Supplemental Appendix to "Aggregate Productivity Gains from AI: a Sectoral Perspective"

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I. Task-level productivity gains

To inform our assumption of the average task-level productivity gain in AI-exposed tasks, π, we review seven studies employing credible experimental or quasi-experimental methods, covering a range of different tasks, across the US, Europe, and Asia. Table 1 summarizes the documented productivity effects while Table 2 provides additional details on the studies considered. On average, the reported estimates indicate a 37% improvement in productivity attributable to AI use, measured either as a reduction in time required to complete a given task or as an increase in output, sometimes reported log changes. We note that several of the studies with the largest estimated effects focus specifically on coding tasks, which tend to show the highest gains but also estimate them with low precision. To address potential concerns about external validity, we also compute an average excluding coding-focused studies, obtaining an average of 31% productivity gains.

To project the aggregate gains from AI, we assume that the average potential productivity improvements in AI-exposed tasks is 30%. This number is close to the average gains excluding coding in Table 1, and also to the assumed task-level gains of Acemoglu (2025). We see this assumption as relatively conservative. One reason is explored in the last column of Table 1, where we report the *harmonised* estimates of productivity gains implied by different studies, translating measures of time-saving into measures of increased output per unit of input. We note that, for instance, Brynjolfsson, Li and Raymond (2025) report a 15% increase in the number of customer service tasks completed per hour (i.e. a % increase in output) while others such as Noy and Zhang (2023) find a 40% reduction in the completion time of writing tasks. Previous papers interpreted these estimates as equivalently corresponding to a 15% and 40% increase in productivity (Acemoglu, 2025; Aghion and Bunel, 2024), based on a log-approximation.[1] Yet, this approximation underestimates productivity gains for larger time savings. For example, a 40% reduction in completion time corresponds to a $1/(1-40\%) = 67\%$ increase in the number of tasks completed per hour. For consistency, we also harmonize log changes reported in Gambacorta et al. (2024) into non-approximated % changes. Harmonized effects are often much higher and entail average task-level productivity gains around 50%.[2]

[1] If a study estimates *%time saved* per task, the log change in task-level output is $-\ln(1-\%time\,saved) \approx \%time\,saved$.

[2] A further reason why our assumption 30% task-level gains assuption may be conservative is that many studies also report AI-driven increases in the quality of output on top of time-savings, which could further increase the implied productivity gains (Haslberger, Gingrich and Bhatia, 2023; Noy and Zhang, 2023). Gains can also rise in the future as AI models become more powerful (Merali, 2024).

TABLE 1—SUMMARY OF MICRO ESTIMATES OF AI PRODUCTIVITY GAINS

Paper	Outcome in the paper	Estimate	SE	Harm. effect
Brynjolfsson et al. (2025)	% increase in output	15%	0.015	15%
Peng et al. (2023)	% time saved per task	56%	0.169	126%
Noy and Zhang (2023)	% time saved per task	40%	0.051	67%
Dell'Acqua et al. (2023)	% increase in output	39%	0.019	39%
Haslberger et al. (2023)	% time saved per task	29%	0.032	41%
Cui et al. (2024)	% increase in output per task	26%	0.103	26%
Gambacorta et al. (2024)	Log increase in output	53%	0.078	70%
	Mean % prod. effect	**37%**		**57%**
	– (excl. coding)	**31%**		**41%**

Notes: The table summarizes the estimates of micro-level (task-level) productivity gains from AI, as reported in the existing literature. The third and fourth column report the original estimate in the respective papers, expressed either as a %increase in output per unit of time or as % time savings per task. The last column reports the harmonized % productivity effects, defined as the % increase in output. Whenever the original studies report estimates of time savings, the harmonized productivity effects is computed as $\frac{1}{1-(time\,saved)}$. When the original studies report log changes, the harmonized estimate is obtained taking the exponential of the original one minus one. The last line excludes the studies focusing on coding tasks, namely Peng et al. (2023), Cui et al. (2024) and Gambacorta et al. (2024). Standard errors of % productivity effects are approximations given estimates in the original papers. The estimates from Dell'Acqua et al. (2023) are effects on the quality of the responses for the experimental task inside the AI frontier. The estimates from Haslberger, Gingrich and Bhatia (2023) is the median among the different writing tasks covered in the study, from an email writing task.

