BETTER POLICIES FOR BETTER LIVES

Miracle or Myth?

Assessing the macroeconomic productivity gains from Artificial Intelligence

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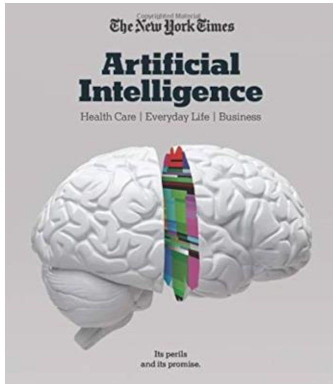
Productivity growth across the OECD has been disappointing…

Can AI turn this around?

- Seems very promising…
  - Large documented gains in specific activities (coding, translation, writing, etc.)
- But these are only a fraction of all economic activities…
  - Typically cognitive, knowledge intensive jobs
- AI adoption is still limited…
  - According to official surveys by statistical agencies, which ask about core business functions and regular use
- Aggregate productivity gains also depend on demand through general equilibrium effects
  - Is there demand for the increased output of AI-boosted sectors, e.g. legal services?
  - Changing relative output prices and sectoral reallocation?



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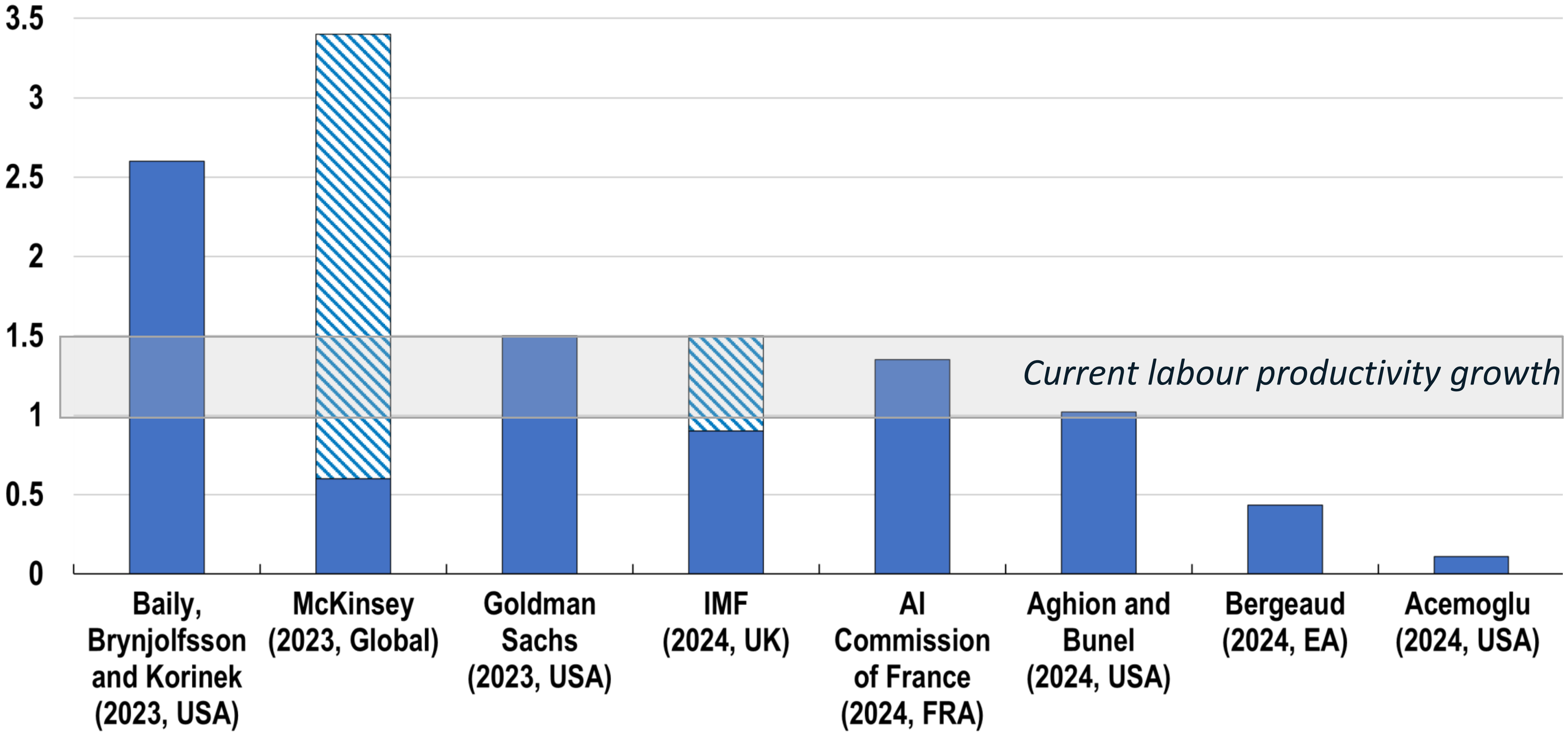
Lively debate about the expected productivity gains from AI

Predictions for AI's impact on aggregate *labour* productivity growth over the next 10 years (annualized, pp.)



Existing approaches and our contribution

I. Theoretical approaches based on **aggregate production functions**

- Explore how AI may affect aggregate growth by changing the **parameters** and inputs to this function
  (Aghion et al., 2019; Trammell and Korinek 2023; Baily, Brynjolfsson, and Korinek, 2023; AI Commission of France, 2024)

II. Empirically grounded approaches starting from **micro-level estimates** of productivity gains

- Rely on an **aggregation approach** to derive macro-level productivity gains
  - Goldman Sachs, 2023, using a simple atheoretical framework
  - Acemoglu, 2024, using Hulten's theorem to derive aggregate effects
  - Aghion and Bunel, 2024, exploring the role assumptions by Acemoglu, 2024

→ We start from **II.**, but add a **sectoral perspective**

1. Predict sector-level productivity gains
2. Derive aggregate productivity gains using a **calibrated multi-sector general equilibrium model** that accounts for
   - input-output linkages
   - and sectoral reallocation (Baumol's growth disease)

→ Compare the macroeconomic productivity gains from AI under different scenarios for exposure to AI, the speed of AI adoption, and drivers of Baumol's growth disease

We follow a micro-to-macro approach
with a key role for sectors

I. Prediction of sector-level productivity gains

A) Micro-level productivity gains of AI (based on estimates in the literature)

X

B) Sectoral exposure to AI (based on task composition of sectors and measures of task-level exposure to AI)

X

C) AI adoption scenarios over the next 10 years (based on historical experience with previous GPTs)

II. Aggregation through a macro model

featuring…

...**sectoral input-output linkages**

…**sectoral reallocation** of factors and changing **relative output prices**

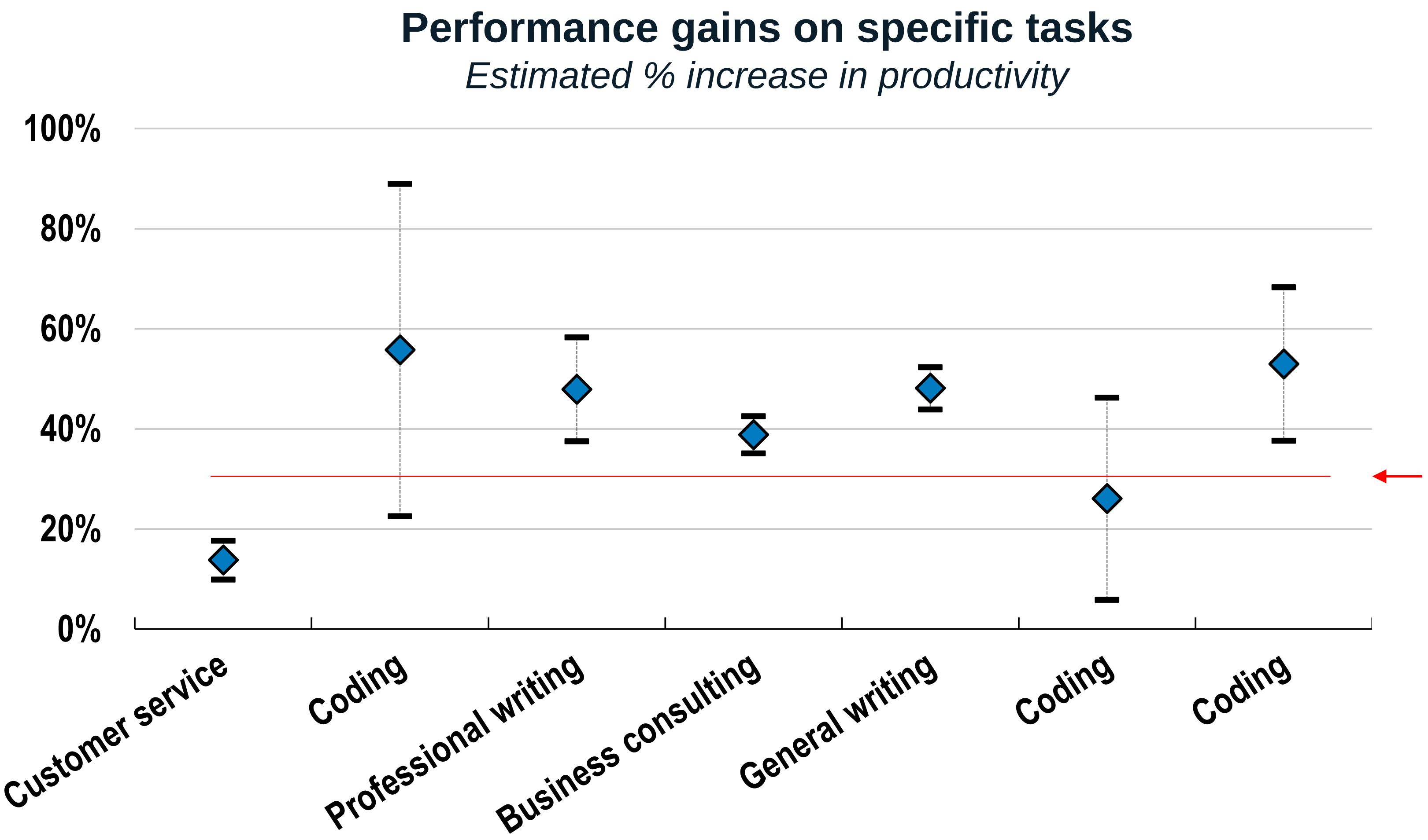
(→ *possibility of Baumol effect*)

Aggregate gains from AI

Note: Step I. is inspired by Acemoglu (2024), adapted to our sector-level framework.
Step II. builds on the multi-sector model in Baqaee and Farhi (2019).

