November 2025

Working Paper

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Konrad Kording and Ioana Marinescu

This working paper is available online at: https://www.brookings.edu/center/center-on-regulation-and-markets/

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(Artificial) Intelligence Saturation and the Future of Work

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November 10, 2025

Abstract

Macroeconomic models typically treat AI as just another form of capital, and predict a slowly evolving world, while computer science scaling laws applied to the whole economy predict explosive growth and the potential for a singularity-like event. Both views gloss over the asymmetric reality that intelligence capital or AI scales at computer-science speeds, whereas physical capital and labor do not. What's missing is a unified, parameter-driven framework that can nest assumptions from both economics and computer science to generate meaningful predictions of AI's wage and output impacts. Here we use a constant elasticity of substitution (CES) production function framework that separates *physical* and *intelligence* sectors. Whereas physical capabilities let us affect the world, intelligence capabilities let us do this well: the two are complementary. Given complementarity between the two sectors, the marginal returns to intelligence *saturate*, no matter how fast AI scales. Because the price of AI capital is falling much faster than that of physical capital, intelligence tasks are automated first, pushing human labor toward the physical sector. The impact of automation on wages is theoretically ambiguous and can be non-monotonic in the degree of automation. A necessary condition for automation to decrease wages is that the share of employment in the intelligence sector decreases; this condition is not sufficient because automation can raise output enough to offset negative reallocation effects. In our baseline simulation, wages increase and then decrease with automation. Our interactive tool shows how parameter changes shift that trajectory. Wage decreases are steeper at high levels of automation when the outputs of the physical and intelligence sectors are more substitutable. After full automation, more AI and more physical capital increase wages, a classic prediction from standard production functions in capital and labor. Yet, when intelligence and physical are complementary, the marginal wage impact of AI capital saturates as AI grows large. More broadly, the model offers a structured way to map contrasting intuitions from economics and computer science into a shared parameter space, enabling clearer policy discussions, and guiding empirical work to identify which growth and wage trajectories are plausible.

1 Introduction

The power of new AI technologies became apparent to the public when OpenAI released ChatGPT in November of 2022, and the advent of capable large language models ushered a new era of uncertainty (and therefore debate) about the future of work. This debate is dominated by two groups with rather different ways of thinking, AI experts and economists. This paper is co-written by one author from each field and aims at providing a high-level consensus by moving the debate from disagreement about outcomes to disagreements about parameters.

On the one hand, many tech experts boldly predict that most human labor can be replaced by AI, ushering an astounding new era of economic growth – sometimes dubbed "singularity" (Kurzweil, 2005). This stance is probably culturally driven by the fact that many indicators in AI are exponential with very short doubling times (Denning et al., 2016), often of the order of months (Appenzeller, 2024). If computers can become twice as fast every two years and tokens for large language models can become half the price within a few months, why shouldn't the economy undergo similar trajectories?

On the other hand, many economists cautiously foresee a more vanilla future: AI is a general purpose technology embodied in a new form of capital, with positive but ultimately limited effects on growth, and with some negative but ultimately transitory effects on workers whose work is substitutable with AI capital. Economists arrived at this stance observing a slow but steady growth since the dawn of the Industrial Revolution, partially driven by an accumulation of general purpose technologies such as electricity (Gordon, 2016), and more generally an innovation economy (Aghion et al., 2015).

Which view is closer to the truth is highly consequential for workers' welfare and for policy. If the full labor replacement view is closer to the truth, sweeping new policies may be needed to ensure that displaced workers can continue to receive an income. If the new but limited general purpose technology view is correct, there is less concern about the future of work, while policies to smooth the adaptation to the new technology may still be in order. We tackle the overarching question: When does automating intelligence tasks help workers, and when does it harm them? And what are the relevant timescales?

Here we aim to use economic theory to bridge the two views and illustrate plausible scenarios. Following the takes of the AI folks, we allow AI to replace humans in many tasks: specifically, we assume AI may fully replace humans in intelligence tasks, i.e. those that can be done in a disembodied way, or virtually. These disembodied intelligence tasks plausibly represent a large share of all tasks, since 60% of workers could telework at the height of the COVID-19 pandemic (Barrero et al., 2021). We also acknowledge that there are domains where the production of artificial intelligence capital may grow at rates typical in computer science but unheard of in economics.

Following the takes of the economics folks, we argue that the marginal returns to intelligence saturate because intelligence is complementary with physical inputs. This idea parallels standard economic reasoning about capital–labor complementarity, and it helps explain why rapid improvements in AI may have bounded growth and wage effects. Evidence to date regarding the returns to intelligence is consistent with this view. For instance, some research shows that higher IQ individuals are not proportionately more successful (Terman and Oden, 1947), and, in fact, cognitive ability slightly declines with earnings among the very highest earners (Keuschnigg et al., 2023). Scientific research shows decreasing returns: more researchers and publications yield smaller contributions to science (Jones, 2009; Park et al., 2023) and to economic growth (Bloom et al., 2020). This evidence pertains to the effect of human capital, but the effects of adding more intelligence-producing capital also

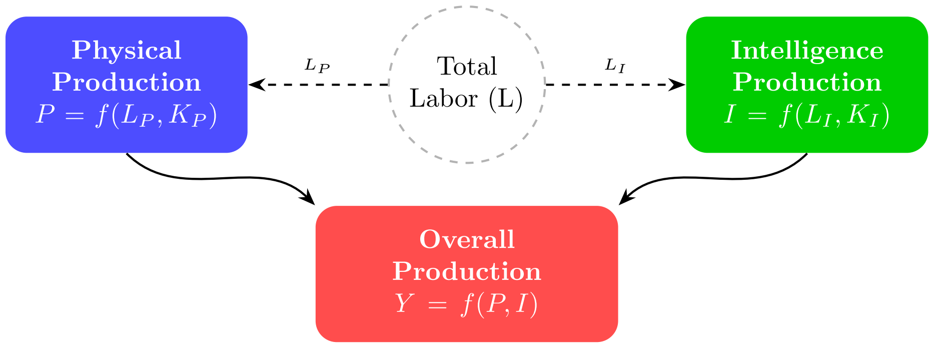

Figure 1: Production framework with endogenous labor allocation. Total labor (L) is allocated between physical production and intelligence production sectors, with shares L_P and L_I respectively. Both sectors combine labor with capital to produce intermediate inputs physical P and intelligence I, which then combine to generate overall production Y.

suggest decreasing returns. The Information and Communication Technologies (ICT) revolution brought dramatic cost declines yet only moderate contributions to economic growth (Venturini, 2009; Spiezia, 2012; Eden and Gaggl, 2018). Finally, recent advances in AI (Large Language Models) have so far yielded small productivity increases across the economy (Humlum and Vestergaard, 2025; Bick et al., 2025). We develop these ideas and review the evidence more thoroughly in Section 2, where we formally distinguish physical from intelligence production and introduce the concept of intelligence saturation.

The key focus of our paper is on intelligence saturation due to physical-intelligence complementarity. The idea is that you build things through physical means, and intelligence can at best make you maximally efficient at that. Both physical and intelligence components are needed in production. To illustrate, take education: it has both a physical and an intelligence component. Quality education has a physical component (co-located interaction, classroom management, hands-on activities) that many learners benefit from, even when materials are excellent. Consequently, COVID-19 lockdowns negatively impacted student academic performance (Cortés-Albornoz et al., 2023), and districts with virtual learning fared significantly worse (Jack et al., 2023). Therefore, we need teachers and classrooms – the physical component. Of course, education also has an intelligence component: the teaching materials. AI could improve teaching materials, but it is likely that such improvements would saturate as the teacher ultimately needs to deliver the materials effectively, and the classroom setup needs to be conducive to learning. Similarly, the production of cars needs machines and controllers, the production of health requires physical components and intelligence components, and the production of food requires a cook and a recipe. Smarter controllers can raise throughput and reduce scrap, but mechanical limits, safety, and line balance bound the gains. Clinical productivity can improve with better triage, documentation, and decision support, but is ultimately bounded by physical throughput and safety. And as far as we know there are no recipes that dramatically improve the enjoyment we get out of food. We see intelligence saturation as unfolding across the many tasks in the economy.

To capture these insights, our theoretical approach uses an aggregate production function (how the output of the economy depends on inputs like labor) that takes a Constant Elasticity of Substitution (CES) form over the outputs of the physical and intelligence sectors. The two sectors are assumed to be complementary in our baseline scenario. Each sector uses its own type of capital, i.e. Physical and Intelligence capital, augmented by human labor that is assumed to flow freely between the two sectors. The resulting model (see Figure 1), a nested CES type model, allows us to then quantify how changing AI inputs, both in terms of which tasks can be automated and how much AI capital accumulates over time, affects production and wages.

We make the standard assumption about capital-labor substitution. In intelligence tasks, AI and labor are good substitutes, like in the task model of Acemoglu and Restrepo (2018); Acemoglu et al. (2024) also used by Jones and Liu (2024); Korinek and Suh (2024). The difference is that we only assume good substitution for intelligence tasks, not for all tasks. We assume that substitution is considerably harder in the physical domain. The scaling of capabilities of robots with their limited bodies is simply much slower (Korus, 2019) than the scaling of pure intelligence (Samborska, 2025; Lu, 2025). This asymmetric treatment of capital-labor substitution in intelligence vs physical tasks mirrors the long-run differences in learning curves in the two areas.

We find that increasing automation of intelligence tasks increases the share of workers in the physical sector when physical and intelligence outputs are less substitutable than are intelligence tasks among themselves (a sufficient condition formalized in Lemma A.1; roughly $\rho \lesssim \rho_I/\theta_I$). Stronger decreasing returns in the intelligence sector (smaller θ_I) make this sectoral shift even more likely. The effect of automation on wages is theoretically ambiguous and depends on two forces: (i) how much automation raises intelligence output and, ultimately, overall output (the scale effect), and (ii) how much the employment share in the physical sector rises (the reallocation effect). When the first force dominates, wages increase; when the second dominates, they decrease (see equations (18) and (21)). Based on examining the intelligence sector alone, a sufficient condition for wages to fall is that the (weighted) decrease in the share of employment in the intelligence sector exceeds the automation-induced growth of the intelligence sector output (Eq. (26)). In our model and given our assumptions, if automation does not increase the physical employment share (or decrease the share of employment in the intelligence sector), wages cannot fall. This offers a useful empirical test as a minimal condition for additional automation to potentially decrease wages.

We parameterize our model using calibration for parameters that can be readily estimated in the economics literature; other parameter values are intended to be illustrative. For the substitutability between physical and intelligence, we use the same elasticity of substitution as between labor and capital in the manufacturing sector (Oberfield and Raval, 2021), which means that intelligence and physical outputs are complements and the impact of additional intelligence on output and wages saturates when all other factors of production are held fixed. Under our baseline parameters, we find that automation in the intelligence sector first increases and then decreases wages: at first, productivity gains in intelligence more than offset the wage pressure from workers crowding into fewer tasks, but eventually the negative effects dominate as most workers get iced out of intelligence tasks. This result presents a cautionary tale: initial wage increases could turn into wage declines as automation progresses.

We then analyze the dependency of the model on parameter changes focusing on effects of automation on wage and production, and on parameters that can be empirically estimated. To help readers intuit the interacting components of our model we make available an interactive tool, with the code available on github, that makes it easy to analyze the effect of the various parameters. Stronger decreasing returns in intelligence dampen positive wage effects of automation. Lower substitutability between intelligence tasks within the intelligence sector leads to a more pronounced hump-shaped pattern in wages as automation progresses. The interactions between the physical and intelligence sectors are critical for the impact of automation on wages and output because workers crowd in the physical sector as automation progresses. Higher substitutability between the physical and intelligence sectors makes the wage effects of high automation more negative (at high levels of automation) but the output effects more positive. Intuitively, it is bad for wages if physical goods and in person services can easily be substituted with fully disembodied or virtual intelligence products. But from the output perspective, the conclusions are opposite: for the economy to maximally benefit from automation and AI, we need more substitution between the outputs of the physical and intelligence sectors. While intelligence tasks are still being automated, this situation would allow the economy to be dominated by the intelligence sector where AI can contribute the most to productivity.

Finally, we simulate scenarios in which the stock of AI capital keeps expanding while automation unfolds, and expands further beyond full automation of all intelligence tasks. If AI capital doubles every six months — a pace reminiscent of recent GPU-cost curves — wages no longer trace the hump-shaped path of our baseline: they rise monotonically during the automation phase and ultimately saturate sometime after AI has replaced all workers in the intelligence sector. When AI growth is slower, doubling every 24 months, and when physical and intelligence products are substitutes rather than complements, wages increase and then decrease with automation, just as in our baseline scenario with fixed AI capital. In this substitutable intelligence-physical case, wages can grow without bound *after* full automation, as further AI accumulation increases output, despite fixed physical production. The simulations thus spotlight a core property of the CES structure: with complementary physical and intelligence sectors, the marginal product of AI and its wage impact quickly saturate, whereas with substitutable sectors, ongoing AI growth can sustain wage gains long after full automation of intelligence tasks.

Our analysis helps frame disagreements between economists and AI experts about the impact of AI on the economy in general, and on the labor market in particular. To have a "doom" view about the impact of automation on wages as we approach full automation, you need to think that the outputs from the physical and intelligence sectors are substitutable. The picture is somewhat different in the very long run, past full automation of intelligence production: if you are bullish about the impact of AI on output and wages in the long run, you need to think that intelligence and physical sectors are highly substitutable or that technological progress progressively turns physical tasks into virtual intelligence ones, effectively raising substitutability over time. If, instead, intelligence saturates because the two sectors remain complements, automation still raises wages at first but the gains eventually saturate as additional AI capital yields diminishing returns. Broadly speaking, economists can rationalize their view of a mild AI impact by assuming that intelligence and physical sectors are complementary, while AI experts can justify their transformative, singularity-like expectations by treating the two as substitutes, that is, by assuming physical tasks can readily be replaced by intelligence tasks.

From a policy perspective, our model suggests that reducing potential negative effects of automation on wages could be accomplished by slowing down automation while stimulating investing in physical capital. Slowing down automation obviously reduces potential wage losses but is costly in terms of foregone growth (but less costly the more intelligence saturation there is), and it could be seen as gaining time to make necessary investments in physical capital. Physical capital investments are helpful because they increase the marginal productivity of labor in the physical sector, and therefore prop up wages as workers transition into the physical sector. An additional policy lever would be the taxing of virtual substitutes to in-person services or physical goods, at least while automation is ongoing. Such a policy would prevent increasing substitutability between physical and intelligence sectors, which would increase the extent to which workers in the physical sector benefit from increasing automation.

We make three contributions to the literature. First, we offer a conceptual classification of tasks that distinguishes embodiment from cognition. This classification is related to but different from that of classifying tasks into routine vs non-routine and cognitive vs manual tasks (Autor et al., 2003). Specifically, we divide production into physical and intelligence sectors. All manual jobs from Autor et al. (2003) are physical in our classification, but some cognitive jobs are also physical if they require in-person execution or yield a uniquely differentiated in-person output. For instance, surgery, live courtroom advocacy, or in-classroom teaching are cognitively intensive yet physical in our sense. This reclassification isolates automation constraints due to embodiment from those due purely to cognition, enabling us to model asymmetric substitution elasticities between physical and intelligence sectors and making it possible to capture "intelligence saturation" when the two sectors are complements.

