AI as an Innovation in the Method of Innovation: Implications for Productivity Growth in the US and Europe*

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Abstract

This paper estimates the possible AI contribution to future labor productivity growth assuming that AI is *both* a "general purpose technology" *and* an "innovation in the method of innovation." The framework used in this paper separates an upstream innovation sector from a downstream production sector. The impact of AI is modelled as (a) boosting upstream total factor productivity (a "production effect") and (b) enhancing intangible capital use downstream (a "use effect"). The framework can be used to show how AI's boost to upstream total factor productivity growth can drive long-term labor productivity growth. We relate this framework to the "task accounting" framework commonly used. We have two main findings. First, we argue that AI can already be seen in productivity statistics for the United States. The production and use effects of software and software R&D (alone) contributed (a) 50 percent of the 2 percent average rate of growth in US nonfarm business labor productivity from 2017 to 2024 *and* (a) 50 percent of its 1.2 percentage point acceleration relative to the pace from 2012 to 2017. Second, taking additional intangibles and data assets into account, we calculate a long-run contribution of AI to labor productivity growth based on assumptions that follow from the recent trajectories of investments software, software R&D, other intangibles, and their contributions to growth in both US and Europe. Our central estimates are that AI will boost annual labor productivity growth by as much as 1 percentage point in the United States and about .3 percentage point in Europe.

Keywords: Artificial intelligence (AI), innovation, productivity growth, intangibles
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1 Introduction

What will be the impact of AI on productivity growth? Research reviewed in Filippucci, Gal, and Schief (2024) shows a broad range in AI's projected impact on annual labor productivity growth over the next decade, from 3.5 percentage points (Chui et al 2023) to just 0.12 points (Acemoglu 2025). The prevailing methodology adopted by most of these studies is "task accounting" as set out for the examination of AI in series of papers by Acemoglu and Restrepo (Acemoglu and Restrepo 2018, 2019, 2020; see also Autor 2013).

Task accounting is a bottom-up approach that involves identifying job tasks exposed to AI, estimating the wage share affected, determining the fraction of those tasks that could be profitably automated, and calculating the consequent cost savings over a specified implementation timeline.[1] The framework focuses on an important mechanism through which AI impacts productivity—the activities of workers without regard to industry of employment—and illustrates the nature of AI as a general-purpose technology (GPT).

Many studies of GPTs and productivity growth measures the impact of the new technology by evaluating the "production and use" effects of the capital embodying the new technology—the production and use of railway engines/factories/computer equipment to assess the impact of steam/electricity/ICT technologies, e.g., as discussed in Crafts (2021). This paper extends this line of work by conceptualizing AI as a GPT *and* as an "innovation in the method of innovation" or IMI. The concept of an IMI is attributable to Whitehead (1925) and Griliches (1957), and AI seen as *both* a GPT and IMI in discussed in Cockburn, Henderson, and Stern (2019) and Crafts (2021).[2]

To understand the rationale for conceptualizing AI as an IMI, consider Allen's (2020) observation regarding the distinct difference between contemporary AI and earlier expert system models. Previously, software tools were "hand-crafted," for example, where the programmer tells the computer the rule of chess and programs "good" moves on the advice of chess masters. Now, software is based on "machine learning" where software is developed by the computer following training on a dataset from which the software learns the rules and good moves. This suggests that the starting point for studying the effect of AI is to look at the improved productivity of AI-enabled software tools, including when those tools are used in R&D, to capture the impact of AI as an IMI.

Our growth accounting approach is a complementary exercise to task accounting. To see this, note that the main measure used for the fraction of tasks/activities exposed to AI is the "broad exposure" measure from the widely quoted study by Eloundou, Manning, Mishkin, and Rock (2024a). Their broad exposure measure is defined as when "*additional software* could be developed on top of the LLM that could reduce the time it takes to complete the specific activity/task with quality by at least half" [Eloundou et al 2024b, Table section 3.1.1,

[1] For example, Filippucci, Gal, and Schief (2024) assume (roughly) that (a) about 30 percent of tasks are exposed to AI, of which (b) about 20 percent will be profitably automated, leading to (c) about a 30 percent cost improvement, taking (d) 10 years, yielding an assumed annual cost-saving/TFP improvement of $0.3*0.2*0.30*(1/10) = 0.18$ percentage points per year.

[2] Whitehead and Griliches spoke in terms of "invention," not innovation. Whitehead's exact quote is, "The greatest invention of the nineteenth century was the invention of the method of invention" (Whitehead, 1925, p. 120). Griliches (1957, p. 502) says "Hybrid corn was the invention of a method of inventing, a method of breeding superior corn for specific localities."

This paper uses IMI as an "innovation in the method of innovation" in addition to IMI in its original form (with the word invention) to signal that AI is as applicable to marketing, design, and logistics as it is to scientific R&D.

emphasis is ours]. Given that software is fixed capital in national accounts, it seems natural to interpret "additional software" as, in the language of growth accounting, increased software capital deepening.

The spirit of an analysis that looks at new technologies as, essentially, shifts in the composition of investment, takes us further: First, AI requires substantial use of data, and accounting for the effects of AI should include the use of data assets, for which we have some very recent survey evidence and advancements in measurement (Bontadini, Corrado, Iommi, and Jona-Lasinio 2024; Corrado et al. 2025). Second, much evidence suggests that AI boosts productivity in a range of intangible, or knowledge-based, capital building activities—evidence of improved productivity in marketing and customer relations as well as scientific R&D (Brynjolfsson, Li, and Raymond 2023; Chui et al. 2023; Baily, Byrne, Kane, and Soto 2025). Thus, it seems important to examine the impact of AI on productivity in a framework where AI operates as an IMI and impacts all knowledge-based capital, i.e., intangible capital, not just software capital.

The specific framework we use distinguishes between an "upstream" innovation sector that generates new commercial knowledge (software capital and other intangible assets), and a "downstream" production sector that uses this intangible/knowledge along with tangible capital and labor to produce final goods and services (Corrado, Haskel, Jona-Lasinio, and Iommi 2022). This framework is amenable to the analysis of AI as an IMI because, first, AI potentially changes total factor productivity growth (TFPG) in the upstream sector, which raises labor productivity in proportion to the size of the upstream sector (the "production effect" from AI as an IMI). Second, as the improved knowledge is applied downstream, there is an additional contribution from increased AI-enabled capital deepening (the "use effect," which potentially affects many industries when the technology is a GPT). Third, borrowing from Oulton (2012; see also Byrne and Corrado 2017 and Corrado et al 2025), we calibrate a steady-state solution to this model where the *relative* strength of upstream TFPG (i.e., the relative strength of the IMI effect) endogenously induces downstream capital deepening, yielding a sense of the potential longer-run impact of AI on labor productivity growth.

To anticipate our findings, we have four main results. First, previous GPTs, such as steam and electricity are often cited as an indication that even a GPT with fast TFPG results in slow-growing contributions to LPG (David 1990). The intuition is that the production and use effects of an innovative technology require an extended period to influence LPG, as the adoption and widespread use of new technologies develop gradually over time. Take steam. The production effect is TFPG in the production of steam engines (which grew extremely fast as better engines were continuously invented), times the share of steam engine production in GDP. But when the steam technology first starts, its share is very small: the industry took time to expand. Similarly, the use effect is the capital deepening of steam engines times the share of capital payments in GDP. Though this capital deepening eventually grew very fast (as railways expanded rapidly), initially its share was very small and its contribution modest.

We shall argue that the AI effect on LPG will be *higher* than previous GPTs/IMIs. The main reason is that the income and production shares for AI-enabled capital are potentially much larger than was the case for technologies like steam, and even IT. Modern deep learning-based AI is a breakthrough development in the creation of software, and more generally, knowledge production, activities with already significant footprints in advanced, and increasingly, emerging economies (WIPO 2025). The GDP share of software production and software delivery systems is currently about 4 percent in some economies—the share of steam engine production in GDP only reached 4 percent by the 1860s, around 100 years after steam technology was first introduced (Crafts 2021). The current share of "intangible" knowledge production (software, R&D, design, marketing, and other business processes) in GDP is even higher, at about 10 to 15 percent (WIPO 2025), reflecting the fact that intangible investment includes many data-driven business processes as well as software.

Even though larger capital bases result in smaller proportional increases in capital per unit of net investment, our analysis suggests that the combination of high shares and plausible rates of capital deepening implies that the impact of AI on economies is potentially much greater than the impact of earlier technological advancements.

Second, our calculations suggest there are already indications of significant impact of AI in the official productivity figures for the nonfarm business sector of the United States, bearing out the analysis of Baily, Brynjolfsson, and Korinek (2023) that the uptake of AI will not be as slow as previous new technologies. From 2012 to 2017, US nonfarm business LPG and TFPG grew at historically low rates of, 0.8 and 0.4 percent, respectively (average annual rate). These rates rose to 2.0 and 0.9 percent between 2017 and 2024, during a time of accelerating progress in LLMs owing to the discovery of the "breakthrough" transformer learning architecture by eight Google Brain researchers (Vaswani et al. 2017) and other efficiencies; see Baily et al. (2025) for further discussion. The production and use effects of software capital (about 6 percent of the US *nonfarm business* economy including its own upstream R&D and software R&D embedded in other R&D activities) contributed 50 percent of the acceleration in LPG and more than 40 percent of the acceleration in TFPG. Ignoring production on own account outside software-producing industries, software capital production currently accounts for 30 percent of labor productivity growth in the United States. These are very large contributions.

Third, our comparative data shows Europe to be lagging the United States, with lower production and lower use effects from 2010 to 2019. Why is this? The lower production effect is widely thought to be due to Europe having a smaller ICT and digital services sector.[3] While we find that the sizes of sectors (as measured by software/digital services production) are smaller for Europe, the most striking differences are in (measured) total factor productivity and pace of capital deepening. We do not (yet) have sufficient post-pandemic productivity data for Europe to evaluate its very recent performance.

Fourth, our estimates of the possible steady state increases in productivity due to AI reveal a wide range of possibilities depending upon how much AI as a technology is an improvement upon "average" technologies. Our evaluation of these possibilities suggests that AI could continue to boost LPG in the United States by as much as 1 percentage point annually. A lower, but still large, steady state boost of 0.3 percentage points to LPG in Europe is more likely. The large impacts of AI on productivity stem from our modelling of AI as an IMI.

In the remainder of this paper, section 2 sets out a definition of terms and guide to how we understand AI in growth accounting with intangibles. Section 3 sets out the measurement framework, section 5 our data, section 6 our current data results, section 7 some forward projections, and section 8 concludes.

