

The Simple Macroeconomics of AI*

Daron Acemoglu

Massachusetts Institute of Technology

May 12, 2024

Abstract

This paper evaluates claims about large macroeconomic implications of new advances in AI. It starts from a task-based model of AI's effects, working through automation and task complementarities. So long as AI's microeconomic effects are driven by cost savings/productivity improvements at the task level, its macroeconomic consequences will be given by a version of Hulten's theorem: GDP and aggregate productivity gains can be estimated by what fraction of tasks are impacted and average task-level cost savings. Using existing estimates on exposure to AI and productivity improvements at the task level, these macroeconomic effects appear nontrivial but modest—no more than a 0.66% increase in total factor productivity (TFP) over 10 years. The paper then argues that even these estimates could be exaggerated, because early evidence is from easy-to-learn tasks, whereas some of the future effects will come from hard-to-learn tasks, where there are many context-dependent factors affecting decision-making and no objective outcome measures from which to learn successful performance. Consequently, predicted TFP gains over the next 10 years are even more modest and are predicted to be less than 0.53%. I also explore AI's wage and inequality effects. I show theoretically that even when AI improves the productivity of low-skill workers in certain tasks (without creating new tasks for them), this may increase rather than reduce inequality. Empirically, I find that AI advances are unlikely to increase inequality as much as previous automation technologies because their impact is more equally distributed across demographic groups, but there is also no evidence that AI will reduce labor income inequality. Instead, AI is predicted to widen the gap between capital and labor income. Finally, some of the new tasks created by AI may have negative social value (such as design of algorithms for online manipulation), and I discuss how to incorporate the macroeconomic effects of new tasks that may have negative social value.

JEL Classification: E24, J24, O30, O33.

Keywords: Artificial Intelligence, automation, ChatGPT, inequality, productivity, technology adoption, wage.

*Paper prepared for *Economic Policy*. I am grateful to Can Yeşildere for phenomenal research assistance, and to Leonardo Bursztyrn, Mert Demirer, Lauren Fahey, Roberto Galbiati, Isabelle Méjean, Shakked Noy, Sida Peng, Julia Regier, and Whitney Zhang as well as participants in the MIT Solow Memorial conference and the *Economic Policy* conference for useful comments. I am especially grateful to my discussants, David Hémous and Benoît Coeuré, for insightful comments and suggestions. I thank Pamela Mishkin and Daniel Rock for generously sharing their data on AI exposure. I am also heavily indebted to my collaborators on several projects related to these topics, David Autor, Simon Johnson and Pascual Restrepo, from whom I learned a great deal and who have also given me very useful comments on the current draft. Financial support from the Hewlett Foundation is gratefully acknowledged. All remaining errors are mine.

1 Introduction

Artificial intelligence (AI) has captured imaginations. Promises of rapid, even unparalleled, productivity growth as well as new pathways for complementing humans have become commonplace. There is no doubt that recent developments in generative AI and large language models that produce text, information and images—and Shakespearean sonnets—in response to simple user prompts are impressive and even spellbinding. ChatGPT, originally released on November 30, 2022, soon became the fastest spreading tech platform in history, with an estimated 100 million monthly users only two months after launch.

AI will have implications for the macroeconomy, productivity, wages and inequality, but all of them are very hard to predict. This has not stopped a series of forecasts over the last year, often centering on the productivity gains that AI will trigger. Some experts believe that truly transformative implications, including artificial general intelligence (AGI) enabling AI to perform essentially all human tasks, could be around the corner.¹ Other forecasters are more grounded, but still predict big effects on output. Goldman Sachs (2023) predicts a 7% increase in global GDP, equivalent to \$7 trillion, and a 1.5% per annum increase in US productivity growth over a 10-year period. Recent McKinsey Global Institute (2023) forecasts suggest that generative AI could offer a boost as large as \$17.1 to \$25.6 trillion to the global economy, on top of the earlier estimates of economic growth from increased work automation. They reckon that the overall impact of AI and other automation technologies could produce up to a 1.5 – 3.4 percentage point rise in average annual GDP growth in advanced economies over the coming decade.²

Are such large effects plausible? And if there are going to be productivity gains, who will

¹Korinek and Suh (2024) predict a “baseline” GDP growth of 100% over the next 10 years, and also entertain the possibility of much higher “aggressive” AGI growth rates, such as a 300% increase in GDP. Many others are seeing recent developments as a confirmation of the forecasts in Kurzweil (2005) about the impending arrival of “singularity” and “explosive” economic growth (Davidson, 2021).

²Three caveats are in order. First, although most recent advances are in generative artificial intelligence, the economic forces explored here apply to other types of AI, and estimates of exposed tasks I use come on the basis of anticipated improvements in a range of AI-related technologies, including computer vision and software building on large language models. Hence, I consider the numbers here to apply to all of artificial intelligence and thus typically refer to “AI”, unless there is a reason to emphasize generative AI.

Second, I focus on the US economy because much of the existing evidence on microeconomic effects of AI and prevalence of exposed tasks is from the United States. The impact on other industrialized nations should be similar, whereas the consequences for the developing world are harder to ascertain and require much more in-depth research.

Third, some commentators use “productivity” to refer to output per worker (or average labor productivity), while others mean total factor productivity (TFP). Throughout, I distinguish between aggregate TFP and GDP (per capita/worker) effects, and I use productivity improvement at the micro/task level as synonymous to cost savings.

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be their beneficiary? With previous automation technologies, such as robotics, most gains accrued to firm owners and managers, while workers in impacted occupations experienced negative outcomes (e.g., Acemoglu and Restrepo, 2020a). Could it be different this time? Some experts and commentators are more optimistic. A few “proof-of-concept” experimental studies document nontrivial productivity gains from generative AI, largely driven by improvements for less productive or lower-performing workers (e.g., Peng et al., 2023; Noy and Zhang, 2023; Brynjolfsson et al., 2023), and this has prompted some experts to be cautiously optimistic (Autor, 2024), while others are forecasting a “blue-collar bonanza” (The Economist, 2023).

This paper uses the framework from Acemoglu and Restrepo (2018, 2019b, 2022) to provide some insights for these debates, especially relevant for the medium-term (about 10-year) macroeconomic effects of AI. I build a task-based model, where the production of a unique final good requires a series of tasks to be performed, and these tasks can be allocated to either capital or labor, which have different comparative advantages. Automation corresponds to the expansion of the set of tasks that are produced by capital (including digital tools and algorithms). In this framework, AI-based productivity gains—measured either as growth of average output per worker or as total factor productivity (TFP) growth—can come from a number of distinct channels (see Acemoglu and Restrepo, 2019a):

- *Automation* (or more precisely extensive-margin automation) involves AI models taking over and reducing costs in certain tasks. In the case of generative AI, various mid-level clerical functions, text summary, data classification, advanced pattern recognition, and computer vision tasks are among those that can be profitably automated.
- *Task complementarity* can increase the productivity in tasks that are not fully automated and may even raise the marginal product of labor. For example, workers performing certain tasks may have better information or access to other complementary inputs. Alternately, AI may automate some subtasks, while at the same time enabling workers to specialize and raise their productivity in other aspects of their job.
- *Deepening of automation* can take place, increasing the productivity of capital in tasks that have already been automated. For example, an already-automated IT security task may be performed more successfully by generative AI.
- *New tasks* may be created thanks to AI and these tasks may impact the productivity