TABLE 2—SUMMARY OF CHARACTERISTICS OF STUDIES ESTIMATING AI PRODUCTIVITY GAINS

Paper	Time of exp.	Treatment	Sample	Task	Method
Brynjolfsson et al. (2025)	2020-2021	AI-based assistant	Call centers employees, mostly Philippines	Customer service	RCT
Peng et al. (2023)	Jun-22	GitHub Copilot	Software developers from US firm Upwork	Coding	RCT
Noy and Zhang (2023)	2022	ChatGPT	College-educated professionals, US	Professional writing	Online RCT
Dell'Acqua et al. (2023)	2023	ChatGPT-4 & prompt eng.	Consultants, US	Business consulting	RCT
Haslberger et al. (2023)	2023	ChatGPT	Working-age population, UK	Email writing, text assessment and comprehension	Online RCT
Cui et al. (2024)	Sep. 2022- Dec. 2023	GitHub Copilot	Workers at Microsoft (US), Accenture (SE Asia), and unknown firm	Coding	RCT
Gambacorta et al. (2024)	Sep. - Oct. 2023	CodeFuse	Workers at Ant Group, China	Coding	DID

Notes. DID refers to Difference-in-Differences, and RCT refers to Randomized Controlled Trial. Online RCT indicates that the experiment was conducted via an online platform rather than in a controlled physical setting.

II. A decomposition of aggregate labor productivity growth

Under constant prices, aggregate labor productivity growth can be decomposed into the sum of two terms, a *within-industry effect* and a *labor reallocation effect*,

$$\underbrace{\frac{LP_t - LP_{t-1}}{LP_{t-1}}}_{\text{Aggregate productivity growth}} = \underbrace{\sum_{j\in J} s^{VA}_{j,t-1}\left(\frac{LP_{j,t}-LP_{j,t-1}}{LP_{j,0}}\right)}_{\text{Within-industry effect}} + \underbrace{\sum_{j\in J}\Delta w_{jt}\frac{LP_{j,t}}{LP_{t-1}}}_{\text{Reallocation effect}}, \tag{1}$$

where LP_t is aggregate labor productivity at time t, $LP_{j,t}$ is labor productivity in sector j at time t, $s^{VA}_{j,t-1}$ is sector j's last period share in total value added, and $\Delta w_{j,t}$ is the change in sector j's employment share. The within-industry effect is a weighted sum of labor productivity growth in each sector. The labor reallocation term depends on how labor moves across sectors with different rates of productivity growth and tends to be negative in historical data.[3]

Given the decomposition in equation (1), it appears that labor moving from high to low-growth sectors should slow aggregate productivity growth. Conversely, preventing labor from moving to low growth sectors should benefit aggregate productivity growth as it eliminates the negative reallocation term in the above formula. Such a conclusion is puzzling, however, since introducing frictions to prevent labor from moving between sectors should harm rather than support productivity growth.[4] The key to resolving this apparent puzzle is to recognize that aggregate productivity growth also depends on changes in relative prices, which the above formula omits.

Productivity growth is the difference between the growth rate in the volume of output and the growth rate of an appropriate index of the production inputs.[5] If the output under consideration is a homogeneous good, then the *volume* of output can be defined in terms of quantities and is independent of prices.[6] In contrast, at the economy-wide level output is by definition composed of many different types of goods and services, which need to be converted into their respective monetary values so that they can be compared and summed up. As a consequence, changes in the volume of aggregate output cannot be derived by directly adding up changes in the volume of the different components. Doing so would introduce a substitution bias as the composition of aggregate output can change if movements in relative prices induce agents to adjust their expenditure patterns.

