Aggregate Productivity Gains from AI: a Sectoral Perspective

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Artificial Intelligence (AI) is expanding what machines can do, but opinions diverge on its macroeconomic impact: some see AI as poised to significantly boost productivity (Aghion and Bunel, 2024), while others expect only modest aggregate gains (Acemoglu, 2025). We project AI's contribution to total factor productivity (TFP) growth in 65 US industries over the first 10 years following the introduction of ChatGPT, estimating that it ranges from 0.1 pp annually in manual task intensive activities to 2.8 pp in knowledge intensive services, implying aggregate gains of 0.9 pp per year. We show that sectoral heterogeneity can limit this aggregate gain through a *Baumol effect*, but this effect is quantitatively small as long as elasticities of substitution in consumption are close to one or factors can freely reallocate across sectors.

Our paper contributes to a growing literature on the potential aggregate productivity gains from AI (Acemoglu, 2025; Aghion and Bunel, 2024; Haskel et al., 2025), and to the literature on technology-driven structural change (Nordhaus, 2008; Duernecker, Herrendorf and Valentinyi, 2024). In particular, we are the first to assess whether Baumol's growth disease, as emphasized in Aghion, Jones and Jones (2017), could significantly limit AI-driven aggregate productivity growth over the next decade.

I. Productivity gains from AI in 65 US industries

We leverage Hulten's theorem to project *sectoral* productivity gains from AI. Specifically, we build on the approach of Acemoglu (2025) and project sector-level gains from AI as

$$\Delta \log A_j = \pi \cdot (VA_j^{exp}/VA_j) \cdot ado_j, \tag{1}$$

where π is the average task-level gain from using AI in an AI-exposed task, VA_j is total value-added in sector j, VA_j^{exp} is the value-added of AI-exposed tasks in sector j, and ado_j is the AI adoption rate in sector j in ten years time. In what follows, we will discuss what we consider to be reasonable values for the terms on the right-hand side of Equation 1 and, where appropriate, will contrast them with the values chosen in Acemoglu (2025).

For task-level productivity gains, we assume $\pi = 30\%$ based on a review of empirical studies (see Tables 1 and 2 in the Supplemental Appendix).[1] We interpret these studies as documenting TFP gains since AI seems to increase the joint productivity of workers and capital in a given task. For example, the time savings from using AI for writing tasks imply not only reduced worker time but also reduced

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[1] 30% is a conservative estimate of the typical AI-driven productivity gains found in the literature. Some studies report time savings, which prior work has interpreted as output gains, using log-approximations, which understate the true productivity gains when time savings are large. For example, Noy and Zhang (2023) find a 40% reduction in writing time, which previous papers interpret as a 40% productivity gain, whereas the productivity gain measured as percentage increase in output per unit of time is $1/(1-40\%) = 67\%$.

use of office space and equipment per completed task.[2] In comparison, Acemoglu (2025) assumes that AI-generated productivity gains imply exclusively labor cost savings and thus downscales the estimates in the literature by the labor share in the economy.

Turning to AI exposure, we estimate each sector's value-added share of tasks that can potentially benefit from AI, VA_j^{exp}/VA_j. We rely on estimates in Eloundou et al. (2024), which assess whether a given O*NET task can be completed at least 50% faster with the help of a large language model (LLM) together with complementary software.[3] In contrast, Acemoglu (2025) relies on a significantly more conservative "automation index" from the Online Appendix of Eloundou et al. (2024), which considers a task not exposed to AI unless 90% of its subtasks can be autonomously performed by LLMs. We aggregate task-level exposure to occupations using O*NET task composition, then to detailed industries using occupational composition from BLS and weighting by wage-bill, and to 65 sectors of BEA Input-Output tables weighting detailed industries by their value-added shares.[4]

Finally, for AI adoption rates, we follow Filippucci, Gal and Schief (2024) and base our projections on the diffusion path of recent digital general-purpose technologies. Specifically, we assume that AI reaches an economy-wide adoption rate of 40% in AI-exposed tasks within ten years, which corresponds to the pace at which the personal computer and the internet were adopted by firms, respectively. In comparison, Acemoglu (2025) assumes an adoption rate of 23%, based on estimates of the current cost-effectiveness of computer vision in Svanberg et al. (2024). As we note in Filippucci, Gal and Schief (2024), an adoption rate of 23% within ten years roughly matches the comparatively slower diffusion of electricity following the introduction of the electric motor.