2 AI and productivity

2.1 Definition of terms and technologies

In seeking to explain what is different about the modern wave of AI, Allen (2020) distinguishes between two AI types, "Handcrafted Knowledge" AI and "Machine Learning" AI. Figure **1**, upper panel shows "handcrafted" AI. The AI chess-playing system Deep Blue, which defeated the reigning world chess champion Garry Kasparov in 1997, was developed through a collaboration between computer programmers and human chess grandmasters. The "knowledge" of the computer was the hand-typed computer code that told the

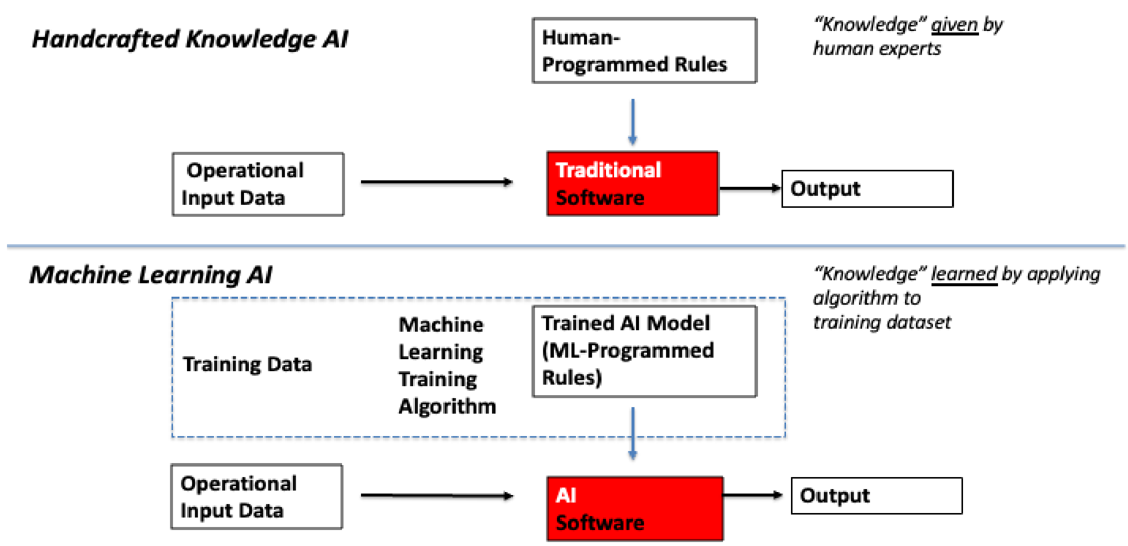
[3] Draghi (2024, Box 2, p. 27) writes "The EU has less activity in sectors in which much of the productivity growth has originated in recent years, notably the ICT sector and the exploitation of large-scale digital services".

computer the rules but also the potential moves and countermoves written in the light of what grandmasters thought was winning play.[4]

The lower panel shows Machine Learning AI. Here, knowledge is not programmed by humans. Rather, the knowledge is learned by the computer from data. The initial impetus is a training dataset on which a ML algorithm runs, producing then an AI model. This model is the basis of AI software into which the user inputs their operational data to be processed for output.

The more complex and computationally intensive generative AI applications where the computer generates answers to queries are called "deep learning," which may be thought of as a subset of machine learning.[5] Facial recognition is another example of the complexity computers can now handle. The recognition of images, which humans can do easily, was previously too hard to program in in Handcrafted style. But with ML/DL the computer, once trained, can be used to recognize faces and images.

Figure 1. Software creation pre- and post-machine learning



Source. Authors' adaptation of Allen (2020).

Baily et al. (2025) provide a history of advancements in AI. A conference held in 1956 at Dartmouth spurred early research on AI, which concentrated on classification applications rather than generative AI or question answering. Progress was constrained by the limited computational power available at the time. By the 2010s systems such as Alexa and Siri had been introduced, and the large technology firms were using machine learning algorithms to forecast demand. Computational power and near-free storage made this era popularly described as one of "Big Data."

[4] This logic is in line with Cockburn, Henderson, and Stern (2019) who point out that rather than relying on programmed symbolic logic, learning AI systems such as neural networks create predictions based on various inputs.
[5] McKinsey (Chui et al. 2023) have a helpful glossary of terms, summarized in the appendix for reference.

A significant turning point in artificial intelligence research occurred in 2012, initiating the deep learning revolution. The AlexNet model, developed by University of Toronto researchers, achieved a decisive victory at the ImageNet Large Scale Visual Recognition Challenge in that year, thereby demonstrating the effectiveness of deep learning techniques for image recognition tasks. By this time large language models (LLMs) had emerged, and newspapers were generating some stories by machine, but only for well-defined tasks, like reporting sports scores, or financial data. The previously mentioned breakthrough in neural architecture in 2017 greatly improved the speed and accuracy of language processing in LLMs, kicking off the current era of generative AI.

2.2 General purpose technologies (GPTs) and invention in the method of invention (IMI)

Figure 2 sets out a schema of GPT and IMIs based on Cockburn, Henderson, and Stern (2019) and Crafts (2021). As Crafts describes, IMIs raise productivity in generating advances in technology, while GPTs raise productivity in widespread goods/services production. In general IMIs and GPTs are distinct. Steam and electric power are GPTs, applicable in many areas, but not an IMI. Hybrid corn is an IMI, but not widely applicable. Cockburn et al/Crafts argue for deep learning as both an IMI and GPT, and Crafts adds ICT.[6] We follow this approach in this paper.

Figure 2. General purpose technologies (GPTs) and inventions in the method of inventing (IMIs)

		General purpose technology	
		No	**Yes**
Invention in the method of inventing	**No**	Bessemer converter Industrial robots	Steam power Electricity Autonomous vehicles
	Yes	Hybrid corn	ICT Deep learning

Source. Adapted from Cockburn, Henderson, and Stern (2019) and Crafts (2021).

The impact of deep learning on productivity in knowledge generation is complex but, like studies of the impact of ICT on the economy, its impact can be parsed as follows: Using computers to train AI models in commercial labs represents upstream *tangible* capital deepening in upstream production; using proprietary software and data to develop AI-enabled software represents upstream *intangible* capital deepening. Open-source software, shared data, and R&D spillovers constitute TFPG in upstream production.

2.3 Relation with the "task accounting" literature

Eloundou et al. (2024a, 2024b) analyse potential workers exposed to AI by exploiting O*NET data, which includes a list of the tasks and activities undertaken in various occupations (e.g. a surgeon performs operations, talks to the patient etc.). What the authors call "direct exposure (E1)", or an "alpha" measure is when an LLM "can decrease the time required to complete the task by at least half." What is called "LLM + exposed (E2)," or "expanded capabilities" in Filippucci et al. (2024), is the potential for additional software to decrease time, see the quote provided in our introduction. This second measure also counts access to image recognition

[6] Crafts (2021) includes Bessemer convertors as neither a GPT or IMI, autonomous vehicles as a GPT but not an IMI, Algorithms as an IMI but not GPT. Cockburn et al (2019) include specific algorithms as an IMI but not GPT.

systems, which are a bit broader than the strict definition of LLMs. Consider the specifics of the extra software included with the E2 prompt:

"*Examples of software built on top of the LLM that may help complete worker activities include:*

- ***Software** built for a home goods company that quickly processes and summarizes their up−to−date internal data in customized ways to inform product or marketing decisions.*
- ***Software** that is able to suggest live responses for customer service agents speaking to customers in their company customer service interface*
- ***Software** built for legal purposes that can quickly aggregate and summarize all previous cases in a particular legal area and write legal research memos tailored to the law firm's needs*
- ***Software** specifically designed for teachers that allows them to input a grading rubric and upload the text files of all student essays and have the software output a letter grade for each essay*
- ***Software** that retrieves up−to−date facts from the internet and uses the capabilities of the LLM to output news summaries in different languages."* (Eloundou et al 2024b, Table in section 3.1.1; emphasis is ours).

The following points are worth noting. First, the OECD (Filippucci et al. 2024) and Acemoglu (2025) use both the EI and E2 measures, emphasising the second one. The OECD work uses an average across sectors to assign 35 percent of jobs exposed to AI, while Acemoglu (2025) uses 20 percent. Second, the "E1" measure can be understood as evaluating whether current software, combined with existing AI technology, can perform a task. The "E2" measure refers to the potential for new, yet-to-be-developed software to perform tasks.

Third, it is notable that the software examples are all in commercial applications. This then is congruent with our view of AI as manifesting itself in the production sector's implementation of commercially useful AI-driven intangible assets.

3 Model: AI as an IMI

3.1 Intangibles and AI

In our upstream/downstream framework, the economy consists of three producing sectors:

Sector (N): Intangible capital of type a (e.g. software, R&D) where, ignoring time subscripts, the new intangible capital produced is N^a at an asset price P^{N_a} and the existing stock of intangible capital is R^a with (rental) price P^{R_a};

Sector (I): Tangible capital of type b (e.g. buildings, machines), where new tangible capital is denoted I^b with price P^{I_b} and with existing stock K^b at rental price P^{K_b}; and

Sector (C): A consumption good (understood to be all other goods and services).

All sectors use tangible and intangible capital and s labor types, and the perpetual inventory model with geometric depreciation describes the relation between flows and stocks of capital: $K_t^b = I_t^b + (1-\delta^{K_b})K_{t-1}^b$ for tangible capital and $R_t^a = N_t^a + (1-\delta^{R_a})R_{t-1}^a$ for intangible capital.

Sector (N) is the upstream, knowledge-producing sector. Conceptually, it consists of individual firms producing long-lasting commercially valuable knowledge as a primary product, as well as all knowledge-producing activities *within firms*, the "innovation factories within factories" as described in Corrado, Haskel, Jona-Lasinio and Iommi (2022). Sectors (C) and (I) are the downstream knowledge-using sectors in the Corrado et al (2022) schema. An important feature of the schema used here is that the upstream sector uses its own-produced AI capital (an asset type in the list of a's), which is the mechanism for treating AI as an IMI.

Denoting Hicks-neutral technical change in each sector as da, and assuming competition and ignoring intermediates, we may write the production functions in each sector in log differentiated form, where the change in log sectoral output is (a) the rental share-weighted change in log value added inputs plus (b) TFP growth. Formally the three producing sectors are:

Intangible, asset type a

$$dn^a = \sum_{s \in L} \frac{P_{L_s} L_s^{N^a}}{P_{N^a} N^a} d(\theta_s l_s^{N^a}) + \sum_{b \in K} \frac{P_{K_b} K_b^{N^a}}{P_{N^a} N^a} dk_b^{N^a} + \sum_{a \in N} \frac{P_{R_a} R_a^{N^a}}{P_{N^a} N^a} dr_a^{N^a} + da^{N^a}$$

Tangible, asset type b

$$di^b = \sum_{s \in L} \frac{P_{L_s} L_s^{I^b}}{P_{I^b} I^b} d(\theta_s l_s^{I^b}) + \sum_{b \in K} \frac{P_{K_b} K_b^{I^b}}{P_{I^b} N^b} dk_b^{I^b} + \sum_{a \in N} \frac{P_{R_a} R_a^{I^b}}{P_{I^b} N^b} dr_a^{I^b} + da^{I^b} \tag{1}$$

Consumption

$$dc = \sum_{s \in L} \frac{P_{L_s} L_s^C}{P_C C} d(\theta_s l_s^C) + \sum_{b \in K} \frac{P_{K_b} K_b^C}{P_C C} dk_b^C + \sum_{a \in N} \frac{P_{R_a} R_a^C}{P_C C} dr_a^C + da^C$$

In (1) lower case letters denote natural logs and superscripts denote sector of use, and we have additionally allowed for labor augmenting technical progress at rate $d\theta_s$ for labor type s, assumed the same for each labor type across sectors. We can then express the (log change in) economy-wide value added, dv, as the sector share-weighted (changes in log) value added

$$\begin{aligned}
&dv = \frac{P_C C}{P_V V} dc + \frac{P_I I}{P_V V} di + \frac{P_N N}{P_V V} dn \\
&\textit{where} \\
&P_V V = P_C C + P_I I + P_N N, \\
&dn = \sum_{a \in N} \frac{P_{N^a} N^a}{P_N N} dn^a \;, di = \sum_{b \in I} \frac{P_{I^b} I^b}{P_I I} di^b \;, \\
&P_N N = \sum_{a \in N} P_{N^a} N^a \;, P_I I = \sum_{b \in I} P_{I^b} I^b
\end{aligned} \tag{2}$$