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3 of the whole production process.³
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5 In this paper, I focus on the first two channels, though I also discuss how new tasks en-
6 abled by AI can have positive or negative effects. I do not dwell on deepening of automation,
7 because the tasks impacted by (generative) AI are different than those automated by the
8 previous wave of digital technologies, such as robotics, advanced manufacturing equipment
9 and software systems.⁴ I also do not discuss how AI can have revolutionary effects by chang-
10 ing the process of science (a possibility illustrated by neural network-enabled advances in
11 protein folding and new crystal structures discovered by the Google subsidiary DeepMind),
12 because large-scale advances of this sort do not seem likely within the 10-year time frame
13 and many current discussions focus on automation and task complementarities.
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20 I show that when AI's microeconomic effects are driven by cost savings (equiva-
21 lently, productivity improvements) at the task level—due to either automation or task
22 complementarities—its macroeconomic consequences will be given by a version of Hulten's
23 theorem: GDP and aggregate productivity gains can be estimated by what fraction of tasks
24 are impacted and average task-level cost savings. This equation disciplines any GDP and
25 productivity effects from AI. Despite its simplicity, applying this equation is far from trivial,
26 because there is huge uncertainty about which tasks will be automated or complemented,
27 and what the cost savings will be.
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33 Nevertheless, as an illustrative exercise, I use data from a number of recent studies, in
34 particular, Eloundou et al. (2023) and Svanberg et al. (2024), as well as the experimental
35 studies mentioned above, to obtain some back-of-the-envelope numbers. Eloundou et al.
36 (2023) provide the first systematic estimates of what tasks will be impacted by generative
37 AI and computer vision technologies. Their methodology does not fully distinguish whether
38 the impact will take the form of automation or task complementarities, and does not provide
39 information on when we should expect these impacts to be realized and how large their cost
40 savings will be.⁵ For computer vision technologies, Svanberg et al. (2024) provide estimates
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47 ³New tasks in this framework also capture the possibility of productivity-enhancing reorganizing produc-
48 tion. The role of AI in enabling such reorganization is emphasized by, among others, Bresnahan (2019) and
49 Agrawal et al. (2023).

50 ⁴Eloundou et al. (2023) report negative statistical associations between their measure of exposure to AI,
51 which I use below, and measures of exposure to robots and manual routine tasks.

52 ⁵More specifically, I use the most granular information that Eloundou et al. (2023) present, which is their
53 “automation index”, coded with help from GPT-4. This index provides information on how much of the
54 activities involved in a task/occupation can be performed by AI. Although this index has somewhat greater
55 emphasis on automation, it does not systematically distinguish between automation and task complemen-
56 tarities. As I discuss further below and Eloundou et al. (2023) themselves note, their exposure measure
57 often captures the possibility that generative AI and related digital technologies can perform some of the
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future effects will come from “hard-to-learn” tasks, where there are many context-dependent factors affecting decision-making, and most learning is based on the behavior of human agents performing similar tasks (rather than objective outcome measures). Productivity gains from AI in these hard tasks will be less—though, of course, it is challenging to determine exactly how much less. Using a range of (speculative) assumptions, I estimate an upper bound of 73% easy tasks among Eloundou et al.’s exposed tasks. I suppose that productivity gains in hard tasks will be approximately one quarter of the easy ones. This leads to an updated, more modest increase in TFP and GDP in the next 10 years that can be upper bounded by 0.53% and 0.90%, respectively.

New tasks created with AI can more significantly boost productivity. However, some of the new AI-generated tasks are manipulative and may have negative social value, such as deepfakes, misleading digital advertisements, addictive social media or AI-powered malicious computer attacks. While it is difficult to put numbers on good and bad new tasks, based on recent research I suggest that the negative effects from new bad tasks could be sizable. I make a very speculative attempt using numbers on the negative welfare effects of social media from a recent paper by Bursztyn et al. (2023). These authors find that consumers have positive willingness to pay for using social media (in particular Instagram and TikTok) when others are using it, but they would prefer that neither themselves nor others use it. Roughly speaking, their estimates imply that revenue can increase by about \$53 per user-month, but this has a negative impact on total GDP/welfare equivalent to \$19 per user-month. Combining these numbers with an estimate of the fraction of activities that may generate negative social value (in practice, revenues from social media and spending on attack-defense arms races in IT security), I suggest that with more intensive use of AI, it is possible to have nontrivial increases in GDP. For example, AI may appear to increase GDP by 2%, while in reality reducing welfare by -0.72% (in consumption equivalent units).

Finally, I explore AI’s wage and inequality effects. My framework implies that productivity gains from AI are unlikely to lead to sizable wage rises. Moreover, even if AI improves the productivity of low- and middle-performing workers (or workers with limited expertise in complex tasks), I argue that, theoretically, this may not translate into lower inequality. In fact, I show by means of a simple example how an increase in the productivity of low-skill workers in certain tasks can lead to *higher* rather than lower inequality. Adapting the general equilibrium estimates from Acemoglu and Restrepo (2022) to the setting of AI, I find that the more intensive use of AI is unlikely to lead to substantial wage declines for

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2 affected groups, because AI-exposed tasks are more evenly distributed across demographic
3 groups than were the tasks exposed to earlier waves of automation. Nevertheless, I estimate
4 that AI will not reduce inequality and is likely to have a negative effect on the real earnings
5 of low-education women (especially white, native-born low-education women). My findings
6 also suggest that AI will further expand the gap between capital and labor income as a
7 whole.
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12 In the conclusion, I argue that as originally suggested in Acemoglu and Restrepo (2018),
13 more favorable wage and inequality effects, as well as more sizable productivity benefits,
14 will likely depend on the creation of new tasks for workers in general and for middle- and
15 low-pay workers in particular. While this is feasible in theory and I have argued elsewhere
16 how it could be achieved (Acemoglu, 2021 and Acemoglu et al., 2023), I also discuss why
17 this does not seem to be the focus of artificial intelligence research at the moment.
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22 In sum, it should be clear that forecasting AI's effects on the macroeconomy is extremely
23 difficult and will have to be based on a number of speculative assumptions. Nevertheless,
24 the gist of this paper is that a simple framework can discipline our thinking and forecasts,
25 and if we take this framework and existing estimates seriously, it is difficult to arrive at very
26 large macroeconomic gains.
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30 The rest of the paper is organized as follows. The next section outlines the concep-
31 tual framework I use throughout the paper and derives a number of theoretical insights
32 on aggregate productivity gains, investment responses, and wage and inequality effects. It
33 also discusses the crucial distinction between easy-to-learn and hard-to-learn tasks and their
34 productivity implications, and introduces the contrast between good and bad new tasks.
35 Section 3 provides a preliminary quantitative analysis of new AI breakthroughs within this
36 framework. It first presents a baseline (upper bound) estimate on the basis of the fraction
37 of existing tasks that are likely to be impacted by AI within the next 10 years and existing
38 estimates of cost savings (productivity improvements) from AI. It then refines this estimate
39 by introducing the distinction between easy-to-learn and hard-to-learn tasks and undertakes
40 a preliminary classification of AI-exposed tasks into the easy and hard categories. I also
41 make an even more speculative attempt at incorporating the macroeconomic implications of
42 bad new tasks into this framework. Finally, I report estimates on the wage and inequality
43 implications of recent AI advances. Section 4 concludes with a general discussion, while
44 the Appendix includes additional information on how tasks are classified into exposed and
45 non-exposed and easy-to-learn and hard-to-learn categories.
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2 Conceptual Framework

The model here builds on Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018, 2019b, 2022), and I focus on the main elements of the framework, referring the reader to these papers for further details and refinements. The economy is static and involves the production of a unique final good, and all markets are competitive.⁷

The production of a unique final good takes place by combining a set of tasks, with measure N , using the following production function

$$Y = B(N) \left(\int_0^N y(z)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}}, \quad (1)$$

where $Y(z)$ denotes the output of task z for $z \in [0, N]$, $\sigma \geq 0$ is the elasticity of substitution between tasks and the parameter $B(N)$ depends on N to capture the possible system-wide effects of new tasks, though in what follows I will suppress this dependence to simplify the notation. For now, the elasticity σ can take any value, but it is reasonable to presume $\sigma \leq 1$, so that tasks are gross complements. I later set the elasticity of substitution between tasks to $\sigma \simeq 0.5$, as estimated by Humlum (2021) and also imposed in Acemoglu and Restrepo (2022).

