Artificial Intelligence and Economic Growth: Can AI Mitigate the Empty Planet Scenario?

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Abstract

How can artificial intelligence (AI) reshape the future of economic growth in a world constrained by declining population dynamics? This paper addresses this question by extending the semi-endogenous growth framework to incorporate AI as a distinct, non-rival input in the R&D process. Unlike prior studies that focus on AI as a tool for task automation or capital substitution, we highlight its potential to complement human intelligence in idea production. Our model introduces "semi-human intelligence," combining human labor and AI through flexible production functions, including Cobb-Douglas and constant elasticity of substitution (CES) specifications. The results reveal that while AI significantly enhances research productivity and raises per capita GDP, it cannot fully overcome the demographic constraints inherent in semi-endogenous growth models. Long-run growth remains tied to population expansion, underscoring the irreplaceable role of human creativity. This paper offers a fresh perspective on AI's role in sustaining innovation and challenges overly optimistic views of AI-driven exponential growth. By highlighting the synergy between AI and human intelligence, it provides valuable insights for addressing global challenges in productivity and innovation.

1 Introduction

Ideas are the engine of economic growth. Since Romer (1990) introduced endogenous growth theory, the understanding that innovation drives sustained economic progress has become foundational to modern economics. Ideas, being non-rivalrous, can be endlessly reused and recombined, making their generation essential for long-term prosperity. However, as Brynjolfsson and McAfee (2014) noted, the process of innovation relies heavily on recombining existing knowledge, which is fundamentally tied to human intelligence—and, by extension, population growth.

This dependency faces unprecedented challenges due to global demographic trends. Fertility rates have more than halved over the past 70 years, and projections indicate further declines, with population growth stagnating or reversing in many regions (Schumacher et al., 2024; United Nations, 2022). Growth theorists are starting to predict an "empty planet" scenario where declining populations constrain the generation of new ideas and, consequently, economic growth (Jones, 2022). This raises a critical question: can artificial intelligence (AI) mitigate these demographic constraints and sustain innovation? Recent macroeconomic analyses suggest that AI's impact on long-run growth is complex and depends on its role as a complement or substitute for human intelligence (Acemoglu, 2024). While AI has the potential to boost productivity, its ability to generate sustained growth remains uncertain, as it operates within the structural constraints of knowledge creation.

Recent empirical evidence supports the notion that AI enhances productivity, particularly for less experienced workers, and operates as a scalable, non-rival input (Brynjolfsson et al., 2025). Their findings suggest that AI can significantly improve efficiency in knowledge-based tasks, aligning with our assumption that AI enhances idea production in research and innovation. However, their results also highlight that AI's impact is uneven across skill levels, benefiting routine cognitive tasks more than high-level creative problem-solving. This reinforces our theoretical argument that while AI can amplify research efficiency, it remains constrained by its dependence on existing knowledge and does not fundamentally alter the constraints imposed by semi-endogenous growth models. Against this backdrop, we develop a theoretical framework to examine AI's role in sustaining long-run economic growth. This paper argues that AI, while transformative, cannot independently replace human intelligence in the production of ideas. Unlike traditional capital or labor inputs, AI operates as a probabilistic system that updates its beliefs based on existing data through a Bayesian framework. Crucially, Bayesian systems are inherently limited: if a hypothesis or event is initially assigned a probability of zero, no amount of new evidence can alter this state. In contrast, human intelligence has the unique ability to

assign positive probabilities to entirely novel hypotheses, even in the absence of prior data. This capacity to create new domains of exploration underscores the essential complementarity between AI and human intelligence in research and development (R&D).

Building on these insights, we incorporate AI as a distinct, non-rival input in the idea production function, examining its interaction with human intelligence under different scenarios of complementarity and substitutability. Our findings show that while AI significantly enhances R&D efficiency and delivers substantial level effects, it cannot sustain exponential growth in the absence of population growth. The long-term growth rate remains proportional to demographic dynamics, consistent with the constraints of semi-endogenous growth theory. However, AI's ability to augment human creativity highlights its critical role in mitigating the productivity decline associated with demographic stagnation.

This paper contributes to the literature by shifting the focus from AI's role in task automation and labor substitution (Aghion et al., 2017) to its impact on idea production, a key driver in semi-endogenous growth models. Unlike Jones (2022), who emphasizes the demographic constraints on growth, this paper explores how AI can mitigate these constraints by enhancing research productivity, albeit within the bounds of semi-endogenous growth dynamics.

The paper proceeds as follows: Section I explores how AI can contribute to innovation and reviews the existing literature on AI and growth. Section II describes the model and its implications for long-term growth. Finally, Section III concludes.