Second, we introduce the concept of "intelligence saturation" and embed it into standard economics modeling. We add to the macro growth and production function literature (Ray et al., 2022) by considering the role of intelligence as a specific capital input into production rather than an overall technology factor. Our nested CES structure captures the diminishing marginal productivity of intelligence that arises from its complementarity with physical inputs. We use the structure of prior automation models (Acemoglu and Restrepo, 2018; Acemoglu et al., 2024; Jones and Liu, 2024; Korinek and Suh, 2024) for the production of the intelligence sector. However, those models apply a uniform substitution structure to the whole economy: labor and capital are perfect substitutes within each task, while all tasks are gross complements, with substitution across tasks governed by a single parameter. By introducing the physical sector in a nested CES specification, we relax this uniformity constraint, allowing substitution patterns to differ within the physical and intelligence sectors and between them. This flexibility is essential for capturing "intelligence saturation" and for showing how complementarity between the intelligence and physical sectors can bound the growth and wage effects of rapid AI progress. This economic substitution mechanism explains why rapid gains in AI capability – well documented in computer science – need not translate into unbounded economic growth. In doing so, the model clarifies a central source of disagreement between AI experts who focus on AI's fast learning curves and economists who are attentive to diminishing returns from complementary constraints.

Third, our model presents a unifying, parameterized framework for automation's wage effects, with a corresponding interactive tool. By embedding asymmetric automation into a macro framework, we can show parameter ranges under which wages rise or fall, in terms of e.g. substitution elasticities and factor shares. This allows varying perspectives from economists and AI experts to be expressed as different points in the same parameter space, turning disagreements about outcomes into disagreements about measurable parameters.

In section 2, we discuss the background behind the assumption of intelligence saturation. In section 3, we discuss the modeling setup, and the theoretical impacts of automation and AI on wages (in section 3.4). We provide model simulations in section 4. Our discussion is in section 5. Finally, section 6 concludes.

2 Why intelligence saturation

2.1 Physical vs. intelligence sectors and scaling

The division of the economy into labor and capital inputs has served the economics discipline well for decades, why do we need to also divide it into physical and intelligence sectors? First, we introduce the distinction between physical effectors and intelligence based on insights from neuroscience and robotics. Then, we make the argument that physical and intelligence production at this point of time in history scale in fundamentally different ways, and that, therefore, this distinction is necessary to drive meaningful predictions about AI.

We see fundamental differences between physical and intelligence sectors based on models of control in robotics (Roy et al., 2021), psychology, and neuroscience (Segado et al., 2025). Within these areas, we talk about effectors. An effector can be thought of as something physical that has an effect on the world. An arm is an effector. As is the shovel of an excavator. Effectors have the capability to change the physical world. More and bigger effectors have the capability of changing the world more rapidly. And for every effector and task, we use intelligence to make these changes be as positive for us as possible (Wolpert et al., 2003), and that is what AI is about. More intelligence allows the effectors to be less wasteful. Consistent with this distinction, recent papers using actual Large Language Models (LLM) data from Anthropic's Claude (Handa et al., 2025) and Microsoft's Copilot (Tomlinson et al., 2025) show that these tools tend to be both less used and less applicable in physical occupations like transportation and material moving, food preparation and serving, or healthcare support.

Taking this distinction between physical and intelligence to a production function framework in economics, both effectors and intelligence can be supplied by either capital or labor. It is important to consider how these different sectors scale because it will determine which ones can be used most efficiently to accomplish a certain task or produce a final good.

Computer science has long scaled in a way that is entirely different from the scaling of the rest of the economy. Moore's law states that the number of transistors on a microprocessor doubles every 2 years. And while the traditional Moore's law has ended, the tendency of computers to become roughly twice as fast every other year is continuing (Leiserson et al., 2020). This scaling has been going on for more than 70 years. Microprocessors are now rapidly getting better through other channels, e.g. multicores (Smith, 2023). Computation thus becomes cheaper, roughly by a factor of two every two years (see Figure 3 in Nordhaus, 2007). This rapid scaling prompted computer science experts to focus on how scaling affects algorithms and systems.

Recent cost/performance scaling in AI has often been steeper than in general-purpose computing. At the moment, for a given task that AI can solve, e.g. text generation, the price decreases rapidly. The price currently halves roughly every 6 months (DeepLearning.AI, 2024). These decreases come from multiple sources. First, compute becomes cheaper by a factor of two roughly every two years (see Figure 3 in Nordhaus, 2007). Second, compute becomes cheaper in terms of energy, with energy efficiency improving roughly two orders of magnitude per decade (Koomey et al., 2011). Third, improving AI algorithms makes running AI cheaper (Hernandez and Brown, 2020). There are no indications that this trend is changing (Guo et al., 2025). Clearly the price of AI is decreasing exponentially at a rate much faster than most inputs in the economy. The fact that AI is getting cheaper so fast makes it more and more economically advantageous to use AI for all tasks where it can be used.

We can also talk about the scaling of labor and capital. Labor in the US is increased through population growth (currently less than 1% per year, see Congressional Budget Office, 2025) and the supply of higher quality labor (but increases in years of schooling have been slowing (Autor et al., 2020)). Capital input increased 3.4% per year between 1987 and 2024, and 2.9% in 2024 (Bureau of Labor Statistics Total Factor Productivity data). Relatively to the breakneck speed of AI developments, the other economic inputs are essentially stationary.

A special case of the scaling of capital is the scaling of robotics; progress at this endeavor could make human physical labor far more substitutable. However, the price of robots, like that of most goods, tends to rather decrease as a power law than exponential. For example, the average price of industrial robots decreased from more than \$100k to about \$20k from 1995 to 2025 (in 2015 dollars) and the decrease is slowing down considerably (ARK Investment Management LLC, 2021). Generally, when it comes to physical goods like household appliances, prices tend to transition from an early phase of rapid price decline towards a slower longer run price decline (Greenwood et al., 2005).

Thus, AI scales much faster than labor, capital or even robots. This has two main implications for modeling. First, the incentives for replacing humans by different types of inputs are starkly different: because AI becomes cheaper much faster, it becomes much more advantageous to replace labor by AI when possible. This leads us to focus our modeling on AI-labor substitution. Second, in comparison to AI, other inputs are stationary, so it makes sense to focus on what happens when AI is abundant and/or scales up quickly.

2.2 From complementarity to intelligence saturation

The distinction between effectors and intelligence naturally leads to the idea that intelligence saturates, in the sense that adding infinitely more intelligence does not lead to infinitely better results for given effectors - the losses from inefficiencies go away with enough intelligence. With perfect intelligence, effectors are used at their physical and institutional limits; beyond that, additional intelligence yields no more returns. In other terms, effectors act as a bottleneck. In this AI focused framework, intelligence saturation is natural.

Traditionally, economists discuss the production function in terms of capital and labor inputs. In a simplified way, you could think of capital as effectors and labor as intelligence. This view acknowledges that the production of goods usually has a component that requires capital, say trucks, or desks, and a component that requires labor, say driving those trucks or solving computer science problems on those desks. Capital is usually abbreviated as

K while labor is abbreviated as L. Popular conceptualizations of their interactions then give rise to production functions for goods or tasks: the amount of goods produced in a task i is a function of the amounts of capital K_i and labor L_i allocated to it. The micro or local production function for tasks is then $Y_i = f(K_i, L_i)$. Economists usually assume that capital and labor are not perfectly substitutable, e.g. through a CES function (like $\left[\alpha\, K_i^{\rho} \;+\; (1-\alpha)\, L_i^{\rho}\right]^{1/\rho}$) [1]. The intuition behind this function is that adding more capital or more labor both increase output, but the two are not perfectly substitutable, so that the marginal productivity of either decreases when the other is held fixed; the elasticity of substitution is regulated by ρ.

It is commonly assumed that capital and labor are complements, which is supported by firm-level empirical evidence (Oberfield and Raval, 2021). Saying that capital and labor are complements in a CES production function means that $\rho < 0$, and this leads to saturation of production (convergence to a finite limit) when capital goes to infinity as the labor input remains fixed. Thus, the idea of saturation is already baked in to commonly used production functions in economics, and is a direct consequence of capital-labor complementarity.

The key insight here is that intelligence saturation naturally follows from commonly used production functions. If we model production as a CES function of physical and intelligence sector outputs, and assume the two are complements, intelligence saturation occurs.

2.3 Intelligence saturation: empirical evidence

Decreasing returns to individual intelligence. While cognitive ability predicts achievement and earnings, the correlation is far from perfect. In fact, cognitive ability slightly declines with earnings for the top 3 percentiles of the wage distribution (Figures 3B and 3C in Keuschnigg et al., 2023). Children with IQ above 140 selected for The Genetic Studies of Genius, later known as the Terman Study of the Gifted, achieved a reasonable amount of success but were not all widely successful, leading Terman to remark that "intellect and achievement are far from perfectly correlated" (Terman and Oden, 1947, 352). In fact, the study tested but rejected two future Nobel prize winners because their IQs were too low (Warne et al., 2020).

Decreasing returns to scientific research. The literature suggests that the returns to scientific research are decreasing. Bloom et al. (2020) show that the number of researchers is rising but research productivity is falling, i.e. we observe decreasing returns of research for economic growth. They examine specific fields like computers, chips, agriculture and medicine and find decreasing returns in each. Overall, across all fields, research productivity declines 8-10% per year. The low-hanging fruit has likely been harvested, so research and patents are getting less disruptive over time (Park et al., 2023), with progress especially difficult in fields where knowledge is already deep (Jones, 2009). It is notable though that patents in computers and electronics show increasing innovativeness since the 1980s (Kelly et al., 2021), which contributes to the expansion of AI capabilities. In other words, we see decreasing returns to intelligence when it comes to converting intelligence into physical

[1] We use ρ-notation for CES everywhere with $\sigma = 1/(1-\rho)$ A negative ρ means gross complements, a positive $\rho \in (0, 1)$ means gross substitutes.

innovation, while intelligence capital used for intelligence innovation may show more positive signs.

Positive but time-limited impact of ICT on economic growth Information and Communication Technology (ICT) was the major technological transformation prior to the rise of AI and deep learning. This wave of technological innovation has arguably increased intelligence production in the economy by increasing the availability of information and the ability to process such information through both hardware (e.g. computers) and software. While this technological wave did increase economic growth, its contribution was no more than 1 percentage point of annual economic growth at the height of its impact in the 1990s and the 2000s, and this finding holds both for the US (Eden and Gaggl, 2018) and OECD countries more broadly (Colecchia and Schreyer, 2002; Spiezia, 2012). Interestingly, Spiezia (2012) shows that the growth contribution of ICT was driven by computing equipment, i.e. physical capital. The limited growth impact of adding ICT demonstrates that prior increases in intelligence production had growth effects that were nothing to sneeze at, but also nowhere near the scaling implied by e.g. Moore's law. This finding is compatible with intelligence saturation: adding ICT contributes to intelligence production and ultimately to growth, but it does not have effects that are commensurate with the kinds of scaling we see in computer science.

Further, Bloom et al. (2020) show that medical research productivity has been declining at least since the 1980s. Since the ICT contribution to growth peaked in the 1990-2000, this shows that adding more ICT was not able to stem the decrease in research productivity. Since the 1990s more ICT (machine intelligence) was used for research as well as more researchers (human intelligence), and yet the impacts of more researchers on economic growth declined. This means the decreasing returns to intelligence are even steeper once we account for the fact that we threw not just more humans but also more machine intelligence at our problems. This again is consistent with intelligence saturation.

Limited productivity effects of recent AI advances Finally, we have some early evidence about the impact of generative AI, and so far the impact has been fairly modest, especially in studies that cover all economic sectors rather than focusing on particular industries or occupations. While generative AI led to large productivity increases of 15-56% in some cases(Noy and Zhang, 2023; Peng et al., 2023; Dell'Acqua et al., 2023; Cui et al., 2025; Brynjolfsson et al., 2025)[2], studies that examine impacts across all industries tend to find more limited effects. Humlum and Vestergaard (2025) use administrative data from Denmark and show that the adoption of generative AI chatbots at the firm level had zero effect on employment. Workers who used AI chatbots saw some some small time savings of about 3%. Using a nationally representative US data of working age adults interviewed in August and November 2024, Bick et al. (2025) document self-reported time savings from generative AI use of 5.4% for people who use genAI, translating to 1.4% for the whole population. This shows that merely adding more intelligence in the form of chatbots has small effects on labor productivity, consistent with intelligence saturation.

[2]Productivity is measured as time saved in Peng et al. (2023); Noy and Zhang (2023); Dell'Acqua et al. (2023), as tasks completed in Cui et al. (2025), and as hourly productivity in Brynjolfsson et al. (2025).

In a report based on public disclosures of AI initiatives at the firm level and interviews with businesses (Challapally et al., 2025), only 5% of firms successfully implemented custom enterprise AI tools, while 40% implemented general purpose LLM tools. Given the results from Humlum and Vestergaard (2025); Bick et al. (2025), we know that general LLMs provide limited productivity gains: custom enterprise AI tools could be more powerful, but they appear difficult to implement successfully, which may again indicate intelligence saturation.

2.4 Modeling implications

The empirical evidence is consistent with intelligence saturation: there are decreasing returns to intelligence, and adding more intelligence has positive but limited growth effects. Further, physical occupations are less impacted by the newest wave of generative AI. This suggests that it is meaningful to distinguish physical and intelligence sectors, and that economic models should build in mechanisms that allow for intelligence saturation in order to better predict the impact of AI on the economy in general, and on labor in particular.

3 Model

Assume a good Y (or bundle thereof) for final consumption is produced using two inputs: P for the physical input produced by the physical sector and I for the intelligence input produced by the intelligence sector. Each sector uses capital and labor to produce.

We use ∂ for direct (*holding allocation fixed*) effects, e.g. $\frac{\partial}{\partial \alpha_I}\Big|_\beta$ (sometimes the β is implicit), and d for total derivatives along the equilibrium path $\beta^*(\alpha_I)$.

3.1 Marginal productivity of intelligence, AI, and labor in the general case

The marginal productivity of artificial intelligence K_I is (envelope theorem):

$$\frac{dY}{dK_I} = \frac{\partial Y}{\partial I}\frac{\partial I}{\partial K_I} \tag{1}$$

This equation implies that there are two ways to model a decreasing marginal productivity of AI: either reduce the output gains of adding more intelligence ($\frac{\partial Y}{\partial I}$) or reduce the effectiveness of AI in producing more intelligence ($\frac{\partial I}{\partial K_I}$). We will explore both of these avenues.

As long as we haven't automated all intelligence tasks, labor is used in both the physical and intelligence sectors, so the marginal productivity of labor is:

$$\frac{dY}{dL} = \frac{\partial Y}{\partial P}\frac{dP}{dL} + \frac{\partial Y}{\partial I}\frac{dI}{dL} \tag{2}$$

Labor in the physical sector is L_P and in the intelligence sector L_I, with $L = L_P + L_I$. When labor is allocated optimally between the sectors, we have the following equality between the marginal productivity of labor in each of the sectors, which also determines the competitive wage:

$$w = \frac{\partial Y}{\partial P}\frac{\partial P}{\partial L_P} = \frac{\partial Y}{\partial I}\frac{\partial I}{\partial L_I} \tag{3}$$

Therefore, to understand the impact of automation on the wage, we need to determine how automation affects the marginal productivity of labor in the two sectors.