Tasks can be produced using capital or labor according to the production function

$$y(z) = A_L \gamma_L(z) l(z) + A_K \gamma_K(z) k(z) \text{ for any } z \in [0, N],$$

where A_L and A_K are labor-augmenting and capital-augmenting productivity terms, $\gamma_L(z)$ and $\gamma_K(z)$ are labor's and capital's task-specific productivity schedules, and $l(z)$ and $k(z)$ denote labor and capital allocated to performing task z . This task production function implies that capital and labor have different productivities in different tasks, but within a task they are perfect substitutes.⁸

⁷Acemoglu and Restrepo (2018) provide a dynamic version of this economy with capital accumulation and endogenous technological choices, while Acemoglu and Restrepo (2022) provide a generalization with multiple types of labor and multiple sectors, and Acemoglu and Restrepo (2023) consider a non-competitive version of this economy. Extending the framework in any of these directions does not materially affect the results I discuss here.

⁸One important simplification is to assume that tasks assigned to labor do not require any capital or tools, which is clearly unrealistic. The online Appendix of Acemoglu and Restrepo (2018) shows that the results are very similar if the task production function is modified such that:

$$y(z) = A_L \gamma_L(z) [l(z)^{1-\kappa} k_C(z)^\kappa] + A_K \gamma_K(z) k(z),$$

where $\kappa \in (0, 1)$ and $k_C(z)$ is labor-complementary capital in task z (while $k(z)$ denotes capital used for automating task z). Because $\kappa < 1$, tasks assigned to labor are still less intensive in capital than are fully-automated tasks.

Throughout, I assume that $\gamma_L(z)/\gamma_K(z)$ is increasing in z , so that labor has a *comparative advantage* in higher-indexed tasks. This implies that there exists a threshold I such that tasks $z \leq I$ are produced with capital and those above this threshold are produced with labor.

I normalize the total population to 1 and assume that different workers have different units of effective labor. To simplify the discussion, I assume that there are two types of labor, high-skill and low-skill, and there is no comparative advantage difference between these two types of labor (I generalize this later). The only difference is that high-skill workers, which make up a fraction ϕ^H of the population, have λ^H units of effective labor, while the remaining $\phi^U = 1 - \phi^H$ low-skill workers have only $\lambda^U < \lambda^H$ units of effective labor. This specification ensures that both high-skill and low-skill workers could be performing some of the same tasks. It also implies that wage inequality is pinned down by λ^H/λ^U —a feature I relax later.

I also assume that all labor is supplied inelastically, so I write the total supply of labor as

$$\phi^U \lambda^U + \phi^H \lambda^H = L.$$

The labor market-clearing condition is

$$L = \int_0^N l(z) dz, \quad (2)$$

and I denote the wage rate by w .

Capital is specialized for the tasks in which it is used, and I assume that capital of type z is produced linearly from the final good with unit cost

$$R(z) = R(K)\rho(z), \quad (3)$$

where

$$K = \int_0^N k(z) dz$$

is the total capital stock of the economy. All firms take the cost of capital for task z , $R(z)$, as given. The first term in (3) implies that the required rate of return on capital can increase when the capital stock of the economy is larger and the second term is task-specific, representing the possibility that different types of capital could have different costs. For tasks that are not yet technologically automated—meaning that they cannot be produced by capital—we can either set $\gamma_K(z) = 0$ or take $\rho(z)$ to be very large.

Finally, I assume that there exists a (non-satiated) representative household that consumes the final good (net of capital expenditures) and I denote the consumption of this household by C .

specialize in other subtasks, where their performance improves. This channel would require the explicit modeling of the range of subtasks making up each task. In this case, new AI technologies would perform some of these subtasks and do so with sufficiently high productivity, so that the subtask-level displacement would be weaker than the productivity gains, expanding the demand for labor and the marginal productivity of labor in these tasks. The possibility that the productivity effect could be larger than the displacement effect and expand labor demand is the same as in the basic models of automation, as exposited in Acemoglu and Restrepo (2018, 2019b). Even more interestingly, AI may enable workers to specialize in the non-automated subtasks and raise their expertise in these activities (e.g., when humans spend less time in writing standard subroutines, they can become better at other parts of programming). I represent task complementarities by an increase in $\gamma_L(z)$ in some tasks $z \leq I$, or when they happen in all tasks, by an increase in A_L .

3. AI could induce *deepening of automation*—meaning improving performance, $\gamma_K(z)$, or reducing costs, $\rho(z)$, in some previously capital-intensive tasks (tasks $z \leq I$). Examples include IT security, automated control of inventories, and better automated quality control (see Acemoglu and Restrepo, 2019a).
4. AI can generate *new labor-intensive products or tasks*, which corresponds to an increase in N . As argued in Acemoglu and Restrepo (2020b), Acemoglu (2021) and Acemoglu et al. (2023), there are many pathways for such new tasks. Later I also discuss the case where some of these new products and tasks can be manipulative and have negative social value.

The effects of new AI tools will depend on the extent of each one of these effects, and I will try to provide more specificity on these possibilities later. In the rest of this section, I derive the consequences of different effects of AI.

2.3 Equilibrium Wages and Comparative Statics

As a first step, let us combine (4) and (6), so that the equilibrium wage can be expressed as

$$w = \left(\frac{Y}{L}\right)^{\frac{1}{\sigma}} (BA_L)^{\frac{\sigma-1}{\sigma}} \left(\int_I^N \gamma_L(z)^{\sigma-1} dz\right)^{\frac{1}{\sigma}}. \quad (10)$$

This equation is intuitive. The first term shows that the wage is proportional to labor productivity (raised to the power $1/\sigma$), and the second term captures the contribution to

the marginal productivity of labor coming from Hicks-neutral and labor-augmenting technologies, while the third term represents the contribution of the allocation of tasks to the marginal productivity of labor. The effect of any small technological change (potentially altering multiple dimensions of the production technology, such as B ; A_L and A_K ; $\gamma_L(z)$ and $\gamma_K(z)$; and I and N) can then be written as:

$$d \ln w = \frac{1}{\sigma} d \ln \left(\frac{Y}{L} \right) + \frac{\sigma - 1}{\sigma} (d \ln B + d \ln A_L) + \frac{1}{\sigma} d \ln \left(\int_I^N \gamma_L(z)^{\sigma-1} dz \right). \quad (11)$$

The effect of further extensive-margin automation—an increase in I —is given by

$$\frac{d \ln w}{dI} = \frac{1}{\sigma} \frac{d \ln Y}{dI} - \frac{1}{\sigma} \frac{\gamma_L(I)^{\sigma-1}}{\left(\int_I^N \gamma_L(z)^{\sigma-1} dz \right)}.$$

In general, this expression has ambiguous sign, so automation can increase or reduce wages. More specifically, there are two opposing effects (Acemoglu and Restrepo, 2018, 2019b): (a) automation always produces a positive effect on wages (and labor demand) because it increases productivity (or equivalently, reduces costs). This positive productivity effect is represented by the first term; (b) simultaneously, automation displaces workers from the tasks they used to perform. The negative displacement effect is represented by the second term. In the special case where $R(K)$ is constant, it can be verified that automation increases wages. This is not the case, in general, when $R(K)$ is increasing, as shown in Acemoglu and Restrepo (2018), because the displacement effect can be larger than the productivity gains.¹⁰

Overall, the impact of (extensive-margin) automation on the equilibrium wage is closely tied to its productivity effect, to which I next turn.