A) Micro-level productivity gains

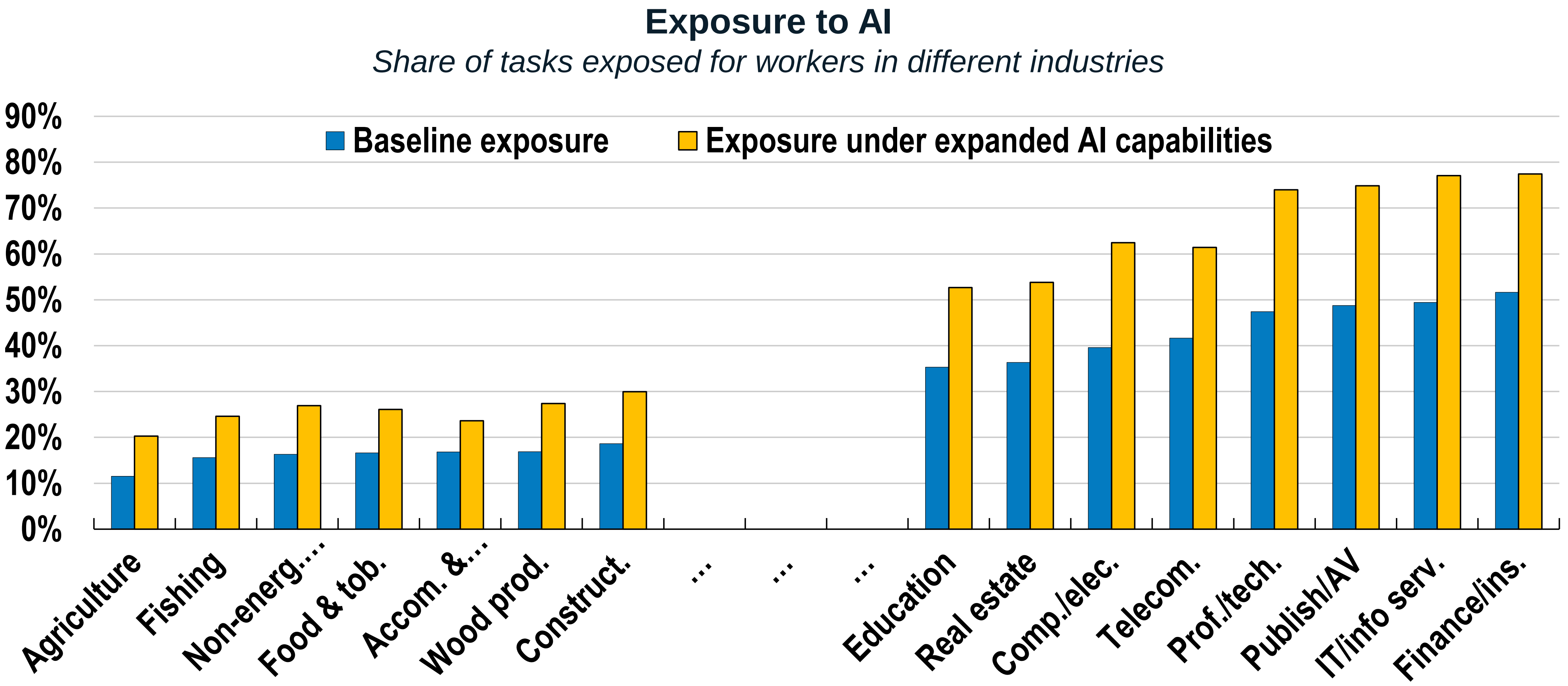
Large but vary across tasks



We assume a 30% micro-level productivity gain

B) Sectoral exposure to AI: strongest in knowledge-intensive services

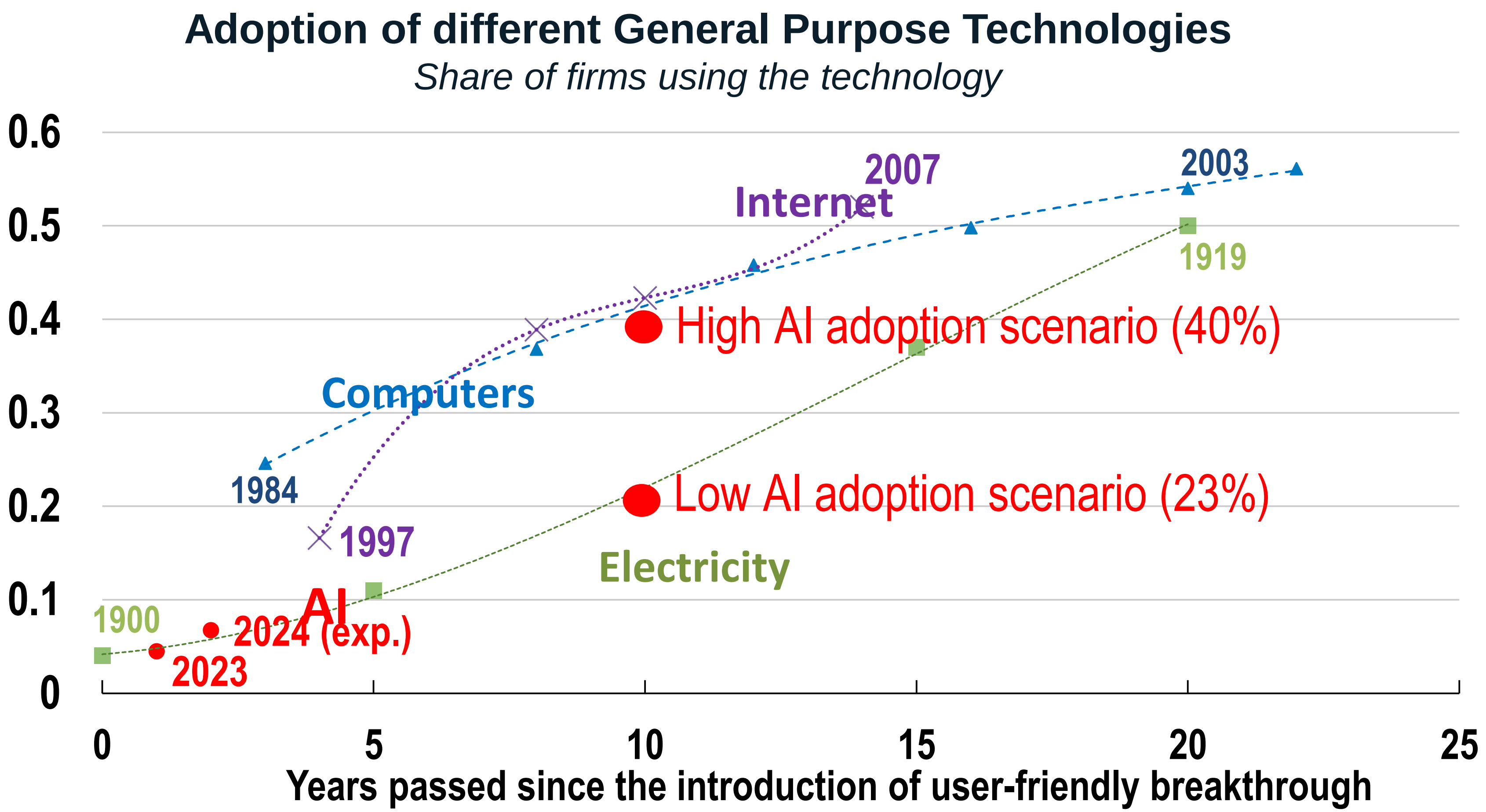
With current and with expanded capabilities



Source: Eloundou et al. (2024) and authors' calculations based on sectoral occupational structure

C) Adoption paths of previous General Purpose Technologies in the US

Help inform our assumptions for AI



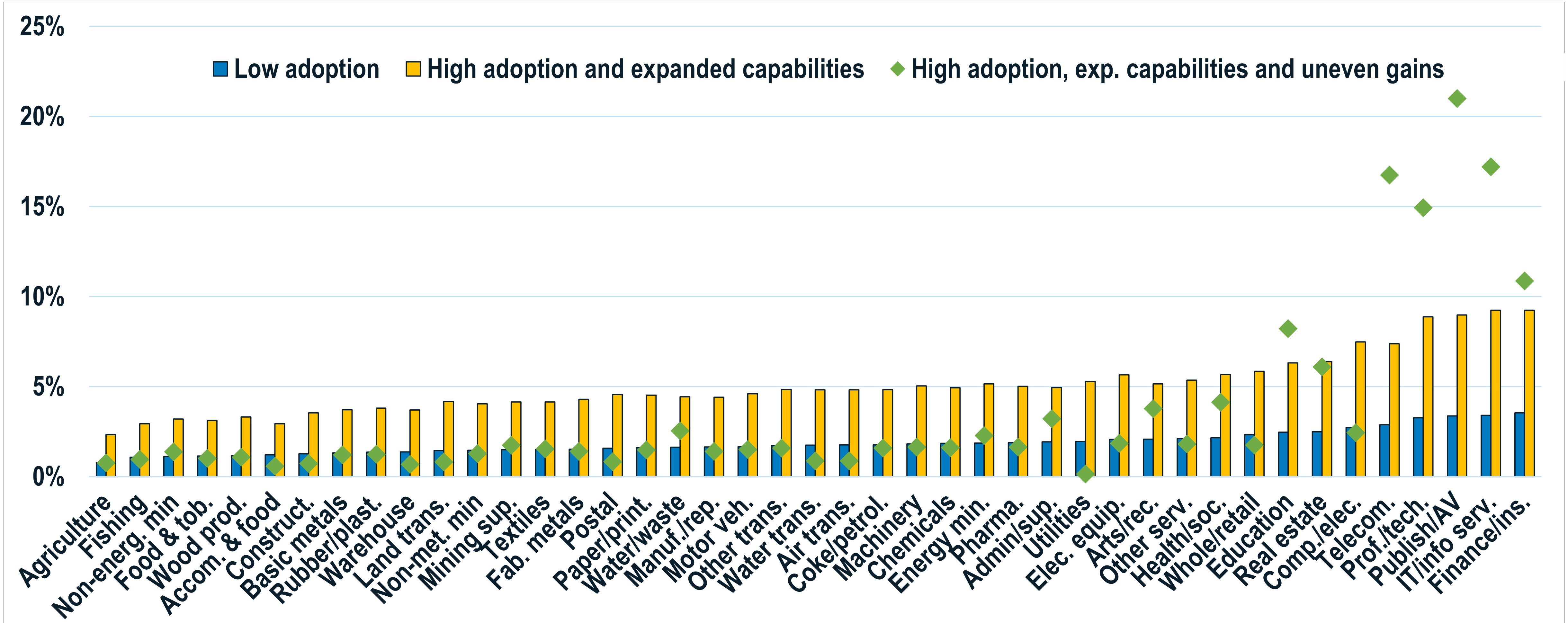
Note: The 2024 value for AI is the expectation (exp.) as reported by firms in the US Census Bureau survey.
We consider for the introduction of the user-friendly breakthrough variant of the technology the following: for electricity, development of electric motor; for PC, introduction of IBM PC; for AI, launch of ChatGPT. For more details, see the sources.
Sources: For PC and electricity, (Goldman Sachs, 2023[6]); for AI, United States Census Bureau, Business Trends and Outlook Survey.

Main scenarios

	1. Low adoption	2. High adoption and expanded capabilities	3. Scenario 2 plus uneven gains across sectors
A) Micro-level gains from AI	30%	30%	30%
B) Exposure to AI	Eloundou et al. (2024), baseline	Eloundou et al. (2024), expanded AI capabilities	Eloundou et al. (2024), expanded AI capabilities
C) AI adoption	23%	40%	Uneven, but with same average as in 2

Sectoral productivity gains over 10-years

Obtained as $Micro\ Level\ Gains * \ Exposure_{\boldsymbol{i}} * \ Adoption\ Rate_{(\boldsymbol{i})t}$



Aggregation of sectoral gains

Straightforward approach: Summing up sectoral gains (weighted by their value-added shares)

→ Can be seen as first-order approximation to aggregate gains (Hulten's theorem)

Historically, sectors with above average productivity growth have experienced shrinking GDP shares.

→ Aggregate productivity gain ≤ sum of sectoral gains

This phenomenon is often referred to as Baumol's growth disease (Nordhaus, 2008))

"Growth may be constrained not by what we are good at but rather by what is essential and yet hard to improve" (Aghion, Jones, and Jones, 2019)

Aggregation of sectoral gains (cont.)