2 AI and innovation

Generative AI represents a radical departure from past technologies due to its ability to emulate complex human tasks and assist in idea production. At its core lies the Transformer architecture (Vaswani et al., 2017) which processes vast datasets using unsupervised learning and dynamically assigns importance to input data. Applications such as OpenAI's ChatGPT-4 and AlphaFold2 demonstrate AI's ability to recombine knowledge and reveal hidden patterns, accelerating discovery in domains ranging from drug development to material sciences (Gomes et al., 2019; Mak et al., 2023). Notably, AlphaFold2 earned the 2024 Nobel Prize in Chemistry for predicting protein structures, underscoring AI's transformative impact on R&D (Nobel Prize Outreach AB, 2024).

These capabilities position AI as a non-rival input in the idea production function. Unlike early technologies, generative AI can analyze large volumes of unstructured

data, revealing relationships that would elude human researchers. This aligns with the hypothesis generation process modelled by A. Agrawal et al. (2024), where predictive modelling increases the likelihood of successful innovation and accelerates search durations.

Empirical studies further support AI's role in enhancing idea generation. For example, Babina et al. (2024) show that AI adoption drives firm growth through product innovation, as evidenced by increased trademarks and patents. However, AI does not significantly impact firm-level productivity or process innovation, highlighting its primary role in expanding the scope of research and development.

Existing growth models, however, have predominantly focused on AI's automation potential. Early frameworks such as Zeira (1998) emphasized labor-replacing technologies, while more recent studies framed AI within task-based models (Acemoglu & Restrepo, 2018). In contrast, this paper integrates AI as a distinct, knowledge-based input in the idea production function, complementing human intelligence and addressing demographic constraints on innovation (Jones, 2022). The role of AI in complementing labor productivity aligns with historical patterns of technological change. Empirical evidence suggests that while AI enhances routine cognitive tasks, its effect on high-level creative problem-solving remains limited (Autor et al., 2003). This supports our assumption that AI functions as an amplifier of human intelligence rather than a full substitute for knowledge creation.

Building on Aghion et al. (2017), who framed AI as a form of capital-driven task automation, this paper shifts the focus to AI's role in idea production. Unlike Lu (2021), who modeled AI alongside human capital accumulation, we align with Cozzi (2023) to focus on semi-endogenous growth, assuming declining research productivity in line with empirical evidence (Bloom et al., 2020; Herzer, 2022). This allows us to examine AI's potential to mitigate the reliance on population growth without departing from the constraints of semi-endogenous models.

3 Model overview

3.1 How to model AI in growth models?

The focus of our paper is to explore the potential impact of AI on long-term growth. In this regard, as discussed in Section II, we are interested in the impact of AI not merely as a new form of automation performing predefined tasks, but as a broader enabler of knowledge creation. This section section elaborates on the rationale for our chosen approach to modeling AI.

AI differs fundamentally from traditional production factors, which prompts us not to categorize it as a conventional factor in the production of goods and services. Unlike labor and capital, which are tangible and can be quantified by workforce size and market values, respectively, AI consists of intangible components like knowledge, codes, and algorithms that lack standardized pricing mechanisms. Additionally, while traditional factors are rivalrous — a machine or worker cannot be used by more than one entity at a time within the same organization — AI exhibits the non-rival nature typical of knowledge goods. Once developed, an AI system can be deployed across multiple users simultaneously without diminishing its utility. While the computational infrastructure required to run AI models imposes physical limits, these are generally large enough to accommodate far more users than the actual demand. As a result, absent artificial restrictions by AI providers, AI effectively behaves as a non-rival good in practice. Consequently, the productive capabilities of AI are less constrained by capital and are more closely aligned with non-rival knowledge capital, which can be replicated and distributed at near-zero marginal cost, enhancing productivity without direct reliance on capital accumulation.

AI's democratization further strengthens its categorization as a distinct knowledge good. Increasingly accessible AI models allow not only data scientists but also people with basic computing skills to integrate AI into their daily tasks and research. The accessibility of generative AI has significantly increased thanks to platforms such as ChatGPT, Claude, and Gemini which bring the technology within everyone's reach. The increasing prevalence of open-source AI models has facilitated broad adoption across sectors without requiring firms to make proprietary capital investments. According to recent data, open-source foundation models comprised 65.7% of all AI foundation models released in 2023, a notable increase from 44.4% in 2022 and 33.3% in 2021, underscoring the accessibility of AI as a non-capital-intensive resource (Perrault & Clark, 2024). The performance of AI models is based on three main factors: computational power, amount of training data, and AI training methods. Recent innovations in AI training methods seem to suggest that it is increasingly possible to replicate highly effective AI models with limited capital investments, for example the Sky-T1-32B-Preview model created by a team at UC Berkley is said to match OpenAI's o1 model and required just 19 hours and less than 450 USD to train (NovaSky, 2025). As mentioned previously, there is already substantial evidence about the use of AI across an array of different sectors from pharmaceutical to finance and AI can enhance the efficiency of both human labor and physical capital. These characteristics position AI as a cross-cutting input to innovation.