Once full automation of intelligence tasks is achieved, labor is used only in the physical sector, so the marginal productivity of labor now is:

$$\frac{dY}{dL} = \frac{\partial Y}{\partial P}\frac{dP}{dL} \tag{4}$$

After full automation is achieved, increasing the amount of AI in the economy unambiguously benefits workers, because more AI increases the physical sector productivity (where labor is employed), that is:

$$\frac{\partial}{\partial K_I}\left(\frac{dY}{dL}\right) = \frac{\partial^2 Y}{\partial P\,\partial I}\,\frac{dI}{dK_I}\,\frac{dP}{dL} > 0 \tag{5}$$

The cross-partial $\frac{\partial^2 Y}{\partial P\,\partial I}$ is positive for a CES with exponent $\rho < 1$, which is our maintained assumption. Here it is worth noting that the marginal productivity of labor increases with AI only as long as the cross-partial $\frac{\partial^2 Y}{\partial P\,\partial I}$ is positive, and intelligence increases with AI ($\frac{dI}{dK_I} > 0$). If we have intelligence saturation so that either of these terms approaches zero, then wages stop increasing with AI.

3.2 Production function for the intelligence and physical sectors (CES)

We assume a separate production function for the physical and intelligence sectors, each produced with labor and capital. We model each sectors as CES-like, with a parameter regulating the substitution properties, and joined by an overall CES aggregator at the macro level. This lets us vary substitution elasticities and scale parameters independently for physical and intelligence sectors as well as overall aggregation.

Table 1 summarizes the parameters used in this model, together with their domain assumptions, and Figure 1 above describes the model graphically. Assumptions on parameter domains are generally standard.

Parameter	Notation	Description	Domain / Assumption
Physical Sector P			
Physical capital	K_P	Physical capital input to physical P	$K_P \geq 0$
Physical labor	L_P	Labor input to P	$L_P \geq 0$
Labor share in physical tasks	β	Share of total labor assigned to P: $L_P = \beta L$	$0 \leq \beta \leq 1$
Physical capital CES share	α_P	CES weight on K_P vs. L_P in P	$0 \leq \alpha_P \leq 1$
Physical CES exponent	ρ_P	CES exponent in P	$\rho_P < 1,\ \rho_P \neq 0$
Intelligence Sector I			
AI capital	K_I	AI-capital input to I	$K_I \geq 0$
Intelligence Labor	L_I	Labor input to I: $L_I = (1-\beta)L$	$L_I \geq 0$
Automation fraction / AI CES share	α_I	Fraction of I-tasks performed by AI/ weight on K_I vs L_I in I	$0 \leq \alpha_I \leq 1$
Intelligence CES exponent	ρ_I	CES exponent in I	$\rho_I < 1,\ \rho_I \neq 0$
Intelligence returns to scale	θ_I	Allows I to scale sub-linearly with inputs	$0 < \theta_I \leq 1$
Overall production Y			
Aggregate labor	L	Total labor used in production	$L \geq 0$
Macro CES share	τ	CES weight on P vs. I in Y	$0 < \tau < 1$
Macro CES exponent	ρ	CES exponent in Y	$\rho < 1,\ \rho \neq 0$

Table 1: Production parameters.

Physical Sector (P) To incorporate the potential for substitution between physical capital K_P and physical labor L_P in the physical sector we use a standard CES function. Only a fraction $\beta \in [0,1]$ of the total labor in the economy is allocated to P). We denote $L_P \equiv \beta\, L$ (and correspondingly $L_I \equiv (1-\beta)L$ for the intelligence sector).

$$P \;=\; \Bigl(\alpha_P\, K_P^{\rho_P} \;+\; (1-\alpha_P)\, L_P^{\rho_P}\Bigr)^{1/\rho_P}. \tag{6}$$

Intelligence Sector (I) For the intelligence sector, we use a CES-like equation of the following form:

$$I \;=\; \Bigl[{\alpha_I}^{1-\rho_I} \mathrm{K_I}^{\rho_I} \;+\; (1-\alpha_I)^{1-\rho_I} {L_I}^{\rho_I}\Bigr]^{\theta_I/\rho_I} \tag{7}$$

where K_I is AI capital, $L_I = (1-\beta)L$ is the labor allocated to the intelligence sector, and $\rho_I > 0$ indicates high substitutability between intelligence tasks. We allow for $\theta_I \leq 1$, capturing potential decreasing returns to scale in the production of the intelligence sector.

This allows for the second intelligence saturation channel in equation (1), i.e. reducing the effectiveness of AI in producing more intelligence.

We can think of AI capital K_I as *effective compute*: hardware FLOPS multiplied by utilization and an algorithmic-efficiency factor. This reduced-form stock bundles hardware, software, data, and training gains. This is consistent with benchmarks from the AI literature, where log model performance correlates strongly with log compute (FLOPS) both for inference and training and log data scale (Kaplan et al., 2020). In this sense, intelligence capital K_I reflects a set of factors (hardware FLOPS $\times$ utilization $\times$ algorithmic-efficiency factor). It thus also includes software innovations that improve efficiency, for example, algorithmic improvements that reduce the FLOPS required to achieve a certain performance level (Hernandez and Brown, 2020). Under this definition, AI scaling trends translate directly into rapid growth in K_I, distinguishing it from the much slower growth rates of physical capital or labor.

Equation (7) is micro-founded in Korinek and Suh (2024) based on a CES in intelligence tasks (e.g. write text, make tables, etc.), and is also consistent with the assumptions in Jones and Liu (2024), with the difference that we use this production function only for the intelligence sector, and not for the whole economy. Specifically, assume the following production function for the intelligence tasks:

$$I = \left[\int_i y(i)^{\rho_I} d\Phi(i)\right]^{\theta_I/\rho_I}, \quad \rho_I = \frac{\sigma_I - 1}{\sigma_I}, \tag{8}$$

where $\Phi(i)$ reflects the cumulative mass (or fraction) of tasks with a complexity level less than or equal to i, and σ_I is the elasticity of substitution between tasks. θ_I is a returns to scale parameter. In Korinek and Suh (2024), there are constant returns to scale ($\theta_I = 1$), but we allow for decreasing returns to scale if $\theta_I < 1$.

Decreasing returns to scale in the production of intelligence from AI capital are captured by θ_I, and it allows us to model the empirical regularities observed in AI scaling; it allows us to capture any power law in the components. Crucially, it separates aggregation from scaling, which are coupled in the standard CES. Many recent studies (e.g. Kaplan et al., 2020; Hoffmann et al., 2022) document power-law relationships between model performance and compute, e.g. doubling compute leads to sublinear performance improvements. Our modeling of the intelligence sector reflects this behavior through $\theta_I < 1$, which yields power-law diminishing returns to K_I in the aggregate. This parameter thus serves as a bridge between economic modeling and AI empirical scaling trends.

Let $\Phi(i) = \alpha_I \in [0, 1]$ represent the fraction of intelligence tasks that is automated. Let i^* denote the task-complexity cutoff with $\Phi(i^*) = \alpha_I$. As shown in Korinek and Suh (2024), the above assumptions lead to a CES function in the capital and labor inputs that takes the form in equation (7) above.

Equation (7) is only a correct derivation from the micro foundations if AI is sufficiently abundant so that the wage – aka the marginal productivity of labor – is greater than the marginal productivity of AI $\partial Y/\partial K_I$. As long as this holds, labor is only used in the not-yet-automated tasks. The condition is after normalizing the unit prices/productivities so that AI and labor efficiencies are one within tasks:

$$\frac{K_I}{L_I} > \frac{\alpha_I}{1 - \alpha_I} \tag{9}$$

We assume that this condition holds: AI is abundant.

Aggregate CES production function with physical and intelligence sectors The final output is obtained by aggregating the two intermediate composite inputs – physical and intelligence – via a CES aggregator:

$$Y = F(P, I) \; = \; \Big[\tau \, P^{\rho} \; + \; (1-\tau) \, I^{\rho}\Big]^{1/\rho}, \qquad 0 < \tau < 1, \tag{10}$$

where τ is a distribution parameter that measures the importance of the physical sector and determines the share of income that goes to the physical sector.

Given the assumptions on the production of the physical and the intelligence sectors, the final output is given by a weighted CES:

$$Y = \Big[\tau \left(\alpha_P K_P^{\rho_P} + (1-\alpha_P) L_P^{\rho_P}\right)^{\rho/\rho_P} + (1-\tau) \left(\alpha_I^{1-\rho_I} K_I^{\rho_I} + (1-\alpha_I)^{1-\rho_I} L_I^{\rho_I}\right)^{\theta_I \rho/\rho_I}\Big]^{1/\rho}. \tag{11}$$

where $L_P = \beta L$ and $L_I = (1-\beta)L$. In this production function, we normalized all productivity shifters[3] to 1.

This construction introduces modeling flexibility relative to the basic task setup of Acemoglu and Restrepo (2018) (also used in Jones and Liu (2024); Korinek and Suh (2024)), where the elasticity of substitution between tasks is closely linked to the substitution between labor and capital. Here, we have a macro elasticity of substitution between the outputs of the physical and intelligence sectors that can differ from the substitution patterns for labor and capital inputs within the physical sector and within the intelligence sector. This allows us to meaningfully talk about how physical and intelligence production sectors behave differently and ultimately affect workers differently.

3.3 Scaling behavior

Since the amount of AI capital K_I is increasing exponentially and very rapidly, it is important to understand how this scales up the intelligence sector output I, and ultimately overall output Y.

First, while the aggregate production function has constant returns to scale in P and I, we allow for diminishing returns to scale $\theta_I \leq 1$ in the intelligence sector I. This means that the scaling up of AI has more strongly diminishing returns at the aggregate level than in a case where the production function has constant returns to scale at all levels.

Second, the CES production function in P and I has the well-known property that output Y saturates when intelligence and physical outputs are complements ($\rho < 0$), and only one of the two outputs is increased. When I goes to infinity while P is held fixed, the

[3] The more general form of the production function using shifters A_Y, A_P and A_I is $Y = A_Y \left[\tau \, (A_P P)^{1-\rho} + (1-\tau) \, (A_I I)^{1-\rho}\right]^{\frac{1}{1-\rho}}$. Throughout, we normalize $A_Y = A_P = A_I = 1$ (i.e., measure P and I in efficiency units) so the arguments of the CES are dimensionless; all simulations will hold these shifters fixed. Equivalently, define $\tilde{P} \equiv A_P P$ and $\tilde{I} \equiv A_I I$, or scale by a base year so that $\tilde{P} = P/P_0$ and $\tilde{I} = I/I_0$; then set A_Y to pin the units of Y.

marginal productivity of I tends to zero, and output Y plateaus. This means that no matter how quickly AI capital K_I increases, the complementarity between physical and intelligence sectors means that output is bounded, and P becomes the bottleneck.

The complementarity between physical and intelligence sectors is a way to use a standard macro setting to represent insights from neuroscience and psychology that using more intelligence with fixed effectors cannot yield unbounded output growth.

3.4 Labor allocation and wages as automation progresses

We seek to answer two questions. As α_I, the share of automated tasks, increases:

1. How does labor shift from intelligence to physical production?
2. What is the evolution of the wage, operationalized as the marginal productivity of labor?

Later we distinguish automation (replacing labor with AI) from simply adding more AI capital (capital deepening). We will see that they expand output through different channels, and with different wage consequences.

3.4.1 Wages and labor allocation

We can derive explicitly the marginal productivity of labor in each sector, which is equal to the wage in a competitive equilibrium. At the optimal, output maximizing, allocation of labor between the two sectors, the marginal value productivity of labor must be equalized[4]:

$$\tau Y^{1-\rho} P^{\rho-1} \frac{\partial P}{\partial L_P} = (1-\tau) Y^{1-\rho} I^{\rho-1} \frac{\partial I}{\partial L_I} \tag{12}$$

where $L_P = \beta L$ and $L_I = (1-\beta)L$.

Sectoral marginal wages and β-monotonicity. It is useful to name the two marginal wage schedules that Eq. (12) equates. Define

$$w_P(\beta) \equiv \tau\, Y^{1-\rho}\, P^{\rho-1}\, \frac{\partial P}{\partial L_P} = \tau\, Y^{1-\rho}\, (1-\alpha_P)\, P^{\rho-\rho_P}\, (\beta L)^{\rho_P - 1}, \tag{13}$$

$$w_I(\beta, \alpha_I) \equiv (1-\tau)\, Y^{1-\rho}\, I^{\rho-1}\, \frac{\partial I}{\partial L_I}. \tag{14}$$

Writing out the derivative of I with respect to L_I,

$$\frac{\partial I}{\partial L_I} = \theta_I\, (1-\alpha_I)^{1-\rho_I}\, I^{1-\rho_I/\theta_I}\, \big((1-\beta)L\big)^{\rho_I - 1}.$$

Under $\rho_P < 1$ and $\rho_I < 1$, $w_P(\beta)$ is strictly *decreasing* in β, while $w_I(\beta, \alpha_I)$ is strictly *increasing* in β (proof deferred to Appendix A).

[4] If wages are below the marginal productivity of labor (markdown), which is a realistic assumption (Azar and Marinescu, 2024), then the important question is whether the markdown differs between physical and intelligence tasks. If the wage markdown is markedly different, it would affect firms' decisions to allocate workers to physical vs. intelligence sectors. Such markdowns would also obviously lower the actual wage received by workers.

Proposition 3.1 (Existence and uniqueness of β^*)**.** *Suppose $\rho_P, \rho_I < 1$ and an interior allocation is feasible ($\beta \in (0,1)$). Then $w_P(\beta)$ is strictly decreasing in β and $w_I(\beta, \alpha_I)$ is strictly increasing in β; hence there exists a unique $\beta^*(\alpha_I) \in (0,1)$ such that $w_P(\beta^*) = w_I(\beta^*, \alpha_I)$.*

Lemma 3.2 (Implicit-function comparative statics for β^*)**.** *Let $F(\beta, \alpha_I) \equiv w_P(\beta) - w_I(\beta, \alpha_I)$. Under $\rho_P < 1$ and $\rho_I < 1$ we have $\partial_\beta F = \partial_\beta w_P - \partial_\beta w_I < 0$, so the unique interior solution $\beta^*(\alpha_I)$ satisfies*

$$\frac{d\beta^*}{d\alpha_I} = -\frac{\partial_\alpha F(\beta, \alpha_I)}{\partial_\beta F(\beta, \alpha_I)} = \frac{\partial_{\alpha_I} w_I(\beta, \alpha_I)}{\partial_\beta w_P(\beta) - \partial_\beta w_I(\beta, \alpha_I)}.$$

In particular,

$$\operatorname{sign}\Big(\frac{d\beta^*}{d\alpha_I}\Big) = -\operatorname{sign}\big(\partial_{\alpha_I} w_I(\beta, \alpha_I)\big), \tag{15}$$

where the partial derivative $\partial_{\alpha_I} w_I$ is taken holding β (hence L_I) fixed.