We also allow AI adoption to vary across sectors. Data from the US Census Business Trends Outlook Survey (BTOS) suggest that in 2024-Q3 the share of businesses using AI to produce goods and services varied from 18% in the Information sector to 1.5% in Transportation. Industries more exposed to AI currently report higher adoption, possibly reflecting stronger incentives for more exposed firms to adopt earlier. Assuming relative differences across sectors will persist over our horizon, we model $ado_j = 40\% \cdot \eta_j$, where η_j is current adoption in sector j relative to the aggregate.[5]

Figure I shows the projected annual contribution of AI to TFP growth over the next decade in 65 industries. AI-driven TFP gains vary considerably across sectors, ranging from 0.1 pp in manual activities (agriculture, fishing, mining) to 2.8 pp in knowledge-intensive services (ICT services, finance, professional services). Variation across sectors is driven by uneven exposure and adoption, with positive correlation between sectoral exposure and adoption increasing both the variance across sectors and the aggregate TFP gain.[6] Pronounced sectoral disparities in productivity gains are not unprecedented. In the 1996–2005 period - often referred to as the ICT-boom in the US - some sectors

[2] In support of this interpretation the US Census BTOS finds that at the beginning of 2024 three-fourth of firms using AI for "tasks previously done by employees" also use AI for "operations previously performed by existing equipment or software".

[3] Eloundou et al. (2024) also provide a measure of exposure to LLMs without any additional software, but the availability of complementary software is realistic given our projection horizon of ten years. In addition, the AI-exposure measures in Eloundou et al. (2024) can be seen as conservative as they require time savings of 50%, whereas our assumed task-level gains are only half as large.

[4] These are sectors in the "summary" tables, excluding Housing, Used Goods and government sectors (except federal enterprises).

[5] The divergence in the early years may at some point give way to convergence, as high-adoption sectors reach full adoption and laggards keep progressing. Since we don't project full adoption within our horizon, relative dispersion in 10 years may thus resemble today's. Data are from US Census BTOS between June and September 2024. We take adoption rate of agriculture from the more detailed US BTOS AI supplement between December and February 2024, and augment it by the same percentage increase as the whole economy. We impute the utility sector based on the correlation between other sectors' adoption and AI exposure.

[6] By a similar argument, Equation 1 may underestimate the sector-level productivity gains from AI if firm-level adoption is positively correlated with firm-level exposure *within* an industry. In this sense, ours is a conservative projection.

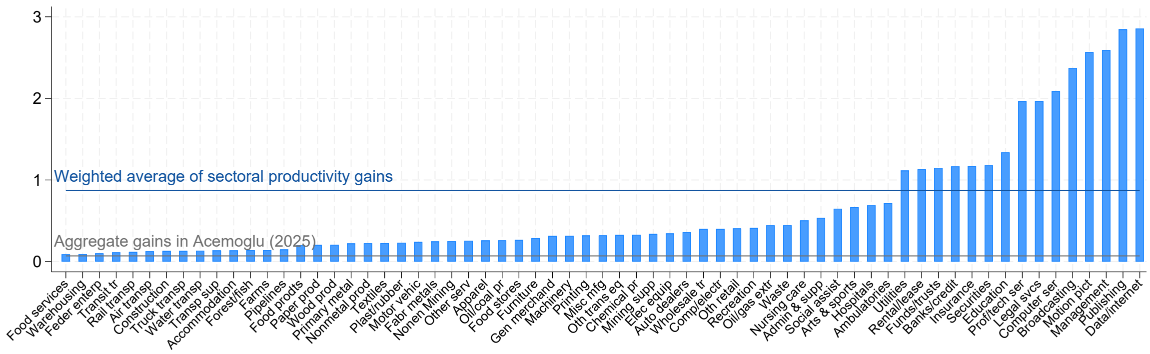

FIGURE 1. ANNUALIZED CONTRIBUTION OF AI TO TFP GROWTH OVER A 10 YEARS HORIZON, BY INDUSTRY (PP.)

