

Labor, Productivity, and the Sabbatical Expectations of Artificial Intelligence

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The idea of Sabbath can be traced to Genesis when God declared rest after that very first week of worldly activity. What was the motivation for resting and how does it inform our expectations of work today? A lay interpretation of the origin generally emphasizes the word, “rest,” but in Hebrew, the word *Shabat* is derived from the verb in the first phrase of Genesis 2:2: “God *finished* his work which he had done.” That is, the blessings of rest come when we have *completed* our work, not simply when we need or want a break from it.

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In modern liberal economics, the notion of quality of life—our capacity to enjoy the fruits of our labor, or the ability of labor to generate disposable time—are built on the principle of Productivity and are surprisingly consistent with the original meaning of the Sabbath. Economists ask, “What tools are at the disposal of industry and public policy so that our workers can become more productive—increase their output, and the earnings that come from that output—without having to devote more time to work?” In other words, “How can we *finish* our work more quickly so we can rest more?”

This fundamental question should impact everything from public investment plans to tax incentives, from training and education policies to labor laws. Workplace regulations that mandate minimum leave, maternity and paternity leave, holidays, sick leave, and even the construct of the work week and weekends are all forms of sabbatical, according to both the original and more generous interpretation of the word.

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Technology's role in productivity

Before we set policies for work, we must understand what drives productivity. The traditional factors understood to drive the growth of economic output—labor and capital—do not explain *all* of the growth in our economies or firms from one year to the next, nor do they explain the years of contraction. Something is missing when we add labor and capital together. This x-factor is presumed by most economists to be the ability of an economy to absorb new technology, to derive more efficient ways of producing, conducting business, and offering services. When innovations allow us to do more without the need for more work hours or more capital investment, then economic growth needs to account for this ephemeral input. That input is “Productivity,” and it generates output as economic growth on the one hand and room for workers to rest on the other.

To offer an example, if a research assistant can produce, say, three times as much information in a workday as that same worker could before internet access—and if an internet search engine costs less than two additional research assistants—then we need to include the contributions of that innovation when we look at economic output.

To estimate what the technology and innovation contributions are to economic growth, changes in Productivity are calculated as the *residual* of an economy's overall growth—what is left after we account for changes in the economy's labor and capital markets. Because we cannot measure it or see it at an aggregate level, we infer its existence from the wake that it leaves—much as we identified the planet Neptune in the nineteenth century based on disturbances in Uranus's orbit.

Technological revolutions thus bring us both expectations (higher growth) and aspirations (higher quality of living). Outside of academia, we experience productivity gains through observation, trying to apply what we have seen from *past* technology changes to the emerging technologies we are witnessing. We ask, “How will self-driving vehicles change the value of our commuting time?” “How will the use of battery storage, in combination with the sun and wind as sources of energy, impact our national accounts, or our economic efficiency, if they displace thermal power?” And more than ever, “Now that Artificial Intelligence can generate whole research papers, answer confused customers' most urgent questions, produce better forecasts, and spot both anomalies in deep outer space and hidden treasures under rainforest canopy, how will our Productivity change?” We look at what the Internet brought us and try to imagine what AI's marginal contribution will be to our own way of doing and building—and resting.

The expectation that comes from technological advances is that new levels of output and wealth, and, with them, disposable time, are generated by their benefits even when the other resources at hand remain fixed. This goes back to the invention of bronze, the wheel, the concept of “zero,” antibiotics, fertilizers, washing machines. Did these inventions not give our societies greater productivity, the room to extend life expectancy, increase time with family, and more comfortable lives? Did they not give us the Sabbath we had earned?

The first corollary to the notion of asymmetric gain from new technology is the disruptive or “counter-productive” element of human behavior. Alfred Nobel discovered this contradiction when his invention of dynamite—which he thought would primarily revolutionize construction—was quickly deployed for political violence purposes. Hardly had prototype self-driving vehicles begun to emerge than guerrilla videos followed showing people standing over bridges, hacking into the cars, and propelling them to crash. On a larger scale, social media may be the early 21st Century’s poster child for technologies that work against their own potential. One day, not long ago, we were using the new platforms to reconnect with old friends and crowdsource funds for new inventions, and seemingly the next day, a generation of mental health issues had emerged from cyber-bullying and a tsunami of self-obsessiveness.