Thus, we argue that while it may be extremely capital intensive to be at the forefront of AI technological breakthroughs, the use of AI algorithms and predictive models for research is not constrained by physical capital investments. Consequently, we neither model AI as a new factor of production nor as a new form of capital automation. Instead, we conceptualize it as a gross-complement of R&D labor underscoring its role in enhancing the efficiency of research processes, thereby increasing the productivity of knowledge creation.

3.2 Why complementarity between human intelligence and artificial intelligence? A Probabilistic Perspective

The assumption of complementarity between human intelligence and AI in the innovation process is not merely a modeling convenience but a reflection of a fundamental epistemological distinction. While AI excels at identifying patterns and optimizing solutions within the bounds of existing knowledge, it remains inherently constrained by its reliance on data. Specifically, generative AI systems, such as LLMs, operate as probabilistic systems that update beliefs following a Bayesian framework. In Bayesian terms, AI can adjust probabilities assigned to hypotheses that have already been given a non-zero prior probability. However, the Bayesian formula imposes a strict limitation: if an event or hypothesis is initially assigned a probability of zero, no amount of new evidence can alter this state.

Mathematically, for any event H, the posterior probability given evidence E is:

$$P(H \mid E) = \frac{P(E \mid H)P(H)}{P(E)}. \tag{1}$$

If $P(H) = 0$, then $P(H \mid E) = 0$ regardless of $P(E \mid H)$ or $P(E)$. This constraint implies that AI, being trained on existing data, cannot assign a positive probability to hypotheses or ideas that are entirely outside the realm of its training set. AI cannot imagine or conceive what it has never observed, nor can it assign relevance to events or constructs that have no precedent in its data.

In contrast, human intelligence is not bound by this probabilistic limitation. Humans possess the unique ability to assign positive probabilities to ideas or hypotheses that have no prior evidence, thus expanding the space of knowledge itself. This process is not merely extrapolative but often involves intuitive leaps, creativity, and abstraction—traits that are quintessentially human. For example, scientific breakthroughs such as the formulation of Einstein's theory of relativity or the inception of quantum mechanics were not derived from existing patterns but from radical reimaginations of physical laws. Similarly, the hypothesis of new chemical elements or novel

paradigms in mathematics often emerges without prior observational data. Human intelligence, therefore, is capable of *transforming null probabilities into positive ones*, thereby creating entirely new domains of exploration.

This distinction underscores the essential complementarity between human and artificial intelligence. A. K. Agrawal et al. (2023) introduce the concept of the *Turing Transformation*, which highlights that AI-driven automation of tasks requiring specialized high-value skills can create opportunities for workers with broader, generic skillsets. In this sense, while AI replaces certain high-skill tasks, it augments the participation of others by enabling access to previously exclusive opportunities. This complements the argument that AI enhances the efficiency and scope of exploration within a predefined knowledge space, optimizing the search for solutions and refining existing ideas. However, it is the human capacity to redefine the boundaries of this space that allows for true innovation.

In formal terms, if A represents the set of known ideas, AI can only explore and recombine elements within A. Human creativity, on the other hand, can generate a superset $A' > A$, introducing new dimensions and hypotheses that were previously inconceivable. This ability to transcend existing knowledge domains makes human input irreplaceable in the innovation process. This creates a broader complementarity between AI and human labor, further strengthening its role as an enabler of innovation.

Consequently, any growth model that incorporates AI must recognize this dual role: AI as an optimizer within established domains and human intelligence as the driver of domain expansion. Without the human capacity for radical ideation, AI would be limited to iterative improvements, incapable of generating the kind of disruptive innovations that characterize long-term economic growth. This probabilistic argument not only justifies the assumption of complementarity but also highlights its necessity: AI cannot innovate autonomously without the continual creative input provided by human intelligence.