Before doing so, I also note that the effects of task complementarities may be a little more complex than typically assumed. Even though an increase in $\gamma_L(z)$ raises the marginal physical product of labor, the equilibrium wage is determined by the *value* of the marginal product of labor, which depends on the adjustment of task prices. As tasks produced by labor become more abundant/easier to perform, these task prices are reduced, and in the empirically relevant case where $\sigma < 1$, task prices decline more than the increase in physical productivity. The equilibrium wage may still increase because of productivity gains, but

¹⁰In particular, for any differentiable constant returns to scale production function $F(K, L)$, Euler's theorem implies: $F(K, L) = wL + RK$. Suppose R is fixed. Then any change in technology that increases $F(K, L)$ at the initial factor supplies must increase $w = \frac{F(K, L) - RK}{L}$. This is not the case when K is fixed, because R can increase more than $F(K, L)$. In Acemoglu and Restrepo (2018, 2019b), the capital stock is taken as given, so a negative impact is possible.

In neoclassical growth models with exponential discounting and time-separable preferences, R is fixed in the long run. However, Acemoglu et al. (2024) show that with more general preferences, R tends to increase following automation and other technological changes, so a negative wage effect is possible.

the benefits to labor may be limited overall. For example, holding I and N constant, an increase in A_L will leave wages constant when $\sigma = s_K$ where s_K denotes the capital share in national income (Acemoglu and Restrepo, 2018). When $\sigma < s_K$, higher A_L can actually reduce real wages. Since $s_K \simeq 0.4$ currently in the US economy, Humlum's estimates of σ mentioned above, of about 0.5, imply that task complementarities or labor-augmenting technological improvements will not raise wages much. Even when they increase wages, these technological shifts reduce the labor share, just like automation does (Acemoglu and Restrepo, 2018, 2019b).

Finally, I note that deepening of automation (which is less likely to be relevant in the case of AI for the reasons discussed in the Introduction) and new tasks always increase wages and the latter always raises the labor share of national income as well (and thus tends to narrow the gap between capital and labor income). I return to a discussion of new tasks later.

2.4 Hulten's Theorem

The nexus of the many effects of AI on the economy is its impact on productivity. To gauge the extent of this impact, we can appeal to Hulten's theorem, which provides a simple formula for competitive economies with constant returns to scale, specifying how micro-level productivity improvements translate into macro changes. Since the economy here is competitive, this theorem applies and disciplines the productivity effects. I now explain this theorem and for ease of exposition, I first take the capital stock of the economy, K , as given. Consider an arbitrary small change in all/any aspects of technologies (B ; A_L and A_K ; $\gamma_L(z)$ and $\gamma_K(z)$; and I and N), so that the potential effects of AI based both on automation and complementarities in existing tasks are taken into account. Recall that GDP can be equivalently expressed as the price-weighted aggregate of task outputs:

$$Y = \int_0^N p(z)y(z)dz.$$

Since I am considering small changes in technology and the competitive equilibrium is efficient, the impact of all reallocations of factors across tasks and indirect effects via prices

which fraction of affected tasks are easy and hard. Specifically, denoting the fraction of easy tasks among those that are impacted by AI as μ^E , and the average cost savings for easy and hard tasks, respectively, as $\bar{\pi}^E$ and $\bar{\pi}^H$, (14) becomes

$$d \ln \text{TFP} = (\mu^E \bar{\pi}^E + (1 - \mu^E) \bar{\pi}^H) \times \text{GDP share of tasks impacted by AI.} \quad (15)$$

I also attempt to provide estimates using this updated TFP equation below, which will lead to gains that are about 25% less than those that do not take the distinction between easy and hard tasks into account.

2.6 Investment Responses

To go from TFP responses to total GDP responses, we need to see how much capital increases. This is also relevant for understanding what magnitude of an investment boom generative AI may trigger.

With this aim, consider a change in technology, for example due to AI. Its effects on capital and investment can be gleaned from (7), which implies

$$k(z) = \frac{B^{\sigma-1} A_K^{\sigma-1} \gamma_K(z)^{\sigma-1} Y}{(R(K) \rho(z))^\sigma},$$

and hence

$$d \ln k(z) = (\sigma - 1) d \ln B + (\sigma - 1) d \ln A_K + (\sigma - 1) d \ln \gamma_K(z) + d \ln Y - \sigma d \ln R(K) - \sigma d \ln \rho(z). \quad (16)$$

In what follows, I suppose that B and A_K do not change. If AI significantly improves the practice of science and invention and/or creates new high-productivity tasks, such changes may occur in the future. But I assume that they are constant within the next 10 years.

First, consider the use of AI in some task $z < I$, meaning that AI adds to and improves the performance of existing capital equipment in tasks already performed by capital.¹⁷ Then:

$$d \ln k(z) = (\sigma - 1) d \ln [A_K \cdot \gamma_K(z)] + d \ln Y - \sigma d \ln R(K).$$

Notice, however, that when $\sigma < 1$, and in particular for the empirically-plausible value of $\sigma = 0.5$, the first term is negative—an increase in the productivity of AI-augmented capital in capital-intensive tasks reduces investment and the equilibrium capital stock. The last term is also nonpositive, provided that total investment increases. Hence, a natural upper

¹⁷The expression for the case in which labor-intensive tasks also use capital, as in footnote 8, is similar and leads to the same conclusion.

bound for the proportional increase in the capital stock of tasks already performed by capital is the proportional increase in output.

Additionally, if I increases, investment will jump from zero to a positive amount in the newly-automated tasks.¹⁸ Because in the estimates I report below, only a modest fraction of tasks will be automated with AI, this increase may be small as well. Hence, I start with a first estimate that takes the proportional increase in the capital stock to be the same as the increase in aggregate productivity. I then provide another estimate incorporating the full structure of between-industry and between-task substitution, based on the framework and results of Acemoglu and Restrepo (2022). This will enable me to estimate implied changes in the capital share and then use the expressions in footnote 12 to derive updated investment response and GDP estimates.

I finally note that it is straightforward to show that consumer welfare (and consumption) in this economy is proportional to TFP divided by one minus the capital share (i.e., $d \ln C = d \ln \text{TFP} / (1 - s_K)$). In particular, if the capital-output ratio rises and the increase in GDP is more pronounced than that implied by equation (13), then the GDP response would overstate the increase in consumer welfare, as investment comes at the expense of consumption (Acemoglu and Restrepo, 2022).

2.7 New Good Tasks

Adding new tasks will expand productivity, and this effect could be in principle larger than the cost savings due to automation and task complementarities. In addition, new tasks will tend to increase wages. In particular, using the same steps as before,

$$\frac{d \ln w}{dN} = \frac{1}{\sigma} \frac{d \ln Y}{dN} + \frac{1}{\sigma} \frac{\gamma_L(N)^{\sigma-1}}{\left(\int_I^N \gamma_L(z)^{\sigma-1} dz \right)} + \frac{\sigma - 1}{\sigma} \frac{B'(N)}{B(N)}. \quad (17)$$

This is always positive and could be large. Note also that the wage and productivity impact of new tasks can be potentially larger than cost savings in existing tasks, and this is particularly likely to be the case when new tasks improve the entire production process (as captured by the B term), or when they add new sources of cost improvements or complementary functions. Despite new tasks' central role in wage and productivity growth and in reducing labor income inequality (see Acemoglu and Restrepo, 2018, and Autor et al.,

¹⁸Around I , this amount is given by $k(I) = \frac{B^{\sigma-1} A_K^{\sigma-1} \gamma_K(I)^{\sigma-1} Y}{(R(K)\rho(I))^\sigma}$. If labor-intensive tasks were previously using capital as well, then the jump would be smaller but still positive.

3. As already discussed, some early studies show that within narrow occupations, lower-performing or lower-expertise workers are the ones benefiting from generative AI. This raises the possibility that AI could be more complementary to lower-skill workers and may reduce labor income inequality. In my framework, this would be captured by an increase in λ_U relative to λ_H . However, even in this case, inequality between capital and labor will rise (provided that $\sigma < 1$).
4. If AI created new (good) tasks, these would reduce inequality between capital and labor, and if enough new tasks were targeting lower-skill workers, this could also reduce labor income inequality (Acemoglu and Restrepo, 2018).