Artificial intelligence encounters disruptive human behavior

Even if we are to assume that AI will bring more productivity gains than anti-social behavior, there remains a real risk that human nature will intercede to diminish the new technology’s full potential. As the first hard-to-refute generated videos of political and social leaders speaking against their own interests begin to penetrate the social media landscape, we begin to imagine how AI can contribute further to the erosion of verifiable forms of information, and the diminution of institutions needed to propel economic activity and social productivity. That is, there is no reason to assume that we ourselves will not work against the gains that could have been fully inherent in the same technologies that are intended to produce growth and productivity premia. The hope remains that an arms race that pits AI-enabled virtuous policing against anti-social or vicious abuse of AI will protect the promise of machine learning, but it is hard to imagine that there will be no expenditure of time and resources in combatting the misuses of AI that are already emerging.

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AI vs. a free lunch

A second constraint on the potential of AI to fulfill its productivity potential comes from the physical inputs required to deploy AI services. First, we see the massive amounts of capital required to build the chips that drive AI. We are already witnessing a concentration of equity market value capitalizations in mega-firms that are invested heavily in AI development and the associated chip manufacturing, a massive deployment of capital at historical levels which may or may not survive the next wave of technological change.

The other dislocation from physical inputs to AI can be found in the staggering volumes of energy required to run the data centers that fire AI’s algorithms. The cost to utilities, consumers and corporations of having to increase investments and expenditure on energy brings its own disruption. By 2030 we expect AI to consume about one-fifth of all growth in energy demand. Depending upon a system’s availability

of excess installed power generation, and the structure of the local power market, those costs may be hard to incorporate into current consumer fees. Indirectly but importantly, this increase in demand without a commensurate set of increases in supply of power generation, means competition among consumers and higher prices. Where power generation *can* be piled onto the systems quickly, it means more competition for scarce natural resources, and greater risk of stranded assets if the future forms of generating AI algorithms do not require as much power.

And yet...

Despite these two constraints—the behavioral, or anti-productivity risks, and the physical costs—the original promise of AI can already be found across every field of natural and social science that depends on data analytics, modeling and forecasting, research, and problem solving. AI is already embedded in the workflow of a growing number of fields, and, in many cases, reshaping productivity.

The distributional effects of AI

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Service sector jobs now provide most employment opportunities for unskilled and lower wage workers in higher income countries. The early data suggests that this will also be an area of vulnerability. For middle and upper middle income developing regions, such as Latin America and the Caribbean, the majority of the region's poor live in the wealthier countries of the region where service sectors —such as home care, logistics, warehousing and delivery, tourism, retail, and customer service back offices—employ a disproportionate share of low-skilled and semi-skilled workers, many informally employed.

Growth Theory and empirical evidence suggest that long-run productivity growth is driven not primarily by the accumulation of physical capital, but by the generation,

adoption, and spread of new ideas, skills, and organizational capabilities.¹ Viewed through this lens, large portions of the service sector may continue to struggle to become dynamic sources of growth. When service activities fail to integrate technological change, provide workforce training, or offer improved modes of organization, workers tend to remain confined to low-value tasks. This dynamic helps explain why poverty may endure even in relatively high-income economies: low-productivity services not only mirror existing inequalities, but can also reinforce them by constraining wage growth and limiting paths for social mobility.

The countervailing promise of AI

In the labor market, early analysis of real-world deployments show that generative AI systems capture the patterns of top performers and diffuse them to newer workers. In customer support, for example, randomized adoption of an AI assistant raised issues resolved per hour by about 15 percent on average, with the largest gains accruing to less-experienced agents—shortening the journey from apprenticeship to competence without expanding the workday.