[3] The reallocation effect in (1) can be further decomposed into a static reallocation effect capturing movements of factors between sectors with different productivity *levels*, and a dynamic reallocation effect capturing movements of factors between sectors with different productivity *growth rates*. See, for example, the *OECD* (OECD, 2024) or the *European Commission* (European Commission, 2024). The static reallocation term is sometimes also called the 'Denison effect', while the dynamic term is usually associated with the Baumol effect. Since we are interested in the Baumol effect, we will frame our discussion in terms of factor reallocation between high and low-growth sectors rather than between sectors with different productivity levels. We also note that in a competitive economy, the true Denison effect would be zero, and that estimates of non-zero Denison effects can be an artifact of focusing on sectoral differences in the level of *labor* productivity (rather than total factor productivity), which does not account for differences in other inputs, such as physical and human capital (Nordhaus, 2001).

[4] The idea that aggregate productivity cannot be improved by introducing frictions that prevent factors from reallocating towards sectors with lower productivity growth is self-evident in models where equilibrium is efficient by construction. However, reallocation of factors towards lower productivity sectors can also improve aggregate productivity in models with endogenous technological progress and imperfect competition (Herrendorf and Valentinyi, 2022).

[5] Much of the literature on productivity estimation revolves around the question of how to correctly measure the combined quantity of inputs of different types (most prominently, labor and capital).

[6] In practice, accounting for quality improvements may still require construction of an appropriate price deflator

More formally, following Tang and Wang (2004), the relationship between aggregate nominal value added per worker and sectoral nominal value added per worker can be written as follows:

$$\frac{P_t Y_t}{L_t} = \sum_{j \in J} \underbrace{\frac{L_{j,t}}{L_t}}_{\text{Sector } j\text{'s employment share}} \times \underbrace{\frac{P_{j,t} Y_{j,t}}{L_{j,t}}}_{\text{Sector } j\text{'s value added per worker}}$$

where P is the aggregate price index, Y is aggregate real output, L is labor, and P_j and Y_j are the respective output price and real output of sector j. To obtain the relationship between aggregate real labor productivity ($LP = \frac{Y}{L}$) and sectoral real labor productivity ($LP_j = \frac{Y_j}{L_j}$), we divide by the aggregate price index to get:

$$LP_t = \sum_{j \in J} \underbrace{\frac{P_{j,t}}{P_t}}_{\text{Sector } j\text{'s relative output price}} \times \underbrace{\frac{L_{j,t}}{L_t}}_{\text{Sector } j\text{'s employment share}} \times LP_{j,t}$$

Hence, aggregate real labor productivity growth depends on changes in sectoral real labor productivity as well as on changes in the sectors' employment shares, L_{jt}/L_t, and relative output prices, P_{jt}/P_t. In particular, for given sectoral labor productivity growth rates, aggregate labor productivity growth will be diminished to the extent that sectors with high productivity growth see their relative output price and employment share decline relative to sectors with low productivity growth.