Note: Sectoral estimates assume 30% task-level productivity gains, sectoral exposure from Eloundou et al. (2024) (60% in the aggregate), and aggregate adoption at 40% varying across sectors proportionally to current adoption rates in US BTOS. Acemoglu (2025) assumes 14.4% task-level gains; 20% exposure based on the "automation index" of Eloundou et al. (2024); and 23% adoption.

experienced several-fold increases in productivity, with others seeing only marginal improvements (Filippucci, Gal and Schief, 2024). Aggregating sectoral TFP gains at current value-added shares implies an aggregate annual contribution of AI to TFP growth of .87 pp, significantly higher than the one expected by Acemoglu (2025) (.06 pp). The combination of moderately more optimistic and compounding assumptions on task-level gains, exposure, and adoption relative to Acemoglu (2025), and accounting for faster adoption in more AI exposed sectors, result in much larger aggregate gains.[7]

II. Aggregate productivity gains from AI under uneven sectoral growth and structural change

Uneven productivity gains from AI across sectors may affect the structure of the economy in important ways, especially if there is limited willingness to substitute consumption of output from sectors with modest AI-driven productivity gains for consumption of output from AI-boosted sectors. In this case, a growing fraction of income will be spent on the relatively scarce and expensive output of the less AI-exposed sectors, which will expand as a share of GDP. The aggregate gains from AI will then be smaller than the average sectoral productivity gains in Figure I, weighted by their *current* value-added shares, and aggregate growth would be reduced by a *Baumol effect* (Nordhaus, 2008).[8] To account for this possibility, we re-assess the aggregate gains from AI using a calibrated multi-sector general equilibrium model, featuring input-output linkages and allowing for AI-induced changes in sectoral prices and quantities. In each sector j, gross output is produced by combining a single factor, L_j, representing both labor and capital[9], and a composite of intermediate inputs, $\hat{X}_j$, according to

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

[7]A similar argument is made in (Aghion and Bunel, 2024) who also find gains of comparable magnitude to our estimates.

[8]Using Hulten's theorem to derive aggregate gains, as done in the previous literature, ignores the potential Baumol effect.

[9]We therefore avoid distinguishing between labor- or capital-augmenting AI gains. Whether productivity gains reduce employment in a sector depends on the output from that sector demanded in equilibrium.

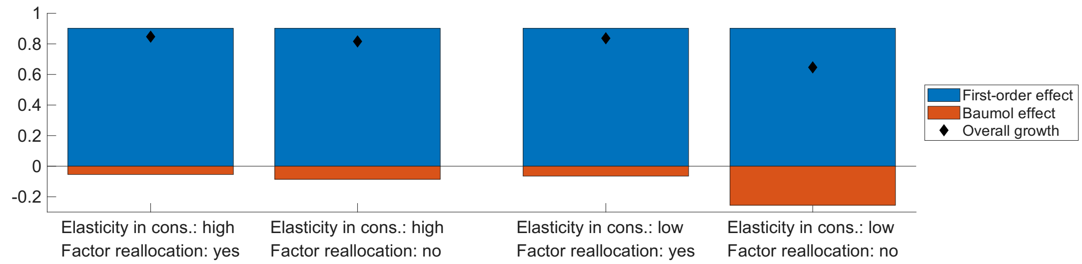

FIGURE 2. AGGREGATE TFP GAINS FROM AI OVER A 10 YEARS HORIZON, BY INDUSTRY (ANNUALIZED, PP.)

Note: The first and second columns assume an elasticity of substitution in consumption of 0.9, while the last two columns assume an elasticity of 0.01. The first and third columns assume that factors of production can freely reallocate across sectors, while the second and fourth column do not allow for sectoral reallocation of factors.

where A_j denotes the level of (factor-augmenting) productivity in sector j, x_{jk} is output from (upstream) sector k used by (downstream) sector j as intermediate input, ω_j and γ_{jk} are weight parameters, θ is the elasticity of substitution between factors and intermediate inputs, and ε is the elasticity of substitution across intermediates. Final demand Y is represented by a constant elasticity of substitution aggregator over sectoral final consumption, $Y = \left(\sum_{j\in J} \alpha_j c_j^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$, where α_j are weight parameters and σ is the elasticity of substitution across final consumption outputs. Sectoral productivity gains, shown in Figure I, enter the model as positive shocks to A_j.[10]