Will aggregate gains from AI be limited due to a Baumol effect? Under what conditions?

Baumol effect arises in general equilibrium as (uneven) sectoral productivity growth induces…

- …changes in relative output prices
- …changes in the sectoral input-output structure
- …reallocation of factors across sectors (from high to low growth sectors)

→ We need a multi-sector general equilibrium model to answer these questions!

A multi-sector general equilibrium framework (building on Baqaee and Farhi, 2019)

Sectoral output is produced by combining a single factor (representing labour and capital) with intermediate inputs:

$$y_i = A_i\left(\omega_i L_i^{\frac{\theta-1}{\theta}} + (1-\omega_i)\,\hat{X}_i^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}} \quad ; \quad \hat{X}_i = \left(\sum_{j=1}^{N} \gamma_{ij}\, x_{ij}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$$

Final demand is represented by a CES aggregator:

$$Y = \left(\sum_{i=1}^{N} \alpha_i c_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

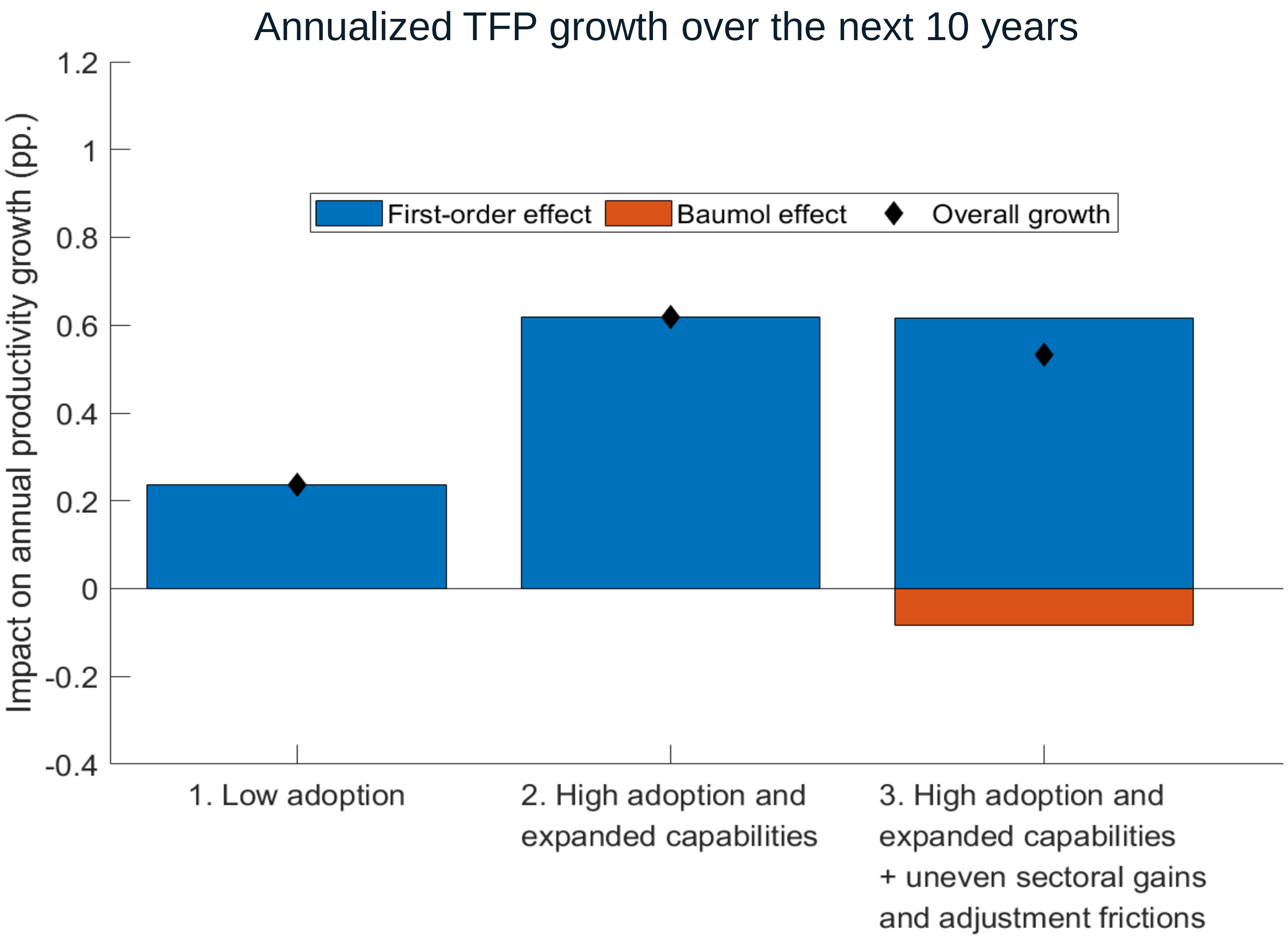
Weight parameters $(\omega_i, \gamma_{ij}, \alpha_i)$	Structural elasticities of substitution $(\theta, \varepsilon, \sigma)$
Calibrated to observed sectoral value-added shares and input-output tables	Standard values taken from the literature Or Illustrative scenario with very low σ (inelastic demand)

Main scenarios

	1. Low adoption	2. High adoption and expanded capabilities	3. Scenario 2 plus uneven gains across sectors
Micro-level gains from AI	30%	30%	30%
Exposure to AI	Eloundou et al. (2024), baseline	Eloundou et al. (2024), expanded AI capabilities	Eloundou et al. (2024), expanded AI capabilities
AI adoption	23%	40%	Uneven, but with same average as in 2*
Demand	Relatively elastic	Relatively elastic	Inelastic*
Factor reallocation across sectors	Mobile / fully flexible	Mobile / fully flexible	Restricted*

*Scenario 3 represent conditions that induce a more severe Baumol effect.

Macro-level productivity gains in the main scenarios

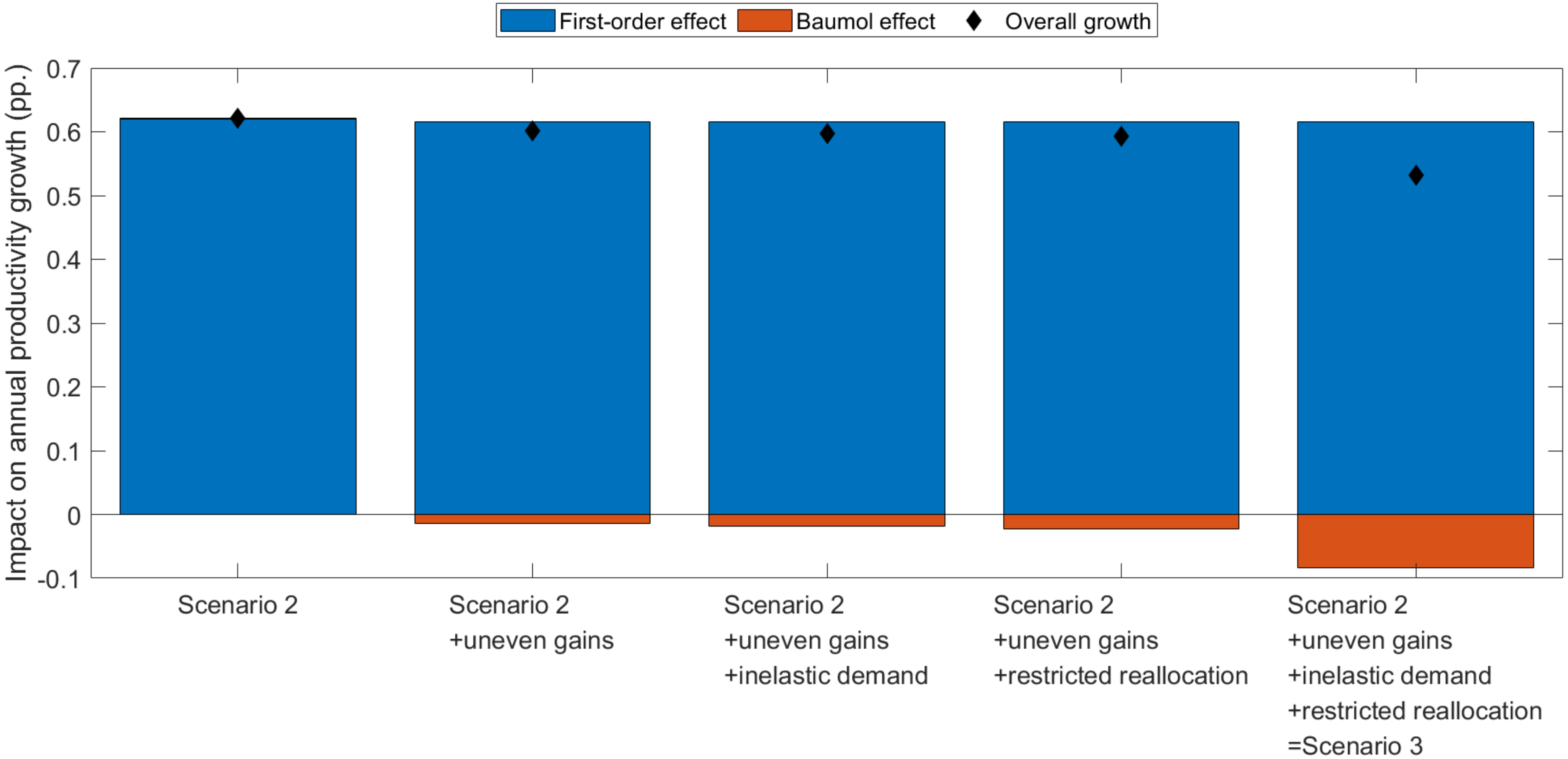


$$\boldsymbol{d}\,\mathbf{log}(\boldsymbol{TFP}) = \underbrace{\sum_{i\in I} \lambda_{i0} d\,\log(\mathrm{A_i})}_{First-order\ effect} + Baumol\ Effect$$

Adjustment frictions = inelastic demand
+ no reallocation of factors across sectors

Macro-level productivity gains under various scenarios

Understanding the role of frictions



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Sectoral reallocation and Baumol's growth disease

Baumol effect arises as factors of production are reallocated towards low-growth sectors