3.3 Introducing AI in semi-endogenous growth models

We extend the semi-endogenous growth framework to incorporate AI as a complementary input in the idea production function. Following Jones (2022), we omit capital accumulation, as it is not essential to sustaining long-run growth. The production function for goods and services is:

$$Y_t = A_t L_{Yt}, \tag{2}$$

where L_{Yt} represents labor in production, and A_t is the stock of ideas. Let

us remind the reader that in semi-endogenous growth models, the idea production function (R&D) is traditionally:

$$\dot{A}_t = \delta A_t^{\phi} L_{At}, \quad \phi < 1, \tag{3}$$

where δ measures the efficiency of R&D, and $\phi < 1$ captures intertemporal knowledge spillovers reflecting diminishing returns to idea generation. Labor supply is divided between production and R&D:

$$L_{Yt} + L_{At} = L_t, \tag{4}$$

with $L_{At} = s_A L_t$ denoting the share of labor allocated to R&D, and population grows at a constant rate g_L:

$$L_t = L_0 e^{g_L t}. \tag{5}$$

From this framework, the long-run growth rate of ideas is derived as:

$$g_A = \frac{g_L}{1-\phi}. \tag{6}$$

Recent estimates suggest that AI-driven productivity gains are substantial but not unlimited, reinforcing the assumption that AI enhances rather than revolutionizes idea generation (Filippucci et al., 2024). While AI contributes to research efficiency, its long-term impact on growth is constrained by diminishing returns in innovation. Consistently, we introduce AI as a complementary input of a semi-endogenous growth setting, by redefining the idea production function as:

$$\dot{A}_t = \delta A_t^{\phi} S_{At}, \tag{7}$$

where S_{At} represents "semi-human intelligence," combining human labor (L_{At}) and AI input (I_t). To highlight complementarity, we first explore a Cobb-Douglas formulation for S_{At}:

$$S_{At} = (L_{At})^{\alpha} (I_t)^{1-\alpha}, \quad 0 \leq \alpha \leq 1, \tag{8}$$

where α determines the relative contribution of human labor to idea production. Assuming AI grows at a constant rate g_I, the long-run growth rate of ideas becomes:

$$g_A = \frac{\alpha g_L + (1-\alpha) g_I}{1-\phi}. \tag{9}$$

This equation highlights that long-term growth depends on the weighted contributions of population growth (g_L) and AI growth (g_I), adjusted for diminishing

returns to R&D. For AI to increase the growth rate, g_I must exceed g_L, which raises questions about the feasibility of sustained exponential growth in AI.

A realistic scenario assumes that AI input grows proportionally to GDP:

$$I_t = s_{IA} Y_t. \tag{10}$$

Substituting this into the model, the idea production function becomes:

$$\dot{A}_t = \delta A_t^{\phi} \left(s_A L_t\right)^{\alpha} \left(s_{IA} A_t L_t\right)^{1-\alpha}. \tag{11}$$

In this setup, the long-run growth rate simplifies to:

$$g_A \sim \frac{g_L}{\alpha - \phi} \quad \text{if } \alpha > \phi. \tag{12}$$

This result shows that AI can raise the growth rate of ideas if its contribution (α) outweighs the diminishing returns to knowledge (ϕ). However, if $\alpha < \phi$, growth could become explosive as AI amplifies the idea production process. Empirical estimates ($\phi \approx -2$) suggest that such scenarios are unlikely, supporting the robustness of semi-endogenous growth dynamics.

An alternative assumption is that AI input grows proportionally to the stock of accumulated ideas:

$$I_t = s_{IA} A_t. \tag{13}$$

This captures the fact that AI systems rely on existing knowledge, as they are trained on vast amounts of books, academic papers, and structured data reflecting past innovations. Under this assumption, the development of AI itself becomes a function of the accumulated stock of ideas, reinforcing its role as a non-rival input that enhances research productivity.

Substituting this into the model, the idea production function becomes:

$$\dot{A}_t = \delta A_t^{\phi} \left(s_A L_t\right)^{\alpha} \left(s_{IA} A_t\right)^{1-\alpha}. \tag{14}$$

In this setup, the long-run growth rate simplifies to:

$$g_A \sim \frac{\alpha g_L}{\alpha - \phi} \quad \text{if } \alpha > \phi. \tag{15}$$

Empirical estimates of ϕ suggest that it is typically negative ($\phi \approx -2$), making the condition $\alpha > \phi$ generally plausible. This implies that AI enhances idea production but does not lead to unbounded growth, preserving the structure of semi-endogenous models. This further reinforces the role of AI as a scalable, non-rival

knowledge input that supports research productivity without fundamentally altering the semi-endogenous nature of long-run economic growth. Each of our two assumptions reflects a different mechanism driving AI progress: assuming $I_t \propto Y_t$ ties AI development to economic output and investment, while $I_t \propto A_t$ emphasizes the role of accumulated knowledge as the primary driver of AI's growth. Both lead to similar long-run implications but capture different sources of AI expansion.