Assuming constant returns, labor productivity growth in the economy described by (1) and (2) is given by

$$d(v/l)=\underbrace{\sum_{a\in N}\frac{P_{N_a}N_a}{P_V V}da^{N^a}+\sum_{b\in I}\frac{P_{I_b}I_b}{P_V V}da^{I^b}+\frac{P_C C}{P_V V}da^C+\frac{P_L L}{P_V V}\left(\sum_{s\in L}\frac{P_{L_s}L_s}{P_L L}d\theta_s\right)}_{\text{Technical change}}$$

$$+\underbrace{\frac{P_K K}{P_V V}\left(\sum_{b\in K}\frac{P_{K_b}K^N}{P_K K}d(k_b/l)^N+\sum_{b\in K}\frac{P_{K_b}K^I}{P_K K}d(k_b/l)^I+\sum_{b\in K}\frac{P_{K_b}K^C}{P_K K}d(k_b/l)^C\right)}_{\text{Capital deepening, tangibles}}$$

$$+\underbrace{\frac{P_R R}{P_V V}\left(\sum_{a\in N}\frac{P_{R_a}R^N}{P_R R}d(r_a/l)^N+\sum_{a\in N}\frac{P_{R_a}R^I}{P_R R}d(r_a/l)^I+\sum_{a\in N}\frac{P_{R_a}R^C}{P_R R}d(r_a/l)^C\right)}_{\text{Capital deepening, intangibles}}$$

where (3)

$$P_K K^N=\sum_{b\in K}P_{K_b}K_b^{N^a},P_K K^I=\sum_{b\in K}P_{K_b}K_b^{I^b},P_K K^C=\sum_{b\in K}P_{K_b}K_b^C,$$

$$P_R R^N=\sum_{a\in N}P_{R_a}R_a^{N^a},P_R R^I=\sum_{a\in N}P_{R_a}R_a^{I^b},P_R R^C=\sum_{a\in N}P_{R_a}R_a^C,$$

$$P_R R=P_R R^N+P_R R^I+P_R R^C,P_K K=P_K K^N+P_K K^I+P_K K^C,$$

$$P_L L=\sum_{s\in L}P_{L_s}L_s$$

The decomposition shown in equation (3) is conventional and shows two sources of labor productivity growth, technical change and capital deepening. For each source, there are contributions from the upstream sector *N* and the downstream sectors *C* and *I*. For technical change, there are two sources (a) *da*, the Hicksian "shifter" in the production function for each sector weighted by its share in overall value added and (b) *dθ*, labor-augmenting technical change, weighted by the share in value added of the wage bill of the labor type experiencing the change. The two mechanisms are indistinguishable under constant returns when taking (3) to the data; the distinction is carried in (3) solely for exposition. For capital deepening, (3) distinguishes between the use of tangible and intangible assets, where each detailed type (*a* or *b*) is weighted by its share in total capital payments of their sector-asset capital rental payments, weighted again by the major asset type share in total value added.

3.2 Interpreting technical change and capital deepening in this model

This framework is broadly applicable and measurable, but it raises the question of the determinants of the technical change terms. Following endogenous growth theories, total factor productivity as the Hicksian production function "shifter" is a "costless" source of growth that results from the nonrival character of intangible capital, i.e., TFP represents knowledge spillovers, or diffusion. We assume the knowledge-producing sector draws upon a stock of basic "free" knowledge generated by unmodeled entities—such as universities or government labs (at home or abroad)—whose work provides the seed for ideas that turn into the investments that become new and improved production processes or products. For new AI software (or AI-enabled machines), one "costless" source-of-growth is open-source software code, which according to Calderon et al (2022) grew more than 10 percent per year from 2010 to 2019; see also Hoffman, Nagle and Zhou 2024).

Thus, while some factors affecting the diffusion of technology in this model can be identified, the model is not very specific about the underlying mechanisms that drive technological diffusion via the *da* and *dθ* terms. By contrast, the task approach frames technical change in terms of specific mechanisms. Tasks are set as the fundamental unit of production in this approach, where tasks are performed by unskilled labor, skilled labor and capital (e.g., machines and software) in various combinations. By parameterizing these combinations via certain elasticities, e.g., capital-labor substitution, the task model is amenable to considering displacement of tasks by automation as well as reinstatement via new tasks (i.e., augmentation), where the impact of augmentation varies according to complementarities and market forces affecting labor supply. This modeling is a sharp departure from traditional skill-biased technical change models, which usually assume augmentation works as a uniform boost to productivity of all tasks that labor performs.

We believe our growth accounting approach complements the rich bottom-up nature of the task framework even though the underlying task reallocation and its separate processes (automation and augmentation) are not visible. As described above, automation is a driver of capital deepening, while the pace of augmentation moderates the ultimate impact of AI on job loss. The task model also suggests that augmentation will be greater or smaller depending on the extent to which technology complements labour, i.e., the extent to which labour has been made more productive overall. When taking (3) to the data, and thinking in terms of the task model, measured TFPG then reflects the net savings from both the displacement and reinstatement of workers due to technical change. In the classic interpretation of the microeconomics of change due to a GPT, as Bresnahan (2021) explains, TFP rather reflects the net impact of the cost savings due to the organizational change that complements the technology. Our approach is congruent with both these views of the underlying forces at work in the economy.

Though the model summarized by (3) is a generalized model of sectoral production, we have assumed constant returns and competitive factor payments; not that once intangibles are included in a production framework such as the above, these assumptions turn out to be not terribly strong empirically (see the discussion in Corrado et al. 2022). That said, using (3) to estimate the impact of a new technology on productivity rests on a foundational result in productivity and growth accounting due to Hulten that predicts, without knowing the full structure of the economy, the first order macro effects of micro/sectoral shocks under constant returns and competition (Hulten 1978). Theoretically, nonlinearities (e.g., complementarities), network effects (which tend to manifest as increasing returns), and misallocation can alter the aggregate impacts implied by Hulten's theorem (Baqaee and Farhi 2019). In their work using the task approach to estimate the aggregate impact of AI, Filippucci et al (2024) examined the impact of these distortionary influences on the applicability of Hulten's theorem. After including the terms Baqaee and Farhi (2019) suggest are needed when non-linearities and barriers to reallocation are present, in most cases, the impact of additional terms turned out to be relatively small compared with the first-order effect; see their Table 2.

3.3 Upstream/downstream steady-state solution

In the model of section 3.1, labor productivity growth stems from technical change and capital deepening. As is well-known, higher TFP induces more capital formation.[7] Oulton (2012) sets out a model that features this mechanism in a two-sector model of an (upstream) ICT-producing sector and a (downstream) other output-producing that uses ICT capital along with conventional capital; in this model the productivity "advantage" of the ICT capital drives additional ICT capital deepening. Amending his model to have an upstream intangible-producing sector with TFPG of da^N, and, for ease of notation combining the consumption and tangible

[7] At a given K, more TFP grows output Y leading to a falling K/Y and hence a rising marginal product of capital; K must then rise to restore the marginal product of capital to its former value.

investment sector, with TFPG of da^{CI} , the model reveals how persistent $da^N > da^{CI}$ affects steady-state labor productivity growth in the whole economy:

$$d(v/l)^* = \frac{da^{CI}*}{s_V^L*} + \omega_V^N*(da^N - da^{CI})* + \frac{s_V^R*}{s_V^L*}(da^N - da^{CI})* \tag{4}$$

$$\textit{where}$$

$$\omega_V^N* = \left(\frac{P_N N}{P_V V}\right)*, s_V^L* = \left(\frac{P_L L}{P_V V}\right)*, s_V^R* = \left(\frac{P_R R}{P_V V}\right)*$$

ω_Y^{N*} is the production share of the N sector, and s_Y^{L*} and s_Y^{R*} are the income shares of labor and intangible capital and we denote steady-state values by a star. If there is no upstream productivity advantage, then steady state productivity growth reduces to the familiar one-sector formula of TFPG times the reciprocal of the labor share (which is the equation used by Acemoglu (2025) to calculate his steady state impact of a rise in TFP on GDP, see his note 12). Thus, the *contribution* of superior upstream TFPG to long-run LPG is given as

$$d(v/l)'* = \omega_V^N*(da^N - da^{CI})* + \frac{s_V^R*}{s_V^L*}(da^N - da^{CI})* \tag{5}$$

which is the extra kick to TFPG from superior upstream production, plus the additional capital deepening induced by the superior upstream TFPG.

3.4 Earlier technologies: steam and ICT and the importance of weights

Before turning to AI, let us summarise the historical labor productivity impacts of steam and ICT using (3). Thinking of new technologies as new types of capital goods suggests their effects will be captured by the contribution to LPG of (a) TFP productivity growth in the sector producing the investment good and (b) the use of the investment goods in the economy. We might write this as

$$d(v/l)' = \underbrace{\sum_{b \in ICT, steam} \frac{P_{I_b} I_b}{P_V V} da^{I^b}}_{\text{Production effect}} + \underbrace{\frac{P_K K}{P_V V}\left(\sum_{b \in ICT, steam} \frac{P_{K_b} K_b}{P_K K} d(k_b/l)\right)}_{\text{Use effect}} \tag{6}$$

where the (‘) denotes contribution.[8] The capital deepening term includes the relevant asset types whether tangible or intangible; for steam, it is steam engines (a tangible good), for ICT it reflects tangibles (computers, communications equipment) and an intangible (software).

[8] We note that Crafts and Oliner/Sichel worked with gross output and hence the production effect is gross output TFPG times the Domar-Hulten weight. In other influential work on the industrial revolution, Harley’s approach to the contribution of new technology is multiply TFP growth in the “modernised sectors”: cotton, wool, iron, canals, ships, railways, by their (gross) output production weights (Crafts and Harley 1992; Harley 1982) .

This framework has an important lesson for the analysis of the productivity impact of new technology. Even if the new technology has fast (total factor) productivity growth in production and is ultimately adopted/used very widely, its *initial* contribution to *d(v/l)* is likely to be small because (a) for the production effect, however large TFPG may be, the size of the technology-producing sector is likely to be small, at least initially, and (b) for the capital deepening/adoption/use effect, the share of rental payments to the new technology is also likely small initially.

To give some sense of numbers, steam technology started in the 1760s, Watt's patent expired around 1800 and the railway age, which is conventionally dated from the opening of the Liverpool and Manchester Railway in 1830, began even later. Between 1760 and 1800, the (Domar) weight on the steam industry was 0.2 percent and its capital income share 0.1 percent of GDP. Even as late as 1830-60, the Domar weight was 3.4 percent, and the capital income share 0.85 percent. In Oliner and Sichel's work, from 1973 to 1995, i.e., before the ICT sector took off, the Domar weight of ICT production was 1.4 percent and the ICT capital rental share 3.3 percent (Oliner and Sichel 2000). Thus, even with steam TFP growing at 3 percent annually and steam capital deepening growing 4 percent in the early period and more than 10 percent later, the contributions to productivity growth were 0.01 percentage points per year in the early period and 0.29 in the latter. By contrast, Oliner/Sichel's estimate of the early contribution of ICT to labor productivity growth, i.e., from 1973 to 1995, was 0.67 percentage points per year.

3.5 AI and productivity growth

To use the frameworks of sections 3.1 and 3.3 to study AI there are choices to be made about the sphere of AI activity. The AI production value chain spans from advanced manufacturing, e.g., chips and massively parallel computers, to the production of AI software and related services, e.g., cloud services, data services. The use of AI likewise spans from AI-enabled machinery, e.g., robotics, to AI-enabled software and services, where there are now many LLM models in the marketplace with services surrounding them, e.g., Google's Gemini and Microsoft's Copilot.

