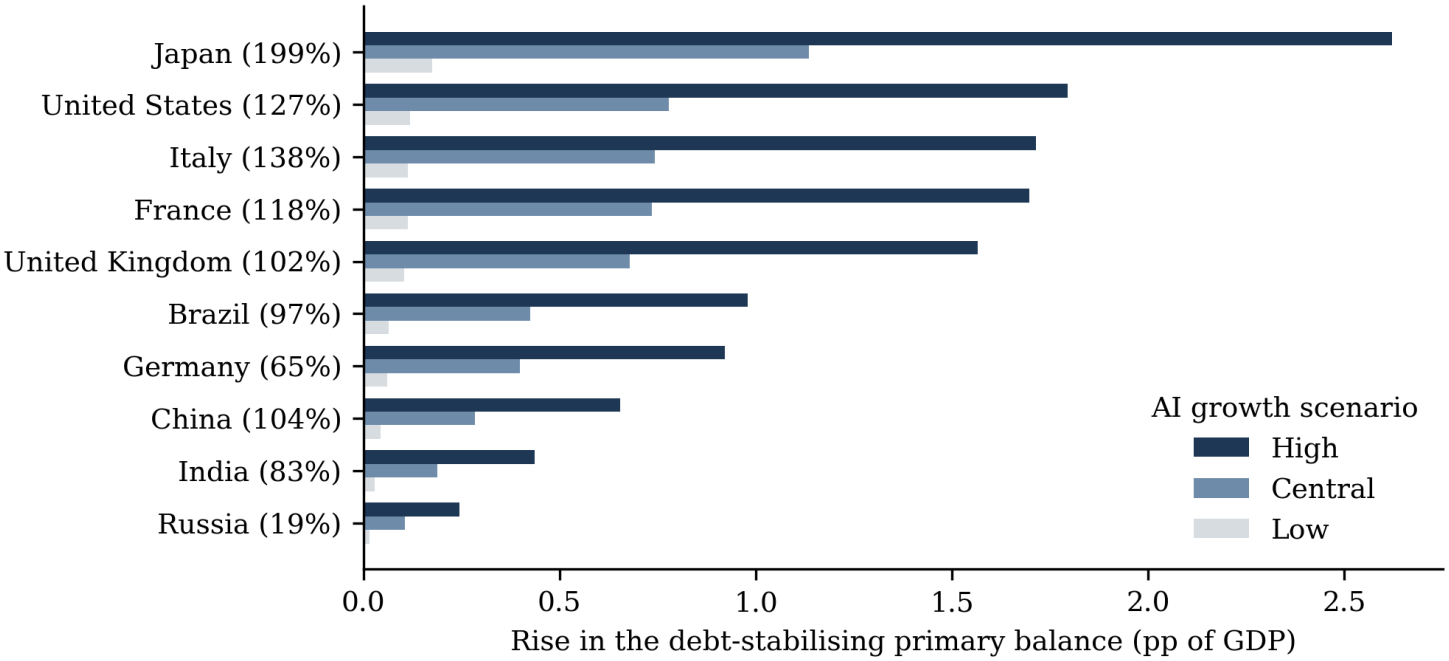

Figure 3

Rise in the debt-stabilising primary balance (percentage points of GDP) implied by an AI-driven increase in trend growth, by scenario, with an intertemporal elasticity of substitution of 0.5 and full pass-through to the effective interest rate on public debt. Gross public debt in 2026 (% of GDP) in parentheses. Scenarios: US labour-productivity gain of 0.10 (low), 0.65 (central) and 1.50 (high) percentage points per year, scaled by relative occupational exposure.