When an AI tool was integrated into customer support interactions, average output increased by nearly 14 percent.² The largest improvements—around 35 percent—were concentrated among junior and lower-skilled agents, while top-performing and highly experienced workers experienced few or no gains. Similar field experiments in software development report over 25 percent more completed tasks among developers using AI code assistants, again with disproportionate benefits for junior staff. This creates a subtle paradox: younger and less experienced workers are often the quickest to integrate AI into their daily tasks and reap immediate productivity gains, yet they are also the most exposed to some of its side effects.

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If the Sabbath follows the *finishing* of our work, then part of AI's promise should be inter-generational—the acceleration of productivity can be captured by the many—as both workers and as consumers, not only the few. This of course presumes that entire fields—such as customer support, radiology, architectural drafting, translation, or paralegal services, to name a few—are not displaced by AI so rapidly that we witness great dislocation costs at the sectoral and at the human level. At the very least, it presumes that the savings from reduced labor on those services accrue to other, yet unforeseen, work arenas. But these shifts are neither automatic nor instantaneous.³

1. See Romer (1994).

2. See Brynjolfsson *et al.* (2026), and Cui *et al.* (2025).

3. Jaffe *et al.* (2024) show that the influence of generative AI varies by role, function, and organization, and is contingent on adoption and utilization.

The shape of AI's coming benefits?

The “J-curve” of complements suggests that intangible investments made today translate into measurable productivity gains later. To reap society-wide benefits, general-purpose technologies rarely deliver free lunches; they demand complementary investments—process redesign, data integrity and robustness, managerial routines, or new human capital—that national accounts often under-measure. The literature describes a *Productivity J-curve*, meaning an early dip in output while organizations absorb the costs of those hard-to-value complements, followed by a rise in productivity once those assets bear fruit.⁴ Recent evidence in U.S. manufacturing finds short-run productivity losses, higher work-in-process, robot investment, and uneven impacts across firm types during early AI adoption.⁵

The above implies that the sabbatical of greater leisure is *deferred* while firms and workers both learn how to produce more efficiently. During the transition, the costs and benefits of productivity are distributed unevenly—across different workers, among firms within the same sector, and across firms in different sectors—unfolding with distinct temporal dynamics. One of those “uneven distributions” appears to be the way young workers are impacted versus older workers.

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While the young coders and customer service support workers saw jumps in productivity vis workers less able to integrate AI into their work, early evidence suggests that as generative AI tools take over the drafting, summarizing, and templating once done by junior professionals, firms that have depended on those particular kinds of functions are beginning to hire fewer entry-level roles.⁶ That said, they are shifting demand toward positions that require experience, judgment and domain stewardship. In software, postings for junior developers have fallen relative to senior roles since the public diffusion of GenAI, while field experiments show that quality and speed gains are “jagged,” strongest where tasks align with AI's frontier and weaker where human context and verification are indispensable.⁷

Preparing for AI

The way firms prepare for AI will have an outsized role in how the labor market in those fields develops. Labor policies can shape that preparation. Comprehensive, long-term labor policies that establish a balance between preserving career ladders (apprenticeships, co-ops, mentorship) and investing in skills that *complement* automation, so the benefits borne of higher Productivity do not foreclose the learning that makes future masters. There is no evidence yet that whole areas of economic activity can function without living

4. See Brynjolfsson *et al.* (2018).

5. McElheran *et al.* (2025) examine the prevalence and productivity dynamics of artificial intelligence in American manufacturing.

6. See Westby and Modestino (2025).

7. See Dell'Acqua *et al.* (2023).

memory—the uncoded knowledge, lived experience and relationships that drives our understanding of the markets in which we work—and, therefore, that AI can come to substitute for shared intergenerational knowledge among workers.

AI can boost productivity by improving decision-making, allowing full or partial automation of tasks and processes, while outcomes hinge on adoption depth and complements.⁸ As with a cooking recipe, these complements are the key. They are what can either ruin a dish completely or elevate it into a work of art. The divine is also in the details.

The accelerated adoption of AI forces us to redouble our focus on preventing social fragmentation and youth unemployment. Intergenerational bridges between experienced workers and younger generations will protect the stability of our institutions. Robust pillars for these bridges, in turn, require some sharing of the dividends from the AI-generated sabbatical.