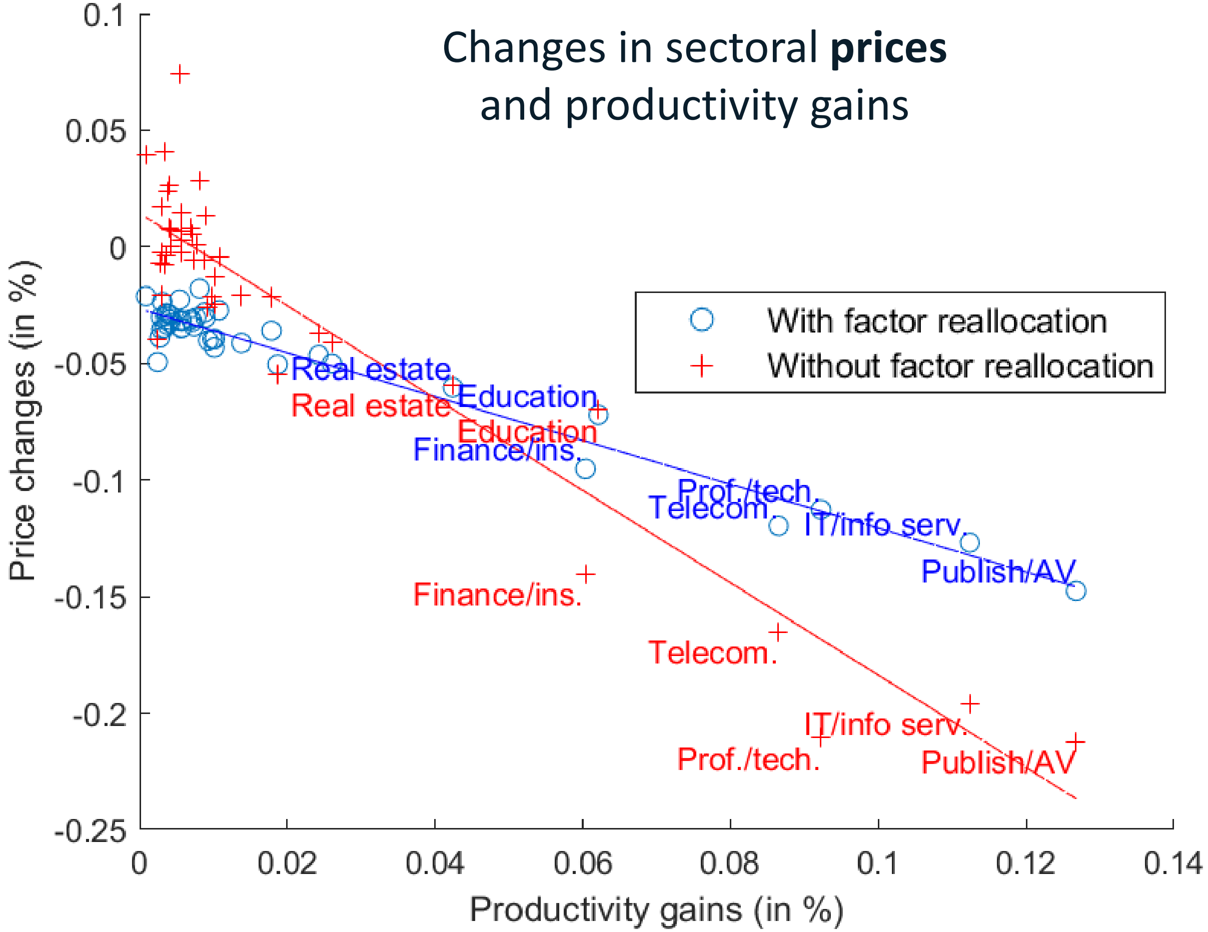
So, why does preventing factor reallocation **increase** the Baumol effect?

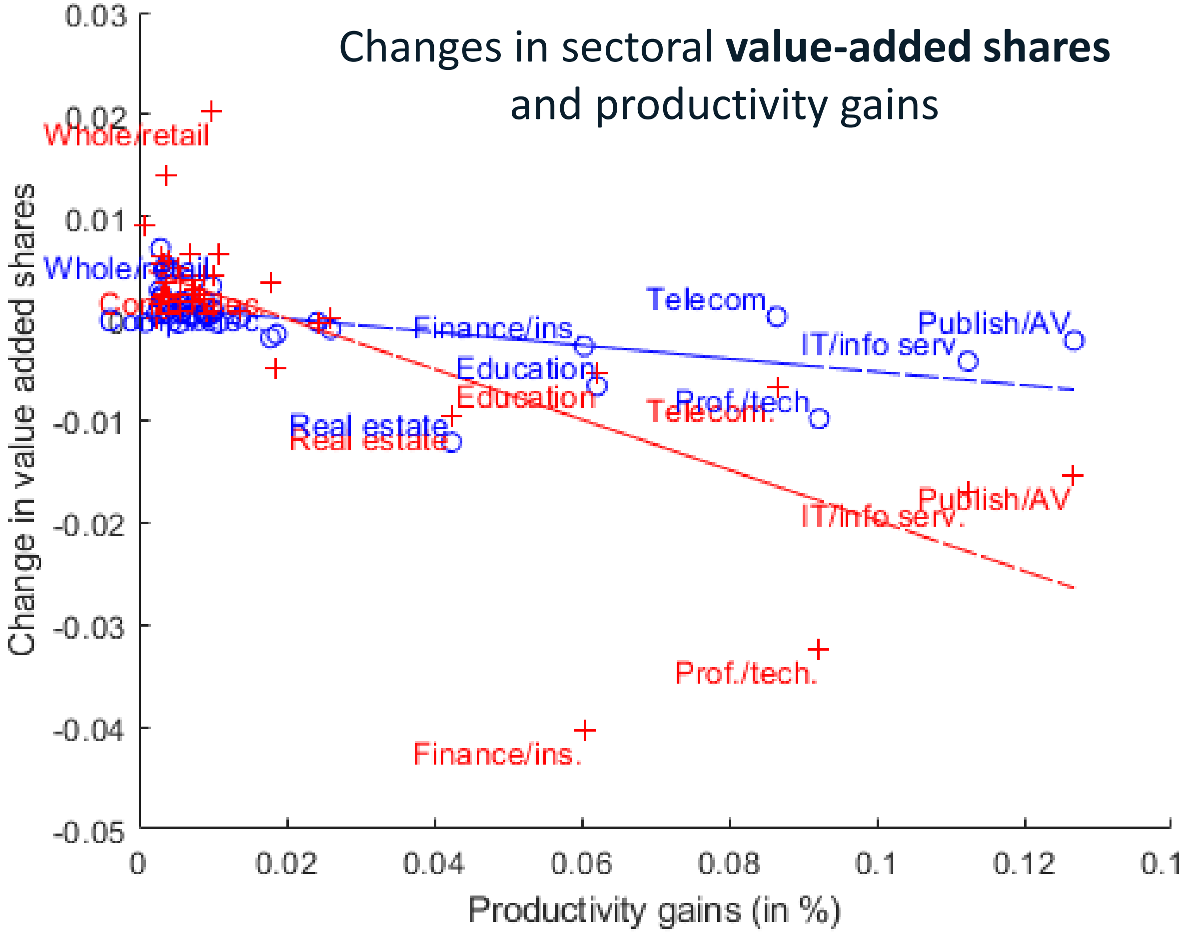
$$\underbrace{\frac{LP_t - LP_0}{LP_0}}_{\substack{Aggregate\ real \\ LP\ growth}} = \underbrace{\sum_{j\in J} s_{j0}^{VA}\left(\frac{LP_{jt} - LP_{j0}}{LP_{j0}}\right)}_{Within-industry\ effect} + \underbrace{\sum_{j\in J} \Delta w_{jt}\frac{LP_{jt}}{LP_0}}_{Labor\ reallocation\ effect} + \underbrace{\sum_{j\in J} w_{jt}(\Delta p_{jt})\frac{LP_{jt}}{LP_0}}_{Valuation\ effect}$$

It can be shown that limiting factor reallocation increases the valuation effect by more than it reduces the labor reallocation effect!

AI and Baumol's growth disease (in our model)

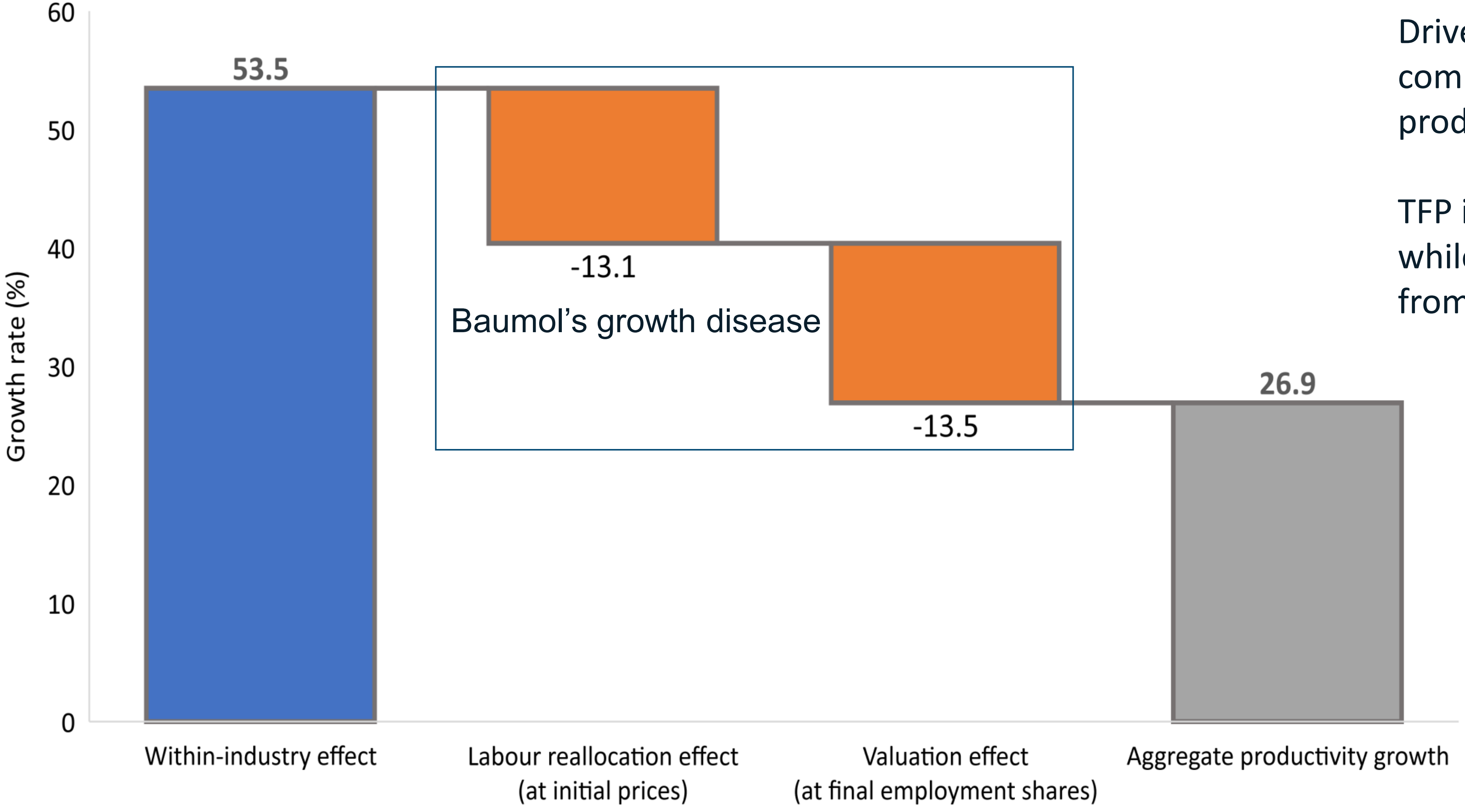
Without factor reallocation, value-added shares of high-growth sectors decline more!





ICT and Baumol's growth disease (in the data)

Decomposition of aggregate labour productivity growth (United States, 1995-2007)



Driven by C26 (Manufacture of computer, electronic and optical products):

TFP increased by around 800%, while value-added share dropped from 2.2% to 1.7%.