To define the equilibrium wage, we have to find β^*, which is the share of labor in the physical sector that equates the marginal productivity of labor in physical and intelligence sectors. The ratio of the two FOCs for physical and intelligence is:

$$\frac{(\beta^*)^{\rho_P - 1}}{(1-\beta^*)^{\rho_I - 1}} = \frac{(1-\tau)\,\theta_I\,(1-\alpha_I)^{1-\rho_I}}{\tau\,(1-\alpha_P)}\;L^{\rho_I - \rho_P}\;\frac{I^{\rho - \rho_I/\theta_I}}{P^{\rho - \rho_P}}. \tag{16}$$

Here, note that I and P themselves depend on β^*, and there is no closed-form solution for β^*. Existence and uniqueness of β^* follow from Proposition 3.1. By Lemma 3.2, $\beta^*(\alpha_I)$ varies smoothly with α_I wherever the interior solution holds, so we compute $\beta^*(\alpha_I)$ numerically.

Also, note that, once full automation is achieved ($\beta^* = 1$), the intelligence sector production function can be written as $I = K_I^{\theta_I}$, so the ρ_I parameter drops out. This means that the substitutability between intelligence tasks does not influence the level of output Y after full automation, nor the marginal productivity of labor after full automation.

The wage can be recovered for the optimal allocation by plugging β^* into the marginal product of labor in the physical task[5]:

$$w = \tau\,Y^{1-\rho}\,(1-\alpha_P)\,P^{\rho-\rho_P}\,(\beta^*\,L)^{\rho_P - 1}. \tag{17}$$

Automation generally moves labor toward the physical sector, i.e. β^* increases with α_I when $\rho < \rho_I/\theta_I$ (sufficient condition), i.e. when intelligence and physical sector outputs are less substitutable that intelligence tasks among themselves, a reasonable assumption that we will maintain moving forward. Intuitively, higher α_I directly lowers the marginal product of L_I in the intelligence sector through $(1-\alpha_I)^{1-\rho_I}$; to re-equalize wages across sectors, labor shifts from I to P, so β^* rises (see Appendix A for a more formal argument). As automation moves labor into the physical sector, the marginal productivity of labor in the physical sector decreases, which has a negative impact on wages. But this negative effect on wages can be overshadowed by a strong enough increase in the output of the intelligence sector. We now discuss the impact of automation on wages.

[5]At the optimal allocation, one can also plug it in to the intelligence task, obtaining the same wage as long as $0 < \beta^* < 1$.

3.4.2 Wage Dynamics as Automation Progresses

We study how the competitive wage responds to an incremental rise in the automated share α_I, holding K_P and K_I fixed. To simplify notation and consistent with what we will assume in the simulations, we normalize total labor to $L = 1$, so that $L_P = \beta^*$ and $L_I = 1 - \beta^*$. To derive the wage effect of automation, we take the log of the equilibrium wage expression (17) and differentiate with respect to α_I :

$$\frac{d \ln w}{d\alpha_I} = \underbrace{(1-\rho)\left.\frac{\partial \ln Y}{\partial \alpha_I}\right|_\beta}_{(A)>0,\ \text{Scale from } I} + \underbrace{(\rho - \rho_P)\left.\frac{\partial \ln P}{\partial \alpha_I}\right|_\beta}_{(B)\ P\ \text{effect (direct)}} + \underbrace{\left[-(1-\rho_P)\frac{d \ln \beta^*}{d\alpha_I}\right]}_{(C)<0,\ \text{Reallocation to } P}. \tag{18}$$

Equation (18) is useful to (i) estimate the sign of the wage effect of automation and (ii) obtain an intuition for the wage effect of automation in terms of observable quantities.

The first term (A) in (18) is the positive scale effect: automation increases the output of the intelligence sector I (under the abundant AI condition) and thus the output Y. Specifically:

$$\left.\frac{\partial \ln Y}{\partial \alpha_I}\right|_\beta = \underbrace{\frac{(1-\tau)I^\rho}{\tau P^\rho + (1-\tau)I^\rho}}_{\omega_I \in (0,1)} \cdot \left.\frac{\partial \ln I}{\partial \alpha_I}\right|_\beta \tag{19}$$

To note, stronger decreasing returns to scale, i.e. a smaller θ_I, blunt this positive effect (A) holding β^* fixed, as:

$$\frac{\partial \ln I}{\partial \alpha_I} = \frac{\theta_I(1-\rho_I)}{\rho_I}\frac{\alpha_I^{-\rho_I}K_I^{\rho_I} - (1-\alpha_I)^{-\rho_I}(1-\beta^*)^{\rho_I}}{\alpha_I^{1-\rho_I}K_I^{\rho_I} + (1-\alpha_I)^{1-\rho_I}(1-\beta^*)^{\rho_I}}. \tag{20}$$

The second term (B) in (18) is the effect of automation on sector P output. Automation increases β^*, which increases P by moving labor toward it $\partial \ln P/\partial\alpha_I > 0$ (see Lemma A.1 for conditions), so $(B) > 0$ when $\rho > \rho_P$, and $(B) < 0$ when $\rho < \rho_P$. This means that the output increase in the physical sector can be good or bad for wages depending on whether physical and intelligence are more substitutable than labor and physical capital in the physical block.

The third term (C) in (18) is the effect of the reallocation of labor from I toward P. More labor available in P should intuitively lower wages. Indeed, (C) is negative because $\rho_P < 1$ by assumption, and $\partial\beta^*/\partial\alpha_I > 0$, i.e. the share of labor in P increases with automation (see Lemma A.1 for conditions).

Overall, the sign of the wage effect of automation is clearly ambiguous, and depends on whether the positive effects of more efficient physical labor outweigh the negative effects of labor migrating out of I in equation (18). The role of parameters like θ_I on the wage trajectory as intelligence automation progresses cannot be evaluated analytically because β^* is defined implicitly, and both $\partial Y/\partial\alpha_I$ and $\partial \ln P/\partial\alpha_I$ depend on β^*.

Equation (18) is a handy decomposition because the substitution parameters ρ and ρ_P can be estimated. The derivatives can also be estimated, and they have intuitive interpretations: (A) is proportional to the effect of automation on overall output Y, (B) is proportional to the effect of automation on physical output (P), and (C) is proportional to the effect of automation on the share of labor employed in the physical sector β^*. This conceptualization suggests future ways of calibrating this class of models against empirical data.

Simpler decomposition of wage effects of automation when $\rho = \rho_P$ There are cases where the (B) term in equation (18) vanishes. If we assume that the substitutability between physical and intelligence ρ is the same as the substitutability between capital and labor in physical production ρ_P. This assumption is a reasonable simplification if labor is more similar to the intelligence input, and capital is more similar to the physical input. In this case, the wage effect of automation can be written as:

$$\frac{d\ln w}{d\alpha_I} = (1-\rho)\left(\frac{\partial \ln Y}{\partial \alpha_I}\bigg|_{\beta} - \frac{d\ln \beta^*}{d\alpha_I}\right) \tag{21}$$

We thus learn that if $\rho = \rho_P$, the wage effect of automation is positive as long as the percent increase in output induced by automation $\partial \ln Y/\partial \alpha_I$ exceeds the percent increase in the share of workers in the physical sector $\partial \ln \beta^*/\partial \alpha_I$. Further, for a given observed effect of automation on Y and β^*, the effect on wages is amplified (larger in magnitude, positive or negative) when ρ is smaller[6], i.e. when the physical and intelligence sectors are more complementary.

We can also derive a sufficient condition for automation to increase wages that is based on the intelligence sector alone. Let $s_I \equiv \dfrac{(1-\tau)I^\rho}{\tau P^\rho + (1-\tau)I^\rho}$ be the (observable) revenue share of the intelligence sector (the equivalent share s_P can be defined for the physical sector). Since automation reallocates labor toward P, we have $\frac{\partial \ln P}{\partial \alpha_I} \geq 0$, hence

$$\frac{\partial \ln Y}{\partial \alpha_I} = s_P\,\frac{\partial \ln P}{\partial \alpha_I} + s_I\,\frac{\partial \ln I}{\partial \alpha_I} \;\geq\; s_I\,\frac{\partial \ln I}{\partial \alpha_I}. \tag{22}$$

Therefore, we obtain a *testable sufficient condition* for wages to rise with automation:

$$s_I\,\frac{\partial \ln I}{\partial \alpha_I} \;>\; \frac{\beta^*-1}{\beta^*}\,\frac{\partial \ln(1-\beta^*)}{\partial \alpha_I} \tag{23}$$

which uses only the I sector output response to automation and the *semi-elasticity* of the I sector employment share. This condition means that, up to some weights, the semi-elasticity of intelligence output must exceed the semi-elasticity of the employment share in the intelligence sector. More loosely stated, a sufficient condition for automation to increase wages is that the greater intelligence output can compensate for the employment losses in the intelligence sector. This condition is conservative because it neglects that automation also increases output in P, which increases wages.

Symmetrically, we can derive a sufficient condition on the I sector that ensures the wage effects of automation are negative. Using the share decomposition equation (22) above, we can find an upper bound for $\frac{\partial \ln P}{\partial \alpha_I}$, which then gives an upper bound for $\frac{\partial \ln Y}{\partial \alpha_I}$. Automation affects P only through the reallocation of labor. Using the chain rule,

$$\frac{\partial \ln P}{\partial \alpha_I} = \frac{\partial \ln P}{\partial \ln L_P}\,\frac{\partial \ln L_P}{\partial \alpha_I} = \frac{\partial \ln P}{\partial \ln L_P}\,\frac{\partial \ln \beta^*}{\partial \alpha_I} \;\leq\; \frac{\partial \ln \beta^*}{\partial \alpha_I}$$

[6] Remember that ρ affects $\partial \ln Y/\partial \alpha_I$ and $\partial \ln Y/\partial \beta^*$ so this statement is indeed not about the full effect of ρ.

$\frac{\partial \ln P}{\partial \ln L_P}$ is the labor share in P, so it is below 1, explaining the above inequality. Using this together with equation (22), we obtain an upper bound for $\frac{\partial \ln Y}{\partial \alpha_I}$:

$$\frac{\partial \ln Y}{\partial \alpha_I} = s_P \frac{\partial \ln P}{\partial \alpha_I} + s_I \frac{\partial \ln I}{\partial \alpha_I} \leq s_P \frac{\partial \ln \beta^*}{\partial \alpha_I} + s_I \frac{\partial \ln I}{\partial \alpha_I},$$

Since wages fall whenever $\partial \ln Y/\partial \alpha_I < \partial \ln \beta^*/\partial \alpha_I$ (see equation (21)), using the upper bound for $\frac{\partial \ln Y}{\partial \alpha_I}$ we just derived, a sufficient condition for wages to fall is:

$$s_P \frac{d \ln \beta^*}{d\alpha_I} + s_I \left.\frac{\partial \ln I}{\partial \alpha_I}\right|_{\beta} < \frac{d \ln \beta^*}{d\alpha_I} \tag{24}$$

$$\iff \quad \left.\frac{\partial \ln I}{\partial \alpha_I}\right|_{\beta} < \frac{d \ln \beta^*}{d\alpha_I} \qquad \text{(divide by } s_I > 0). \tag{25}$$

where $s_P, s_I \in [0, 1]$ are the revenue shares and $s_P + s_I = 1$. This expression says that wages fall if the semi-elasticity of the intelligence output with respect to automation is smaller than the semi-elasticity of the physical employment share with respect to automation.

As before, we can equivalently express the sufficient condition (25) using the employment share in the intelligence sector $1 - \beta^*$:

$$\left.\frac{\partial \ln I}{\partial \alpha_I}\right|_{\beta} < \frac{1-\beta^*}{\beta^*} \left|\frac{d \ln(1-\beta^*)}{d\alpha_I}\right|. \tag{26}$$

That is, wages decrease when the percentage increase in the intelligence output induced by automation is smaller than the odds-weighted percentage reduction in the employment share in the intelligence sector. Loosely stated, if job loss in the intelligence sector is significant relative to intelligence output growth, wages are more likely to decrease with further automation.

Empirically then, if we have data on the current share of employment in the physical sector, the current share of the intelligence sector in income, and estimates of the recent effect of automation on the output of the intelligence sector and the recent effect of automation on the share of employment in the intelligence sector, we can make predictions about what will likely happen to wages with further automation. Wages will increase if condition (23) is satisfied, and decrease if condition (26) is satisfied.

3.5 Wage effect of increasing AI after full automation of intelligence tasks

We are interested in the wage effects of adding more AI in the economy after all intelligence tasks have been automated. It is important to realize that automation (increasing α_I) is fundamentally different from adding more AI (increasing K_I) in the economy. Automation by definition replaces workers in some tasks that are newly allocated to AI (α_I increases). Adding more AI does not have a direct effect on worker allocation (K_I increases but α_I stays fixed)[7]. Both automation and increasing AI tend to increase production when AI is abundant, albeit through different channels. Automation is a technological transformation that

[7]Prior to full automation, increasing AI can reallocate workers across sectors by changing the marginal productivity of I.

increases production by improving input *allocation* in the intelligence sector, as it deploys the abundant AI across more tasks. Increasing AI increases production simply by increasing capital intensity in the AI sector: it is well understood that, in CES production functions, capital deepening increases output.

After full automation, we have $\alpha_I = 1$, and $\beta = 1$, so $L_P = L$, i.e. all labor is in the physical sector. This makes equations simpler because there is no need to re-optimize β, the allocation of labor between physical and intelligence. Specifically, the output is then given by:

$$Y = \left[\tau\, P^{\rho} + (1-\tau)\, K_I^{\theta_I \rho}\right]^{1/\rho}, \qquad P = \left(\alpha_P K_P^{\rho_P} + (1-\alpha_P) L_P^{\rho_P}\right)^{1/\rho_P}. \tag{27}$$

And the competitive wage is then:

$$w = \tau(1-\alpha_P)\, Y^{1-\rho}\, P^{\rho-\rho_P}\, L_P^{\rho_P - 1}. \tag{28}$$

We can show the effect of adding more AI capital K_I on wages is:

$$\frac{\partial w}{\partial K_I} = \tau(1-\alpha_P)(1-\tau)(1-\rho)\, \theta_I\, P^{\rho-\rho_P}\, L_P^{\rho_P-1}\, Y^{1-2\rho}\, K_I^{\theta_I\rho - 1} \tag{29}$$

This effect is positive: adding more AI increases wages.

Now what happens when we keep adding more AI capital ($K_I \to \infty$)? If $\rho < 0$ (physical and intelligence are complements), as we assumed, then $Y \to (\tau P^{\rho})^{1/\rho}$ (finite), meaning that the marginal returns to AI in terms of increasing overall output Y go to zero, so additional investments in AI eventually yield zero returns. As for the impact on AI on wages as AI goes to infinity, we have:

$$\frac{\partial w}{\partial K_I} \sim C \cdot K_I^{\theta_I\rho - 1} \;\to\; 0^{+}, \quad C = \tau(1-\alpha_P)(1-\tau)(1-\rho)\, \theta_I\, P^{\rho-\rho_P} L_P^{\rho_P-1} \left[(\tau P^{\rho})^{1/\rho}\right]^{1-2\rho} \tag{30}$$

Hence, with full automation, the marginal effect of additional AI capital on wages vanishes when $\rho < 0$, i.e. when physical and intelligence are complements. In other terms, wages saturate as we add more AI. We can also see that more strongly decreasing returns to scale (smaller θ_I) blunt the impact of AI capital accumulation on wages after full automation, an additional channel for intelligence saturation.