Re-arranging terms and normalizing last period's prices to one, we can write

$$\begin{aligned}
&\frac{LP_t - LP_{t-1}}{LP_{t-1}} \\
&= \frac{1}{LP_{t-1}} \sum_{j \in J} \left[\frac{P_{j,t}}{P_t} \frac{L_{j,t}}{L_t} LP_{j,t} - \frac{P_{j,t-1}}{P_{t-1}} \frac{L_{j,t-1}}{L_{t-1}} LP_{j,t-1} \right] \\
&= \frac{1}{LP_{t-1}} \sum_{j \in J} \left[\frac{P_{j,t-1}}{P_{t-1}} \frac{L_{j,t-1}}{L_{t-1}} \left(LP_{j,t} - LP_{j,t-1} \right) + \left(\frac{P_{j,t}}{P_t} \frac{L_{j,t}}{L_t} - \frac{P_{j,t-1}}{P_{t-1}} \frac{L_{j,t-1}}{L_{t-1}} \right) LP_{j,t} \right] \\
&= \sum_{j \in J} \left[\frac{LP_{j,t-1}}{LP_{t-1}} \frac{P_{j,t-1}}{P_{t-1}} \frac{L_{j,t-1}}{L_{t-1}} \left(\frac{LP_{j,t} - LP_{j,t-1}}{LP_{j,t-1}} \right) + \left(\frac{P_{j,t}}{P_t} \frac{L_{j,t}}{L_t} - \frac{P_{j,t-1}}{P_{t-1}} \frac{L_{j,t-1}}{L_{t-1}} \right) \frac{LP_{j,t}}{LP_{t-1}} \right] \\
&= \sum_{j \in J} \left[\frac{P_{j,t-1} Y_{j,t-1}}{P_{t-1} Y_{t-1}} \left(\frac{LP_{j,t} - LP_{j,t-1}}{LP_{j,t-1}} \right) + \left(\frac{P_{j,t}}{P_t} \frac{L_{j,t}}{L_t} - \frac{P_{j,t-1}}{P_{t-1}} \frac{L_{j,t-1}}{L_{t-1}} \right) \frac{LP_{j,t}}{LP_{t-1}} \right] \\
&= \sum_{j \in J} \frac{P_{j,t-1} Y_{j,t-1}}{P_{t-1} Y_{t-1}} \left(\frac{LP_{j,t} - LP_{j,t-1}}{LP_{j,t-1}} \right) \\
&\quad + \sum_{j \in J} \left[\left(\frac{P_{j,t-1}}{P_{t-1}} \left(\frac{L_{j,t}}{L_t} - \frac{L_{j,t-1}}{L_{t-1}} \right) + \frac{L_{j,t}}{L_t} \left(\frac{P_{j,t}}{P_t} - \frac{P_{j,t-1}}{P_{t-1}} \right) \right) \frac{LP_{j,t}}{LP_{t-1}} \right]
\end{aligned}$$

$$(2) \qquad = \underbrace{\sum_{j\in J} s^{VA}_{j,t-1}\left(\frac{LP_{j,t}-LP_{j,t-1}}{LP_{j,t-1}}\right)}_{\text{Within-industry effect}} + \underbrace{\sum_{j\in J} \Delta s^{L}_{j,t}\frac{LP_{j,t}}{LP_{t-1}}}_{\text{Reallocation effect}} + \underbrace{\sum_{j\in J} s^{L}_{j,t}\Delta p_{j,t}\frac{LP_{j,t}}{LP_{t-1}}}_{\text{Valuation effect}},$$

where w_j is sector j's employment share and p_j is sector j's relative output price. Compared to the decomposition in (1), we have an additional term that describes the effect of changes in the relative output prices of the different sectors.

Importantly, in a competitive economy, there is a direct relationship between the reallocation and the valuation effect. Specifically, restricting factor mobility between sectors induces changes in sectoral output prices that more than offset any positive direct effect on aggregate productivity growth of retaining factors in high-productivity sectors. The next section develops this insight using a simplified version of our multi-sector general equilibrium model where we can solve explicitly for the equilibrium nominal output shares in the case with and without factor reallocation.

III. The role of factor reallocation in a simple model of Baumol's growth disease

Consider a stylized multi-sector economy. In each sector $j \in J$, output is produced linearly from a single factor, L_j, according to

$$y_{j,t} = A_{j,t}L_{j,t},$$

where $A_{j,t}$ denotes the level of productivity in sector j at time t. For simplicity, let us call the single factor L_j labor. Final demand is represented by a constant elasticity of substitution (CES) aggregator

$$Y_t = A_t\left(\sum_{j\in J}\alpha_j^{\frac{1}{\sigma}}y_{j,t}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}.$$

where α_j is a weight parameter and σ is the elasticity of substitution in consumption.

Solving for the optimal demand schedule yields

$$y_{j,t} = \alpha_j\left(\frac{p_{j,t}}{P_t}\right)^{-\sigma}\frac{Y_t}{A_t^{1-\sigma}}$$

where $P_t = \frac{1}{A_t}\left(\sum_{j\in J}\alpha_j p_{j,t}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ is the ideal price index for Y.[7] Hence, the ratio of the demand for good j over good k is a function of their relative prices:

$$\frac{y_{j,t}}{y_{k,t}} = \frac{\alpha_j}{\alpha_k}\left(\frac{p_{k,t}}{p_{j,t}}\right)^{\sigma}.$$

If labor is mobile between sectors in the initial steady state, then the marginal product of labor is