I now argue theoretically that there are several reasons why 1 and 2 listed here are unlikely to be major sources of wage growth or significant limits on inequality. First consider a 1% increase in A_L (or an equivalent increase in $\gamma_L(z)$ for labor-intensive tasks). As explained above, this may not increase wages at all, or may lead to only small wage increases. In fact, from equation (11), abstracting from the productivity effect, the direct impact on the equilibrium wage will be a $(\sigma - 1)/\sigma\%$ change. In the plausible case where $\sigma < 1$, this is negative. The overall impact may still be an increase in wages because of the productivity effect, but as already noted, when σ is approximately equal to the share of capital in national income, the overall impact will be essentially zero. In conclusion, without the creation of a sufficient number of new tasks, inequality between capital and labor will increase and wage rises may be limited.

What about a reduction in inequality because lower-skill workers benefit more? In the model here, the earnings of high-skill workers relative to low-skill workers is always pinned down at λ_H/λ_U . So if new technologies reduce this ratio, they will reduce the gap between high-skill and low-skill workers. But even this conclusion needs to be qualified. Acemoglu and Restrepo (2022) show that in more general settings, with multiple skill groups, there will be ripple effects whereby impacted demographic groups can then compete for tasks previously performed by other groups. In such a situation, an overall increase in labor productivity of both high-skill and low-skill workers in some tasks can lead to their displacement from these tasks, and then the ripple effects can, in principle, affect low-skill workers even more adversely than high-skill workers.

While such adverse effects on low-skill workers are a general possibility in the framework of Acemoglu and Restrepo (2022), I am not aware of worked-out examples where an increase in the productivity of low-skill workers increases inequality. I now provide such an example.

2.10 How Greater Low-Skill Productivity Can Lead to Higher Inequality

Let me illustrate this possibility with a simple example, by relaxing the assumption that there are no comparative advantage differences between high-skill and low-skill workers. Suppose that the economy starts from an equilibrium in which tasks below some I are performed by capital, and tasks between I and N are performed by a combination of high-skill and low-skill workers. In particular, suppose that low-skill workers have a comparative advantage in tasks between I and I^* , and denote their (constant) productivity in these tasks by λ_U , while the productivity of high-skill workers in these tasks is also constant and equal to λ_H .

Suppose also that the relative productivity of high-skill workers in tasks between I^* and N is $\omega > \lambda_H/\lambda_U$ —indicating that high-skill workers have a comparative advantage in higher-indexed tasks. However, because there is no strict comparative advantage, the equilibrium may involve both types of workers performing some of the same tasks.¹⁹ Assume also that the elasticity of substitution between tasks is $\sigma < 1$.

Let us start with an equilibrium in which both high-skill and low-skill workers perform tasks $z \in (I, I^*]$, while only high-skill workers perform tasks $z \in (I^*, N]$. In this initial equilibrium, the relative wage of skilled workers will be pinned down by the relative productivities of the two types of workers in the tasks they are both performing—i.e., $z \in (I, I^*]$ —and is given by λ_H/λ_U .

Suppose that labor productivity in $z \in (I, I^*]$ increases due to advances in AI, and this also is more helpful for lower-skilled workers, and so λ_H/λ_U declines. I now show that these advances could boost inequality. Because $\sigma < 1$, the prices of tasks $z \in (I, I^*]$ will decline more than the increase in physical productivity of labor, and there will be less labor assigned to these tasks. If this effect is significant, all high-skill workers may be allocated away from these tasks, and the amount of labor demanded in these tasks may fall short of the supply of low-skill workers. In this case, the post-AI allocation may involve only low-skill workers performing tasks $z \in (I, I^*]$, while both low-skill and high-skill workers perform tasks $z \in (I^*, N]$. Then, regardless of how much λ_H/λ_U declines, the relative wage of skilled workers will be determined by the tasks that both types of workers are performing, which are now those above I^* , and thus will be equal to $\omega > \lambda_H/\lambda_U$. Hence, inequality increases

¹⁹This structure makes the example similar to one that has a finite number of tasks—in this instance, three tasks. But I use the setting with a continuum of tasks for continuity with the rest of the paper. The “paradoxical” result I am highlighting here does not depend on this stark structure or on having just two types of labor.

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2 following the rise in the productivity of low-skill workers.
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4 Therefore, I have just proven that, in this general scenario, even a reduced productivity
5 gap between low-skill and high-skill workers in some tasks *could* lead to greater inequality.
6 Hence, the overall inequality implications of AI cannot be directly deduced from its effects
7 on the performance of workers of different skills in a given set of tasks and requires a fuller
8 empirical exploration. In the next section, I investigate AI's inequality effects by adapting
9 the framework and estimates of Acemoglu and Restrepo (2022) to the current setting.
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14 15 **3 A Preliminary Quantitative Evaluation** 16 17

18 In this section, I provide a preliminary quantitative evaluation of the possible effects of
19 recent breakthroughs in AI over a horizon of 10 years. The centerpiece will be the use
20 of Hulten's theorem and recent estimates of which tasks can be automated using AI and
21 computer vision technologies and the cost savings thereof. Once I obtain these estimates
22 from Hulten's theorem for TFP growth, I convert them to GDP growth estimates using
23 another series of assumptions on how the capital stock of the economy will respond. I also
24 discuss AI's effects through new bad tasks could be estimated. Finally, I combine these
25 numbers with the more detailed framework in Acemoglu and Restrepo (2022) to obtain
26 even more speculative estimates for wage and inequality implications. Before moving to the
27 estimates, I first describe the sources I use, further discuss existing productivity estimates
28 and motivate various parameter choices.
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36 37 **3.1 Data Sources and Parameter Choices** 38 39

40 The centerpiece of the estimates in this paper is equation (14), and its refinement to (15).
41 To implement this equation, two pieces of information are needed:
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- 43 1. GDP share of tasks that are impacted by AI (inclusive of computer vision) within the
44 next 10 years.
- 45 2. Average cost savings in these tasks due to AI, $\bar{\pi}$.
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50 It is impossible to have accurate estimates of either of these two quantities, and hence
51 my repeated caution that the numbers here—and for that matter, other estimates in the
52 literature and the public debate—should be interpreted with great caution as suggestive
53 numbers. Nevertheless, there are studies that have already shed light on these quantities. I
54 now discuss what these are and how I use them.
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elements of “augmentation” or task complementarity. This motivates my interpretation that combining their measure with equation (14) will capture cost savings from both automation and task complementarities.

- Eloundou et al.’s data need to be converted into GDP shares. To do this, I combine tasks into occupations, and then I aggregate across occupations using their wage bills, computed from the US Bureau of Labor Statistics (BLS) National Occupational Employment and Wage Estimates pooled across the years 2019-2022. This procedure yields a wage bill-weighted share of exposed occupations equal to 20%. I interpret this number to be the same as the GDP share of tasks exposed to AI.
- Eloundou et al.’s approach is to determine tasks that can be ultimately performed by generative AI and computer vision technologies (such as the technology already incorporated in Dall-E). Two things are missing from the information they provide. The first is how much of the task impact is likely to be realized within the next 10 years. The second is whether, in all of these cases, it is profitable to use AI (e.g., whether automating using AI is cost-effective). Svanberg et al. (2024) make an attempt to provide answers to these questions in the case of computer vision technologies, which are a subset of the technologies Eloundou et al. consider. I take Svanberg et al.’s estimates and extrapolate them to all of the tasks Eloundou et al. consider.²¹ Namely, Svanberg et al.’s base estimates imply that among computer vision-exposed tasks, 23% can be feasibly (and profitably) automated within 10 years.²² Applying this number to Eloundou et al.’s estimates, I arrive at the GDP share of tasks impacted by AI within the next 10 years as $0.23 \times 0.200 = 4.6\%$ of all tasks (or occupations).