Two points to consider when thinking about using equation (3) to identify the contribution of AI to productivity growth are as follows: First, much of the *AI production value chain* will be reflected in software product R&D and software R&D embedded in other product or process development. This is because the value of R&D reflects the cost of the capital *services* used to conduct the R&D, along with labor costs and materials consumed. For software R&D and embedded software R&D, these capital services will include the *use* of the massive computing resources required to train the AI models. This will be true whether the model is used to produce new or enhanced AI software that is (a) marketed as a software product, (b) used generate other intangible assets, e.g., marketing assets, attributed designs, or (c) becomes a new or improved "brain" in an industrial robot. Second, to fully articulate the *use effects of produced AI capital*, the AI-enabled assets, both tangible and intangible, will need to be identified in the asset type categories for *a* and *b* in equation (3).

So, to the extent that AI is robotics, we might measure the contribution of AI as (a) TFP in the production of new AI-powered robots (which would reflect, at least in part, the *outcome* of the software R&D used in their design); (b) capital deepening of the software R&D used (or embedded) in the newly produced AI-powered robots, and (c) capital deepening of AI-powered robots in the downstream industries of use.

In addition, if there is TFP growth in the production of the foundation models of generative AI, i.e., TFP growth in the knowledge discovery sector (AI as an IMI), the production and use contributions of these AI models would be spelled out analogously, i.e., as (a) TFP in the AI model-producing sector (which in practical terms may be the software industry), (b) capital deepening of AI model software product R&D, and (c) capital deepening of AI model-enabled tools, which in practical terms are software assets, whether for general purpose or specific use, i.e., intangible capital deepening (assuming the production of all intangible assets is amenable to the use of AI).

We have then the following expression as the impact of AI on productivity growth (where all technical change and net effects of task reallocation are attributed to the Hicks-neutral *da* terms):

$$
\begin{aligned}
d(v/l)' = & \underbrace{\boxed{\sum_{a\in \text{AI-enabled Int}} \frac{P_{N_a}N_a}{P_V V} da^{N^a}} + \sum_{b\in \text{AI-enabled Tan}} \frac{P_{I_b}I_b}{P_V V} da^{I^b}}_{\text{Production of AI capital}} \\
& + \underbrace{\frac{P_K K}{P_V V}\left(\sum_{b\in \text{AI-enabled Tan}} \frac{P_{K_b}K_b^N}{P_K K} d(k_b/l)^N + \sum_{b\in \text{AI-enabled Tan}} \frac{P_{K_b}K_b^I}{P_K K} d(k_b/l)^I + \sum_{b\in \text{AI-enabled Tan}} \frac{P_{K_b}K_b^C}{P_K K} d(k_b/l)^C \right)}_{\text{Use of AI tangible capital}} \qquad (7) \\
& + \underbrace{\frac{P_R R}{P_V V}\left(\boxed{\sum_{a\in \text{AI-enabled Int}} \frac{P_{R_a}R_a^N}{P_R R} d(r_a/l)^N} + \sum_{a\in \text{AI-enabled Int}} \frac{P_{R_a}R_a^I}{P_R R} d(r_a/l)^I + \sum_{a\in \text{AI-enabled Int}} \frac{P_{R_a}R_a^C}{P_R R} d(r_a/l)^C \right)}_{\text{Use of AI intangible capital}}
\end{aligned}
$$

where $a \in$ *AI-enabled Int*, $b \in$ *AI-enabled Tan* denotes the intangible and tangible asset type(s) *a* and *b* whose productivity is boosted by AI. The terms in the red outlined boxes capture the impact of AI as an IMI.

3.6 Application

If we (a) ignore the use and production of robots and other AI-enabled machines (but not the software R&D embedded in their R&D) and (b) consider technical progress as TFP in the upstream sector, the contribution of AI to labor productivity growth reduces to the following three terms:

$$
\begin{aligned}
d(v/l)' = & \underbrace{\sum_{a\in AI} \frac{P_{N_a}N_a}{P_V V} da^N}_{\text{Production of AI intang}} \\
& + \left(\underbrace{\sum_{a\in AI} \frac{P_{R_a}R_a^N}{P_V V} d(r_a/l)^N}_{\text{Use of AI intan in AI intang}} + \underbrace{\sum_{a\in AI} \frac{P_{R_a}R_a^{C,I}}{P_V V} d(r_a/l)^{C,I}}_{\text{Use of AI intan in tang \& cons industries}} \right) \qquad (8)
\end{aligned}
$$

In this expression, the production effect stems from TFPG in the production of all intangibles, which will be affected by AI to the extent AI tools are used to produce them. The extent of this use is shown in the second term, AI-intangible capital deepening in the production of intangibles. In addition to these IMI-dominated impacts, we have AI-intangible capital deepening in the other sectors of the economy (here, producers of tangible capital and consumption goods).

We must follow several steps to use (8) to analyze productivity growth. For example, we must confront: How do we identify industries producing *N* (and thus measure da^N) when much *N* is produced within firms? We address this by proceeding in two ways: via backward- and forward-looking exercises.

Our backward analysis uses (8) to estimate the production and use effects of software capital in measured productivity for recent years. A previously explained, the task approach that has been used in many studies to estimate the GPT impact of AI on economies examines, in the language of growth accounting, the impact of cost savings from software capital deepening. To capture this *and* the effect of AI as an IMI, we allow software to be used to produce software and, crucially, we define software capital to include software products R&D and software R&D embedded in other R&D to pick up the entire AI value chain.

The forward-looking analysis calibrates equation (5) to assess the potential for *all* intangible assets to be influenced/transformed by AI. This approach acknowledges that certain applications of AI require supplementary co-investments to adapt general AI models for specific business functions and specific markets (i.e., the use of AI and proprietary data assets for engineering and attributed industrial designs).

Though modelling AI software as an IMI and considering intangible co-investments to AI software are central features of this paper and our approach, like the scope of studies using the task accounting approach, e.g., as stated by Acemoglu (2025, p. 17), "we do not [entertain the prospect of] how AI can have revolutionary effects by changing the process of science." .

4 Production and use: past evidence

We now turn to our evidence, starting with an analysis of recent productivity growth in the United States.

4.1 Software capital and US productivity growth

The Bureau of Labor Statistics (BLS) issues annual total factor productivity estimates for the nonfarm business sector of the United States, along with data on outputs and inputs by detailed industries that provide a starting place for measuring the production and use effects of software capital using equation (8).

4.1.1 The production effect

Isolating the software-producing sector to measure a "production" effect is challenging, as the industries in the North American Industrial Classification System (NAICS) for which there is consistent data on real outputs and inputs (2017 NAICS industries 511, 518-519, and 5415) also generate other products and services. Industry 511 covers newspaper and other publishing along with software publishing and software R&D. Industries 518-519 include data storage, internet publishing, cloud computing and infrastructure services, but also conduct much software R&D. Industry 5415 comprises computer systems design, which spans custom software development and systems management services, as well as much software R&D. The inclusion of other activities in software industries, e.g. newspaper and magazine publishing, might suggest our estimates of the size of the software-producing sector are too large. Offsetting this is the fact that about 20 percent of software investment in the United States is production is on own account, with most production outside the software-producing industries identified above. Our estimates of the "production" effect are thus unlikely to be seriously biased.

4.1.2 The use effect

The use effect is the use of software capital assets in the entire nonfarm business economy. As our model shows, use can be downstream, but also upstream. Upstream use introduces some conceptual issues, however. National accounts capitalize investment in three knowledge assets (software, R&D and artistic originals), collectively described as Intellectual Property Products (IPP). Thus, use of software in upstream production is software use in (a) the software-producing sector itself, i.e., whether in its conduct of R&D (i.e., software R&D) or in its routine production of software, (b) the conduct of R&D in other industry sectors (e.g., for robotics by R&D labs in the motor vehicle industry), and (c) in the creation of entertainment, artistic and literary originals (E&AO). The logic is that if, for example, R&D activity involves writing software to conduct R&D, those expenditures are a component of the software R&D we wish to include.

The foregoing suggests "software capital" overlaps with R&D. The production of software products for end use relies on ongoing R&D, both to develop new software and to maintain existing products. AI-enabled software requires substantial R&D to train and compute parameters for algorithms applicable in research or downstream production. Additionally, AI may be incorporated into software tools used within upstream R&D projects. For the analysis of AI in this paper, "software capital" will be considered as consisting of two primary components: (1) final software assets acquired or internally developed by businesses, and (2) software product R&D and embedded software within other R&D activities funded by the business sector.

4.1.3 Software product and embedded software R&D

To estimate this asset type, we must go beyond the BLS productivity system data and compile survey data on the cost of software product and embedded software R&D from the annual surveys of business R&D spending that otherwise form the basis for R&D capital in the national accounts. Software products and embedded software is a type of activity classified as a "technology focus" in this survey, a concept that crosses industry lines. The underlying data for software R&D investment were developed from the Business Enterprise Research and Development survey (and its predecessors) following Moris (2019). All told, we estimate that software R&D accounted for 45 percent of US domestic business R&D spending in 2022 (national accounts basis) and that nearly 60 percent of that activity was conducted in our three software industries. Figure A1 in the paper's appendix displays these results.

For consistency with BLS's official aggregate productivity statistics, the measures for the software R&D segment of total business R&D developed for this paper (i.e., measures for investment, capital services, and capital rental price) were compiled using the same concepts and assumptions embedded in the BLS system.

4.1.4 Results

Our analysis covers the periods from 2012 to 2017 and from 2017 to 2024, which incorporates developments through the most recent full year (as of this writing).

Table 1 summarizes our main result: The contributions of software production and software capital use to recent growth in US labor productivity are remarkably large. Line 2 of the table shows that the average annual contribution of software production and use rose from 0.4 to 1.0 percentage points between the two periods shown, an acceleration of 0.6 percentage points. Comparing these figures to the reported growth of nonfarm business labor productivity (LPG), shown on line 1, suggests that software production and use contributed half of overall LPG—likewise, software accounted for about half of its 1.2 percentage point acceleration from 2017 to 2024 (column 3).

Turning to TFP growth, line 4, the story is almost equally remarkable: Our results show that overall TFPG increased in recent years, rising from an annual rate of 0.4 percent between 2012 and 2017 to 0.9 percent from 2017 to 2024. TFPG in software industries—about 6 percent of the US nonfarm business economy—contributed about one-third of its overall growth from 2012 to 2024 and accounted for more than 40 percent of its acceleration after 2017.

Do the observed accelerations in LPG and TFPG correspond to the cumulative impact of advancements in AI architectures and large-scale data that have landed us in the generative AI era? Further research would be necessary to provide a definitive, evidence-based answer. The main point here is that, when the production and use of software capital are taken as a reflection of the impact of AI technologies, their combined contributions indicate that AI has already had a significant impact on US productivity growth.

Table 1. Productivity Growth and Software: Summary

US Nonfarm Business Sector		2012 to 2017 (1)	2017 to 2024 (2)	Acceleration (3)
1.	Labor productivity growth (LPG)[1,3]	.8	2.0	1.2
2.	Contribution of software production and use[2,3]	.4	1.0	.6
2a.	*(percentage share of line 1)*	.50	.51	.51
	of which:			
3.	Contribution of software industries	.2	.6	.4
3a.	*(percentage share of line 1)*	.28	.30	.30
4.	*Total factor productivity growth (TFPG)*[1,3]	.4	.9	.5
	of which:			
5.	Contribution of software industries	.1	.4	.2
5a.	(*percentage share of line 4)*	.30	.37	.43

Notes. Software industries are the 2017 NAICS 511, 518-9, and 5415 industries. Software capital is the software component of Intellectual Property Products (IPP) and software product and embedded software R&D component of Business R&D.

1. Percent change
2. Percentage points
3. Based on natural log differences/points

Sources. Authors' elaboration of BLS productivity data files and NSF/NCSES BERD Survey data.