We now turn to simulations.

4 Simulations

We run two types of wage simulation: (i) an automation scenario where we hold capital stocks in the physical sector K_P and AI capital K_I constant, and (ii) an AI explosion scenario where AI doubles at fast rates and continues to do so after all intelligence tasks have been automated. The first type of automation simulation is most relevant to understand what happens in the short run in the event of rapid automation, so that capital does not adjust much. In the longer run, we can expect more adjustments, and in particular increases in physical capital (which we will also simulate below). The second type of simulation is highly relevant to the scaling debate and understanding under what conditions the rapid scaling of AI translates to the broader economy and to wages, as often believed by AI experts.

4.1 Parameter values

Using estimates from the existing literature, we calibrate a subset of parameters (see Table 2).

The calibration of the distribution parameters α_P and τ in CES production functions is well-known to be challenging (Klump et al., 2012; Cantore and Levine, 2012; Temple, 2012). Thus, we pick some illustrative parameter values and sensitivity will be tested through sweeps changing parameters (readers can also change parameters and visualize outcomes using our interactive tool).

First, we set parameters for the physical sector. We set the level of physical capital K_P so that K_P/L_P is equal to the capital-labor ratio in the whole economy[8], which we set to 4.6 (as in Korinek and Suh (2024), but this ratio is itself calibrated within their model). The share of physical workers is defined as the share of workers who need to use their feet or legs (29.6%) in the 2023 Occupational Requirements Survey. Defining physical work in other ways would result in similar estimates: 34.0% of workers do not use keyboarding in the 2023 Occupational Requirements Survey, and 30% is the share of earnings in manual occupations in 2023 in the Occupational Employment and Wage Statistics (see Appendix B). The share of employment in manual occupations is higher at 44%. The capital-labor substitution parameter ρ_P is calibrated so that the elasticity of substitution $\sigma_P = 1/(1-\rho_P)$ is 0.6, corresponding to the middle of the range for US manufacturing (Oberfield and Raval, 2021).

Second, we set parameters for the intelligence sector. The parameter ρ_I determining the elasticity of substitution between AI capital and labor in the intelligence sector is set at baseline to reflect a high degree of substitutability, consistent with the idea that intelligence tasks are somewhat fungible with each other. Thus, for the baseline, we picked an estimate of the elasticity of substitution for similar goods: specifically, we used the smaller estimates for the elasticity of substitution among different physical goods in (Broda and Weinstein, 2006, Table IV, SITC-3, 1990-2001, median), which gives a baseline elasticity of substitution of 2.2. For the baseline returns to scale in intelligence θ_I, we use the 0.94 returns to scale in professional services from Figure 3 in (McAdam et al., 2024), as professional services is an industry dominated by intelligence tasks.

Third, we set parameters for the overall production function Y that combines P and I. There is no direct measurement of ρ, the substitution parameter between physical and intelligence sectors, so we set it to match the historical substitution between capital and labor in manufacturing, with the idea that capital is more like a physical input and labor more like an intelligence input. Practically, we set $\rho = \rho_P$ so that the elasticity of substitution is at the middle of the range of the elasticity of substitution between capital and labor in US manufacturing, i.e. 0.6 (Oberfield and Raval, 2021).

Having set parameters at these baseline values, we vary the share of automated tasks α_I from zero to one, simulating the process of progressively automating the intelligence tasks of the economy. For every setting, we find the share of labor allocated to the physical sector β^* that equalizes the marginal productivity of labor in the physical and the intelligence sectors[9].

[8]This assumes that the capital/labor ratio in the physical sector is the same as the capital/labor ratio in the economy.

[9]We calculate this for each α_I up to $\alpha_I = 0.9$; the abundant AI condition (9) is no longer satisfied when

Before moving on to the results of the simulations, it is worth noting that some intelligence tasks have already been automated as of 2025, so we should not necessarily think of α_I as starting at zero in 2025. As an approximation for the starting point, one may think about the percentage point decline in the share of routine cognitive tasks as a share of all cognitive tasks. Cognitive jobs do not perfectly overlap with intelligence jobs, because some "cognitive" jobs need to be done in person and are therefore "physical" in our classification. Nonetheless, this is a useful starting point. In 1976-1989, the share of routine jobs among all cognitive jobs was 49% (Cortes et al., 2020, Table 1), while this share was about 35% in 2018 (Cortes et al., 2020, Fig. 1), which represents a decline of 14 percentage points. Assuming for the sake of argument that the whole decline in routine jobs is due to ICT, this means that 14% of all jobs have been automated by ICT, implying that α_I might be around 14% in 2018, and somewhat higher today (2025).

4.2 The evolution of wages as automation progresses

In the simulations, we vary parameters as outlined in Table 3. For the lower bound of the substitution parameter for intelligence tasks ρ_I, we used the elasticity of substitution across occupations in Goos et al. (2014), which represents substitution between a broader range of tasks including both physical and intelligence tasks.

Overall, the simulations illustrate that wages increase and then decrease with automation under many parameter values. When automation α_I increases, the share of labor allocated to the physical sector β increases, and output Y increases, as expected given assumptions and the abundant AI condition in eq. (9). Both total output and optimal allocation of workers to physical tasks increase with increasing automation (Fig. 2).

These dynamics raise the question of how wages are affected by increasing automation. Figure 3 plots the trajectory of wages as the automation of intelligence tasks progresses, as a function of parameters. The orange line in each panel represents the trajectory of wages for the baseline set of parameters (note that the scale of the plot varies across panels). In the baseline case, wages increase and then decrease with automation, a trajectory that is frequently anticipated by many AI scientists. For example, this CIO report predicts short-term wage growth, while other works, such as comments by OpenAI CEO Sam Altman, suggest that the era of human work may be coming to an end. Across parameter settings, we can find situations where wages largely decline or increase. The exact trajectories of wages during the transition to intelligence automation will be heavily affected by the underlying substitution parameters, which can be measured in the data.

The substitutability between different intelligence tasks, ρ_I should be one key ingredient. Without easy substitution, human intelligence activity in the non-automatable tasks keeps them employed and wages high. Variations in this parameter have a dramatic impact (Fig. 3 A). As ρ_I decreases, so that intelligence tasks become less substitutable, we see a stark hump-shaped pattern emerge: wages increase with low levels of automation, and then decrease, and the inflection point happens later than in the baseline.[10] The wage at full automation

α_I approaches 1, but it is still satisfied when $\alpha_I = 0.9$ for $K_I >= 9$. Then, at full automation for $\alpha_I = 1$, we set $\beta = 1$ and calculate the output and wage based on these parameters.

[10] The lowest ρ_I we examine in our sweep is negative, but the wage trajectory looks very similar for $\rho_I = 0.1$.

Table 2: Calibration mapping: equations, targets, and baseline values

Parameter	**Description**	**Identification / equation(s)**	**Data / targets used**	**Baseline**
L	Aggregate labor supply	Normalization	–	1.0
L_P	Labor in physical sector at baseline	Share of workers in physical occupations	$s_P = 0.30$	0.30
K_P	Physical capital stock	Match target K_P/L_P ratio	$K_P/L_P = 4.6$; $L_P = 0.30 \Rightarrow K_P = 1.38$	1.38
ρ_P	Substitution in $P(K_P, L_P)$	Choose $\sigma_P = 0.6$; $\rho_P = 1 - 1/\sigma_P$	$\sigma_P = 0.6$ (US manufacturing mid-range, Oberfield and Raval, 2021)	-0.67
α_P	Capital weight in $P(\cdot)$	Exogenous	Set to illustrate a hump-shaped wage trajectory	0.70
ρ_I	Substitution in $I(K_I, L_I)$	Choose σ_I; $\rho_I = 1 - 1/\sigma_I$	$\sigma_I = 2.2$ (Broda and Weinstein, 2006)	0.55
θ_I	Returns to scale in intelligence	External estimate	0.94 in professional services (McAdam et al., 2024)	0.94
K_I	AI input level	Exogenous	Set to ensure "abundant AI" condition (9)	9.0
ρ	Substitution between P and I in $Y(\cdot)$	Choose $\sigma = 0.6$; $\rho = 1 - 1/\sigma$	$\sigma = 0.6$ (US manufacturing, Oberfield and Raval, 2021)	-0.67
τ	Weight on P in $Y(\cdot)$	Exogenous	Set to illustrate a hump-shaped wage trajectory	0.20

Notes: See text for more details.

Table 3: Sweep values for varying parameters and justification of bounds

Parameter	**Sweep values (baseline in middle)**	**Justification of bounds**
ρ_I (intelligence substitution)	{-0.1, 0.55, 0.7}	Lower bound: elasticity $\sigma_I = 0.9$ across occupations (Goos et al., 2014) $\Rightarrow \rho_I = 1 - \frac{1}{0.9} \approx -0.1$. Upper bound: high substitutability with $\sigma_I = 3.3$ $\Rightarrow \rho_I = 1 - \frac{1}{3.3} \approx 0.70$.
ρ (top-nest substitution)	{-1.0, -0.67, -0.1}	Lower bound: elasticity $\sigma = 0.5$ $\Rightarrow \rho = 1 - \frac{1}{0.5} = -1.0$ (strong complementarity). Upper bound: elasticity $\sigma = 0.9$ $\Rightarrow \rho = 1 - \frac{1}{0.9} \approx -0.1$ (higher substitutability).
α_P (weight of K in P)	{0.50, 0.70, 0.80}	Bounds reflect alternative values for the distribution parameter of capital within the physical sector.
τ (weight of P in output)	{0.10, 0.20, 0.35}	Bounds reflect alternative values for the distribution parameter of the physical sector within overall output Y.
θ_I (returns to scale in intelligence)	{0.6, 0.94, 1.0}	Lower bound allows strong decreasing returns; upper bound is constant-returns benchmark.

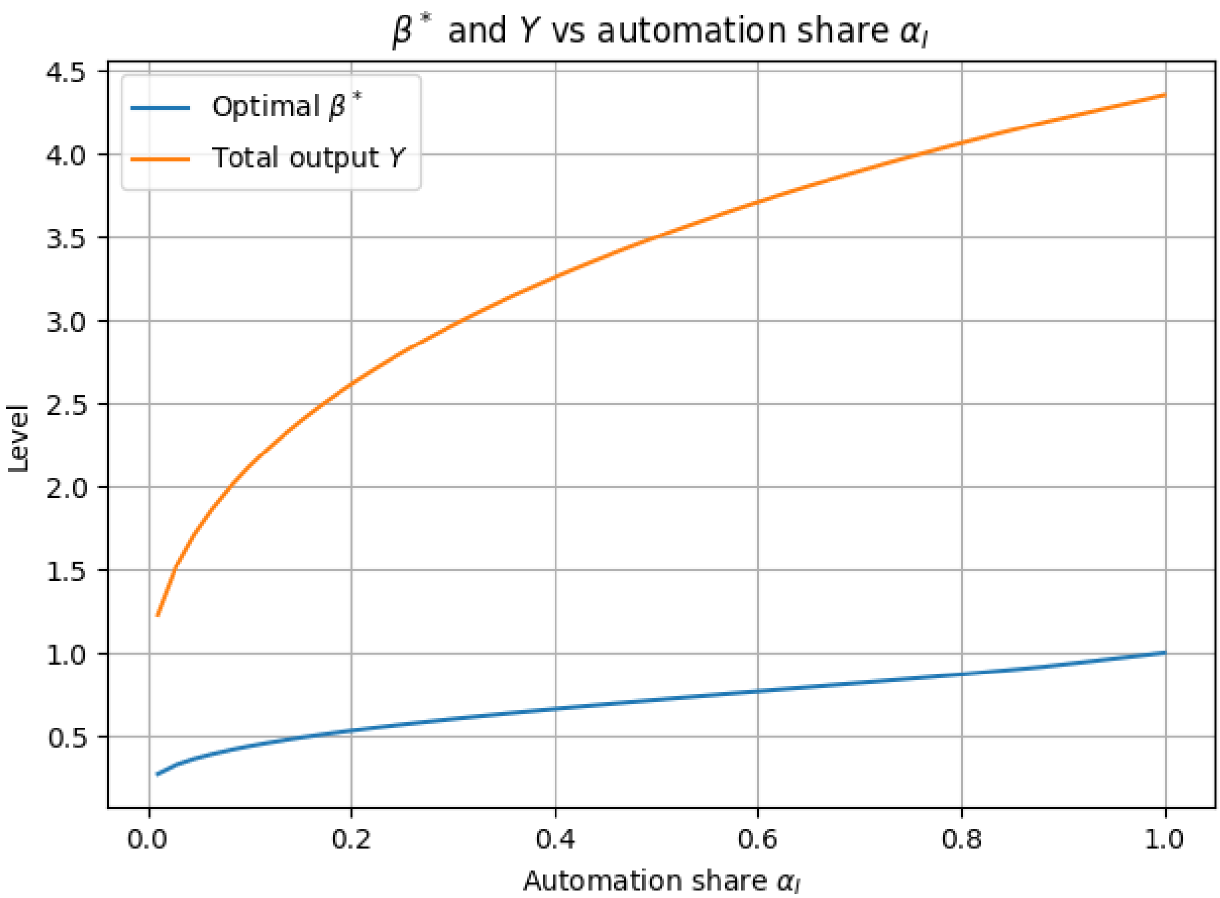

Figure 2: Output and the share of labor allocated to physical tasks increase with automation.

is not sensitive to ρ_I, because, as noted above, ρ_I drops out from the production function once automation is complete.

We have plausibly already automated some of the intelligence tasks, and average wages increased. Therefore, there is a risk of a strong decline in the future if intelligence tasks are relatively complementary. Essentially, more complementarity in intelligence tasks (lower ρ_I) makes the rise steeper but the downfall in wages worse as full automation approaches.

We may also expect ρ, the top-level substitution parameter between physical and intelligence, to be a main driver of wage effects. Similarly to the ρ_I substitution parameter, this parameter markedly changes the trajectory of wages as automation increases (Fig. 3B). As physical and intelligence sectors become less substitutable (smaller ρ), wages are less likely to decline with the automation process. There are dramatic differences in the wage level at full automation: wages are higher than without automation for $\rho = -1$, but they are a lot lower with $\rho = -0.1$. Therefore, a high level of substitution between physical and intelligence sectors drives a large loss for wages at full automation.

The non-monotonic effects of ρ on the wage as automation progresses are a helpful reminder that parameters play a complex role in determining wages. Equation (21) shows that, neglecting the impact of ρ on the Y and β channels, a larger ρ scales down the overall wage response via the factor $(1-\rho)$: it dampens both positive and negative effects. In the full simulation, however, ρ also changes how Y and β^* move with α_I. With our baseline parameters, greater substitutability between intelligence and physical (*higher* ρ) *amplifies* rather than dampens the effect of automation on wages: it tends to amplify early wage gains when automation is limited, and to deepen late-stage losses when automation is extensive.

