BETTER POLICIES FOR BETTER LIVES

Aggregate Productivity Gains from Artificial Intelligence: a Sectoral Perspective

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Can AI reverse the productivity slowdown?

Long-standing **productivity slowdown** in OECD countries (Fernald et al., 2025)

- Some believe **AI will deliver large aggregate gains** over the next decade (Baily et al., 2023; Briggs and Kodnani, 2023; Aghion and Bunel, 2024) or even in the short run (Bick et al., 2024) $\Rightarrow > +1$ pp. annual TFP growth
- Others argue that current AI affects **too few tasks** (Acemoglu, 2024) $\Rightarrow +0.07$ pp. annual TFP growth

Motivation

Approach often used in the literature: **task-based framework + Hulten's theorem**
$\Rightarrow$ Aggregate industry- or economy-wide gains as the product of

- average task-level gains
- share of tasks that enjoy gains from AI
- share of firms actually adopting AI

Abstracts from changes in the sectoral composition of the economy

This paper

- discusses drivers of AI productivity gains and finds large **sectoral heterogeneity**
- studies aggregate gains in a multi-sector GE framework: gains from AI can be limited by **Baumol disease**

AI task-level gains

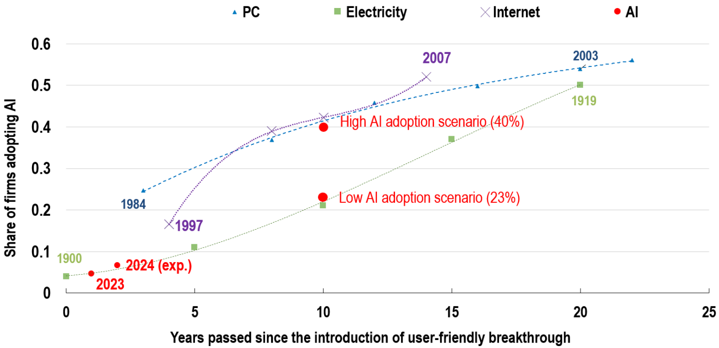
- We interpret task-level performance gains observed in RCTs as **TFP gains**
- We harmonise performance measures:

Paper	**Outcome in the paper**	**Estimate**	**Harmonised effect**
Brynjolfsson et al. (2025)	% increase in output	15%	15%
Peng et al. (2023)	% time saved per task	56%	126%
Noy and Zhang (2023)	% time saved per task	40%	67%
Dell'Acqua et al. (2023)	% increase in output	39%	39%
Haslberger et al. (2023)	% time saved per task	29%	41%
Cui et al. (2024)	% increase in output per task	26%	26%
Gambacorta et al. (2024)	Log increase in output	53%	70%
	Mean % prod. effect	**37%**	**57%**
	– (excl. coding)	**31%**	**41%**

⇒ 30% assumption, quite conservetive

AI exposure and adoption

- **Exposure** from Eloundou et al. (2024):
  - *Automation* exposure (Acemoglu, 2024) (at least 90% of the task autonomously by AI) – **22%**
  - *Baseline* and *expanded* LLM capabilities estimate from the same study – **42% and 68%**
- **Adoption**: benchmarking against past GPTs



A first pass at aggregate gains

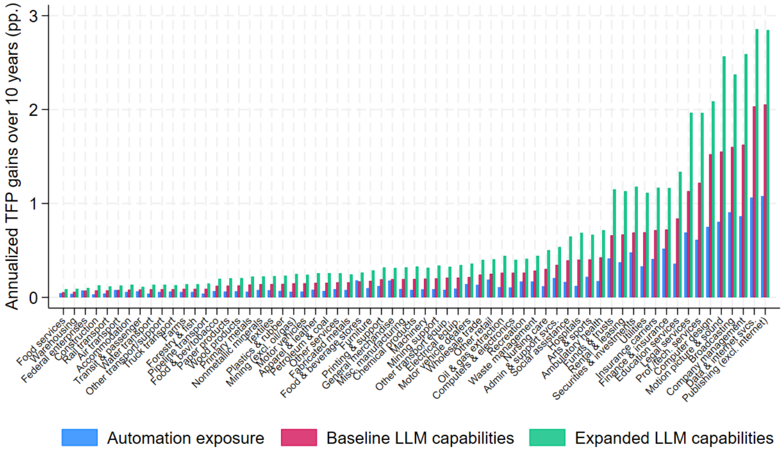
- Based on Hulten's theorem, **first-order aggregate gains** are equal to average task-level gains $\times$ average exposure $\times$ average adoption

Annualized TFP gains from AI over a 10 years horizon (pp.)