Table 2 provides additional details. The production effect, which recall is TFPG in software production times its production share, is presented on lines 1 to 3. These indicate that the software-producing sector's value-added share averaged 0.063 percent in the most recent period and its TFPG posted advances that averaged 5.6 percent per year, with the production effect contributing 0.37 percentage points to overall nonfarm business TFPG from 2012 to 2017. Even more notable, lines 4 to 6 of the table show that the use effect, at 0.67 percentage points per year, is about double that of the production effect. Though the rental share is in line with the value-added share, in latter period, the whopping pace of capital deepening (nearly 10 percent per year) boosts the relative size of the use effect. The production and use contributions (rows 3 and 6) sum to (the rounded figures in) row 2 of Table 1.

Table 2. Software Production, Use, and Software Capital Major Asset Types

	US Nonfarm Business Sector	2012 to 2017 (1)	2017 to 2024 (2)	Acceleration (3)
	Production and Use of Software			
	Production (software industries)			
1.	Share of aggregate value added[1]	.052	.063	.01
2.	Total factor productivity (TFP) growth[2,4]	2.5	5.6	3.1
3	*Contribution to labor productivity growth*[3,4]	.13	.35	.23
	Use (software capital)			
4.	Share of aggregate rental payments[1]	.049	.069	.02
5.	Capital deepening[2,3]	5.9	9.8	3.9
6.	Contribution to labor productivity growth[3,4]	.29	.67	.38
	of which:			
	Software capital use in software industries			
7.	Share of rental payments[1]	.016	.025	.01
8.	Capital deepening[2,4]	5.0	8.5	3.6
9.	Contribution to labor productivity growth[3,4]	.011	.24	.14
	Use of Software Capital Major Asset Types			
	IPP software capital			
10.	Share of aggregate rental payments[1]	.030	.035	.00
11.	Capital deepening[2,3]	5.6	9.3	3.7
12.	Contribution to labor productivity growth[3,4]	.17	.32	.15
	of which:			
13.	Contribution of software industries	.04	.08	.03
	Software R&D capital			
14.	Share of aggregate rental payments[1]	.019	.033	.01
15.	Capital deepening[2,3]	6.3	10.7	4.4
16.	Contribution to labor productivity growth[3,4]	.12	.35	.22
	of which:			
17.	Contribution of software industries	.06	.16	.10

Notes.: Software industries are the 2017 NAICS 511, 518-9, and 5415 industries. Software capital refers to the software component of Intellectual Property Products (IPP), and the software product and embedded software R&D, a component of total business R&D. Shares are Divisia shares. TFP is calculated on a value-added basis.
1. Percentage 2. Percent change 3. Percentage points 4. Based on natural log differences/points

Sources. Authors' elaboration of BLS TFP and IPP capital detail data files. Software R&D capital is estimated using NSF's survey data on R&D by industry and technology focus. BLS data last accessed June 4, 2024; NSF data last accessed June 25, 2025. The paper's appendix reports additional details on the calculation of software R&D.

To get some sense of the historical scale of these numbers, Oliner and Sichel's classic study (Oliner and Sichel 2000) estimated contributions to LPG of capital deepening in software of 0.09, 0.23, and 0.27 percentage points in 1974-90, 1991-85, 1996-99, respectively (see row 5 of their Table 2). Our estimated current contributions are much larger: Notice that their software income shares rose from 0.8 to 2.5 percent of nonfarm business value added (row 11 of their Table 1, data for 1974-90 and 1996-99). As our Table 2, row 4 shows, the income share of software capital is now much larger, and apparently still expanding (rising from 0.049 of nonfarm business value added in 2012/7 to 0.069 in 2017/24).[9]

Next, rows 7 to 9 of Table 2 show the contribution of software use in the software industries themselves. There is a conceptual question of how to treat software written by the software-producing sector for its own use (which is like the question of how to treat software written in the R&D sector). Given that software in national accounts is capitalized, own-account software production provides capital services from its accumulated net stocks just as the purchase of a capital good produced in another sector does. Thus, these rows show the contribution to the overall use effect of software capital-deepening in the software industries. As a comparison of row 9 with row 6 implies, remarkably, this contribution is about one-third of the economy-wide software capital deepening contribution.

Finally, rows 10 to 17 show the components of software capital: US national accounts IPP software assets and our estimate of software R&D assets. The rental shares for both are similar in the second period, though software R&D's share was lower in the prior period. Both components show rapid rates of capital deepening and nearly equal contributions to LPG. About half of the software R&D asset contribution comes from software producers, however, while those industries account for only one quarter of IPP software use in the economy.

4.2 Cross-country comparisons

To make cross-country comparisons we use the EUKLEMS & INTANProd productivity dataset (LUISS 2025). We draw upon data from its analytical module (described in Bontadini et al. 2023) for the European Union measured as an aggregate of 10 member countries for which we have both full growth accounts and substantial history (Austria, Chechia, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, and Sweden) plus the United Kingdom and the United States.

4.2.1 Measuring the production effect

For the production effect we need data on the production of software that are comparable across countries. For the US, we use the NACE industries corresponding to the 2017 NAICS classifications used above. (NACE refers to the standard classification for economic activities used in Europe and incorporated in EUKLEMS & INTANProd.) Comparable industry-level productivity data for Europe are not available, however.

The nearest usable classifications for Europe are NACE sectors J62-J63 (Computer programming, consultancy, and information services) and J58-60, which consists of publishing, including software (J58); motion picture, video programming, sound recording and music publishing (J59); and programming and broadcasting (J60). Thus, for Europe, to capture software we need to include movies and audio/video programming and broadcasting in our comparative analysis (not just other publishers as done for the United States).[10] Appendix Table A1 shows results using only J62-63 for Europe (keeping the US as is), which turns out to make little difference: In general, the broader set of EU industries has a larger production share but lower TFPG than calculated for the narrower set, so the alternative software industry groupings yield similar production effects.

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[9] Note that the rental shares we report for overall software capital are conceptually comparable to those in (Oliner and Sichel 2000). At the time of their writing, BEA's own-account software estimates were designed to include software R&D (Crawford, Jankowski, and Moris, 2014).

[10] Note that we could include movie production in the US results to move to greater comparability, but this would gain us little, as the move still leaves out the audio/video programming and broadcasting component, which is bundled with telecommunications in the available US data on industry value added and fixed investment by asset and industry that are required for productivity analysis.

4.2.2 Measuring the use effect

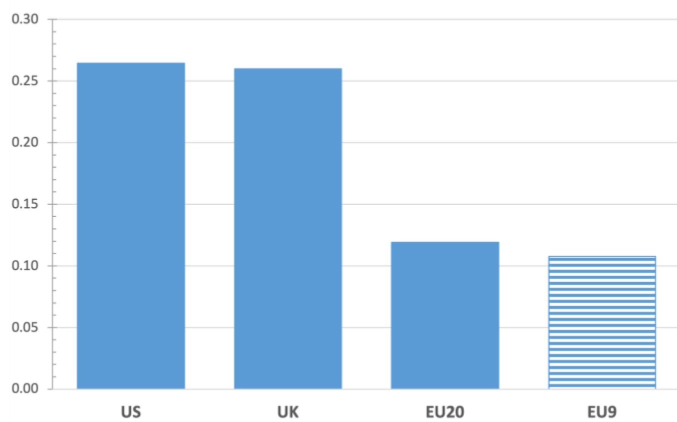
Our data harmonize the quality change component in price deflators for software (and ICT hardware) across countries. While this enhances the cross-country comparability of use effects, the accounting treatment of software R&D is not standardized in the national accounts of all countries, which creates a significant barrier to comparability. European conventions record software R&D as software, whereas the US national accounts include software R&D in business R&D as previously discussed.

In seeking to capture AI as an IMI, our application of the model of Section 3 sets out distinct roles for final product software (as a tool in downstream production) and innovation processes such as software product R&D and software used in R&D projects. The analysis presented in Table 1 and Table 2 on US productivity growth examined this distinction. Harmonizing the EU KLEMS & INTANProd database to make this distinction presents significant challenges requiring extensive cooperation from national statistics offices, which we must leave to further work.

That said, in what follows the software capital deepening figures for European countries include software R&D and, while the figures for the US do not. To aid in interpreting these comparative results, Figure 3 shows a cross-country elaboration of survey results for spending by business enterprises on R&D for NACE Sector J,

Figure 3. R&D Performed by the Information and Communications Services Industry (NACE Sector J)

Share of R&D performed by all Business Enterprises, 2018-2021 average



Notes. EU20 country coverage is explained in footnote 11.
EU9 refers to Austria, Chechia, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, and Sweden.
Source. Business Expenditure on R&D by Sector of Performance in millions of US dollars (PPP converted), OECD Statistics Library (accessed August 12, 2025).

the industry sector including software production and hence software R&D. The data shown cover 22 EU member countries and the UK and US.[11] Though data from this survey are the basis for estimates of business

[11] The 22 EU member countries for which we have BERD data from the OECD are the following: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Slovak Republic, Slovenia, Spain, and Sweden. Data for Sector J are suppressed for Luxembourg and the Netherlands, so the figure displays results for 20 EU member countries. Data for Denmark exclude 2021.

investment in R&D in national accounts, the main concepts used in these surveys (OECD 2015) do not correspond to the national accounts concept of gross fixed capital formation (Ker and Galindo-Reuda, 2017). Additionally, BERD data on R&D performance include investments funded by foreign companies, e.g., the massive amounts for R&D by DeepMind in the UK after Google/Alphabet's acquisition of the company.

Figure 3 reveals that the proportion of R&D investment allocated to software development and ICT services R&D in NACE sector J is considerably lower in the EU compared to the US and UK. This trend persists whether one examines the whole of the EU, to the extent permitted by available data, or focuses on the smaller number of member states with full industry-level growth accounts and substantial history in EU KLEMS & INTANProd and that we use for our comparative results.

4.2.3 Results

Table 3 shows our parsing of the available accounts in EU KLEMS & INTANProd; the left panels show data for 2010-14 and the right for 2015-19. We chose these years because 2019 is the most recent non-pandemic era data available consistently across countries and 2014 is a convenient breakpoint: splitting results in 2017 would leave too few years in the latter period. We show data for the US, UK and a 10 country EU aggregate.[12]

Starting with the production effect, the top left panel, first column, shows the share of total value added of the software-producing group of industries at around 5 percent for the EU and nearly 7 percent in the UK. As the second column shows, TFP growth for these industries is rather different: 2.2 percent per year in the US, .5 percent in the EU and a negative value for the UK (the UK data are affected by one large outlier over this period). Thus the "production" side contribution to labor productivity growth (see the lower panel), is 0.11 percentage points in the US, 0.03 in the EU (and negative in the UK).

The right-hand top panel shows how this changed post-2014. The production shares of software rose somewhat, along with increased TFPG in the US and UK and slowing TFPG in the EU. The production effect is then greater, rising to 0.17 percentage points per year in the US, and lower rates of growth for the EU and UK (0.04, 0.14).

The lower panel shows the use contributions. Income shares (rental payments to software capital as a share of market sector GVA) are consistently higher in the US, as is capital deepening in the second period. The "use" contribution to d(v/l) is then 0.3 percentage points in the US and almost exactly half that elsewhere.

Finally, the "total" panel shows a rise in the contributions of software to d(v/l) in all countries. The US has the largest contribution, at 0.47 percentage points, with the EU and UK in the second period with similar contributions of 0.20 and 0.28, respectively.[13]

There are, we believe, three main findings from these calculations. First, the total effect is mostly a "use" effect: in the US for the most recent period, the use effects are 60 percent of the total effect. In the EU there is effectively no production effect because the TFPGs in the production sectors are so small (the shares are about

[12] All data refer to the non-agricultural market sector (shorthand for the total economy excluding NACE industries A, L, O, P and Q). Computer hardware and software investment deflators used for building capital stocks and capital rental prices are harmonised across countries using the method of the OECD (Colecchia and Schreyer 2002). Hardware and software output deflators are as computed in each country's national accounts.