Cost Savings from AI

I base my estimate of $\bar{\pi}$ on the experimental studies that have already provided “proof-of-concept” estimates of productivity improvements or labor cost reductions due to AI. Three

²¹This is not an innocuous step. Svanberg et al. focus on automation using computer vision, while Eloundou et al.’s exposed technologies include task complementarities as noted above and go beyond computer vision tasks. One could imagine that the share of tasks that can be profitably used with AI within 10 years is different between these two categories. Unfortunately, I do not have another source for such an estimate for non-computer vision AI.

²²Svanberg et al. also make further extrapolations assuming cost declines in computer vision technologies. They base these on estimates from Besiroglu and Hobbhahn (2022), who project a 22% yearly decrease in computation costs attributed to the expansion of compute power from GPUs. However, a doubling of GPU capacity will not necessarily translate into a 50% decline in costs in general due to diminishing returns and bottlenecks created by other inputs, and because of the limitation of the current architecture. I therefore do not include these in the baseline but return to them in the robustness discussion.

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2 studies, which I have already mentioned, are particularly notable here, and I now describe
3 each one of them.
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7 • Peng et al. (2023) design an experiment where freelance computer programmers are
8 given access to and encouraged to use GitHub Copilot, which (at the time of the
9 experiment) was powered by OpenAI Codex (GPT-3). Participants were given the
10 task of implementing a HTTP server on JavaScript, a popular language for which
11 resources and subroutines are readily available, and GPT-3 was already trained on these
12 resources. They compare the experimental treatment group to a control group that is
13 not given access to GitHub Copilot. They find that the treatment group performed
14 the assigned tasks on average 55.8% faster than the control group. As an aside, like
15 the other studies I mention here, Peng et al. find that these improvements come from
16 otherwise less well-performing subjects.
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- 19 • Noy and Zhang (2023) design an online experiment where individuals in a range of
20 white-collar occupations are recruited and presented with simple writing tasks (in
21 particular, tasks like writing press releases, short reports and analyses that are designed
22 to take 20 to 30 minutes and resemble real life tasks in the participants' occupations).
23 The treatment group is given access to and encouraged to use ChatGPT-3.5, while the
24 control group is not. They verify that there is very low usage of ChatGPT in the control
25 group. They estimate that ChatGPT enables, on average, 40% faster completion of
26 the task at hand. They also estimate an 18% improvement in quality scores, as judged
27 by peers and ChatGPT-based scoring of the output. In their case, too, the gains come
28 mostly from subjects that performed less well before the experiment.
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- 31 • Brynjolfsson et al. (2023) is the only study that I am aware of that looks at the use of
32 generative AI tools in a real business setting with a careful experimental design. The
33 business they focus on is a customer service provider, which uses a custom generative
34 AI tool to help customer service associates. The rollout took the form of a treatment
35 group getting access to this tool, while the control group did not. Brynjolfsson, Li
36 and Raymond evaluate the impact of the rollout on cost savings, by focusing on how
37 quickly tasks (open customer tickets) are resolved. They also look at self-reported
38 customer satisfaction. They find a significant improvement in the speed with which
39 tasks are completed by customer service associates—an effect of about 14% on average.
40 However, they additionally estimate a slight and statistically insignificant decline in
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2 quality, as judged by the users themselves. Like the other studies, Brynjolfsson, Li and
3 Raymond find that the results are predominantly among the lower-performing, less
4 expert employees. In fact, they estimate that the top quintile of associates experience
5 no improvement at all.
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10 I interpret all three studies as providing labor cost savings from AI, broadly construed—in
11 particular, meaning that all three studies include both automation and task complementarity
12 elements. For instance, for the GitHub Copilot users in Peng et al., the authors' interpreta-
13 tion is that some of the subtasks previously performed by programmers, such as the writing
14 of common routines, are now done by the Copilot. Along the lines of the discussion in
15 Section 2.2, suppose that programming in JavaScript involves N subtasks, which need to
16 be completed for a successful program. These include initial planning (which approach to
17 adopt, how to organize the program, etc.), composition of subroutines, putting the subrou-
18 tines together, debugging the subroutines, debugging the master program and then assessing
19 whether the program achieves the planned aims. When all of these subtasks are performed,
20 then the task at hand—the writing of a specific computer program—is completed. We can
21 think of generative AI as taking over a subset of the composition of subroutine tasks. Then
22 in line with the framework in Acemoglu and Restrepo (2018, 2019b), the use of this new
23 technology will create displacement and productivity effects. Overall performance will in-
24 crease because of productivity effects, provided that this technology is better than/faster
25 than humans at composing some subroutines (but humans are still needed for the other sub-
26 tasks, including planning, debugging and checking). Demand for human labor in this task
27 may increase or decrease depending on the magnitude of the displacement and productivity
28 effects and the elasticity of substitution between this task and other tasks (as well as the
29 demand elasticity for the product that is ultimately being produced for the market). In
30 addition, when simple subroutines are taken over by the Copilot, this may enable human
31 workers to specialize in other subtasks, potentially generating task complementarities and
32 further productivity gains.²³
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48 What I have just described for programming also applies to the other two studies. Chat-
49 GPT is doing some of the drafting, which human subjects can then take and incorporate into
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51 ²³However, in this experimental setting, we do not see the displacement effects, because each of the
52 treatment subjects are given the task and there is no possibility of reducing the number of workers performing
53 this task. Hence, from these experiments, we can only learn about the productivity gains, inclusive of
54 any task complementarities—and not about the displacement effects. This interpretation clarifies why I
55 am comfortable bundling automation and task complementarities together for the purposes of estimating
56 productivity gains from AI.
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2 their writing with some verification and modification. The same applies for the customer
3 service associates, who are allowed to copy and paste text suggested by the generative AI
4 tool in the setting studied by Brynjolfsson, Li and Raymond.
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7 I also assess that the tasks in these three studies are broadly comparable to the exposed
8 tasks considered in Eloundou et al. (2023), even though I argue later that they are more
9 likely to be in the easy-to-learn category. Hence, these studies are most informative about
10 cost savings (productivity improvements) for the exposed tasks in Eloundou et al.
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13 As a baseline, I ignore the quality effects (which, as noted, are not uniform between
14 the three studies) and focus on the average increase in speed and interpret this as average
15 cost savings. I return to the inequality implications below. Finally, as a baseline, I use the
16 average of the estimates from Noy and Zhang (2023) and Brynjolfsson et al. (2023), and turn
17 to the average of the three studies as a robustness check. The reason for this is that Peng
18 et al.'s setting is less likely to be relevant to other tasks and occupations, since the task in
19 question is a very well-defined one for which Github Copilot was extensively trained, and
20 this has no direct equivalent in the other tasks we are focusing on. Under these assumptions,
21 the average labor cost savings are 27% ($= 0.27$).
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29 Recall that these numbers refer to declines in labor costs in occupations, where many
30 tasks involve use both capital and labor, and what is relevant in equation (14) is overall
31 cost savings. To convert labor cost savings into overall cost savings, I use the industry-level
32 estimates from Eloundou et al. and combine them with industry labor shares from the
33 Bureau of Economic Analysis (BEA), as described in the Appendix.²⁴ This gives an average
34 (AI exposure-adjusted) labor share of 0.535, and thus the average (overall) cost savings from
35 AI are about $0.27 \times 0.535 = 0.144$.
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40 If we add the numbers from Peng et al. to the mix, the average labor cost savings become
41 0.36, and thus the average overall cost savings come to 0.193.
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44 ²⁴Briefly, I follow Eloundou et al. and map exposed tasks to occupations, and then map occupations to 14
45 aggregated NIPA (National Income and Product Accounts) industries using the fractions of workers in each
46 occupation employed across industries. I then compute the labor share of exposed tasks using industry labor
47 shares weighted by the value-added shares of these industries in gross national income. In these calculations,
48 the self-employed are assumed to have the same hourly wage rate as employees in the same industry. I
49 use the 14 NIPA industries to be able to have information on hours worked. These data are for the years
50 2018-2022 from the US BEA NIPA tables, and I provide a list of these 14 industries in the Appendix.