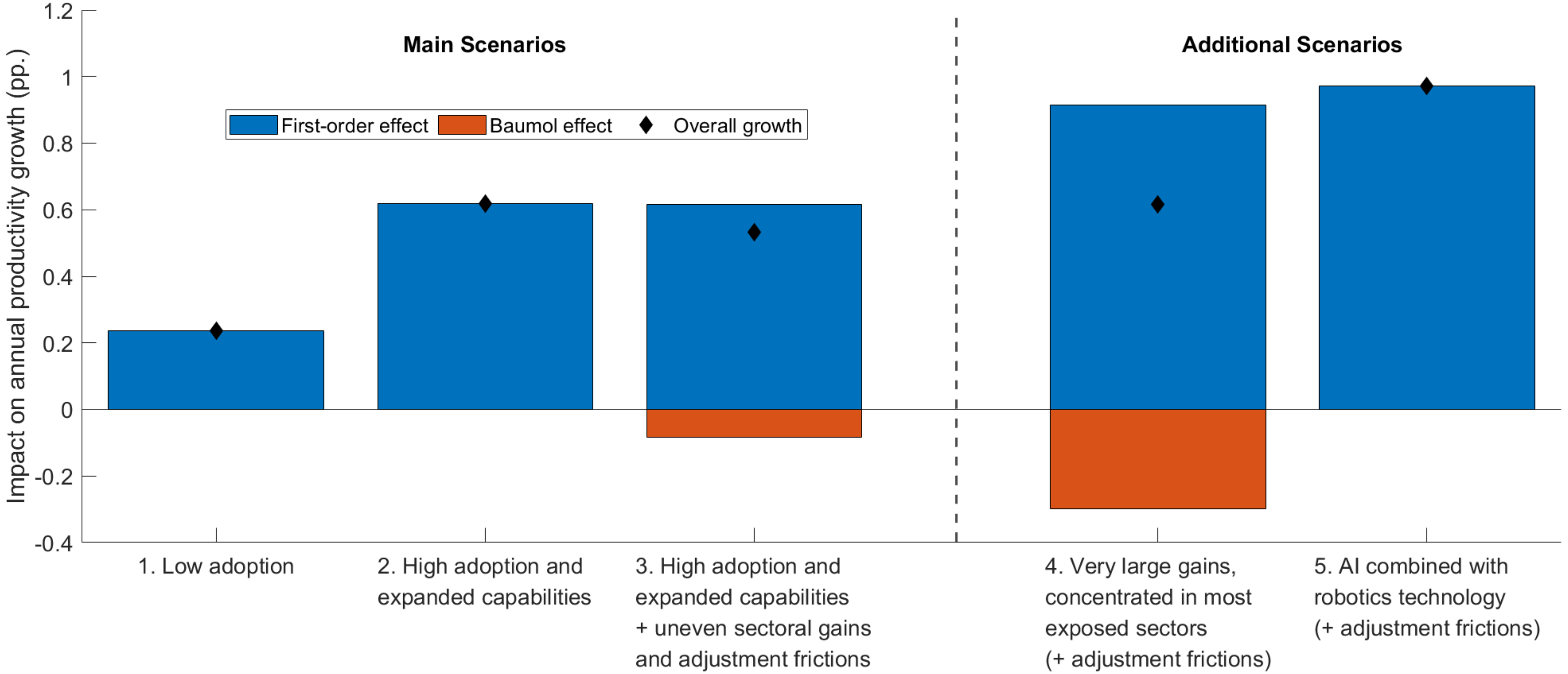
Source: EUKLEMS & INTANProd

Additional scenarios

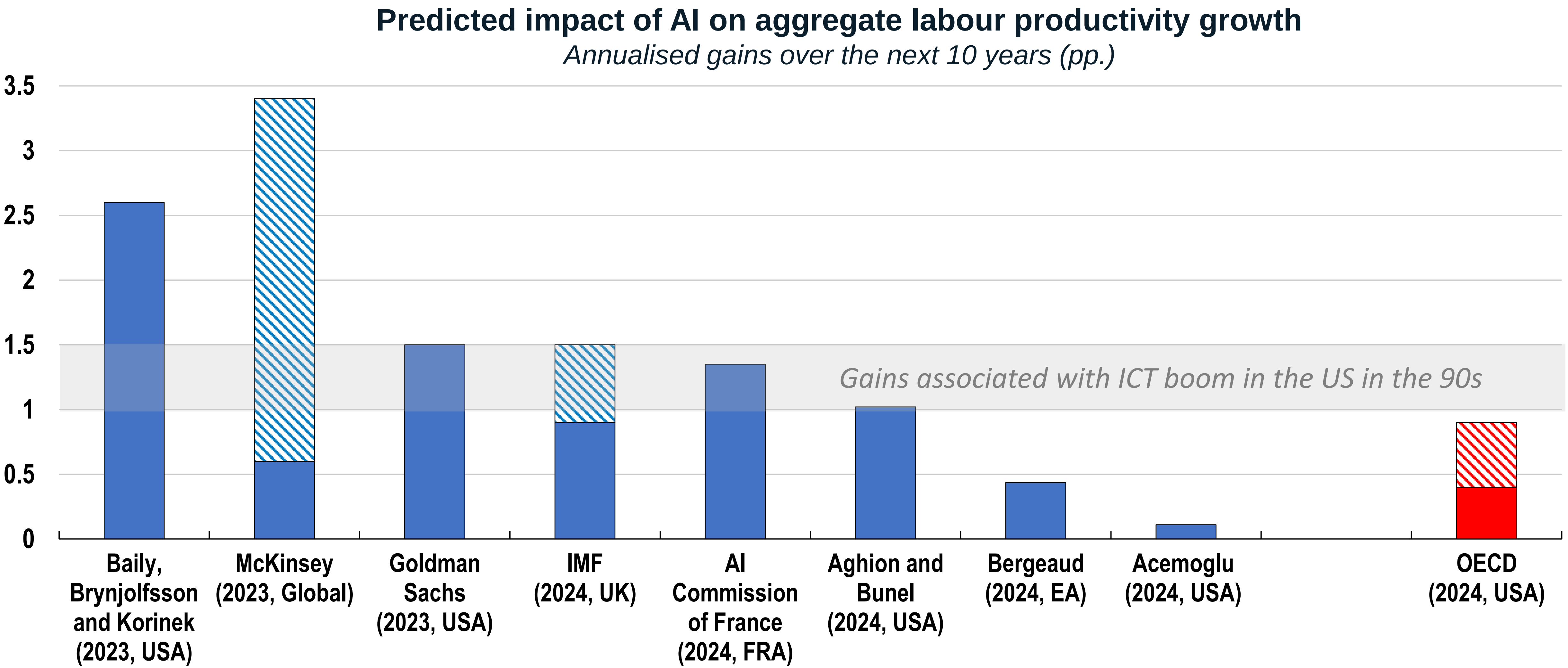
	4. Very large gains, concentrated in most exposed sectors (+ adjustment frictions)	5. AI combined with robotics technology (+ adjustment frictions)
Micro-level gains from AI	100% in the three most exposed sectors and 14% in all other sectors	30%
Exposure to AI	Eloundou et al. (2024), baseline	Eloundou et al. (2024), expanded capabilities + extended to physical tasks
AI adoption	40%	40%
Demand	Inelastic	Inelastic
Factor reallocation across sectors	Restricted	Restricted

Macro-level productivity gains in the main scenarios

Integration with robotics would yield even larger gains…

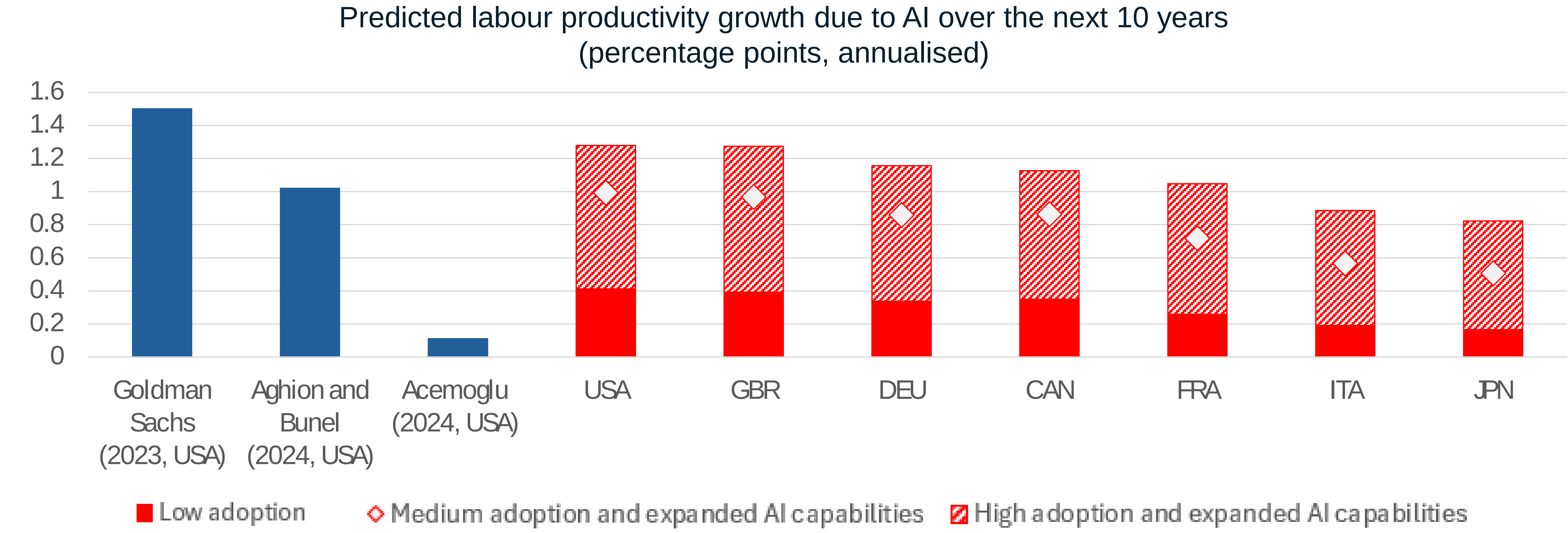


Can AI revert the productivity slowdown?



Source: Filippucci, Gal and Schief (2024).

Extension to G7: large cross-country variation due to sectoral specialisation and differences in projected adoption



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Discussion and policy implications

- **Policies** play a key role in shaping the conditions :
  1. Aggregate gains are strongly affected by speed of adoption
     → Investing in **skills**, **digital infrastructure**, and ensuring **data access** are key conditions for widespread adoption

  2. Uneven productivity growth across sectors is a challenge and may limit aggregate gains
     → Supporting productive and safe use of AI across a wide array of tasks
     → This will increase not only the speed but the breadth of adoption
     → Facilitating reallocation of labour and capital to where they are most productive and most valued by consumers (through **retraining** of workers and well-functioning **capital markets)**

- Sustained long-run productivity growth hinges critically on whether AI will boost **innovation**