[13] Although these are not the same years as those in Tables 1 and 2, these US results are close to the IPP software results detailed in Table 2.

the same). If we use narrower definitions, see Appendix, we get a higher production effect in the UK (contribution of 0.09 percentage points, due to higher TFPG in those industries, but the same EU effect).

Second, the total effect for the US is much larger than in Europe (even though it excludes software R&D), 0.47 percentage points in the US against 0.19 and 0.11 percentage points in the EU and UK. This is in part due to the absence of a production effect in the EU, but we find the use effect is also smaller outside the US. The shares are similar, so what dominates is the higher capital deepening in the US.

Table 3: Comparative contributions of software to labor productivity growth

		2010-14			2015-19		
		1	2	3	4	5	6
Production							
		Production share	TFP (%pa)	*Contrib (%pa)*	Production share	TFP (%pa)	*Contrib (%pa)*
1	US	0.050	2.2	0.11	0.056	3.1	0.17
2	EU	0.051	0.5	0.03	0.056	0.7	0.04
3	UK	0.068	-1.1	-0.08	0.070	2.0	0.14
Use							
		Income share	Cap deep (%pa)	*Contrib (%pa)*	Income share	Cap deep (%pa)	*Contrib (%pa)*
4	US	0.037	5.7	0.21	0.040	7.4	0.30
5	EU	0.022	5.9	0.13	0.024	6.8	0.17
6	UK	0.029	3.6	0.10	0.030	4.8	0.14
Total							
7	**US**			**0.32**			**0.47**
8	**EU**			**0.15**			**0.20**
9	**UK**			**0.03**			**0.28**

Notes: Results are for the non-agricultural market sector industries of these economies based on EU KLEMS & INTANProd (LUISS 2025). Software producing industries for the US are the 2017 NAICS industries 511, 518-9, and 5415; for EU and UK, they are NACE industry sectors J62-J63 and J58-J60. EU refers to a PPP weighted aggregate results for the following 10 countries: Austria, Chechia, Denmark, Finland, France, Germany, Italy, Netherlands, Spain, and Sweden

5 Production and use: forward-looking evidence

What might be the effects of AI be in the future?

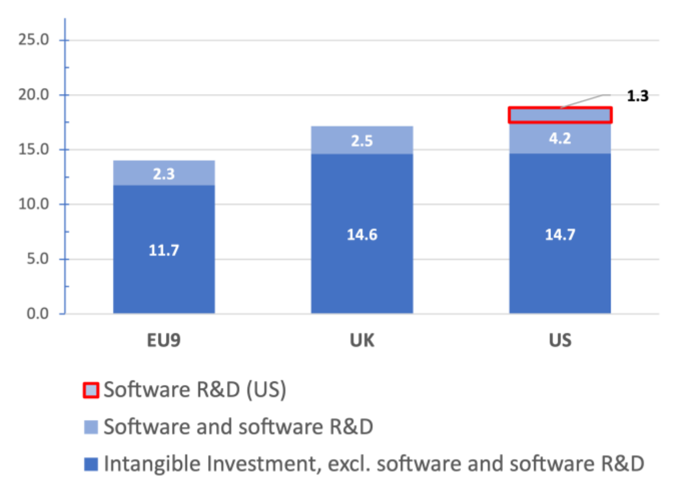
As we have seen in the two-sector model of section 3.3, faster upstream TFPG induces more capital deepening. From (5), the steady state the additional $d(v/l)$ depends on the (a) share in GDP of upstream production (ω^N_V) times the upstream productivity advantage ($da^N - da^{CI}$) and (b) the share of GDP of payments to upstream-created capital assets (s^R_V) times ($da^N - da^{CI}$) divided by the total labor share (s^L_V).

5.1 Assumptions

Theory suggests that in a closed economy with large depreciation rates (which is the case with intangible assets relative to tangible assets) that $\omega^N{}_V \approx s^R{}_V$, i.e., that production and income share are approximately equal.[14] In an open economy, if upstream output is entirely imported then $\omega^N{}_V = 0$. In practice for measures such as software in the tables above, the current production and income shares are quite close. To simplify, in what follows we shall then set them equal.

So, what might be the production share, $\omega^N{}_V$? Analysis by technologists suggests AI is concentrated in new techniques embedded in software and databases. Management consulting analysis suggests AI is being implemented in a several business functions that produce intangible assets, e.g., marketing and R&D. The potential for software to drive all intangibles is dramatically illustrated in Figure 4, where cross-country investment rates for all intangibles compared with software (a component of the total) are shown. As may be seen, investments in asset types other than software are currently substantial, suggesting there may be much potential for AI to automate and streamline the processes used to produce them.

Figure 4. Intangible Investment: Software and software R&D vs other asset types
Percentage of non-agricultural market sector industries gross value added, 2019.



Note. Gross value added is adjusted to include non-national accounts intangibles; see Bontadini et al 2023. Software estimates are national accounts estimates.
Sources. Total intangibles and software, EU KLEMS & INTANProd; software R&D for the United States, this paper.

In addition, software as measured in national accounts will understate the potential AI impact for two reasons. First, in current national accounts, data is not identified as a standalone asset (this will change with the implementation of the 2025 SNA, but this is a way off). The 2008 SNA mandated software and databases as a single asset category, the category we are using and call "IPP software," but in practice purchases of data are excluded. In the past, such purchases have been small, but with the growth of AI activity, a marketplace for data services is also growing. In fact, there is evidence that national accounts understate much investment in

[14] See (Oulton 2012) equation 24. The steady state output share equals the steady state income share times a term with upstream depreciation in the numerator and denominator (and other terms in capital growth, rates of return and TFPG advantage, all of which are likely small in relation to upstream depreciation).

data and databases: we show evidence of this below.[15] Second, surveys of R&D that gather information to use for the estimation of the capital services component of R&D investment expense may be off, but in the opposite way: purchases of data services used to train AI model are likely to be captured in "materials" but the contribution of data assets produced on own account may be missed.

The understatement of data in national accounts has a third twist, namely, that the accumulation of data assets may be suggestive of the readiness of firms to adopt AI to reduce the cost of intangibles. To estimate the extent to which data is understated in national accounts, we exploit a recent, nationally representative survey that asked around 400 firms in the UK about their software and data investment (DSIT 2023; Bontadini et al. 2024). Firms were asked, among other things, to provide time-use information for employees that worked on the organization and development of long-lived raw data, databases (converting raw data into structured format), data intelligence and software. Such information aligns closely with the forthcoming SNA guidance to (a) enumerate data and software separately and (b) specifies specific spending on data as investment. The key finding is that a national accounts-consistent estimate of data investment/production using information from the DIST 2023 survey data was found to be around 10 percent of UK market-sector GVA. This figure is much higher than the comparably calculated value for software investment (about 4 percent) but lower than the value for total intangible investment (about 15 percent) implied by the DIST survey.[16] Interestingly, total intangible investment is estimated to be 15 percent of market sector GVA for United Kingdom in the EU KLEMS & INTANProd database, which is independently derived following Corrado, Hulten, and Sichel (2009); see the Appendix in Corrado et al. (2022) for details of this estimation.

The 10 percent figure for data investment in the UK is also close to that found in a cross-country analysis of data investment (Corrado et al. 2025). They estimated economy-wide database investment on own-account using a sum-of-costs method. This is the method suggested in the manual accompanying the 2025 SNA, which calls for the introduction of data as a fixed asset. For 2023, the comparable UK figure in this study is 9 percent with the EU at 8 percent (figures are not available for the US). The study also presented econometric evidence that there was an overlap between data assets and intangible assets, suggesting a significant share of intangibles could be—or already were being—produced using data assets as an input.

Next, we need data on the productivity advantage of upstream industries, ($da^N - da^{CI}$). We have several different sources of data here, starting with the US data on TFPG shown in Table 2, row 2 and Table 1, row 4. From 2012 to 2017 (column 1 of these tables), the average total factor productivity growth differential between the software sector and all nonfarm businesses was 2.1 percentage points (2.5 TFPG for software industries minus 0.4 for overall nonfarm business). This differential increased to 4.7 percentage points during the period from 2017 to 2024 (column 2 in the tables, i.e., 5.6 percent per year for software and 0.9 for all nonfarm businesses).

Second, productivity gains in specific tasks have been estimated, notably in areas such as call centers (Brynjolfsson et al., 2025); Filippucci et al. (2024) provides a comprehensive survey of these results. Some reported gains are substantial—for example, software programmers leveraging AI have seen improvements of 15–20 percentage points. While caution is advised when extrapolating these figures to sustained productivity

[15] Mitchell (2023) is a very useful survey. To measure own account software, typically data is used on costs of employing various software writers, where the costs are based on identified software professions. In practice, those professions might increasingly include those working on digitisation and interpreting databases which might be better thought of as developing databases and the insights from them; see also Edquist, Goodridge, and Haskel (2021).

[16] The DIST survey also asked about other intangible assets. These figures are drawn from an unpublished analysis of industry-level estimates conducted by the authors and Massimiliano Iommi for DSIT.

growth across broader industries, they nevertheless represent a potentially significant upside to the gains calculated below.

Third, Corrado et al. (2025) offer evidence regarding relative price differentials between intangible assets and overall nonfarm business output in the United States. These relative price movements mirror corresponding changes in total factor productivity (TFP) and, between 2019 and 2022, averaged -2.5, -5.1, and -3.1 percentage points for investment in all intangibles, software, and branding/marketing, respectively.

Given this uncertainty, Table 4 outlines possibilities for AI's contribution to labor productivity growth (LPG) based on equation (8) considering various input shares and TFPG advantages. The top panel assumes a modest share (0.05) of upstream/intangible production and use, with upstream productivity advantages of 0.5, 1, 2.5, and 5 percentage points. Results indicate that an upstream TFPG advantage of 0.5 percentage points, coupled with a 5 percent production share, yields an additional d(v/l) of 0.07 percentage points per year, comprised of a direct production boost of 0.03 and an induced use effect of 0.04 percentage points. Greater upstream advantages amplify this effect, rising to 0.67 percentage points across the top row. The bottom panel examines scenarios where upstream/intangible asset production comprises 0.15 of value added; in this case, the annual LPG increase ranges from 0.2 to 2 percentage points.

The possibilities in table 4 are calibrated with an assumed labor share of 0.6. With a labor share of 0.55, and 0.65, the totals vary little in columns 1 and 2, and maximum of 10 basis points in column 4.[17] Additionally, it is worth noting that the production effects are a roughly 40 percent of the total effects. An economy that wholly imports its upstream production will then have about 40 percent lower total effect.

Finally, these effects reflect a first-order approximation to steady state growth; moreover, the model is silent on how long this takes.

5.2 Central estimates

Our central estimate then depends on the relative advantage and production share. For the US, let us assume that the most recent period, from 2017 to 2024 is evidence of the effects of generative AI, in which case we wish to look at the recent gain in TFPG relative to its rate in the prior "pre LLM machine-learning" era. Using the figures in Table 1 and 2 suggests this *relative* productivity advantage is 2.6 percentage points, which matches the change in relative intangible prices reported in Corrado et al (2025).[18] Let us assume then a TFPG relative advantage of 2.5 percentage points (column 3 of table 4). Turning to production shares, the US intangible investment share of market sector GVA is currently around 18 percent from Figure 4. This share might fall if continued AI use lowers unit costs (AI replaces programmers and marketing analysts) without a concomitant increase in demand. This suggests a central steady-state estimate for the boost to LPG in the United States of 1 percentage point per year. This is a large number but is so because it reflects the impact of AI as an IMI in an economy with an already sizeable knowledge-producing sector.