How does this square with the general condition (18) that determines how automation affects wages when $\rho \neq \rho_P$? In the baseline case for the simulation, we set $\rho = \rho_P$, so (21) applies. In the general case (equation (18)), $\rho < \rho_P$ leads to more negative wage effects through the P channel. Figure 3B varies ρ while keeping ρ_P constant: therefore, the lower value of ρ is such that $\rho < \rho_P$. And indeed, at low levels of automation, a lower ρ leads to more negative effects of automation on wages (compare the orange and the blue line); however, once automation advances further, wages show a more *positive* wage trajectory with a lower ρ. The upshot is that treating the Y, P, and β^* responses as negligible can be misleading about how ρ and ρ_P shape wage impacts.

Next, we examine the impact of the distribution parameter or weight on physical capital within the physical sector (Fig. 3C), as well as the distribution parameter or weight on physical in the upper level CES for overall output (Fig. 3D). A higher weight on physical capital α_P leads to a more negative wage trajectory. As automation progresses, more workers move to the physical sector (β^* increases), and the decreasing marginal productivity of labor in the physical sector is steeper as α_P increases (see the $(1-\alpha_P)$ term in the wage equation (17)).

We then examine the impact of τ, the distribution parameter or weight on the physical sector in the upper level CES between physical and intelligence sectors. This parameter strongly influences the impact of automation on wages (Fig. 3D). A larger weight on the physical sector τ delays any decline in wages. For $\tau = 0.35$, wages monotonically increase with automation, while for $\tau = 0.1$ or $\tau = 0.20$, we see a large decrease in wages as we approach full automation. The wage outcome is highly sensitive to the weight of the physical sector.

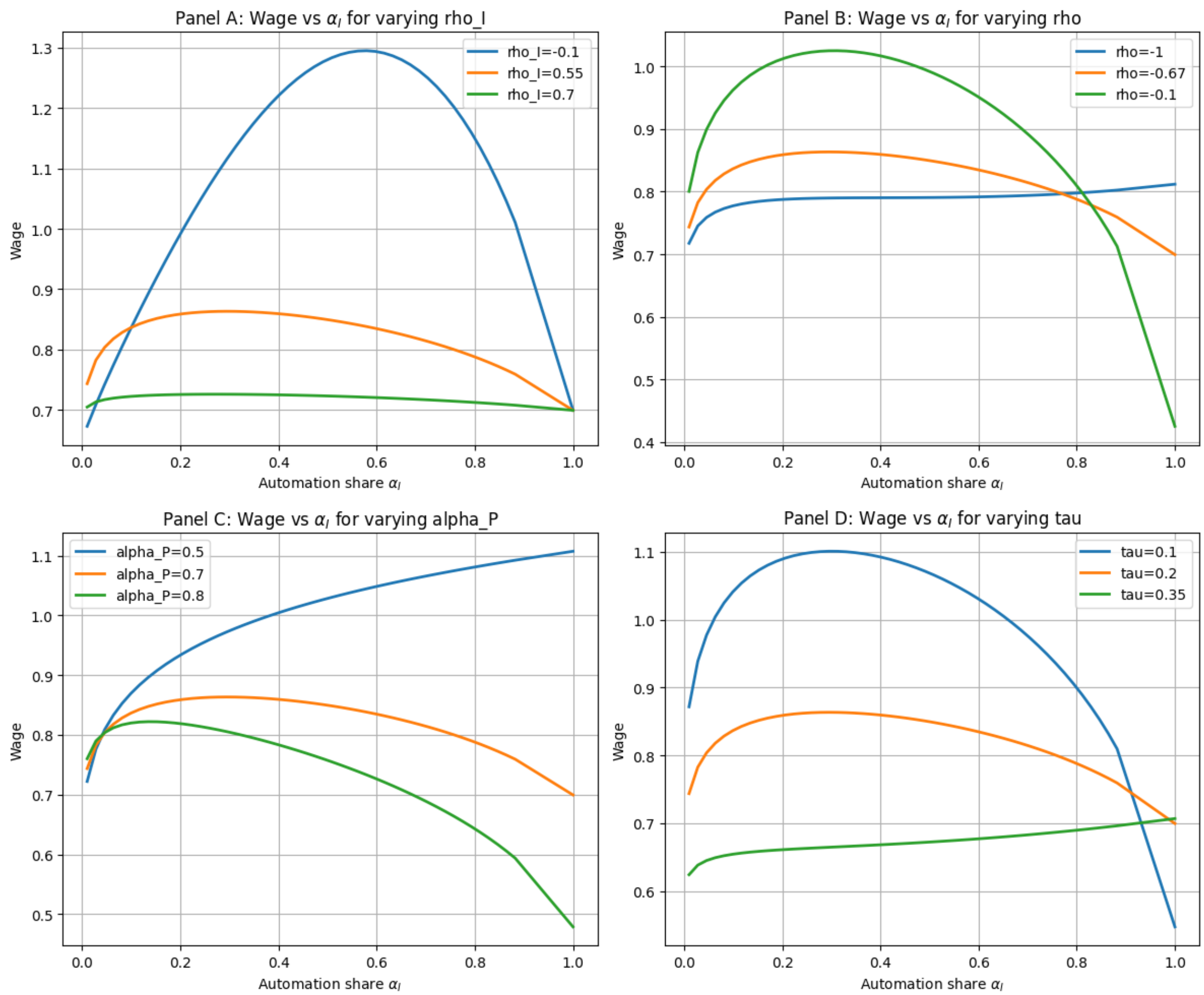

Figure 3: Wage effect of automation: impact of parameters

Finally, we may also believe that decreasing returns to scale in the intelligence production function may have an effect. Equation (20) shows that the scale term θ_I increases the positive effects of automation on wages, holding $\beta*$ constant. The simulation allows us to examine the full effect. We find that returns to scale do play a role that is qualitatively consistent with the fixed β^* prediction: θ_I shifts wages up and down by an almost fixed constant, especially at high levels of automation (Fig. 4, left panel). As decreasing returns to scale become more pronounced (lower θ_I), wages are more likely to decline already in the early stages of automation.

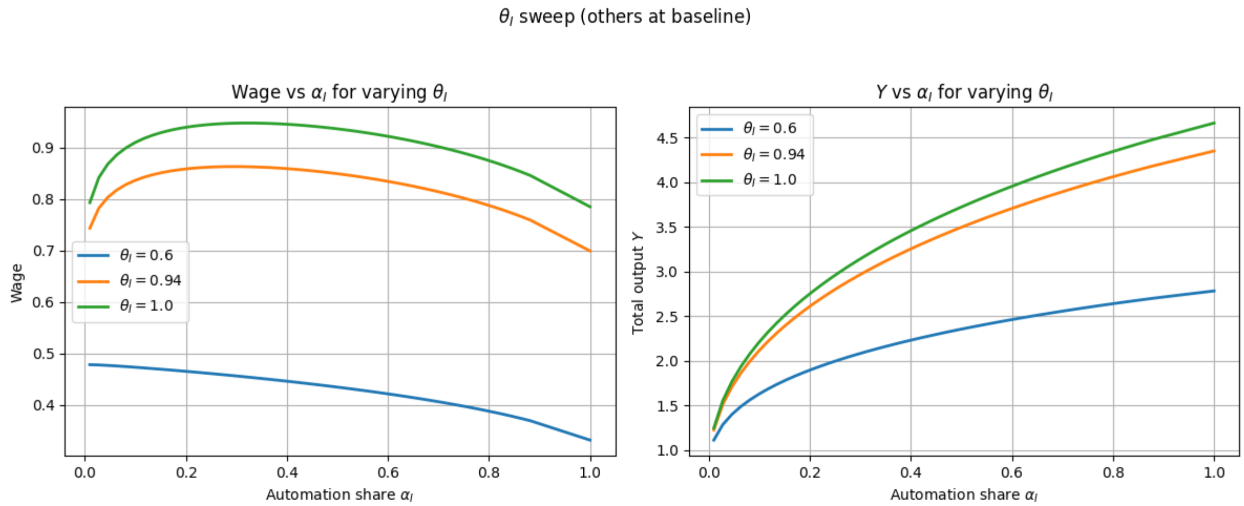

Figure 4: Wage and output effects of automation with varying returns to scale in intelligence

We learned about the effects of these parameters on wages as automation progresses. Wages increase and then decrease with automation in the baseline case. Decreasing returns to intelligence blunt wage increases from automation because the intelligence sector gets a smaller boost from automation. Substitutability between intelligence tasks has a substantial impact on the wage trajectory but does not impact the wage level at full automation. The decrease in wages at high levels of automation is greater and wage levels at full automation are lower when there is high substitutability between the physical and the intelligence sectors (high ρ), a high weight on physical capital in the physical sector (high α_P), and a low weight for the physical sector in overall output (low τ).

While the weights α_P and τ do not have a straightforward empirical counterpart, returns to scale in intelligence θ_I, and substitution parameters ρ and ρ_I can be empirically measured and we can learn about the likely path of wages based on new and updated empirical estimates of these parameters.

We invite readers to experiment with setting high ρ and α_P, and low τ to see effects for themselves in our interactive tool.

Total output will matter on top of the wages. As such, we analyze in our model how automation affects total output (Fig. 5, and Fig. 4, right panel). As we should expect given the abundant AI assumption, automation always increases output, and considerably so. Higher substitutability ρ between intelligence and physical sectors magnifies the positive effect of automation on output (Panel B) but has a negative effect on wages at high levels of

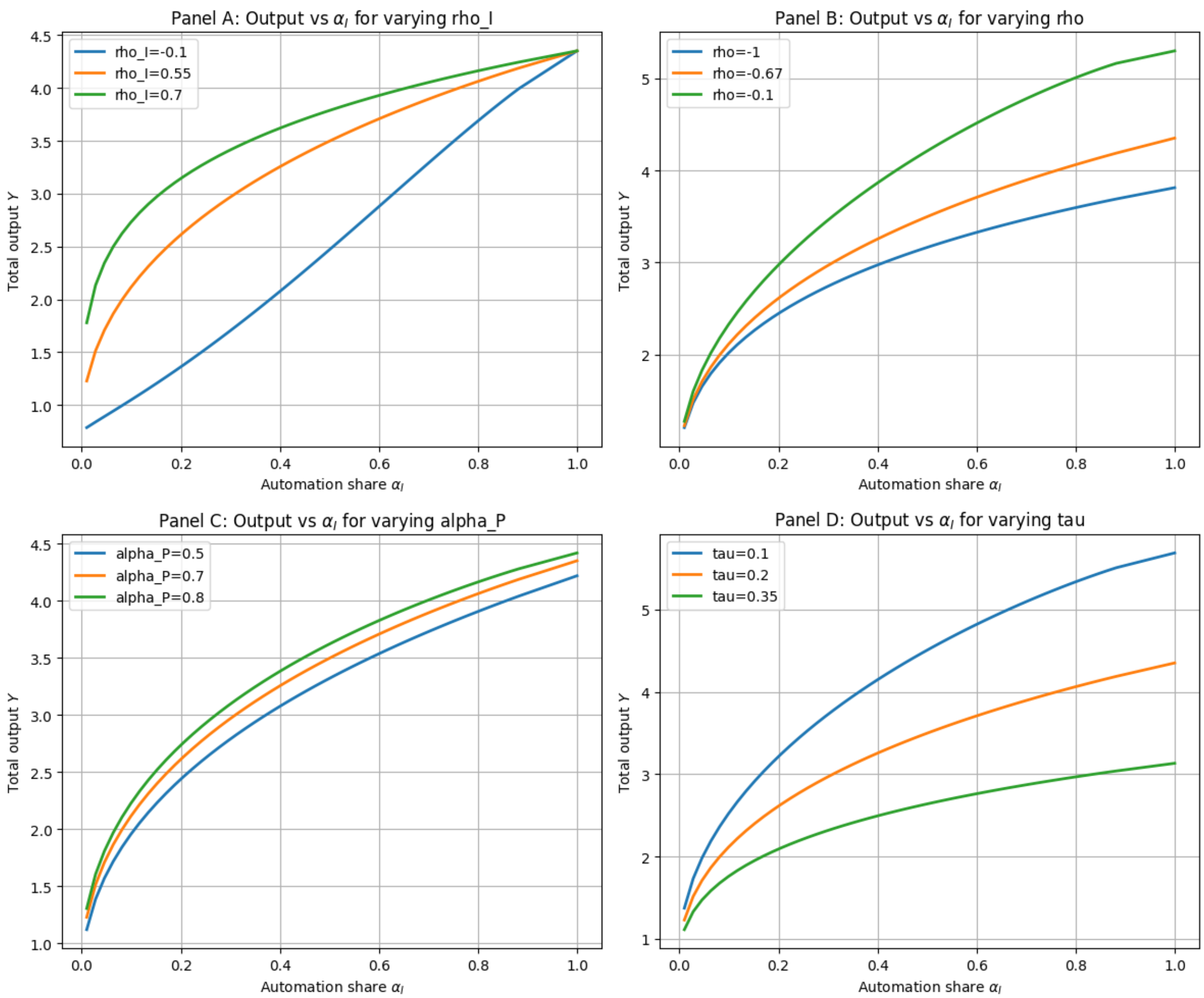

Figure 5: Output effect of automation: impact of parameters

automation (compare panels B in Figure 5 vs. Figure 3). In other terms, there is a trade-off between wages and output as we increase the substitutability ρ between the physical and intelligence sectors in the upper level CES. For wages at high levels of automation, it's best to *protect* the physical sector where workers end up working more and more often as automation progresses: this means more complementarity between the physical and intelligence sectors. This suggests a potential social conflict over the role of the physical sector in the economy when wage and output increases benefit different actors.