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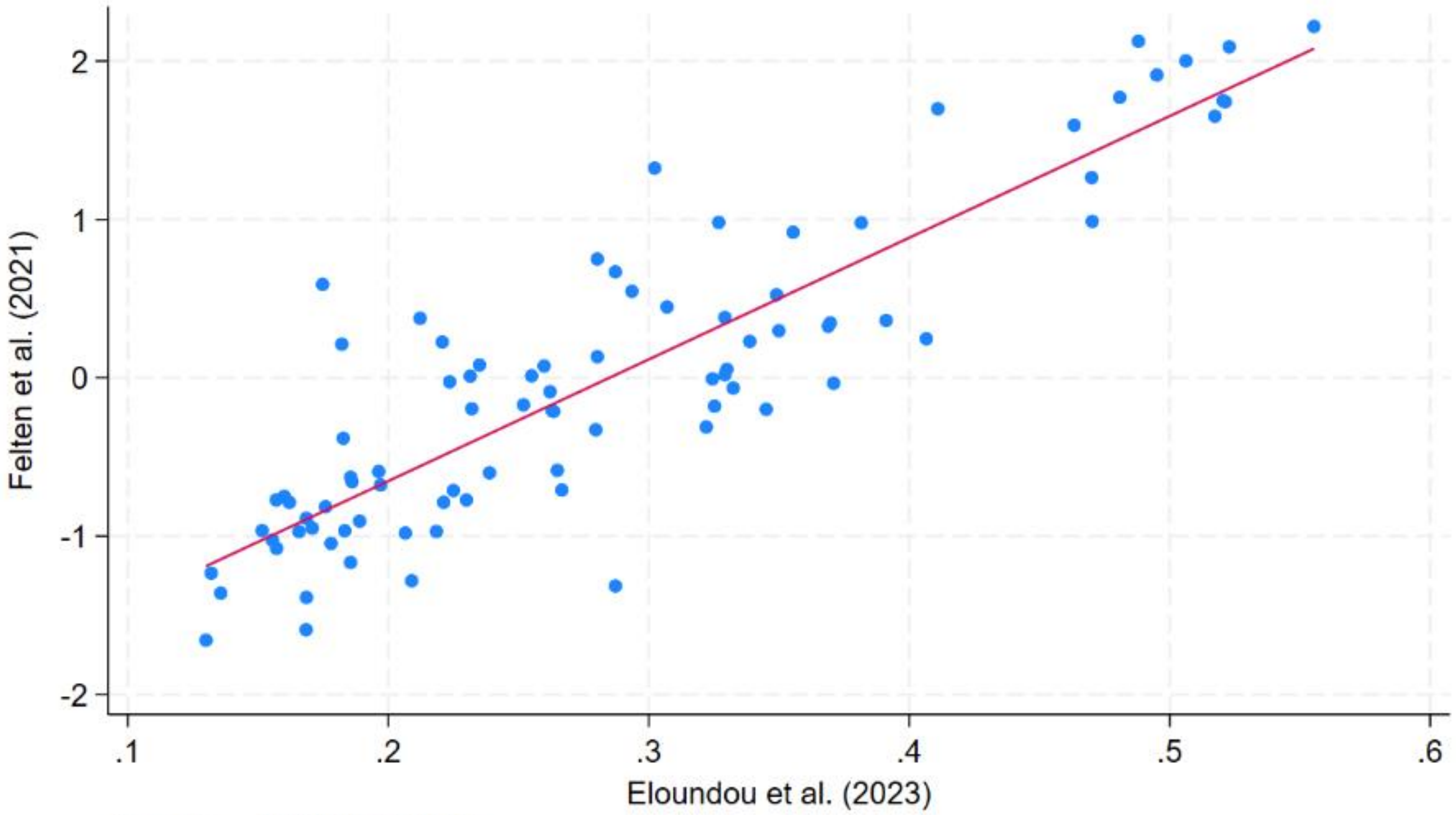
Thank you!

Additional slides

High correlation between alternative AI exposure estimates at the occupation level

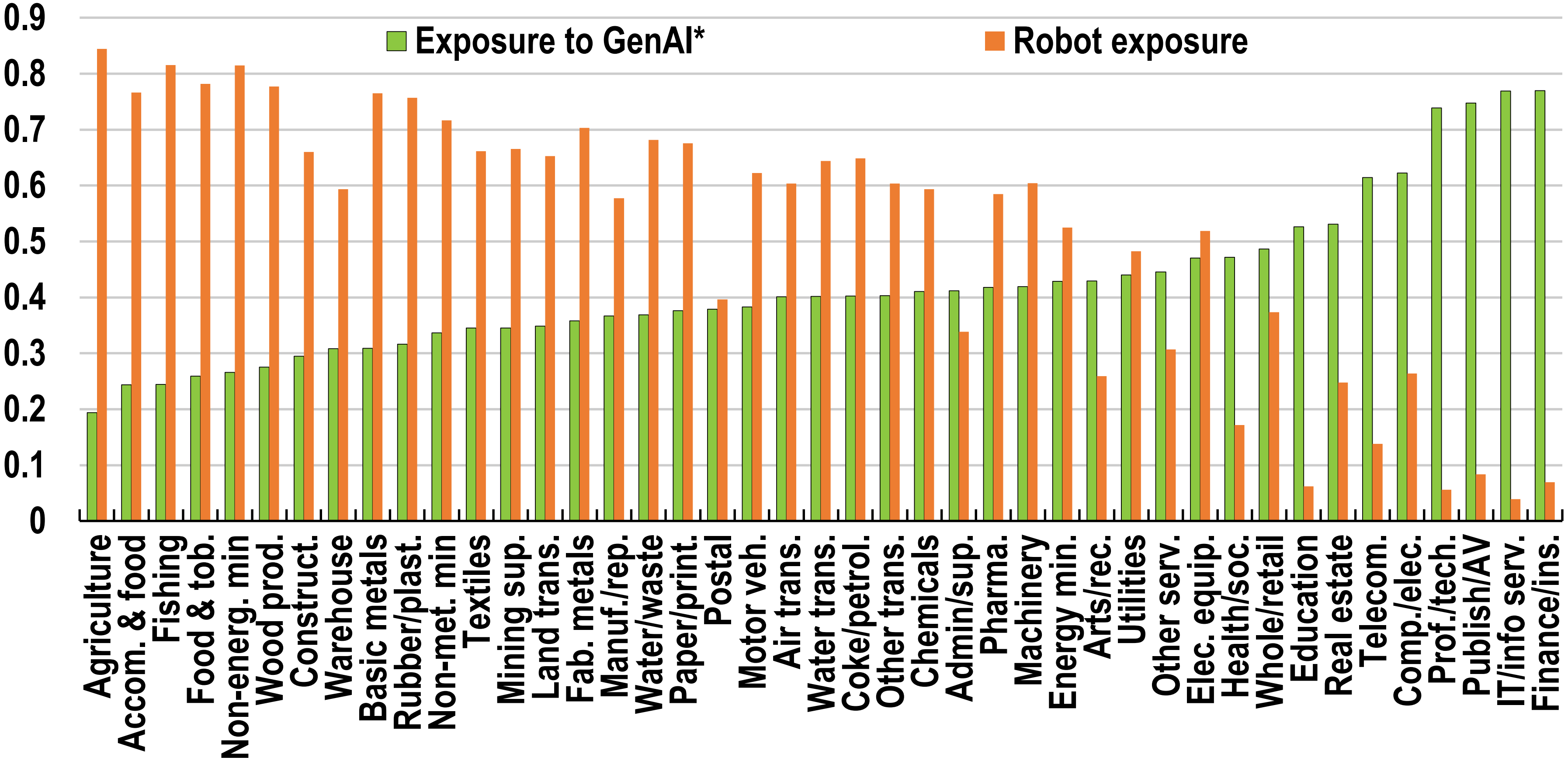


Correlation: .8825269527304795

A comparison of modelling assumptions across a few recent studies and our paper

Key assumptions and modelling choices		Papers: Briggs and Kodnani (2023) (*Goldman Sachs*)	Papers: Acemoglu (2024)	Papers: Bergeaud (2024)	Papers: This paper
I. Overall conceptual framework		Non-model based	Task-based model	Task-based model	Multisector input-output model
II. Assumptions about AI	***Micro-level*** *performance gains / cost savings from AI*	30%	27% labour costs savings	35% labour cost savings	30% productivity gain
	Exposure *to AI*	About two-thirds of all jobs	20% *Based on Eloundou et al, (2024)*	43% *Calculations using Felten et al, (2021)*	12% - 50% (sector specific) *Building on Eloundou et al., (2024)*
	Adoption *rate of AI*	About 50%	23% *Based on cost effectiveness, following Svanberg et al. (2024)*	40% *Based on faster cost effectiveness from Svanberg et al. (2024)*	23% or 40% *Based on previous GPTs adoption speed*
III. Modelling choices related to aggregation	***Reallocation*** *across sectors?*	Partially*	No	No	Yes
	Capital *deepening?*	Unspecified	A multiplier of 1.66	No	A multiplier of 1.5
	Cross-sectoral *links?*	No	No	No	Yes

Figure A.2. Sectoral exposure to Generative AI and robotics technologies



Note: *GenAI denotes the exposure measure based on Eloundou et al. (2024), expanded capabilities (as shown in Figure 3, “Exposure with additional software”; see details there). Robot exposure is obtained by the share of occupations in sectors that are in the upper tercile in terms of routine-manual task intensity, combining Acemoglu and Autor (2011), Autor and Dorn (2013) and following De Vries et al. (2020). Calculations are based on the US task-occupation-sectoral structure.

Figure A.5. The contribution of the Baumol growth disease and reallocation to overall productivity growth in selected countries

Cumulative labour productivity increase relative to the initial year (1995-2005)