	Exposure		
	Automation exposure (22%)	Baseline LLM capabilities (42%)	Expanded LLM capabilities (68%)
Low Adoption (23%)	0.175	0.331	0.527
High Adoption (40%)	0.302	0.570	0.901

However, large sectoral heterogeneity in gains from AI

Annual TFP gains from AI over a 10 years horizon, by industry and different assumption on exposure (pp.)



AI in a multi-sector GE framework

- First-order approximation can be bad if micro gains are large and uneven (Baqaee and Farhi, 2019)
- We use a multi-sector general equilibrium model with input- output linkages
  - Sector's j output is produced combining a single factor and intermediate inputs:

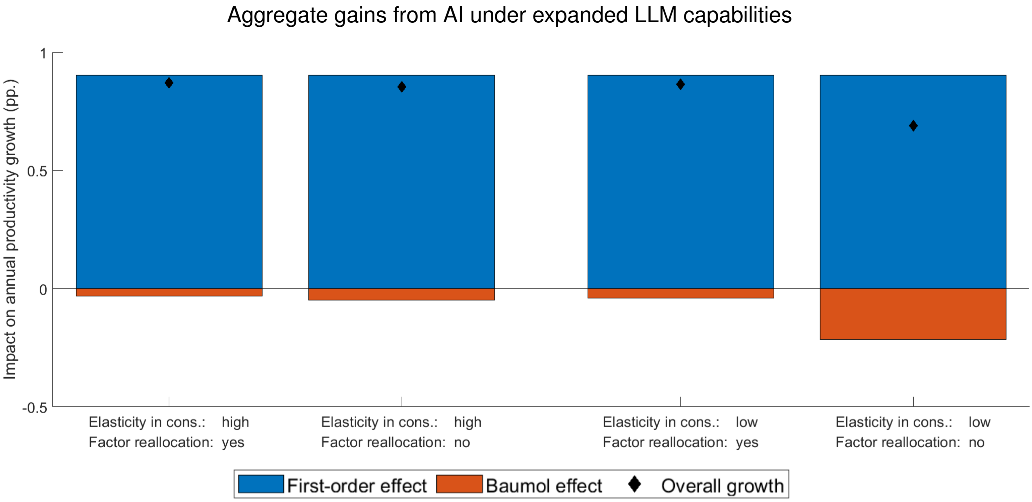
$$y_j = \left(\omega_j (A_j L_j)^{\frac{\theta-1}{\theta}} + (1-\omega_j)\hat{X}_j^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}}, \qquad \text{where} \quad \hat{X}_j = \left(\sum_{k \in J} \gamma_{jk} x_{jk}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$$

  - Final demand is represented by a CES aggregator:

$$Y = \left(\sum_{j \in J} \alpha_j c_j^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

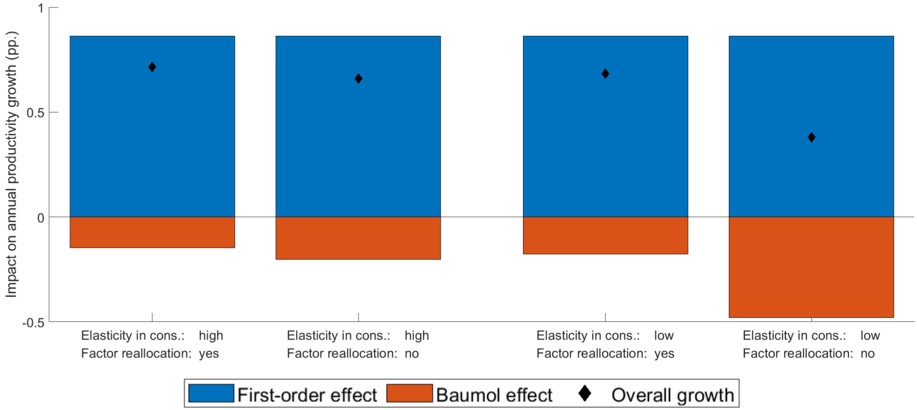
  - Weight parameters $\omega_j, \gamma_{jk}, \alpha_j$ are calibrated on OECD input-output tables
  - Elasticities of substitution between factors and intermediates $\theta = 0.5$, across intermediates $\epsilon = 0.001$, and consumption $\sigma = 0.9$ are from the literature. Low substitutability scenario $\sigma = 0.01$.