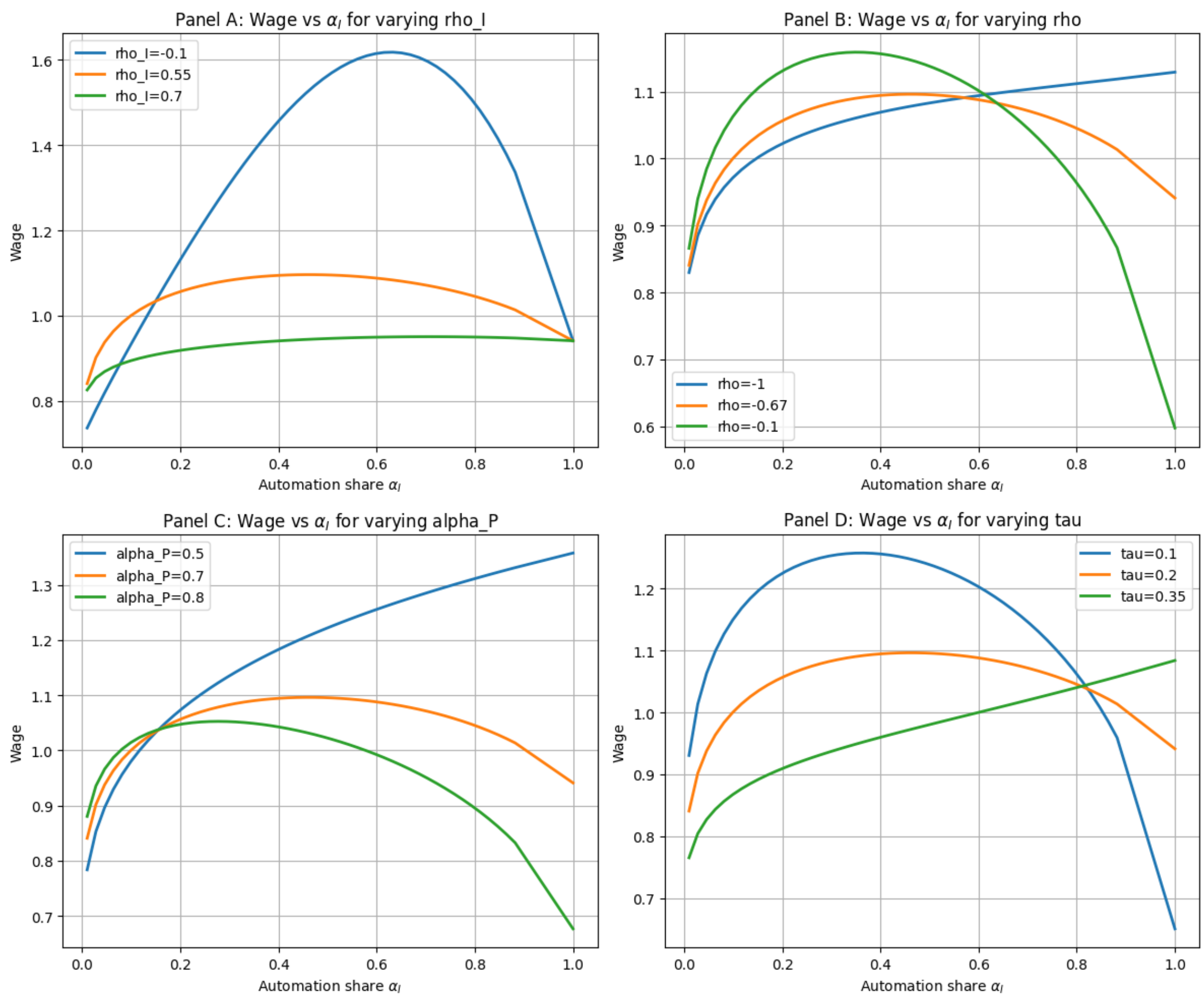

Figure 6: Wage effect of automation with high physical capital: impact of parameters

Given the crucial role of the physical sector, increasing capital in the physical sector can benefit wages because it reduces the negative productivity effects of labor crowding into the physical sector as automation progresses. This is illustrated in Figure 6, which uses the parameters from Table 2, except that physical capital K is doubled to 2.76 instead of 1.38. With a higher level of physical capital, wages increase more with automation: the maximum wage is higher and the initial increase is steeper than in Figure 3. If physical capital were endogenously determined, investments would likely increase because returns to capital increase when there are more workers in the physical sector. Overall, increasing the amount of physical capital can act as a booster for wages.

Readers can explore the evolution of wages using different parameters in our interactive tool, and results are exportable to csv files.

4.3 The evolution of wages as AI increases during and after full automation of intelligence tasks

We now turn to the longer-run effect of AI capital on wages, after all intelligence tasks have been automated. Readers can run this type of simulation in the "Analysis & Charts" section of our interactive tool.

For this simulation, we assume a fixed 5 years for the full automation of intelligence tasks, during which α_I goes from 0 to 1. We further assume that AI capital K_I grows exponentially. All other parameters are as in the baseline, unless otherwise specified. We assume that full automation of intelligence tasks occurs within 5 years. In a first scenario of fast AI growth, AI doubles every 6 months. In this case, wages rise quickly and then saturate (Figure 7). The saturation is driven by the complementarity between physical and intelligence tasks, as our baseline has $\rho < 0$: you cannot add infinitely more AI and get unbounded output growth when the physical input is held fixed by fixed labor and fixed physical capital. In a second scenario with slower AI growth, AI doubles every 24 months. In this case, wages increase more slowly, but do not decline, a difference from the baseline analysis with fixed AI: the absence of a wage decline is explained by the fact that AI increases over time, which has positive effects on wages that offset the negative wage effects observed under fixed AI. Finally, in a third scenario, we continue assuming slower AI growth, but also make physical and intelligence sectors much more substitutable, with $\rho = 0.25$ (corresponding to a 1.33 elasticity of substitution). In this case, we observe a wage decrease before full automation of intelligence tasks, after which wages slowly grow again. Importantly, in this scenario with $\rho > 0$, there is no intelligence saturation, so in the long run adding more AI always keeps increasing wages.

To sum up, as AI increases exponentially, wages saturate when physical and intelligence sectors are gross complements, but can grow without bounds when they are substitutes. However, greater substitutability of intelligence and physical sectors makes it more likely that wages decline as we approach full automation of intelligence tasks. Thus, there is a short-run vs. long-run trade-off in terms of the wage effects of substitutability between physical and intelligence: in the short run, greater substitutability can hurt wages as automation progresses, but in the long run it allows for unbounded wage growth, assuming AI also continues to expand.

5 Discussion

Our model articulates how intelligence saturation may fundamentally limit the extent to which AI can transform the economy. The key insight is that intelligence and physical sectors are likely complements at the macro level. AI may be helpful at producing intelligence at an

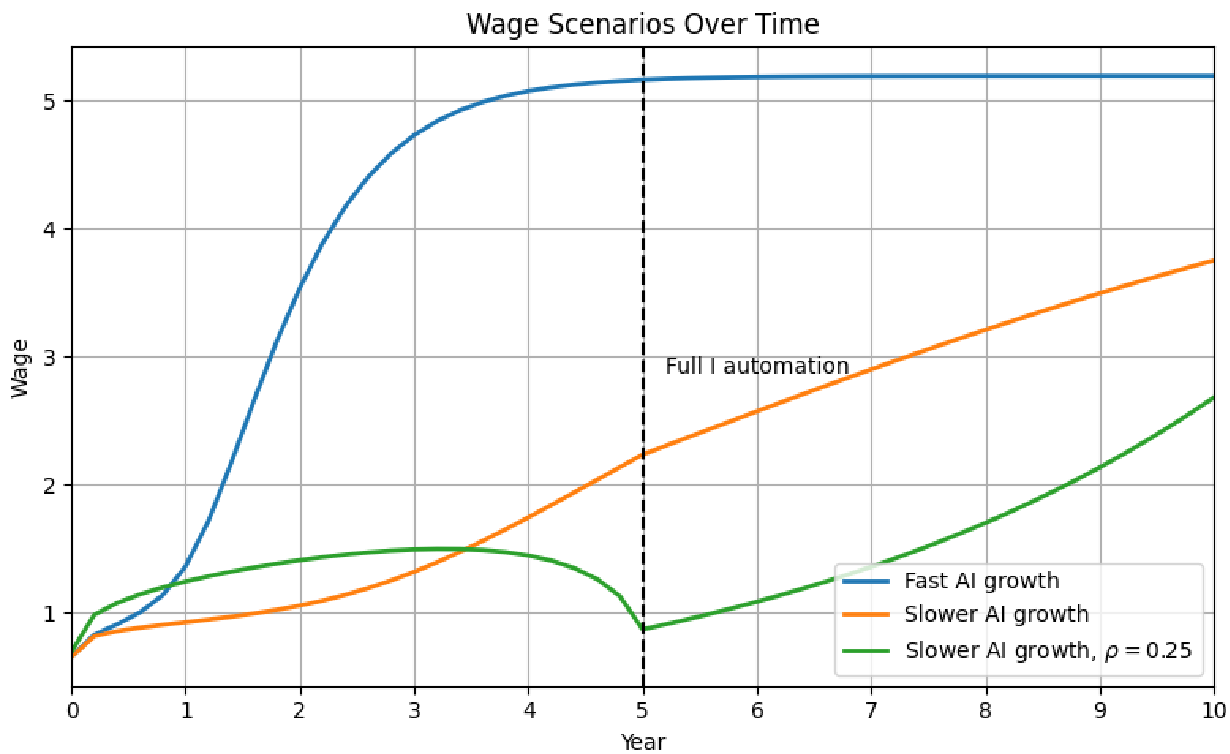

Figure 7: Wage effect of automation with exponentially increasing AI capital

accelerating speed but its effect on the actual economy is limited by the complementarity of physical and intellectual inputs in overall production.

5.1 Intelligence Saturation and the Non-Singularity

The concept of intelligence saturation fundamentally challenges the singularity narrative popularized by some AI researchers. The singularity view implicitly assumes unbounded returns to intelligence - that increasing intelligence inputs will lead to exponentially growing productivity with an exponent typical of the artificial intelligence sector. Our model shows why this assumption fails: the physical world imposes constraints that cannot be overcome by intelligence alone.

For any given set of physical inputs, there exists a saturation point beyond which additional intelligence yields negligible returns. You cannot build a car with pure intelligence; you need steel, rubber, energy, and someone to fix the mess when something goes wrong. Simulations show that strongly decreasing returns to intelligence lead to limited effects of automation on wages and output, even as labor optimally reallocates to the physical sector in response to automation. When physical and intelligence inputs are complementary, no amount of intelligence can remove the need for physical inputs or make them infinitely productive. The extremely rapid exponential growth of intelligence technology thus does not fundamentally alter the overall dynamics of growth.

5.2 Labor Market Implications Through Transition and Beyond

A key insight from our analysis is that labor allocation responds endogenously to automation. As α_I increases (more intelligence tasks become automated), labor shifts toward physical production according to optimal allocation. This reallocation itself depresses wages by increasing the labor supply in physical production relative to demand, but at the same time abundant AI in the intelligence sector makes physical workers more effective and thus boosts wages, so total wage effects depend on the balance of these two factors.

Our model predicts a hump-shaped pattern for wages for most parametrizations, including our baseline parameters. Under some parameters, wages can decrease more with automation, in particular if there is high substitutability between the physical and the intelligence sector.

This wage trajectory differs from the extreme techno-optimist view where wages go to zero while productivity potentially goes to infinity. It also differs from the extreme pessimist view (which predicts permanently depressed wages). Instead, our model suggests a non-monotonic trajectory, with potentially sharp decreases in wages in later stages of automation, in particular when intelligence tasks are assumed to be more complementary. Therefore, it is important to remain cautious: even as automation first increase wages, it can eventually lead to strong wage declines (see also Korinek and Suh, 2024). The substitution between intelligence tasks is critical and therefore should be studied more empirically, especially as this parameter may change with automation. Indeed, as automation progresses, it seems likely that the substitutability between still non-automated tasks and automated tasks decreases, in particular if there is a tail of intelligence tasks where labor has particularly strong advantages.

Given that automation can have a non-monotonic impact on wages, it is important to know where we are in the path to automation and what wage effects are already visible. Labor demand indeed seems to decrease for jobs exposed to AI (Hampole et al., 2025), but overall labor demand increases, leading to muted overall effects. These offsetting effects are consistent with the mechanisms in our model. Their estimates imply that the employment share of overall less exposed occupations like the physical "Food preparation and serving" declines because firms that do not use AI grow less. Through the lens of our model, this pattern means that β, the share of workers in the physical sector, changes little or even declines. From equation (21), wages can fall only if β rises with automation (necessary condition); thus, when β is stable or decreasing, automation should increase wages.

The role of the physical sector is critical because as automation progresses, an increasing share of labor optimally reallocates to the physical sector. There is a trade-off between wages and output as a higher share of the economy in the physical sector and a low substitutability between the physical and the intelligence sectors leads to more favorable automation effects for wages but *less* favorable automation effects for output. The most interesting parameter is perhaps ρ the substitution parameter between the physical and the intelligence sectors: if the goal is to sustain high wages while automation progresses, this parameter should stay low, but if the goal is to increase output the parameter should be increased. Concretely, this means that maximizing output may mean promoting virtual substitutes to physical goods and in person activities, which would then contribute to lowering wages during the automation phase.

The substitution parameter ρ also fundamentally shapes intelligence saturation when other factors are held fixed: when $\rho < 0$, there is intelligence saturation, and the lower ρ, the lower the long-run maximum wage and the quicker this maximum wage is achieved. When $\rho > 0$, i.e. when physical and intelligence sectors are gross substitutes, there is no intelligence saturation and wages can continue to grow forever as AI increases, but the wage trajectory during automation is typically less favorable.

5.3 AI, innovation and wages

AI leads to innovation that can itself spur job and wage growth in line with past introductions of general purpose technologies. This process of innovation is captured implicitly in two ways in our macro model.

First, our model can capture the creation of new labor-intensive intelligence tasks, a reinstatement effect (Acemoglu and Restrepo, 2019). Specifically, the creation of new tasks could manifest through a lower automation parameter α_I in the intelligence sector, because the share of labor in intelligence tasks $1 - \alpha_I$ increases when new labor-intensive tasks are added (Acemoglu and Restrepo, 2019). Thus, negative wage effects of increasing automation α_I could be countered by the creation of new labor-intensive intelligence tasks.

Second, the progress of AI can be represented through innovation embodied in capital, by adding more artificial intelligence capital K_I. This increases the wages of intelligence workers for the same reason that adding more capital in a CES production function increases wages, i.e. because labor benefits from having more capital to work with. Adding more AI also increases the wages of physical workers because it increases intelligence production, which is beneficial for the physical sector to which physical workers contribute.

It is the process of automation by itself, i.e. the replacement of workers with AI, that can lead to negative wage effects if other positive effects are not strong enough to counteract it. While we do not explicitly model innovation, innovation effects are implicitly captured in the evolution of α_I and K_I, and can be interpreted as the aggregate outcome of innovation.

5.4 Factors Moderating the Impact of AI

Several additional factors may moderate AI's economic impact beyond what our model captures. First, there may be intelligence tasks that remain persistently difficult to automate - tasks that require forms of intelligence where AI's capabilities plateau. Our modeling can accommodate this by capping α_I below 1, reflecting a frontier of non-automatable intelligence work.

Second, the rate of AI adoption depends on more than just technical capability - it requires investments, training, complementary innovations, and overcoming institutional inertia. These friction factors explain why technological transitions typically occur more gradually than pure technical capabilities would suggest.

Finally, a lack of competition among AI providers may limit AI development and deployment, or lead to strategic choices that diverge from socially optimal development paths.

5.5 Model Limitations and Future Research

First, our models do not explicitly account for the role of human preferences and values in shaping the economic impact of AI. Even with intelligence saturation, societal choices about AI governance, distributive justice, and work organization will significantly influence realized outcomes.

Second, our models do not explicitly incorporate reallocation costs for labor, while in practice these costs tend to be substantial. As a result, even if automation ultimately increases average wages, there can be significant wage declines in the short to medium run as laid off workers must find new jobs (Jacobson et al., 1993; Couch and Placzek, 2010) and adapt their skills to these new jobs.