A balanced distribution among young people with differing access to educational opportunities. Forms of training need to recognize that even if entry level jobs seem most vulnerable, younger workers adapt faster and will benefit more from AI if given access to AI tools and training. Young workers already make up a disproportionately high share of generative AI use globally (e.g., 46% of ChatGPT messages are sent by users 18–25), indicating strong openness to AI augmented workflows. It is important to identify which junior tasks can become *AI-supported* rather than *AI-replaced* to ensure early-career staff remain owners of *judgment-based* components of work, supported by automation rather than displaced by it.

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A balanced distribution between workers more and less exposed to automation. A humane response will center itself around preparation of the workforce, including investment in structured reskilling pipelines, especially where automation risk is highest. This suggests tailoring country-specific and sector-specific reskilling and upskilling programs to mitigate negative job effects and prepare workers for hybrid roles that combine human judgment with AI systems.

A balanced distribution between workers in industry and services. As AI adoption advances, productivity gains are unlikely to be evenly distributed across sectors, with early and larger effects concentrated on capital-intensive and technologically advanced activities. A policy-relevant response therefore requires deliberate efforts to extend productivity-enhancing technologies to service sectors, where a substantial share of low-wage and informal employment is concentrated. Facilitating the diffusion of AI tools, complementary skills, and improved organizational practices in services can help ensure that productivity growth does not widen existing sectoral gaps, but instead contributes to more balanced productivity gains across the economy.

8. A more detailed discussion is provided in IDB (2025).

Public policy's role in addressing AI's pending challenges

As AI functions expand, the importance of ethical, inclusive workforce planning grows alongside the technology. This means planning for responsible human-AI teaming, and alignment of human capital practices with AI-era realities. It also requires conducting structured workforce impact assessments to identify which junior and low-skilled functions face the highest automation exposure under the new technology; embed “future-skills hiring” criteria—valuing adaptability, reasoning, structured problem-solving—into entry-level recruitment, and ensure policies can mitigate, or prepare for, large-scale displacement. Neither behavioral nor physical constraints should pull us away from a goal that envisions the use of AI for the common good.

In both emerging and industrialized economies, it will become increasingly important to frame policy dialogue around the form in which governments, firms and workers interact with and leverage AI. AI's impacts will ultimately depend on this three-way dialogue—and on the intentionality that we bring to that dialogue. As with AI tools themselves, that coordination must be shaped, guided, and continually directed by human judgment.

References

- Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics*, 140(2), 889-942.
- Brynjolfsson, E., Rock, D., & Syverson, C. (2018). The productivity J-curve: How intangibles complement general purpose technologies. NBER Working Paper No. 25148.
- Cui, K. Z., Demirer, M., Jaffe, S., Musolf, L., Peng, S., & Salz, T. (2025). The effects of generative AI on high-skilled work: Evidence from three field experiments with software developers. Working paper, february.
- Dell'Acqua, F., Rajendran, S., Kraymer, L., Candelon, F., Lakhani, K. R., McFowland III, E., Mollick, E., Lifshitz-Assaf, H., & Kellogg, K. C. (2024). Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality. MIT Sloan School of Management Working Paper No. 24-013.
- Inter-American Development Bank Group (2025). Artificial intelligence framework for the Inter-American Development Bank Group. IDB.
- Jaffe, S., Parikh Shah, N., Butler, J., Farach, A., Cambon, A., Hecht, B., Schwarz, M., & Teevan, J. (2024). Generative AI in real-world workplaces. Microsoft Research Technical Report MSR-TR-2024-29.

McElheran, K., Yang, M.-J., Kroff, Z., & Brynjolfsson, E. (2025). The rise of industrial AI in America: Microfoundations of the productivity J-curve(s). U.S. Census Bureau Working Paper No. CES-25-27.

Romer, P. M. (1994). The Origins of Endogenous Growth. *Journal of Economic Perspectives*, 8(1), 3-22.

Westby, D., & Modestino, A. (2025). GenAI and software developer job vacancies 2. Manuscript submitted to *Management Science* (MS-0001-1922.65).