3.4 Semi-Human Intelligence with CES Complementarity

Generalizing from the Cobb-Douglas function we now model semi-human intelligence as a constant elasticity of substitution (CES) aggregate given by:

$$S_{At} = \left[\alpha \left(L_{At}\right)^{\sigma} + (1-\alpha)\left(I_{At}\right)^{\sigma}\right]^{\frac{1}{\sigma}}, \sigma < 0 \leq \alpha \leq 1 \tag{16}$$

The elasticity of substitution of the two R&D inputs labor and AI is $\frac{1}{1-\sigma}$, where labor and R&D are perfect complements if $\sigma = -\infty$. Note that $\sigma = 0$ yields the Cobb-Douglas case outlined in the section above and, as before, if $\alpha = 1$, the idea production function would become the traditional equation without AI.

As previously, we start by assuming a constant exogenous growth rate, g_I, of AI (I_{At}) as outlined in Eq. (8). This specification implies:

$$\dot{A}_t = \delta A_t^{\phi}\left[\alpha \left(s_A L_t\right)^{\sigma} + (1-\alpha)\left(I_{At}\right)^{\sigma}\right]^{\frac{1}{\sigma}} \tag{17}$$

Then solving for the long-run growth rate, we have:

$$\begin{aligned} g_{At} &= \delta A_t^{\phi-1}\left[\alpha \left(s_A L_t\right)^{\sigma} + (1-\alpha)\left(I_{At}\right)^{\sigma}\right]^{\frac{1}{\sigma}} \\ &= \delta A_t^{\phi-1} L_t \left[\alpha \left(s_A\right)^{\sigma} + (1-\alpha)\left(\frac{I_{At}}{L_t}\right)^{\sigma}\right]^{\frac{1}{\sigma}} \end{aligned} \tag{18}$$

which gives us:

$$g_A \sim \frac{\min\{g_L, g_I\}}{1-\phi} \tag{19}$$

Thus, we have that growth in the long-run depends on the slower-expanding input between labor and AI. This is due to the complementary assumption imposed by the CES aggregator. Once again we would need a realistic assumption for g_I to be able to assert which input is the constraining input in the long-term. As a reliable estimate for g_I is not readily available, we once again model AI (I_{At}) as a constant fraction of final output. We have already shown that this assumption is robust to alternative specifications. Then We then have:

$$S_{At} = \left[\alpha \left(s_A L_t\right)^{\sigma} + (1-\alpha)\left(s_{IA} Y_t\right)^{\sigma}\right]^{\frac{1}{\sigma}} \tag{20}$$

$$\dot{A}_t = \delta A_t^{\phi} \left[\alpha \left(s_A L_t\right)^{\sigma} + (1-\alpha)\left(s_{IA} A_t \left(1-s_A\right) L_t\right)^{\sigma}\right]^{\frac{1}{\sigma}} \tag{21}$$

$$\begin{aligned} g_{At} &= \delta A_t^{\phi-1} \left[\alpha \left(s_A L_t\right)^{\sigma} + (1-\alpha)\left(s_{IA} A_t \left(1-s_A\right) L_t\right)^{\sigma}\right]^{\frac{1}{\sigma}} \\ &= \frac{\delta \left[\alpha \left(s_A L_t\right)^{\sigma} + (1-\alpha)\left(s_{IA} A_t \left(1-s_A\right) L_t\right)^{\sigma}\right]^{\frac{1}{\sigma}}}{A_t^{1-\phi}} \end{aligned} \tag{22}$$

Along BGP, $g_{At} \equiv \frac{\dot{A}_t}{A_t}$ is constant, say equal to g_A. Hence $A_t^{\phi-1}$ shrinks at rate $g_A\left(1-\phi\right)$ while at the numerator we have

$$\begin{aligned} &= \delta \left[\alpha \left(s_A L_t\right)^{\sigma} + (1-\alpha)\left(s_{IA} A_t \left(1-s_A\right) L_t\right)^{\sigma}\right]^{\frac{1}{\sigma}} \\ &= \delta \left[\alpha \left(s_A\right)^{\sigma} + (1-\alpha)\left(s_{IA} A_t \left(1-s_A\right)\right)^{\sigma}\right]^{\frac{1}{\sigma}} L_t \\ &\underset{t\to\infty}{=} \delta \alpha^{\frac{1}{\sigma}} s_A L_t \end{aligned} \tag{23}$$

given that the term $(1-\alpha)\left(s_{IA} A_t \left(1-s_A\right)\right)^{\sigma}$ tends to zero as A_t tends to infinity, due to $\sigma < 0$. Therefore to ensure a BGP, semi-human intelligence $\left[\alpha \left(s_A L_t\right)^{\sigma} + (1-\alpha)\left(s_{IA} A_t \left(1-s_A\right) L_t\right)^{\sigma}\right]^{\frac{1}{\sigma}}$ asymptotically grows at the same rate as L_t, that is at rate g_L. Therefore,