[7]The ideal price index is the minimal cost of achieving a given level of utility and thus captures changes in the true cost of living under given preferences. In practice, statistical agencies approximate this price index by constructing chain-linked price indices constructed from observed prices and quantities (e.g., Laspeyres, Paasche, or Fisher price indices).

equalized across sectors in period $t-1$, which implies the following relative employment shares:

$$\frac{L_{j,t-1}}{L_{k,t-1}} = \frac{\alpha_j}{\alpha_k}\left(\frac{A_{j,t-1}}{A_{k,t-1}}\right)^{\sigma-1}.$$

If employment shares are fixed at their initial equilibrium values, the sectors' real output ratio at time t is a function of their relative productivity levels at time t and at time $t-1$,

$$\frac{\tilde{y}_{j,t}}{\tilde{y}_{k,t}} = \frac{\alpha_j}{\alpha_k}\frac{A_{j,t}}{A_{k,t}}\left(\frac{A_{j,t-1}}{A_{k,t-1}}\right)^{\sigma-1},$$

where $\tilde{y}_{j,t}$ and $\tilde{y}_{k,t}$ denotes the real output of sector j and k under fixed employment shares, respectively.

In contrast, if employment shares adjust so that the marginal product of labor remains equalized across sectors, then the ratio of supply by sector j over supply by sector k is simply a function of the relative productivity levels of these sectors at time t:

$$\frac{y_{j,t}}{y_{k,t}} = \frac{\alpha_j}{\alpha_k}\left(\frac{A_{j,t}}{A_{k,t}}\right)^{\sigma}.$$

Turning to the goods market, its equilibrium requires that sectoral demand equals sectoral supply. If employment shares are fixed, this implies that

$$\frac{\tilde{p}_{j,t}}{\tilde{p}_{k,t}} = \left(\frac{A_{k,t}}{A_{j,t}}\right)^{\frac{1}{\sigma}}\left(\frac{A_{k,t-1}}{A_{j,t-1}}\right)^{\frac{\sigma-1}{\sigma}},$$

where $\tilde{p}_{j,t}$ and $\tilde{p}_{k,t}$ denote the equilibrium prices under fixed employment shares. Similarly, the ratio of the value-added shares of sectors j and k is given by

$$\frac{\tilde{y}_{j,t}\tilde{p}_{j,t}}{\tilde{y}_{k,t}\tilde{p}_{k,t}} = \frac{\alpha_j}{\alpha_k}\left(\frac{A_{j,t}}{A_{k,t}}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{A_{j,t-1}}{A_{k,t-1}}\right)^{\sigma-1+\frac{1-\sigma}{\sigma}}.$$

Instead, if labor is mobile, this implies that in equilibrium

$$\frac{p_{j,t}}{p_{k,t}} = \frac{A_{k,t}}{A_{j,t}},$$

and therefore, that the ratio of the value-added shares of sectors j and k is

$$\frac{y_{j,t}p_{j,t}}{y_{k,t}p_{k,t}} = \frac{\alpha_j}{\alpha_k}\left(\frac{A_{j,t}}{A_{k,t}}\right)^{\sigma-1}.$$

Assume without loss of generality that sector j experiences faster productivity growth than sector

k, so that

$$\frac{A_{j,t}}{A_{k,t}} > \frac{A_{j,t-1}}{A_{k,t-1}}.$$

Aggregate productivity growth is attenuated by Baumol's growth disease if sector j's share of nominal output decreases relative to that of sector k. Comparing equilibrium nominal output shares in the case with and without factor reallocation, we can see that the ratio of sector j's to sector k's nominal output share is smaller when factors are prevented from moving between sectors, that is

$$\frac{\tilde{y}_{j,t}\tilde{p}_{j,t}}{\tilde{y}_{k,t}\tilde{p}_{k,t}} = \frac{\alpha_j}{\alpha_k}\left(\frac{A_{j,t}}{A_{k,t}}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{A_{j,t-1}}{A_{k,t-1}}\right)^{\sigma-1+\frac{1-\sigma}{\sigma}} \leq \frac{\alpha_j}{\alpha_k}\left(\frac{A_{j,t}}{A_{k,t}}\right)^{\sigma-1} = \frac{y_{j,t}p_{jt}}{y_{k,t}p_{k,t}},$$

with strict inequality whenever $\sigma \neq 1$. This results implies that in the decomposition formula in 2, restricting factor reallocation must induce changes in the valuation effect that more than compensate for the elimination of the reallocation effect. Hence, in the context of Baumol's growth disease and against common preconceptions, the movement of factors from high to low growth sectors increases aggregate productivity growth relative to a counterfactual where factors cannot be reallocated.[8]