Aggregate gains with changes in the sectoral composition



Aggregate gains with very uneven gains across sectors

Extreme scenario: exposed tasks in the 5 most exposed sectors are made 100% more productive thanks to AI
(not so different than what observed in EU KLEMS data during ICT revolution)



Why do reallocation frictions increase the Baumol effect?

Historically, **Baumol effect arises alongside reallocation of production factors** towards low-growth sectors, e.g. from manufacturing to services

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

$$\frac{LP_t - LP_{t-1}}{LP_{t-1}} = \underbrace{\sum_{j \in J} s^{VA}_{j,t-1} \left(\frac{LP_{j,t} - LP_{j,t-1}}{LP_{j,t-1}} \right)}_{\text{Within-industry effect}} + \underbrace{\Delta w_{jt} \frac{LP_{j,t}}{LP_{t-1}}}_{\text{Reallocation effect}} + \underbrace{w_{jt} \Delta p_{jt} \frac{LP_{j,t}}{LP_{t-1}}}_{\text{Valuation effect}}, \tag{1}$$

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

Summary

- Reviewing assumptions on AI task-level gains, adoption and exposure yields **TFP gains in the range of 0.3-0.9 pp.** per year
  - For comparison: gains from ICT were $\approx$ 1-1.5 pp. per year
- **Gains differ strongly across sectors**: below 0.3 pp. for 50% of the economy, 1 pp.-2 pp. for 20% of the economy
- Allowing for change in the sectoral composition of the economy, a **Baumol effect** can limit the aggregate gains from AI, in most extreme scenarios up to 50%
  - The Baumol effect grows when sectoral gains are uneven and elasticity of substitution in consumption is low
  - It is largest without factor reallocation (e.g. in the short-run), due to what we call a *valuation effect*

Appendix

Time savings vs. output gains

Let x=% gain in output

$$y_0 = 1 \qquad y_1 = 1 + x$$

1. **Log change in output**

$$\ln y_1 - \ln y_0 = \ln(1 + x) \approx x$$

2. **Percentage change in output**

$$\frac{y_1 - y_0}{y_0} = x$$

the two are approximately the same, but for large x (1)$<$(2)

Let x=% time savings

$$y_0 = 1 \qquad y_1 = \frac{1}{1 - x}$$

1. **Log change in output**

$$\ln y_1 - \ln y_0 = -\ln(1 - x) \approx x$$

2. **Percentage change in output**

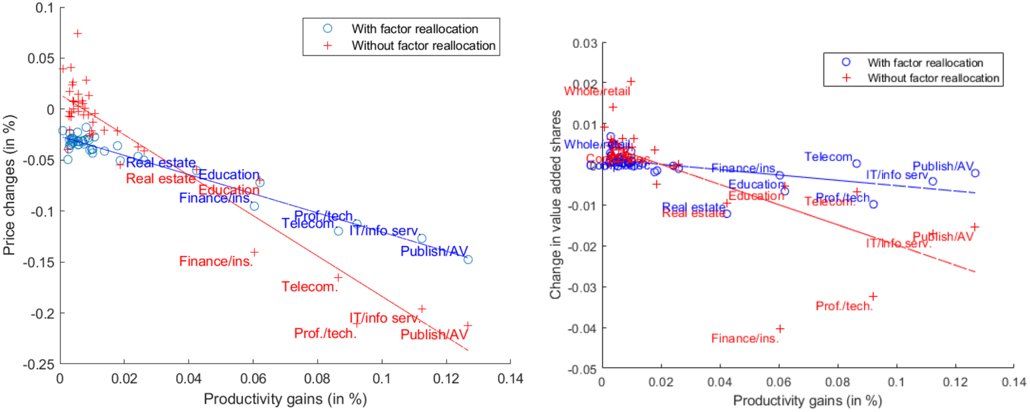
$$\frac{y_1 - y_0}{y_0} = \frac{x}{1 - x}$$

the two are close just for very small x, otherwise (1)$<<$(2)

AI and Baumol’s growth disease, in our model

Without factor reallocation, VA shares of high-growth sectors decline more

Changes in sectoral prices (left), changes in sectoral value-added shares (right) and productivity gains



ICT and Baumol's growth disease, in the data