$$g_A\left(1-\phi\right) = g_L \tag{24}$$

implying

$$g_A = \frac{g_L}{1-\phi} \tag{25}$$

as in Jones (1995). Despite converging towards the traditional semi-endogenous steady-state growth rate, artificial intelligence still delivers a huge level effect. So, along the BGP, the level of per capita GDP will be permanently higher than in the absence of artificial intelligence. This can be seen by comparing the levels of A_t associated with $\alpha = 1$ (no artificial intelligence in R&D) and those with $\alpha < 1$.

Indeed, for $\alpha = 1$, the growth rate simplifies to:

$$\frac{\dot{A}_t}{A_t} = \delta A_t^{\phi-1} \left(s_A L_t\right) \tag{26}$$

While for $\alpha < 1$ we have:

$$\frac{\dot{A}_t}{A_t} = \delta A_t^{\phi-1} \left[\alpha \left(s_A L_t\right)^{\sigma} + (1-\alpha) \left(s_{IA} A_t \left(1-s_A\right) L_t\right)^{\sigma}\right]^{\frac{1}{\sigma}} \tag{27}$$

Noting that all elements except for those inside the brackets are the same in both equations, we just need to show that

$$\begin{aligned}
\left(s_A L_t\right) &< \left[\alpha \left(s_A L_t\right)^{\sigma} + (1-\alpha) \left(s_{IA} A_t \left(1-s_A\right) L_t\right)^{\sigma}\right]^{\frac{1}{\sigma}} \\
\left(s_A L_t\right)^{\sigma} &> \left[\alpha \left(s_A L_t\right)^{\sigma} + (1-\alpha) \left(s_{IA} A_t \left(1-s_A\right) L_t\right)^{\sigma}\right] \\
\left(s_A L_t\right)^{\sigma} &> \left(s_A L_t\right)^{\sigma} \left[\alpha + (1-\alpha) \left(\frac{s_{IA} A_t \left(1-s_A\right)}{s_A}\right)^{\sigma}\right] \\
1 &> \alpha + (1-\alpha) \left(\frac{s_{IA} A_t \left(1-s_A\right)}{s_A}\right)^{\sigma} \\
1-\alpha &> (1-\alpha) \left(\frac{s_{IA} A_t \left(1-s_A\right)}{s_A}\right)^{\sigma} \\
1 &> \left(\frac{s_{IA} A_t \left(1-s_A\right)}{s_A}\right)^{\sigma} \\
1 &< \left(\frac{s_{IA} A_t \left(1-s_A\right)}{s_A}\right)
\end{aligned}$$

which holds for $\sigma < 0$.

$$\begin{aligned}
s_A &< s_{IA} A_t \left(1-s_A\right) \\
\frac{s_A}{\left(1-s_A\right)} &< s_{IA} A_t
\end{aligned}$$

Thus, the last inequality will hold as long as the share of the labor force dedicated to the production of goods and services (1-s_A) is sufficiently large and the technological level A_t is not too low. As the economy continually accumulates knowledge, the right-hand side of the inequality increases, inevitably matching this condition. Therefore, provided that the labor in goods and services does not tend to zero, the system naturally evolves towards a state where this inequality is consistently satisfied.

Therefore, along the BGP, when accounting for both labor and AI contributions, the combined effective input into $R\&D$ exceeds that of labor's contribution in isolation. This outcome is attributed to the convexity of the CES production function,

which ensures that the combined inputs of labor and AI are more productive than their separate contributions.

Notice that our assumption of gross-complementarity ($\sigma < 0$) is key in delivering semi-endogenous growth despite the presence of ever expanding artificial intelligence capacity. Indeed, $I_t = A_t (1 - s_A) L_t$ asymptotically grows at rate $g_L + g_A$ which is bigger than L_{At}'s growth rate, g_L. Hence, $I_t = A_t (1 - s_A) L_t$ will become infinitely larger than L_{At}. However, despite this huge level differences, the CES aggregator dampens it down and forces S_{At} to grow at the same rate as L_{At}.

3.5 Exploring AI-Labor Substitutability

While our Bayesian perspective suggests that AI and human intelligence are inherently complementary in innovation, the possibility of AI replacing human labor cannot be dismissed. As AI continues to advance, future iterations may increasingly automate tasks traditionally performed by researchers.

Recent empirical findings suggest that AI could act as a substitute for human labor, even in high-skilled domains like R&D. For instance, an online experiment with college-educated professionals found that ChatGPT significantly boosted productivity and, in some cases, could act as a substitute for human workers (Noy & Zhang, 2023).