The intuition why factor reallocation towards sectors with lower productivity growth can improve aggregate productivity comes from recognizing that aggregate real productivity growth depends not only on sectoral real productivity growth and factor reallocation, but also on changes in equilibrium prices. Even though keeping factors employed in the sectors with stronger productivity growth would increase the volume of output (aggregated at base period prices), prices in the high-growth sector would need to decline further to induce enough demand for the additional output. As a result, the value-added share of the high-growth sectors would decline by more than if factors could optimally reallocate across sectors. Put differently, when factors of production in an efficient economy move out of high-productivity sectors and into those that did not experience comparable productivity growth, this movement must reflect optimal reallocation of productive resources. Through such reallocation of factors, the strong productivity gains in specific sectors are leveraged to increase output also in other sectors of the economy that did not experience productivity growth, yet produce goods and services that consumers value.

REFERENCES

Acemoglu, Daron. 2025. "The simple macroeconomics of AI." *Economic Policy*, 40(121): 13–58.

Aghion, Philippe, and Simon Bunel. 2024. "AI and Growth: where do we stand." SF Fed WP.

Brynjolfsson, Erik, Danielle Li, and Lindsey Raymond. 2025. "Generative AI at work." *The Quarterly Journal of Economics*, qjae044.

Dell'Acqua, Fabrizio, Karim R. Lakhani, Hila Lifshitz-Assaf, Michael L. Tushman, and Katherine C. Kellogg. 2023. "Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Ef-

[8]For differential sectoral productivity growth to produce a negative Baumol effect, the elasticity of substitution, σ, needs to be below 1, i.e., the goods produced in the different sectors need to be gross complements. If $\sigma > 1$, that is, if the goods are gross substitutes, aggregate productivity growth would exceed within-sector productivity growth, because households would want to increase their expenditure share on the output of the high-growth sectors (akin to a positive Baumol effect). Just as in the case of $\sigma < 1$, but perhaps less surprisingly, factor reallocation across sectors increases aggregate productivity growth relative to a counterfactual where the sectoral factor allocation is kept fixed.

fects of AI on Knowledge Worker Productivity and Quality." Harvard Business School Technology & Operations Mgt. Unit Working Paper 24-013.

European Commission. 2024. "European Economic Forecast. Autum 2024." European Commission, Directorate-General for Economic and Financial Affairs Institutional Paper 296, Brussels.

Gambacorta, Leonardo, Han Qiu, Shuo Shan, and Daniel M Rees. 2024. "Generative AI and labour productivity: a field experiment on coding." Bank for International Settlements Working Paper 1208.

Haslberger, Matthias, Jane Gingrich, and Jaskaran Bhatia. 2023. "No great equalizer: experimental evidence on AI in the UK labor market." Unpublished manuscript.

Herrendorf, Berthold, and Ákos Valentinyi. 2022. "Endogenous sector–biased technological change and industrial policy." *Economic Modelling*, 113: 105875.

Merali, Ali. 2024. "Scaling laws for economic productivity: Experimental evidence in llm-assisted translation." *arXiv preprint arXiv:2409.02391*.

Nordhaus, William D. 2001. "Alternative methods for measuring productivity growth."

Noy, Shakked, and Whitney Zhang. 2023. "Experimental evidence on the productivity effects of generative artificial intelligence." *Science*, 381(6656): 187–192.

OECD. 2024. "OECD Compendium of Productivity Indicators 2024." OECD Publishing.

Tang, Jianmin, and Weimin Wang. 2004. "Sources of aggregate labour productivity growth in Canada and the United States." *Canadian Journal of Economics/Revue canadienne d'économique*, 37(2): 421–444.