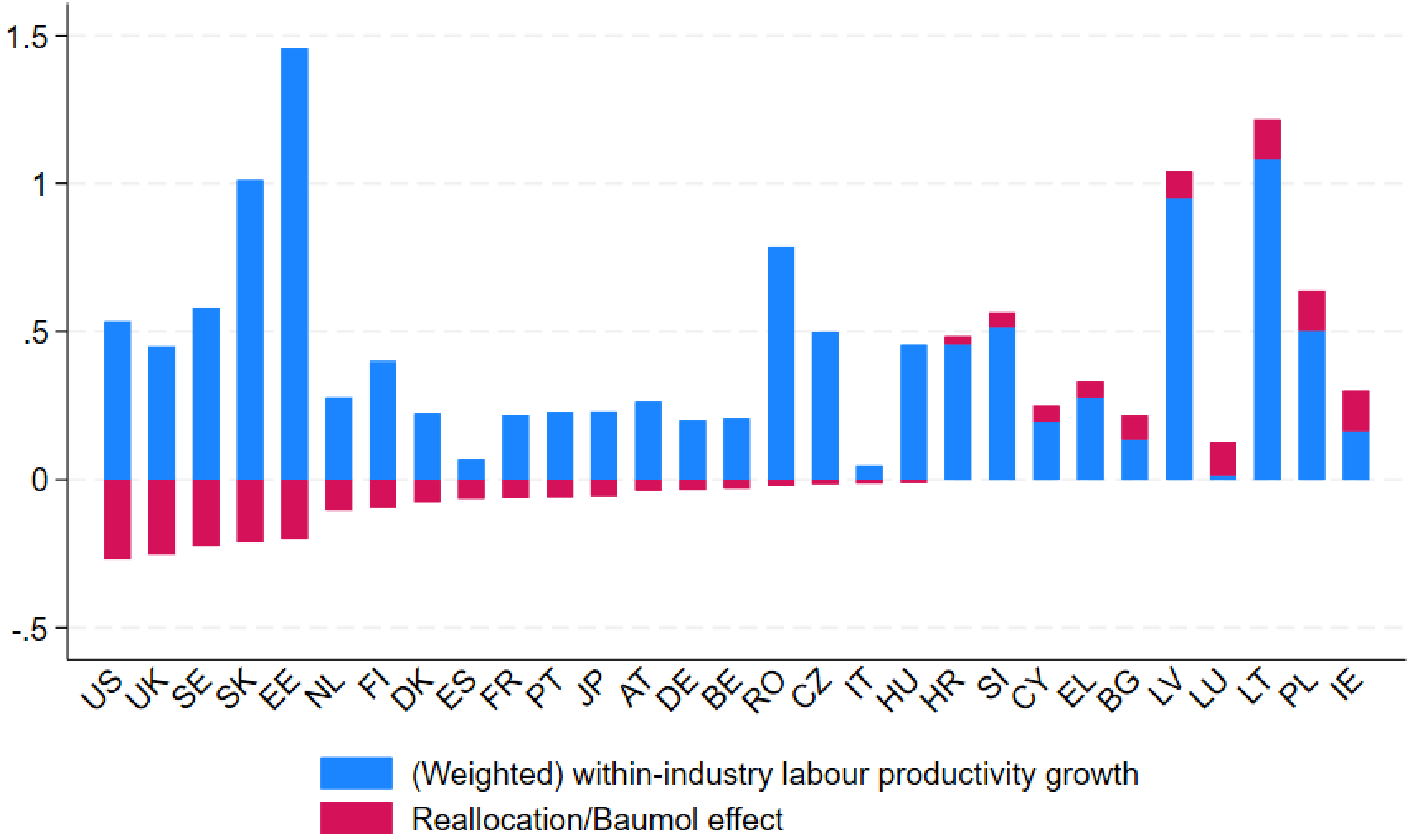
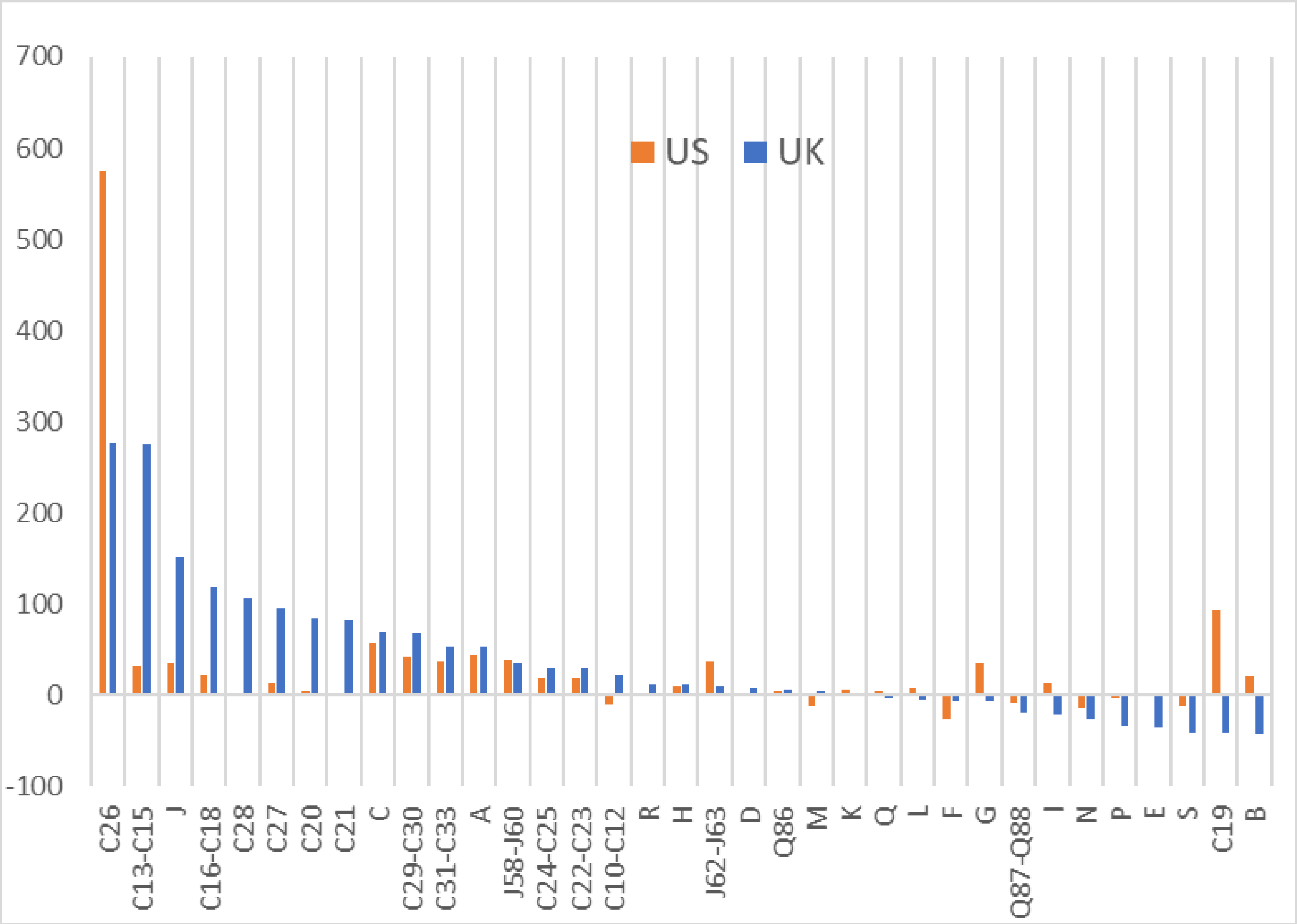
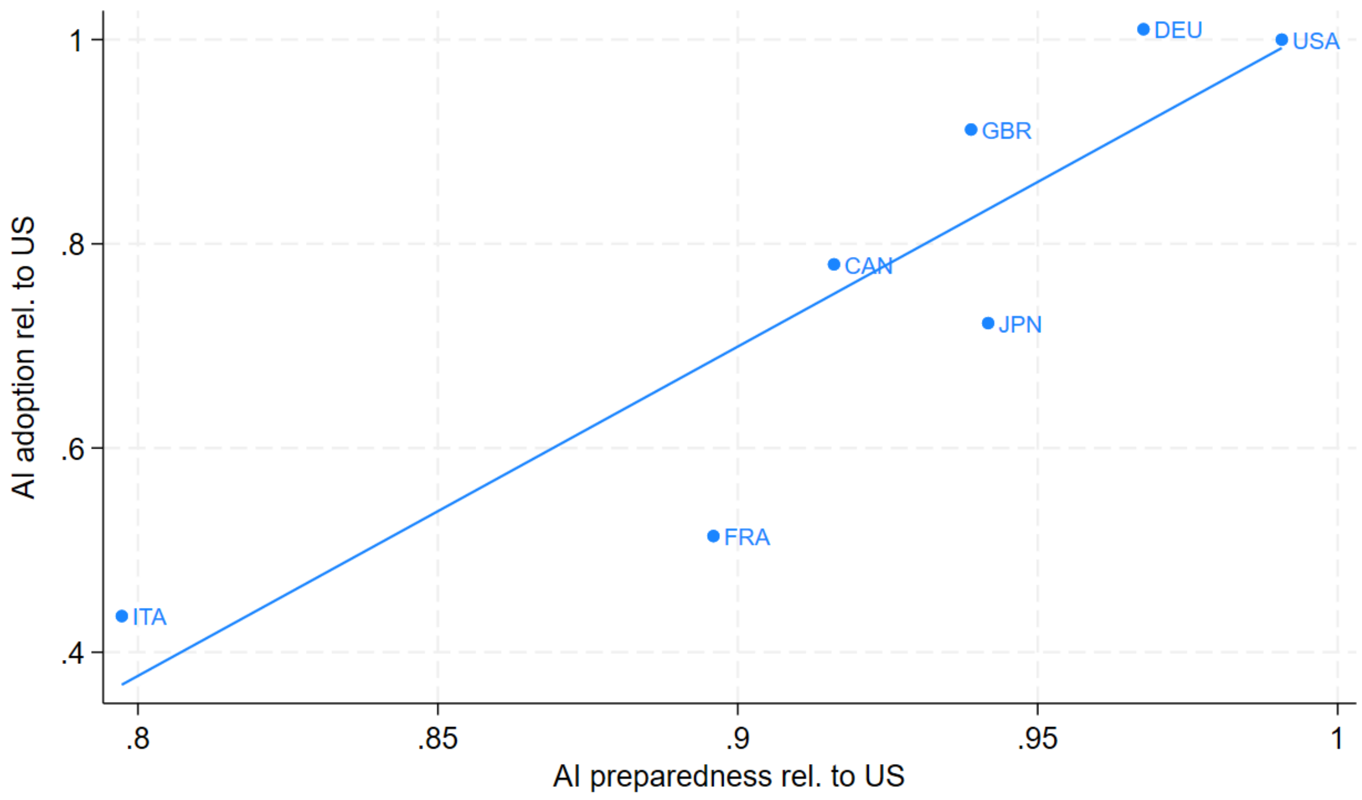


Figure A.4. Sectoral TFP growth during 1995-2005 in the US and UK (in %)



Source: EUKLEMS & INTANProd.

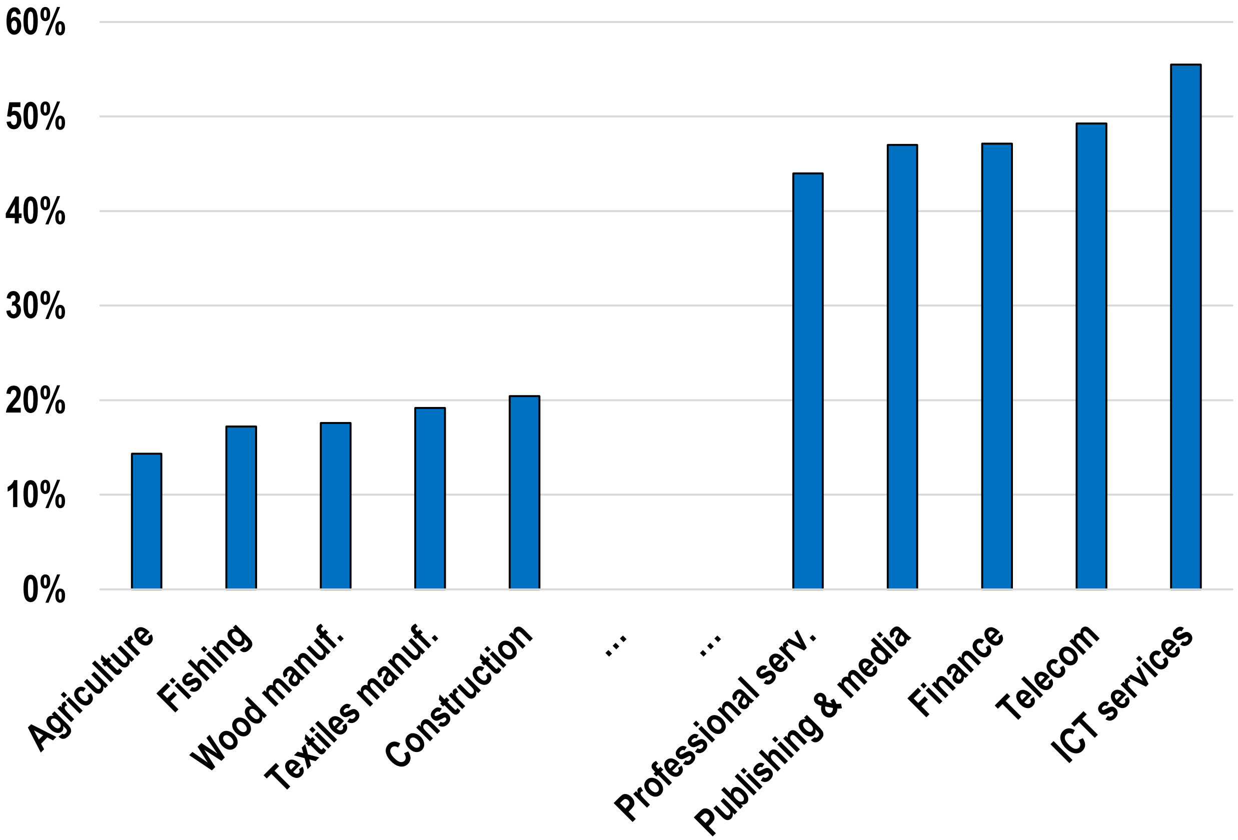
High correlation between predicted future *AI adoption* and current *AI preparedness**