Given this, we now examine how our model behaves under the assumption that AI and human intelligence are gross substitutes. Specifically, we modify equation 8 to adopt the following CES formulation:

$$S_{At} = \left[\alpha (L_{At})^{\sigma} + (1 - \alpha) (I_{At})^{\sigma}\right]^{\frac{1}{\sigma}}, 0 < \sigma \leq 1, 0 \leq \alpha \leq 1 \tag{28}$$

To explore if gross complementarity could lead to explosive growth, let us rewrite the previous derivations as

$$\begin{aligned} g_{A_t} &= \delta A_t^{\phi - 1} \left[\alpha (s_A L_t)^{\sigma} + (1 - \alpha) (s_{IA} A_t (1 - s_A) L_t)^{\sigma}\right]^{\frac{1}{\sigma}} \\ &= \frac{\delta \left[\alpha (s_A L_t)^{\sigma} + (1 - \alpha) (s_{IA} A_t (1 - s_A) L_t)^{\sigma}\right]^{\frac{1}{\sigma}}}{A_t^{1 - \phi}} \end{aligned} \tag{29}$$

Once again along the BGP, g_{A_t} is constant, say equal to g_A. Hence $A_t^{\phi - 1}$ shrinks

at rate $g_A(1-\phi)$ while at the numerator we have that

$$\begin{aligned}
&= \delta\left[\alpha\left(s_A L_t\right)^{\sigma} + (1-\alpha)\left(s_{IA} A_t\left(1-s_A\right) L_t\right)^{\sigma}\right]^{\frac{1}{\sigma}} \\
&= \delta\left[\alpha\left(s_A/A_t\right)^{\sigma} + (1-\alpha)\left(s_{IA}\left(1-s_A\right)\right)^{\sigma}\right]^{\frac{1}{\sigma}} A_t L_t \\
&\underset{t\to\infty}{=} \delta(1-\alpha)^{\frac{1}{\sigma}} s_{IA}\left(1-s_A\right) A_t L_t
\end{aligned} \tag{30}$$

Hence, along the BGP we have

$$\begin{aligned}
g_{A_t} &= \frac{\delta(1-\alpha)^{\frac{1}{\sigma}} s_{IA}\left(1-s_A\right) A_t L_t}{A_t^{1-\phi}} \\
&= \delta(1-\alpha)^{\frac{1}{\sigma}} s_{IA}\left(1-s_A\right) A_t^{\phi} L_t
\end{aligned} \tag{31}$$

So, the right hand side is constant if and only if $A_t L_t$ grows at the same rate as $A_t^{1-\phi}$, which means:

$$(1-\phi)\, g_A = g_A + g_L \tag{32}$$

that yields

$$g_A = \frac{g_L}{-\phi}. \tag{33}$$

This exists if $\phi < 0$. For a positive value of ϕ, growth will be explosive, because $A_t L_t$ will always grow at a rate higher than $A_t^{1-\phi}$.

Taking stock, we can say that with gross substitutability ($\sigma > 0$), there is a growth bifurcation at $\phi = 0$. For lower values ($\phi < 0$) growth will tend to be semi-endogenous, while for higher values ($\phi > 0$) the growth rate will increase without bounds.

Again considering the current literature estimates of $\phi \approx -2$ for the aggregate economy (Bloom et al., 2020) we have that even with the introduction of semi-human intelligence long-term growth does not become explosive.

Gross-substitutability introduces a bifurcation in growth dynamics, with critical thresholds defined by $\phi < 0$. Despite semi-endogenous growth, ongoing advancements in AI could theoretically push the system toward explosive trajectories, with profound economic and social implications. Future work should explore the empirical feasibility of these scenarios and their policy implications.

3.6 Other specifications for semi-human intelligence

This section explores alternative specifications for the role of AI in semi-human intelligence (S_{At}) and their implications for long-term growth dynamics. We examine cases where AI input is proportional to productivity-adjusted GDP, income elasticity, or interacts with human labor in a complementary way.

3.6.1 AI proportional to productivity-adjusted GDP

If AI (I_{At}) is proportional to productivity-adjusted GDP, the long-term growth rate converges back to the classical semi-endogenous growth rate. Specifically, assuming:

$$I_{At} = s_{IA}\frac{Y_t}{A_t},$$

the idea production function becomes:

$$S_{At} = \left[\alpha\left(s_A L_t\right)^{\sigma} + (1-\alpha)\left(s_{IA}\frac{Y_t}{A_t}\right)^{\sigma}\right]^{\frac{1}{\sigma}}.$$

Substituting and simplifying yields:

$$g_A = \frac{g_L}{1-\phi}.$$

This result aligns with the semi-endogenous framework, indicating that AI proportional to productivity-adjusted GDP does not alter long-term growth dynamics but enhances the level of per capita GDP.