51 For reference, the average (value-added-weighted) labor share in 2018-2022, without the exposure adjust-
52 ment, is 0.576. This suggests that exposed tasks are, on average, in industries with slightly lower labor shares
53 than the national average. This labor share estimate is similar to the one reported in Elsby et al. (2013),
54 0.583, for private non-farm business sector for the years 2010-2012 using the same approach as here. Elsby
55 et al. (2013) also report similar numbers under alternative methodologies for incorporating self-employment
56 income.
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3.2 Aggregate Productivity Gains: A First Pass

A first-pass estimate of productivity (TFP) gains at the aggregate level can be obtained simply by combining the numbers derived in the previous subsection with equation (14).

This implies:

$$\begin{aligned} \text{TFP gains over 10 years} &= \text{GDP share impacted by AI over the next 10 years} \\ &\quad \times \text{average cost savings of impact tasks.} \end{aligned}$$

Therefore, on the basis of the numbers from the previous subsection, I can approximate:

$$\begin{aligned} \text{TFP gains over the next 10 years} &= 0.046 \times 0.144 \\ &\simeq 0.0066. \end{aligned}$$

In other words, according to this basic estimation strategy, TFP gains over the next 10 years from AI are about 0.66%—meaning that relative to the baseline without the current suite of AI and computer vision advances, TFP will be higher by 0.66 percentage points in 10 years, or annual TFP growth will be higher by around 0.064%. This is a nontrivial, but modest effect, and certainly much less than both the revolutionary changes some are predicting and the less hyperbolic but still substantial improvements forecast by Goldman Sachs and the McKinsey Global Institute, which I discussed in the Introduction.

If we were to consider the higher productivity numbers from Peng et al., 0.144 would be replaced by 0.193, and the 10-year TFP gains would be 0.89%, instead of 0.66%.

The only modification that would make a sizable difference to these numbers is to increase the fraction of tasks that will be impacted over the next 10 years. One way of doing this is to inflate the numbers from Svanberg et al.. This could be because either the fraction of tasks that can be feasibly automated will be different for generative AI than for computer vision, or because within 10 years this fraction will increase significantly. For example, in Svanberg et al.'s scenarios where costs for computer vision decline very rapidly, such as 10% a year, the fraction of tasks that are feasibly automated may be as high as 30%. This would raise the GDP share impacted by AI to approximately 6%, and correspondingly increase the TFP gains over the next 10 years to about 0.9%. Note that even this number is quite modest, and moreover, 10% per annum cost declines is quite aggressive (since, as already noted above, even if GPU costs were to decrease by 10% or even 20%, this would not lead to a 10% decline in costs of performing computer vision tasks, given the presence of other inputs, such as programming and data, as well as the inherent limitations of the current generative AI architecture).

Finally, I note three important considerations missing from these computations.

1. These adoption numbers ignore the fact that there is still very little investment in AI in the US corporate sector. Acemoglu et al. (2022) estimate that less than 1.5% of US businesses had any investment in AI in 2019, and this is particularly true beyond the very large companies in manufacturing, information services and business services. Since many of the tasks considered in Eloundou et al. (2023) are performed in small and medium-sized enterprises, this is unlikely to change quickly. If generative AI tools become monopolized in the hands of a few companies, this might further slow down their adoption by small and medium-sized firms. These considerations suggest that even the 0.046% number for the share of GDP impacted by AI may be a big overestimate, and the true numbers could be much smaller.
2. Any major technology creates adjustment costs when adopted at large scale, because other organizational aspects need to evolve as well and this is typically quite costly and slow. In the context of digital technologies, Greenwood and Yorukoglu (1997) and Brynjolfsson et al. (2021), among others, have argued that productivity gains will take a J-shaped pattern, and the former paper predicts that the flat part of the J-curve lasts no less than 20 years for digital technologies. If so, the 14.4% overall cost reductions may be a significant overestimate for the next 10 years.
3. As already discussed above, some of the tasks in the list of Eloundou et al. (2023) are hard-to-learn, where productivity gains may be significantly less than those based on the experimental studies that have focused on the easy-to-learn tasks.

In the next subsection, I make a preliminary attempt at incorporating the third possibility, but I will ignore the first two. Nevertheless, these considerations make me conclude that even the 0.66% increase in TFP within the next 10 years due to AI is likely to be an upper bound on this technology's medium-run effects.

3.3 Aggregate Productivity Gains: Incorporating Hard Tasks

In this subsection, I refine the estimates from the previous subsection by switching to equation (15), which can be rewritten as:

$$\begin{aligned} \text{TFP gains} = & \text{GDP share of impacted easy tasks} \times \text{average cost savings from easy tasks} \\ & + \text{GDP share of impacted hard tasks} \times \text{average cost savings from hard tasks.} \end{aligned}$$

I take the 27% labor cost savings, from Noy and Zhang (2023) and Brynjolfsson et al. (2023), to apply to easy-to-learn tasks. The discussion in the previous section suggests that most hard tasks have not been impacted or automated yet, and hence it is impossible to know what their cost savings will be. Here I take those productivity gains to be 7%. My reasoning is as follows. I consider the tasks involved in the Peng et al. (2023) study to be very easy-to-learn for generative AI for reasons explained above. Those studied in Noy and Zhang (2023) are also on the easy side, and led to cost savings of about 40%, which is about two thirds of the cost savings in Peng et al., while the customer service tasks in Brynjolfsson et al. (2023) are already moving towards somewhat more complex tasks, and these had cost savings of only 14%. I imagine that many of the hard-to-learn tasks are more challenging for AI models than the simpler end of the customer service tasks to which Brynjolfsson et al.'s numbers refer. This motivates my choice of half of the cost savings of their study, 7% (which is also about a quarter of the baseline 27% cost reduction estimate I used in the previous subsection).

The cost-saving numbers for both easy and hard tasks are again multiplied with 0.535 to convert them into overall cost savings—0.144 and 0.037 for easy and hard tasks, respectively. To obtain the shares of easy and hard tasks, I start from Eloundou et al.'s data and methodology, and then develop a procedure, implemented using GPT-4 like they do, for sorting these into easy and hard tasks. The key characteristic for easy tasks is the presence of a well-observed outcome and a straightforward rule that links actions/recommendations to characteristics of the problem at hand.

To implement this procedure, I start from the 4089 exposed tasks determined from the above procedure. Each one of these tasks has a statement on O*NET that includes at least one verb. Each task also belongs to the higher level of aggregation of Detailed Work Activities (DWAs) and the (even coarser) 332 Intermediate Work Activities (IWAs). The procedure proceeds in four steps:

1. **Classification of verbs:** Each task statement includes at least one verb which is located at the beginning and can be easily identified. These primary verbs describe much of what is “hard” or “easy” that needs to be learned about the task. We classified tasks manually into easy and hard categories.²⁵ The full list of tasks is provided in the Appendix. As an illustration, verbs for easy tasks include, among others: compute, resolve, count, draft, grade, transcribe, classify, standardize, write, and record. Many

²⁵This step and other manual coding steps in this subsection were carried out by Can Yeşildere.

3.6 Wage and Inequality Implications

Finally, I evaluate the wage and inequality consequences of generative AI advances. To do this, the present framework needs to be extended to include multiple demographic groups that have different comparative advantages across different tasks, as in Acemoglu and Restrepo (2022). To save space, I do not introduce this generalization and refer the reader to that paper. Instead, I start with the following equation from their paper, which is a generalization of (11) above to a setting with multiple sectors and multiple demographic groups (but, for simplicity, without the task complementary and labor-augmenting changes):

$$d \ln w_g = \Theta_g \cdot \left(\frac{1}{\sigma} d \ln y + \frac{1}{\sigma} d \ln \zeta - \frac{1}{\sigma} d \ln \Gamma^{\text{auto}} \right).$$

Here, g refers to demographic group g , and following their paper, I will focus on 500 demographic groups, defined by education, age group, gender, ethnicity and native vs. foreign-born status. In addition, $d \ln y$ is the change in GDP resulting from the technology change (capturing the productivity effect), σ is the elasticity of substitution between tasks, and ζ is the vector of induced industry shifts (e.g., because automation of tasks in one industry affects prices and causes a reallocation of spending across sectors). Most importantly, $d \ln \Gamma^{\text{auto}}$ is the vector of demographic group-level displacement caused by the technology shock—namely, it is a column vector of 500 entries, and Θ_g is the g th-row vector of the propagation matrix, which summarizes how the displacement of other demographic groups affects demographic group g (this is the reason why it is pre-multiplying the vectors of industry shifts and displacements for all groups).