Third, because our model assumes labor is homogeneous, it cannot discuss disparate impacts of AI for different groups of workers. Just like prior waves of technological change (Autor and Dorn, 2013; Kogan et al., 2023), the newest AI technology may lead to wage increases for some workers and wage decreases for others depending on their sectors of activity and whether technology complements or substitutes for their work. It is worth noting that disparate impacts of automation across workers can be magnified in the presence of reallocation costs, which, as mentioned before, we do not explicitly model.

Fourth, our model assumes that in the physical sector, labor cannot be profitably replaced by capital. This reflects the much slower decline in robot costs relative to AI costs. One could imagine, however, a scenario where robots can replace humans at scale in physical production. The key question for the future of work is whether there will remain tasks where replacing labor with capital is not economically advantageous, whether due to high costs or regulation. Call these tasks the "human domain," with the remainder forming the "machine domain." In such a case, we could simply relabel the physical sector as the human domain and the intelligence sector as the machine domain, preserving our model's structure and applicability. If all labor could be replaced by capital, wages would fall to zero, but this extreme scenario appears unlikely given the high cost of complex robotics and the potential for regulation to raise costs. While the specific boundary between physical and intelligence inputs may shift, a framework that divides the economy into automatable and non-automatable tasks is likely to remain relevant for the foreseeable future.

Future research could address these limitations by incorporating heterogeneous task structures with varying substitution elasticities, exploring dynamic adjustment processes in greater detail, and incorporating endogenous technological change in physical production capabilities. Additionally, enriching the models with evidence from recent AI deployments could improve their empirical grounding.

5.6 Policy Implications

Our analysis suggests several policy implications. First, policies that slow automation could help smooth the transition by reducing negative wage effects. The literature has explored the rationale for such policies when worker adjustment is costly (Guerreiro et al., 2022; Lehr and Restrepo, 2022; Costinot and Werning, 2023; Beraja and Zorzi, 2025). Our model suggests an additional rationale: allowing for more time to increase capital investment in physical sectors, which could help smooth the transition by reducing negative wage effects. This does not mean halting AI development, but rather pacing its deployment to allow for investments in physical capital. A tax on the deployment of AI that replaces workers in intelligence tasks might be helpful to maintain high wages, but it is not clear how one could effectively target this technology. As our model outlines, replacing workers tends to reduce wages, but increasing the amount of AI used tends to increase wages; this makes the targeting of any AI tax extra tricky, even if AI could be clearly distinguished from other technologies. A subsidy for investment in capital used in the physical sector is likely easier to target: this could include for example physical investments in construction, and in the hospitality industry.

Second, redistributive policies may be useful during the transition period when wages are depressed by automation. The specifics of these policies depend on political and design considerations beyond our model's scope, but the model clearly indicates a period of adjustment where many workers face significant economic pressure. One possible model is wage insurance (Hyman et al., 2024), which would provide income support to workers displaced by AI that find jobs at lower wages.

6 Conclusion

We have presented a framework for analyzing the economic impact of AI that reconciles insights from both economics and computer science. Our model demonstrates how intelligence saturation - the idea that marginal returns to intelligence tend to zero when physical inputs are held constant - fundamentally constrains AI's long-term economic impact.

The key insight of our analysis is the distinction between intelligence and physical sectors, coupled with the observation that labor is more substitutable with AI in intelligence tasks than with capital in physical tasks. These two features drive the dynamics of our model and lead to our main conclusions: (1) wages may have a non-monotonic path as automation progresses (2) after full automation of intelligence tasks, wages can grow again but are limited by intelligence saturation as long as intelligence and physical sectors are complements, and (3) the ultimate constraint on economic growth shifts from intelligence to physical production.

We use a CES macro model built on a CES physical sector (capital–labor), and a CES-like intelligence sector that aggregates many tasks. Our theoretical analysis shows that increasing automation moves workers from the intelligence sector to the physical sector under mild conditions (see Lemma A.1). The sign of the effect of automation on wages is theoretically ambiguous and mainly depends on whether the positive scale effect of automation (increased intelligence output leading to increased overall output) outweighs the negative effect from workers getting iced out of the intelligence sector and having to find work in the physical sector (see Eq. (18)). If we focus on the intelligence sector alone, then a sufficient condition for automation to lower wages is that the (weighted) share of employment in the intelligence sector decreases more than the intelligence output grows (see Eq. (26)) and (21)). Based on our model, a necessary condition for wages to decrease is that the share of employment in the intelligence sector decreases. This is a useful indicator to watch to understand whether further automation might decrease wages.

We then simulate the model to understand the effect of automation and of AI increases on wages. Holding AI fixed, and under our baseline parameters, rising automation of intelligence tasks increases and then decreases wages, as the labor reallocation drags eventually outweigh the positive impacts on the production of intelligence. This represents a cautionary tale that early days wage gains should not be taken for granted. Varying parameters away from the baseline, we learn three main lessons. First, starker decreasing returns to intelligence dampen the early positive wage effects of automation. Second, less substitutability between intelligence tasks can lead to wages strongly increasing and then steeply decreasing with automation. Third, because automation pushes labor toward the physical sector, the elasticity of substitution between sectors is pivotal: greater substitutability depresses wages yet boosts output as automation progresses further at high levels of automation. The effects of automation depend on key parameters in a subtle way, making predictions parameter-dependent. We then allow AI to grow. This elasticity of substitution between sectors governs whether wages and output saturate as AI capital increases past full automation of intelligence tasks: when physical and intelligence sectors are gross complements ($\rho < 0$), there is intelligence saturation.

Overall, these findings contradict the singularity narrative that posits unbounded returns to intelligence. Even powerful AI faces physical and institutional bottlenecks that bound returns when P is fixed. A car cannot be built by intelligence alone; a building cannot be constructed with pure computation; a meal cannot be cooked with algorithms alone.

Our analysis suggests that AI represents a powerful general-purpose technology that will significantly reshape the economy, but not one that fundamentally alters the laws of economics or physics. The economy after AI will still be constrained by scarcity, still require physical production, and still operate according to principles of marginal returns and substitution that economists have long understood.

This perspective provides a middle ground between the extremes that have dominated much public discourse about AI. Neither the techno-utopian vision of post-scarcity abundance nor the dystopian fear of permanent labor displacement accurately captures what our model predicts. Instead, we foresee a significant but ultimately bounded transformation, with a potentially challenging transition period followed by a new equilibrium where physical production becomes the limiting factor.

Our modeling framework also allows for a clearer understanding of what it would take for the singularity narrative to become reality, and what parameter assumptions can fundamentally differentiate the insights of economists vs. AI experts. Economists' common predictions of a mild effect of AI can be rationalized by complementarity between physical and intelligence sectors, leading to intelligence saturation even as AI continues to scale up. By contrast, AI experts' predictions of an economic upheaval can be rationalized by substitutability between physical and intelligence sectors: if technological progress allows us to substitute more easily intelligence production for physical production, then there is no limit to how much AI can increase output and wages (as long as the physical sector is not fully automated).

Policy can focus on managing the automation of intelligence, while ensuring that the benefits of AI are broadly shared. By recognizing the fundamental constraints on AI's economic impact, we can develop more realistic expectations and more effective strategies for harnessing AI's potential while mitigating its disruptive effects. Policy therefore faces the dual challenge of (i) pacing automation and (ii) accelerating labor-augmenting investment in the physical sector so that wages are less likely to decline with automation.

The future path of the economy depends not only on technological possibilities but also on societal choices. We retain substantial agency in shaping how these technologies are developed and deployed, and AI itself can help us develop scenarios and possible policy responses.

In summary, our paper contributes to the understanding of AI's economic impact by providing a framework that combines insights from economics and computer science, emphasizes the fundamental distinction between physical and intelligence sectors, and demonstrates how intelligence saturation constrains AI's transformative potential. This framework helps resolve apparent contradictions between optimistic and pessimistic AI narratives and provides guidance for policy responses that can smooth the transition to an AI-abundant economy.

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A Conditions for automation to increase the share of labor in the physical sector

Lemma A.1 (Automation raises β^* under mild conditions)**.** *Fix (K, K_I) and an interior allocation $\beta^* \in (0,1)$ that solves $w_P(\beta) = w_I(\beta, \alpha_I)$. Assume each block is CES with $\rho_P < 1$ and $\rho_I < 1$ (concave) and $\theta_I > 0$. Then*

$$\frac{d\beta^*}{d\alpha_I} > 0 \quad \textit{whenever} \quad \frac{\partial \ln w_I}{\partial \alpha_I}\Big|_\beta < 0.$$

Moreover, at fixed β,

$$\frac{\partial \ln w_I}{\partial \alpha_I} \;=\; \underbrace{-\frac{1-\rho_I}{1-\alpha_I}}_{\textit{direct (at fixed } I)} \;+\; \underbrace{\left(\rho - \tfrac{\rho_I}{\theta_I}\right)\frac{\partial \ln I}{\partial \alpha_I}}_{\textit{indirect via } I}. \tag{31}$$

Hence a sufficient condition is

$$\rho \le \frac{\rho_I}{\theta_I} \quad \textit{or, more generally,} \quad \frac{\partial \ln I}{\partial \alpha_I} < \frac{1-\rho_I}{(1-\alpha_I)\left(\rho - \rho_I/\theta_I\right)} \quad (\rho > \rho_I/\theta_I).$$

Proof. Let $G(\beta, \alpha_I) = \ln w_P(\beta) - \ln w_I(\beta, \alpha_I)$; at an interior solution $G = 0$. *Explicit forms.* Using $L_P = \beta L$ and $L_I = (1-\beta)L$,

$$w_P(\beta) = \tau\, Y^{1-\rho}\, P^{\rho-1}\, \frac{\partial P}{\partial L_P} = \tau\, Y^{1-\rho}\, (1-\alpha_P)\, P^{\rho-\rho_P}\, (\beta L)^{\rho_P-1},$$
$$w_I(\beta, \alpha_I) = (1-\tau)\, Y^{1-\rho}\, I^{\rho-1}\, \frac{\partial I}{\partial L_I}, \qquad \frac{\partial I}{\partial L_I} = \theta_I\, (1-\alpha_I)^{1-\rho_I}\, I^{1-\rho_I/\theta_I}\, \big((1-\beta)L\big)^{\rho_I-1}.$$

β-monotonicity. With $\rho_P < 1$ and $\rho_I < 1$, the marginal product of labor in each block is decreasing in its own labor input. As β rises, $L_P = \beta L$ increases and $L_I = (1-\beta)L$ decreases; hence $\partial_\beta w_P < 0$ and $\partial_\beta w_I > 0$. Therefore $G_\beta = \partial_\beta \ln w_P - \partial_\beta \ln w_I < 0$. *IFT sign.* By the Implicit Function Theorem,

$$\frac{d\beta^*}{d\alpha_I} = -\frac{G_{\alpha_I}}{G_\beta} = \frac{\partial_{\alpha_I} \ln w_I}{G_\beta}, \qquad \Rightarrow \qquad \operatorname{sign}\Big(\frac{d\beta^*}{d\alpha_I}\Big) = -\operatorname{sign}\big(\partial_{\alpha_I} \ln w_I\big),$$

since $G_\beta < 0$. This is the denominator sign used in Proposition 3.1.

For (31), note $w_I = Y^{1-\rho} I^{\rho-1}\,(\partial I/\partial L_I)$ and $\partial I/\partial L_I = \theta_I(1-\alpha_I)^{1-\rho_I}\, I^{1-\rho_I/\theta_I}\, L_I^{\rho_I-1}$, so

$$\ln w_I = (1-\rho)\ln Y + \underbrace{\big[(\rho-1) + (1-\rho_I/\theta_I)\big]}_{=\ \rho-\rho_I/\theta_I} \ln I + (1-\rho_I)\ln(1-\alpha_I) + (\rho_I - 1)\ln L_I + \text{const.}$$

Differentiating w.r.t. α_I at fixed β (hence fixed L_I) yields (31). The first term is the direct effect emphasized in the intuition: higher α_I lowers $(1-\alpha_I)^{1-\rho_I}$, reducing the I-block marginal product of labor. The second is the indirect effect via the induced change in I; it is dominated when $\rho \le \rho_I/\theta_I$, or under the stated bound when $\rho > \rho_I/\theta_I$. Under either condition, $\partial_{\alpha_I} \ln w_I < 0$, hence $d\beta^*/d\alpha_I > 0$. □

B Share of earnings in manual occupations in 2023

This appendix estimates the share of total U.S. wage earnings attributable to manual occupations in 2023.

Manual occupations are defined as major occupational categories involving physical labor or skilled trades. The classification follows Cortes et al. (2020), which borrows from Autor et al. (2003).

The categorization is applied using the Occupational Employment and Wage Statistics dataset (U.S. Bureau of Labor Statistics, 2023). Table 5 shows the raw data on employment and average earnings by occupation, and the calculated employment shares and earnings shares of each occupation.

Table 4: Occupation categories and classifications

Occupation Title	**2010 Census Code(s)**	**2010 SOC Code(s)**	**Classification**
Management, professional, and related occupations	0010–3540	11-0000–29-0000	Non-Routine Cognitive
Service occupations	3600–4650	31-0000–39-0000	Non-Routine **Manual**
Sales and office occupations	4700–5940	41-0000–43-0000	Routine Cognitive
Farming, fishing, and forestry occupations	6000–6130	45-0000	Routine **Manual**[a]
Construction and extraction occupations	6200–6940	47-0000	Routine **Manual**
Installation, maintenance, and repair occupations	7000–7630	49-0000	Routine **Manual**
Production, transportation, and material moving occupations	7700–9750	51-0000–53-0000	Routine **Manual**

[a] Data from these workers was excluded from the analysis in Cortes et al. (2020).

Table 5: Employment and earnings by occupation in the 2023 Occupational Employment and Wage Statistics

2010 SOC Code(s)	Employment	Averagee earnings	Share of total employment	Share of total earnings
11–0000	10495770	137750	.0691176	.1454173
13–0000	10087830	90580	.0664312	.0919052
15–0000	5177400	113140	.0340946	.0589166
17–0000	2539660	99090	.0167244	.0253114
19–0000	1389430	87870	.0091498	.0122797
21–0000	2418130	58980	.0159241	.0143448
23–0000	1240630	133820	.0081699	.0166983
25–0000	8744560	66400	.0575854	.0584004
27–0000	2106490	75520	.0138718	.0160004
29–0000	9284210	102060	.0611391	.0953039
31–0000	7063530	38220	.0465153	.0271533
33–0000	3504330	57710	.023077	.0203407
35–0000	13247870	34490	.0872409	.0459567
37–0000	4429070	38320	.0291667	.0170706
39–0000	3040630	38430	.0200234	.0117529
41–0000	13380660	53280	.0881154	.0717054
43–0000	18533450	47940	.1220479	.0893644
45–0000	432200	39970	.0028462	.0017375
47–0000	6225630	61500	.0409975	.0385096
49–0000	5989460	58500	.0394423	.0352414
51–0000	8770170	47620	.057754	.0420056
53–0000	13752760	46690	.0905657	.0645838

Data from the Occupational Employment and Wage Statistics dataset (U.S. Bureau of Labor Statistics, 2023). To obtain the share of total earnings, we first multiply the employment number by the average wage in the occupation, obtaining the wage bill in the occupation. The sum of the occupational wage bill over all occupations is total earnings. And the share of each occupation in total earnings is the wage bill divided by total earnings.

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