3.6.2 AI Following an Isoelastic Function of GDP

Alternatively, if AI follows an isoelastic function of GDP, we assume:

$$I_{At} = s_{IA}Y_t^{\eta}, \tag{34}$$

where η represents the elasticity of AI with respect to GDP. This formulation allows AI to grow at a rate that is not necessarily proportional to output but instead follows a power law relationship, capturing the possibility that AI expansion accelerates or decelerates relative to GDP growth. Then, the long-run growth rate of ideas is given by:

$$g_A = \frac{\left(\alpha + \eta(1-\alpha)\right) g_L}{1-\phi+\eta(\alpha-1)}.$$

This formulation highlights how the growth rate depends on the interaction between the income elasticity of AI (η) and the relative contribution of labor in idea production (α). A higher η implies that AI expands more rapidly with GDP, increasing its contribution to knowledge creation. This, in turn, can partially offset the diminishing returns in R&D (ϕ), potentially sustaining a higher long-run growth rate.

3.6.3 Modeling Semi-Human Intelligence Without AI Dependence

In this case, we model semi-human intelligence (S_{At}) as a CES aggregator that includes both human labor and an interaction term between labor and AI:

$$S_{At} = \left[\alpha \left(L_{At}\right)^{\sigma} + (1-\alpha)\left(L_{At} I_{At}\right)^{\sigma}\right]^{\frac{1}{\sigma}}.$$

This specification ensures that labor remains a necessary input to idea production, even if AI were absent ($I_{At} = 0$).

Complementarity ($\sigma < 0$):

$$g_A = \frac{g_L}{1-\phi}.$$

In this case, growth remains semi-endogenous, with AI enhancing the level of GDP but not altering the fundamental growth dynamics.

Substitutability ($0 < \sigma < 1$):

$$g_A = \frac{2g_L}{-\phi}.$$

Here, growth becomes more responsive to population dynamics, as AI increasingly dominates the idea production process.

4 Conclusion

In this paper, we have explored whether AI might counteract the potential stagnation or decline in global economic growth driven by demographic trends. Our analysis centered on the role of AI in enhancing the idea production function, which is regarded as the engine of economic growth within semi-endogenous growth models. We extended the current understanding of AI's economic impact by shifting the focus from task automation and capital substitution to its role as a non-rival input in research and innovation.

Our findings highlight that AI can significantly enhance research productivity, acting as an amplifier of human intelligence rather than an autonomous driver of economic growth. Unlike traditional production factors, AI does not suffer from rivalrous constraints, allowing it to scale across users and research domains at near-zero marginal cost. However, its effectiveness remains fundamentally tied to human creativity. While AI can accelerate the recombination of existing knowledge, it lacks the ability to generate truly novel hypotheses independently. This distinction underscores why AI, despite its transformative potential, cannot fully replace human-driven innovation.

Through a series of model extensions, we have shown that AI's long-run impact on growth depends on its relationship with labor. When AI complements human intelligence in idea production, it enhances research efficiency but does not fundamentally alter the semi-endogenous structure of growth. If AI were to function as a close substitute for human researchers, the potential for explosive growth would emerge—but empirical evidence suggests that diminishing returns in R&D prevent such dynamics at the aggregate level. These results reinforce the idea that AI can mitigate, but not fully overcome, the demographic constraints on innovation.

Our analysis has important implications for both policy and future research. If AI is to sustain economic growth in a world with declining populations, policies should focus on leveraging AI as an enhancer of human-led innovation rather than as a pure substitute for skilled labor. Further empirical work is needed to quantify the elasticity of substitution between AI and human labor in R&D, as well as the role of AI in offsetting research productivity declines. Moreover, as AI continues to evolve, its impact on economic growth will depend not only on technical advancements but also on institutional frameworks that regulate its integration into innovation processes. Historical evidence suggests that technological shifts, including AI, can reinforce existing economic structures rather than disrupt them (Acemoglu & Johnson, 2023). Whether AI fosters broad-based growth or exacerbates inequalities will depend on how it is integrated into research and development processes.

Ultimately, while AI represents a profound technological shift, its role in long-run economic growth must be understood within the structural constraints of knowledge production. The interplay between AI and human intelligence will determine whether AI serves as a catalyst for sustained innovation or remains a tool for efficiency gains within existing knowledge domains. Future research should aim to disentangle these dynamics, providing deeper insights into AI's evolving role in economic theory and practice.

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