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[17] For a labour share of 0.55, the totals for the 0.10 row are 0.14, 0.28, 0.70 and 1.41 and the 0.15 row are 0.21, 0.42, 1.06 and 2.11. For a labour share of 0.65, the totals are for the 0.10 row 0.13, 0.25, 0.63, 1.27 and 0.19, 0.38, 0.95 and 1.9.

[18] From 2012 to 2017, we have in table 2, row 2, TFPG in software of 2.5 percent, compared with 0.4 for the nonfarm economy (table 1, row 3), yielding a productivity advantage of 2.1 percentage points. From 2017 to 2024, the comparable advantage is 4.7 percentage points. This increase in software's productivity advantage, 2.6 percentage points, may be attributed as the contribution of generative AI.

Table 4. Contributions of AI as an IMI to labor productivity in steady state growth

	Production and income share	Contributions	Upstream Productivity Advantage (percentage points)			
			.05	**1**	**2.5**	**5**
			(1)	(2)	(3)	(4)
1.	**.05**	Production	.03	.05	.13	.25
2.		Use	.04	.08	.21	.42
3.		**Total**	**.07**	**.13**	**.33**	**.67**
4.	**.10**	Production	.05	.10	.25	.50
5.		Use	.08	.17	.42	.83
6.		**Total**	**.13**	**.27**	**.67**	**1.33**
7.	**.15**	Production	.08	.15	.38	.75
8.		Use	.13	.25	.63	1.25
9.		**Total**	**.20**	**.40**	**1.00**	**2.00**

Note. Totals may not add to components due to rounding. Figures constructed assuming the labor share is .60.

What about Europe? The European investment share is lower, at around 14 percent, putting Europe in the middle row of Table 4 if we likewise shave off a few percentage points. From the past data, Europe also seems to have a lower upstream TFPG advantage. Thus, for Europe we might use the upstream advantage in column 2, which is 1 percentage point. This gives a total effect of a sustained boost to labor productivity of 0.3 percentage points, which also no small change.

Europe outpaces the United States in the use of robots, however, especially in manufacturing in Germany. McElheran, Yang, Kroff, and Brynjolfsson (2025) find that AI adoption is complementary with robot use in mechanical processes, suggesting there is an upside for Europe in moving manufacturing into the AI age, a factor not considered in the model solutions displayed in table 4.

6 Robustness

How robust are these conclusions on AI as technology continues to improve?

6.1 J-curve effects

It is often pointed out that adoption of new technologies can be slow and requires co-investment to implement. That co-investment, if unmeasured, can lead to initial falls in TFP growth (the J curve effect, of Brynjolfsson, Rock, and Syverson 2021). Baily, Brynjolfsson, and Korinek (2023) discuss why with AI there may be less of a J curve effect. First, rather than needing whole new industries to be established (e.g. steam) that AI can often be rolled out via existing "rails": updated software via an internet connection, running on existing hardware. Generative AI functions are now part of Google and Microsoft Office 365, and a marketplace is developing for plug-ins and extensions. Second, data suggest fast adoption, e.g., ChatGPT gaining 1 million users in just five days (Duarte 2025). Furthermore, according to some sources, many firms report they already using AI. The 2025 AI index report reports "78 percent of organizations reported using AI in 2024, up from 55 percent the year before." In Europe the increase is from 57 to 80 percent, and in North America, from 61 percent to 82 percent (Figure 4.4.4 in Maslej et al 2025). These considerations align with the significant "backward" effects of AI on productivity documented in this paper.

That said, it could be that the strong impacts that we find are of applications to what Acemoglu (2025) calls the "easy to learn" tasks, which could mean a lower future impacts via a diminishment of the productivity advantages considered in our central estimates based on table 4. Against, this some argue that AI adapts itself to harder tasks; Bergeaud (2024) and Maslej et al (2025) provide informed discussions of this issue.

That the medium- to longer-term effects of AI may weaken are not related to the existence of a "J-curve" but rather boil down to whether there are diminishing returns to AI capital at the macroeconomic level. Some argue this, based in part on the observation of diminishing returns to data in the training of individual models; but however valid this reasoning, it does not necessarily hold when models are aggregated over age cohorts at a given point in time. Not only do diminishing returns seem hard to swallow for advancements in this technology anytime soon, but diminishing returns at the macroeconomic level would preclude Romer-style productivity spillovers (Romer 1990) despite that fact that once developed, AI models can be repurposed for various applications at relatively low marginal cost.

6.2 Productivity spillovers

We have not considered Romer-style productivity spillovers in our estimates, a matter on which there are several additional points to make. First, as suggested in the previous sub-section, one might argue that increased productivity of intangible capital due to use of AI models will generate increased spillovers, thereby raising *downstream* TFPG, and so raising the additional impact of AI. Second there is well documented evidence of the widespread use of open source software (Calderon et al. 2022; Hoffmann et al. 2024), evidence that supports the assumption of increased productivity in software production, i.e., *upstream* TFPG. These considerations suggest our estimates are a lower bound.

Though productivity spillovers to intangibles have a long history of investigation, beginning with the work on R&D spillovers by Griliches (e.g., Griliches 1992) and others, against this some have hypothesized that spillovers have decreased in the modern era and that it has become harder for outside firms to achieve spillover benefits from intangible assets held by large firms. Bessen (2022) discusses how the landscape for software development has changed since 2000, as knowledge held by dominant producers has become closely guarded; Corrado et al (2025) discuss how modern data-driven intangibles are difficult to copy at low cost to the extent proprietary data is used to create them. These considerations suggest our estimates are somewhat less of a lower bound.

6.3 The production and use framework in the age of cloud services.

Recall we include cloud infrastructure services in our grouping of industries producing software because the industry conducts much software R&D and is a delivery mechanism for subscription software services.

Cloud computing is generally defined as the provision of remote access to computing resources on demand and over a network. Before the widespread use of cloud computing companies typically purchased and maintained their own on-premises physical computers and software—the economic structure upon which equation (6) was based. As Reinsdorf (2023) explains, pay-on-demand infrastructure services are intermediate inputs to purchasing firms, and the IT hardware and future investment moves from individual firms to provider firms (e.g., Amazon, Google, Microsoft). Note that providers commonly construct their facilities ("server farms") on site from components, and this own-account investment might be missed by statistical agencies (Byrne, Corrado, and Sichel 2017).

Regarding *software*, the shift from purchases of "prepackaged" software on discs to delivery via cloud services (or software as a service, SaaS) is often regarded as the same, but as purchases via subscription accounts confer more or less the same "rights" as they did in the past, e.g., the right to use Microsoft's office productivity suite, these "rights" continue to be treated as acquisition of software assets by the individual firm and then depreciated. SaaS sales involve many nuances (length of contracts, annual fees, automatic license renewal etc.), discussed in Reinsdorf (2023), but the bottom line is that payments for many subscription software licenses are treated as capitalized software sales (by software "publishers") in national accounts irrespective of delivery mechanism. To the extent payments for software acquisition/use are rather attributed to infrastructure providers as intermediate services, our backward exercise captures their sales in the production effect but not the use effect.

Cloud services prices and quantities are also hard to measure: offerings are complex and the capture of quality change challenging (Byrne, Corrado, Sichel 2021; Coyle 2025). With the 2023 comprehensive revision, BEA included a quality-adjusted price index for cloud infrastructure services in the US data beginning in 2016. These services are intermediate purchases of firms, and the move did not affect US GDP, but it did affect its industrial composition—and the comparability of the cross-country production effects shown on table 3.

6.4 Cost and product quality change

To the extent that AI use leads to lower unit costs of production, the impact of AI capital *will* be accounted for in the statistics used in this paper, though the economics of the impact is complex and ultimately depends on the indirect effects on demand and prices charged for the tools and final products affected by AI. To the extent that AI is used to enhance the *quality* of a product (unit costs and transaction prices aside), the price measures in the data used for this study likely *will not* have captured this change.

For example, the annual cost for a standard (personal) subscription for Microsoft 365 is $70 and has been since the personal plan was introduced in 2017; the additional cost for AI features, available since January 2025, is $30. This includes full access to Copilot, Microsoft's LLM for which the company is spending $13 billion on further development in 2025 alone. We should not be surprised that price collectors have not sorted out how to treat the additional AI functionality in this otherwise "legacy" product, but that said, designating and pricing AI-enabled products in our economic statistics is an urgent matter.

7 Conclusion

In this paper we provide a framework and some fresh estimates for the effects of AI on labor productivity growth (LPG) in the recent past and likely in the future. Our framework consists of an (a) upstream sector producing intangible/knowledge capital (e.g. facial recognition software) and (b) a downstream sector using such capital (e.g. airport security services).

This framework captures an important feature of AI. Although AI is typically described as a GPT, we argue that it is, in addition, an innovation in the method of innovation (IMI). Thus, the effect of AI on LPG comes not only from AI being widely used, but also from the additional productivity in the upstream intangible-producing sector where (commercial) invention is occurring. The "task" approach used to determine the impact of AI is based on the extent to which software can replace tasks. As software is an intangible asset, our growth accounting approach to determining the impact of AI on productivity growth is congruent with the task approach.

Although software is but one intangible asset, AI first and foremost may be seen as a productivity improvement in software production. We estimate the effect of AI on LPG as the (a) "production effect" capturing the gain in upstream TFPG from software product improvement and (b) the "use effect" of software capital deepening, which includes the use of improved software products downstream *and* the conduct of software product and embedded software R&D upstream. Our ability to account for upstream sector software R&D necessitated developing and incorporating additional R&D survey data into the typical dataset used for productivity analysis in the United States.

Our results cover the US and Europe, but because we have more detailed and timely US data, we are able to document the early effects of AI for the United States. Our results can be summarized by adapting the late Robert Solow's famous quote to: You can see the AI age everywhere *including* in the productivity statistics.[19]

Our computations indicate US nonfarm LPG accelerated to 2.0 percent (annual average rate) from 2017 to 2024—and that the production and use effects of software capital alone contributed more than 50 percent of this acceleration. Moreover, software industries, which are 6.3 percent of the US nonfarm economy, are estimated to have accounted for 30 percent of the gain. Indeed, if one were to ask, Has Marc Andreessen's prediction about software's increasing impact, outlined in his 2011 essay "Why Software is Eating the World" (Andreessen 2011), proven prescient? Our answer to this question in a US context would have to be "yes".

Our estimates are high relative to the historic experience of steam and electricity and relative to other AI estimates. The central reason for this is the modelling of AI as both an IMI and a GPT along with already high intangible income and production shares of GDP. Regarding just software, we find much evidence suggesting that AI is a breakthrough in software production. To the extent that new software is readily available to users with hardware and a connection, the potential impact on LPG is rather larger than previous technologies. Steam and electricity required brand new industries for their production and a refashioning of using industries for their use (new railway lines, new ports). AI already has many of the "rails" upon which to run.

Looking ahead, our steady state predictions for the effects of AI on LPG due to the TFPG gain in the "ideas" sector are around 1 percent per annum in the US and around 0.3 percent per annum in Europe. This is mainly driven by the historic evidence suggesting that Europe has a smaller and less productive upstream software/intangibles sector and lower software/intangible capital deepening.