We set $\theta = .5$ and $\varepsilon = .001$, following estimates in the literature, and we consider different illustrative scenarios for the elasticity of substitution in consumption, $\sigma = \{0.9, 0.01\}$. The low elasticity case corresponds to an extreme scenario in which relative sectoral demand responds very little to changes in relative output prices and the economy is therefore most prone to a large Baumol effect. We calibrate all weight parameters in the model on observed sectoral factor shares, value-added shares, and input-output tables. Finally, adjustment frictions that hinder the reallocation of capital and labor across sectors may also be relevant. We study the relationship between reallocation frictions and the Baumol effect by shutting down sectoral factor reallocation in a subset of scenarios.

Figure 2 shows the results, revealing that the Baumol effect is small not only when the elasticity of substitution in consumption is relatively high (the first and second bar), but also in the third scenario where preferences across sectoral outputs are almost Leontief. This may appear surprising, since under Leontief preferences increased output in only a subset of sectors has no value. The Baumol effect is instead significant (about a quarter of the aggregate gains implied by Hulten's theorem) when factor reallocation is limited and the elasticity of substitution in consumption is low.

The intuition behind these result reveals a key insight on the role of factor mobility in Baumol's growth disease: factor reallocation *from sectors with strong productivity gains to sectors with limited productivity gains* can raise aggregate productivity growth by "reinforcing weak links" (Baqaee and

[10]Our model builds on Baqaee and Farhi (2019) but models factor-augmenting TFP gains rather than changes in the joint productivity of factors and intermediate inputs. This is consistent with the notion that AI may lead to a smaller increase in gross output in sectors where intermediate inputs play a more important role in the production process. For instance, one may expect that integrating AI in car manufacturing can improve the efficiency with which workers and assembly line machinery (i.e. labor and capital) assemble components (intermediate inputs) but that AI does not allow to assemble more cars from the same amount of components.

Farhi, 2019). Productivity improvements free up labor and capital in the AI-boosted sector, which can then be redeployed toward sectors that experience smaller productivity gains but produce goods and services that consumers value. Preventing such reallocation of factors (as in the fourth scenario) would force the economy to "overproduce" AI-exposed goods, with detrimental implications for aggregate productivity through adjustments in relative sectoral output prices. Relative output prices in AI-boosted sectors would need to decrease more strongly to clear markets, causing nominal GDP share of less AI-boosted sectors to expand more than under efficient factor reallocation, which in turn amplifies the Baumol effect and reduces aggregate productivity growth.[11]

III. Conclusion

This paper examines the potential productivity gains from AI over its first decade, highlighting that they vary significantly across sectors. Extreme concentration in sectoral productivity gains, as sometimes discussed in the context of AI, can limit aggregate growth through a Baumol effect. Yet, we show that even the substantial variation in sectoral productivity gains that we document in this paper does not generate a large Baumol effect as long as consumption elasticities of substitution are close to one or factors can freely reallocate across sectors.

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[11] The dependence of aggregate productivity growth on sectoral output prices can be illustrated in a decomposition of aggregate labor productivity growth: $\frac{LP_t - LP_{t-1}}{LP_{t-1}} = \underbrace{\sum_{j \in J} s^{VA}_{j,t-1} \left(\frac{LP_{j,t} - LP_{j,t-1}}{LP_{j,t-1}} \right)}_{\text{Within-industry effect}} + \underbrace{\sum_{j \in J} \Delta s^L_{j,t} \frac{LP_{j,t}}{LP_{t-1}}}_{\text{Reallocation effect}} + \underbrace{\sum_{j \in J} s^L_{j,t} \Delta p_{j,t} \frac{LP_{j,t}}{LP_{t-1}}}_{\text{Valuation effect}}$, where $s^{VA}_{j,t-1}$ is sector j's last period value-added share, $s^L_{j,t}$ is sector j's employment share, $p_{j,t}$ is sector j's relative output price, and last period's prices are normalized to unity. In historical data, the reallocation and valuation effects tend to be negative. In the Supplemental Appendix, we present the derivation of this decomposition formula. We also show that by limiting labor reallocation, the implied decrease in the valuation effect more than offsets the increase in the reallocation effect, resulting in lower aggregate labor productivity growth.