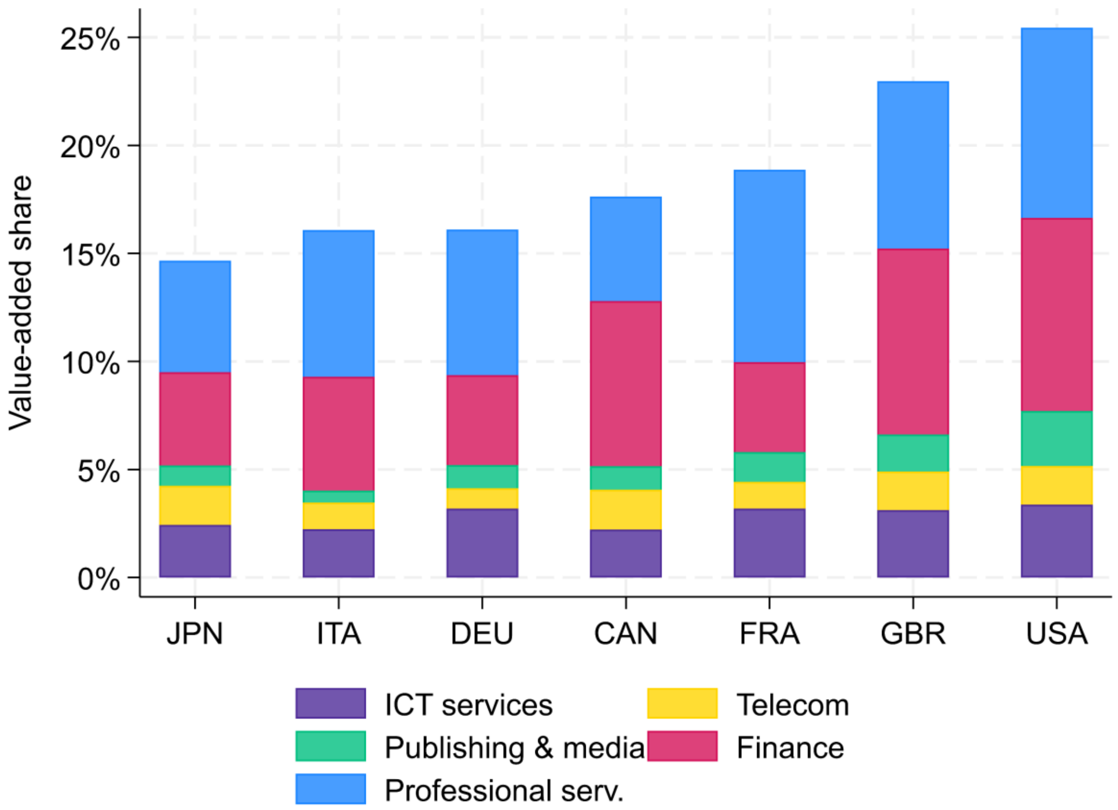
* Source: Cazzaniga et al. (2024)

The size of AI-exposed sectors varies across G7 economies

Share of tasks exposed to AI by sector
Average over G7 economies



GDP-share of the most AI-exposed sectors
(knowledge intensive services)

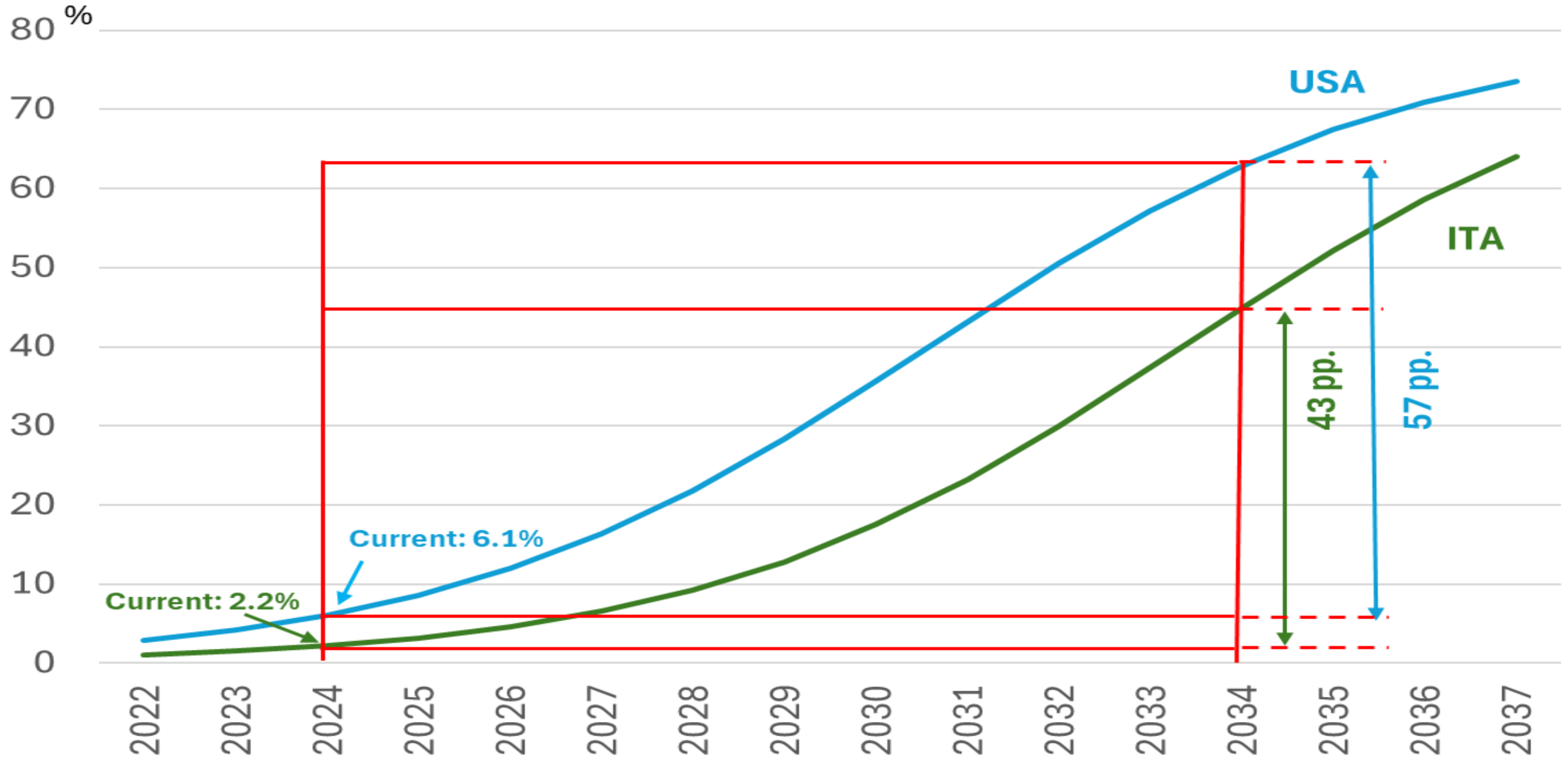


Source: Eloundou et al. (2024, *Science*) aggregated from tasks and occupations to sectors (left panel).
Sectoral value-added data come from OECD Input-Output tables, 2019 (right panel)

Adoption rates differ across countries

Our assumption: AI adoption paths across countries follow a (shifted) logistic function

Projected adoption rates under *fast adoption* speed scenario (similar to mobile phones)



Note: calculations based on the adoption speed of the latest digital technology (mobile phones). Adoption speed is sourced from Tankwa et al (2025).

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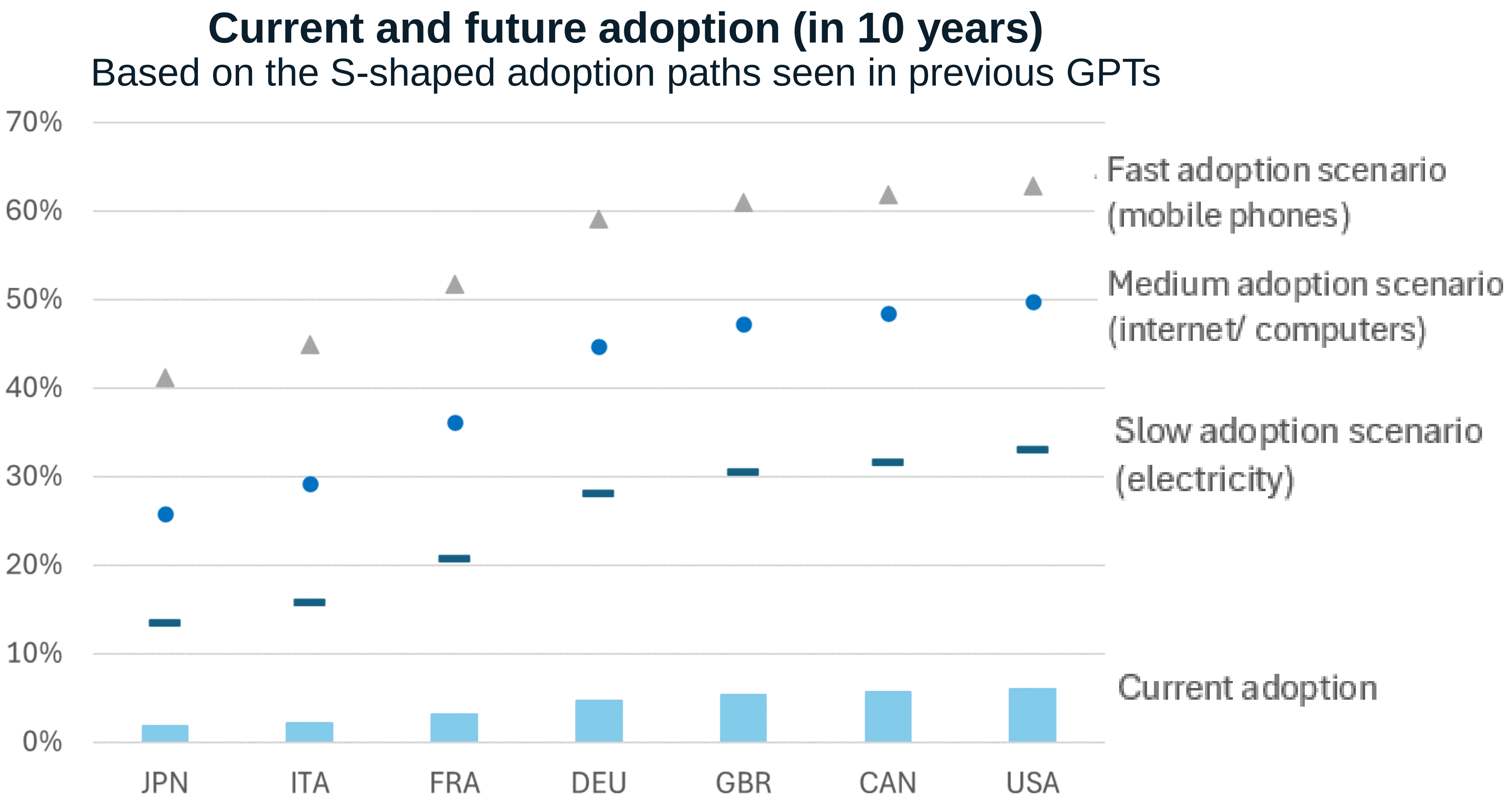
The expected increase in AI adoption varies a lot across countries



Note: current adoption rates are taken from official national statistics after harmonisation steps (CAN, EU, USA) or when this is not possible, using predictions as a function of the digital infrastructure, skills and the sectoral composition (JPN, GBR).