The lagging position of Europe is worthy of more work on the underlying determinants of the continent's position but our results mirror the influential Draghi report documenting Europe's lag in both the implementation and production of (what he called) "hi-tech" goods, which refers to the manufacturing of ICT equipment and provision of ICT services (Draghi 2024). Some point to Europe's regulations of digital economic activity as the culprit, and recent work documents that lower technology venture investment in

[19] Solow's original sentence was "You can see the computer age everywhere but in the productivity statistics" (Solow 1987). As a matter of historical record, when Solow made his famous remark, the BEA had already introduced its quality-adjusted hedonic computer deflator in a revision published in 1985. But Solow was right: it was hard to "see" the computers in 1987 because, in fact, the value of computer sales was still not all that large. Further, the ICT contributions from Oliner and Sichel (2000), quoted previously in this paper, incorporate software that we have seen is not small. Software spending was not introduced as investment in the US national accounts until the 1999 comprehensive revision, well after Solow's observation.

Europe is correlated with, for example, European regulations such as GDPR legislation (Johnson 2022). The lagging position of Europe predates the introduction of GDPR so doubtless there is more to this story.

Though we are rather early in the emergence of generative AI as an accessible new technology to forecast its effects, we believe we have shown that our upstream/downstream approach has proven a useful place to start. The approach emphasizes the IMI character of AI, which leads to relatively optimistic estimates of the beneficial effects of AI on productivity growth—and recall, we have not entertained the possibility that AI-enabled breakthroughs in biomedical and other sciences may significantly benefit human well-being and economic welfare.

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Appendix

A. Glossary of AI terms, adapted from McKinsey (Chui et al. 2023)

Machine learning (ML) is a subset of AI in which a model gains capabilities after it is trained/shown data (data can be structured or unstructured, labelled or unlabeled; ML is particularly suited to unstructured data).

Deep learning is a subset of machine learning that uses "deep neural networks" (layers of connected data) to learn from unstructured data such as images, text, and audio (CNN, RNN and transformer are different types of deep learning).

Foundation models are types of deep learning models trained on unstructured data with *fine tuning* (fine tuning uses unstructured data to train the algorithm but which is labelled, with the labelling typically by humans). Foundation models can be used for *generative* (generating content) or *nongenerative* purposes (for example, classifying user sentiment as negative or positive based on call transcripts).

Large language models (LLMs) are a class of foundation models that can process unstructured text and learn the relationships between words or portions of words (e.g. GPT-4 (which underlies ChatGPT) and LaMDA (the model behind Bard), among others.

Transformers are a type of neural network architecture.

Finally, as described in Allen (2020), there are different types of ML: *supervised*, *unsupervised*, *semi-supervised* and *reinforcement*. In supervised learning, the training data are labelled e.g. cat, dog and the computer then classifies other images. (Allen notes a common rule of thumb being that the algorithm needs at least 5,000 labelled examples of each category to produce a decently performing AI model). With unsupervised learning the computer is trained on broad pattern recognition and produces associated images. For example, financial fraud software is "supervised" i.e., programmed to recognize legally defined illegal acts but also is useful unsupervised, e.g., to detect unusual patterns in activity.

B. Software R&D investment by US business, national accounts basis

Statistics on Software R&D are collected in the R&D surveys sponsored by the National Center for Science and Engineering Statistics (NCSES). The information is obtained via questions on R&D by "technology focus" or "technology area," the results of which have been published in the data tables the Business Enterprise Research & Development survey (BERD, renamed from BRDIS) and its predecessor (the Survey of Industrial R&D, SIRD) since 2001.

Collecting and assembling this information for use in growth accounting with national accounts estimates of business investment in R&D presents involves several steps, from sorting through definitions and concepts to retrieving archived statistics. Most of the steps taken follow Moris (2019).

All told, raw data from BERD and its predecessors are used from 2013 on, and data prior to then are based on a combination of reported survey data and the software R&D estimates used in the national accounts as reported in Crawford et al (2014)

B.1 Survey data definition

Software Product and Embedded Software R&D has been defined in the BERD survey since 2013 as follows:

"R&D activity in software and Internet applications refers to activities with an element of uncertainty and that are intended to close knowledge gaps and meet scientific and technological needs." Respondents are instructed to report expenditures on software R&D regardless of the eventual user (internal or external).

Further, respondents are instructed that "R&D activity in software *includes:*

- Software development or improvement activities that expand scientific or technological knowledge
- Construction of new theories and algorithms in the field of computer science R&D activity in software

and *excludes*:

- Software development that does not depend on a scientific or technological advance, such as supporting or adapting existing systems, adding functionality to existing application programs, and routine debugging of existing systems and software
- Creation of new software based on known methods and applications
- Conversion or translation of existing software and software languages
- Adaptation of a product to a specific client, unless knowledge that significantly improved the base program was added in that process" (BRDIS 2016, page 3, as reported in Moris (2019).

Note that the instruction to include the "construction of new algorithms" in software R&D, suggests that AI-enable software development is captured in the BERD survey's software R&D statistics whether, of course, for eventual sale or for use in R&D projects more broadly.

For the years 2008 to 2012, the survey asked respondents to report software product R&D and embedded software R&D separately, which NCSES believes overstated the combined total; for these years comprehensive survey data on sources of funding also are not consistently available. From 2001 to 2006, the survey asked only for "software product development."

The 2021 and 2022 BERD surveys collected expenditures on AI R&D. In these surveys, respondents are told that AI is defined as: "Artificial Intelligence (AI) is a branch of computer science and engineering devoted to making machines intelligent. Intelligence is that quality that enables an entity to perceive, analyze, determine response, and act appropriately in its environment."

In the event, the survey reported that business expenditures on AI R&D were $37,014 million (all sources of funding) and $33,416 (paid for by the company) in 2022. By contrast, expenditures on software R&D paid for by the company were larger by a *factor of eight*. The new question on AI R&D was added to the section of the form that asks for information on the "technological focus" of R&D activities. With this addition, these areas now include Software Product and Embedded Software, Biotechnology, and Nanotechnology, and Artificial Intelligence. The instruction for the survey's section on R&D by technological focus includes the remark: "You may report the same R&D in multiple areas […of technological focus…]." This enables the survey to capture of embedded software R&D in the biotech and nanotech areas, but it also suggests that there may be an overlap between software product R&D and AI R&D. Reflecting this, one-half of the AI R&D in 2021 and 2022 has been smoothed into the total software R&D figures used in this paper.

B.2 Concepts and international comparability

Internationally, BERD surveys follow the OECD's Frascati Manual (OECD 2015), which instructs countries to include capital expenditures in R&D. The United States, historically and currently, does not follow that instruction for its headline R&D measures. The US BERD survey rather includes depreciation of fixed capital. (Separate tables report capital expenditures related to R&D and depreciation for international comparability.)

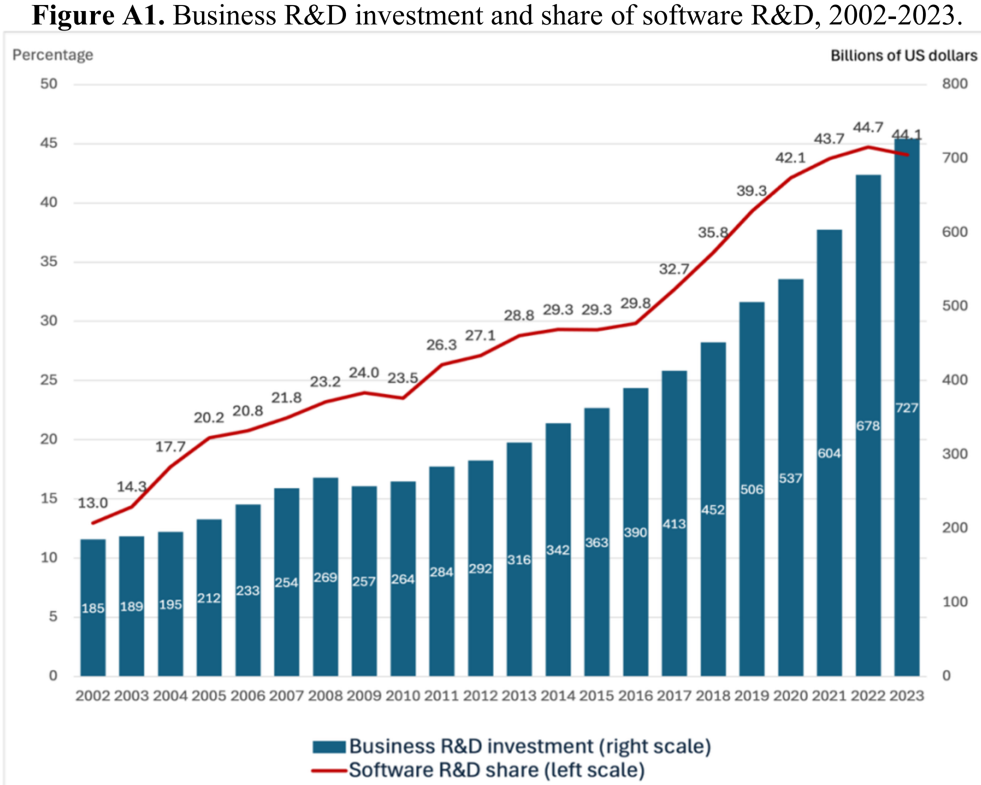
Domestic R&D expenditures in US BERD surveys are on a current cost basis, which means that a company's expenditures on capital and land are not included but that depreciation of fixed capital (e.g., a laboratory facility) is included as a current cost. This concept is consistent with standards for imputing own account production national accounts, which, note, do not currently impute a rate of return on imputed gross output. This may change as international standards for national accounts evolve and are implemented.

As is well known, a large fraction of a company's total cost of research on AI is for the computer resources that power training runs and model development/estimation. Press reports that a given company's AI research plans are to spend *billions* of dollars on AI research are misleading indicators of AI software R&D because figures quoted usually include outlays for building and equipping new research facilities and, possibly, land purchases.

The figures for software R&D are very large—In terms of the BEA data, R&D funded by domestic US businesses totaled $678B in 2022, with nearly 45 percent ($303B) representing the conduct of software R&D, of which nearly 60 percent ($178B) is in our three software producing industries. This would seem to imply that (a) companies spend hefty amounts to develop software products and internet-based software services and (b) software R&D is embedded in other R&D projects (e.g., novel guidance control systems) is also not small (to the extent the non-software producer share is indicative of that).

Figure A1 displays these national accounts consistent estimates, where note, these data are not in real terms. The figure shows that software products R&D as a share of total business R&D rose sharply beginning 2017.

Figure A1. Business R&D investment and share of software R&D, 2002-2023.



Sources. Business R&D, BEA; Software R&D, this paper.

Business R&D also began rising at a relatively fast clip about then, expanding 9.9 percent per year from 2017 to 2023 (US nominal GDP grew 5.9 percent over the same period). With the software R&D share also climbing, software R&D grew 15.5 percent per year, and software R&D conducted by software-producing industries rose 16.3 percent per year.

C. Alternative table 3

The table below shows the equivalent of Table 3 using NACE industries J62-J63 as the software-producing industries for the EU and UK.

Table A1. Production and use effects

		1	2	3	4	5	6
		2010-14			**2015-19**		
	Production						
		Production share	TFP (%pa)	*Contrib (%pa)*	Production share	TFP (%pa)	*Contrib (%pa)*
1	US	0.050	2.2	0.11	0.056	3.1	0.17
2	EU	0.036	1.4	0.05	0.040	0.7	0.03
3	UK	0.041	-2.0	-0.08	0.044	2.0	0.09
	Use						
		Income share	Cap deep (%pa)	*Contrib (%pa)*	Income share	Cap deep (%pa)	*Contrib (%pa)*
4	US	0.037	5.7	0.21	0.040	7.4	0.30
5	EU	0.022	5.9	0.13	0.024	6.8	0.17
6	UK	0.029	3.6	0.10	0.030	4.8	0.14
	Total						
7	**US**			**0.32**			**0.47**
8	**EU**			**0.18**			**0.19**
9	**UK**			**0.02**			**0.23**