The propagation matrix represents the full “ripple effects”—the impact of the displacement of one demographic group on others, as they leave the tasks they were previously performing and compete with other groups to be employed in other tasks. Such reallocations are the key channel via which direct productivity gains for a group may end up harming it (as my example in the previous section illustrated). They are also the mechanism via which the displacement of a demographic group may end up being more damaging to another demographic group.

The ripple effects estimated in Acemoglu and Restrepo (2022) may be context-specific—meaning that the magnitudes of these effects could be quite different for the tasks impacted by AI and automation technologies that my previous work focuses on. Nevertheless, since it is impossible to estimate these ripple effects for the future impact of generative AI technologies, I will use these existing estimates.

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2 the estimate of $\sigma = 0.50$ as in Humlum (2021) and take the elasticity of substitution between
3 sectors in consumption to be $\eta = 0.2$ as in Buera et al. (2022), which was also imposed in
4 Acemoglu and Restrepo (2022).
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7 Figure 1 is the equivalent of Figure 5b in Acemoglu and Restrepo (2022) and presents
8 the distribution of AI exposure across demographic groups sorted by their hourly wage in
9 2018-22. It shows that AI exposure is much more equally distributed across demographic
10 groups than pre-AI automation (which was based on robotics, dedicated advanced machinery
11 and software systems).
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15 Table 1 presents the main results. The seven rows are for the five education groups
16 (aggregating demographic groups according to their education level), for the average of
17 the workforce and for GDP. The first column gives the AI exposure for each one of the
18 demographic groups, using our baseline exposure measure that does not distinguish easy
19 and hard tasks. The second column presents the direct impact of AI exposure on each one
20 of these groups, while the third column contains the full wage impact, taking into account
21 induced substitution between industries and the ripple effects. The next four columns are
22 similar but now refer to the AI exposure measure that separates easy and hard tasks—column
23 4 gives exposure to easy tasks and column 5 is for exposure to hard tasks. Finally, column 8
24 shows the exposure measure from Acemoglu and Restrepo (2022) for comparison (but recall
25 that this measure refers to a 36-year period, rather than the 10-year timescale here). The
26 comparison of columns 1 and 4-5 to column 8 confirms that AI exposure is much more equally
27 distributed across demographic groups than pre-AI automation exposure. Workers with less
28 than high school have the lowest exposure, followed by postgraduates, while workers with
29 college degrees and those with associate degrees or some college have the highest exposure.
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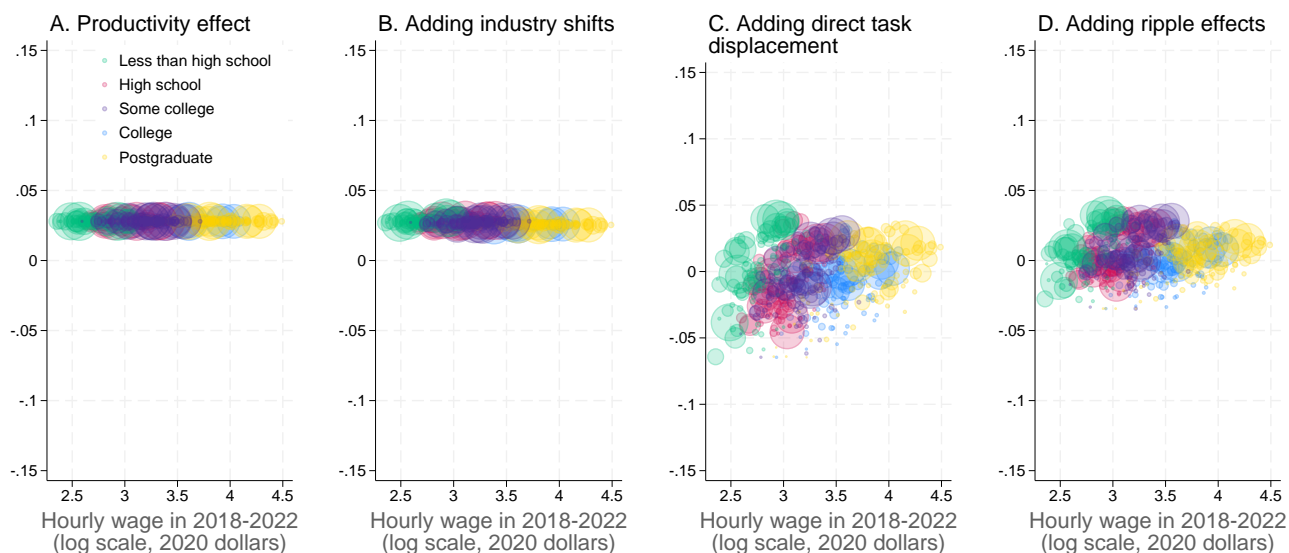
40 Consequently, predicted wage impacts do not appear to have a big impact on inequality
41 between education groups. Focusing on the estimates in column 7, which incorporate easy
42 and hard tasks, there is a slightly higher wage growth for workers with less than a high school
43 degree—about 1.3% within 10 years—but the gap between postgraduate versus high school
44 and college graduate workers also widens somewhat. In fact, the between-group standard
45 deviation of log wages (weighted by employment) increases slightly, from 0.35 to 0.36. The
46 results are quite similar in column 3 for the baseline AI exposure measure.
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	Baseline exposure			Exposure adjusted for easy and hard task				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline AI exposure	Direct effect of AI exposure	Total wage effect of AI exposure	Exposure to easy tasks	Exposure to hard tasks	Direct effect of exposure to easy and hard tasks	Total wage effect of exposure to easy and hard tasks	Direct task displacement 1980-2016
Workers with less than high school degree	0.0318	-0.0323	0.0157	0.0235	0.0083	-0.0356	0.0132	0.2690
Workers with high school degree	0.0464	-0.0617	0.0106	0.0337	0.0128	-0.0649	0.0079	0.2706
Workers with some college	0.0494	-0.0676	0.0139	0.0357	0.0138	-0.0709	0.0112	0.1886
Workers with Bachelor's degree	0.0523	-0.0733	0.0060	0.0382	0.0140	-0.0765	0.0040	0.0684
Workers with postgraduate degree	0.0405	-0.0498	0.0098	0.0299	0.0106	-0.0530	0.0081	0.0343
Average worker	0.0462	-0.0612	0.0101	0.0336	0.0126	-0.0644	0.0077	0.2107
GDP			0.0156				0.0140	

Table 1: Exposure and wage effects by education groups

Note: This table summarizes the effects of AI exposure on the real wages of different education groups and all workers. The first three columns are for the AI exposure measure that does not distinguish easy and hard tasks, while columns 4-7 are for the measure that introduces this distinction. Columns 1, 4 and 5 present levels of AI exposure for these different cuts. Columns 2 and 6 provide the direct effects of AI exposure, while columns 3 and 7 include the full equilibrium wage impacts, incorporating the ripple effects. Column 8, for comparison, includes the direct task displacement measure for 1980-2016 from Acemoglu and Restrepo (2022). The rows are for different education groups as well as for the average worker and for the overall GDP impact. The propagation matrix estimates are for 1980-2016, as reported in column 2 of Table 8 in Acemoglu and Restrepo (2022).

Figure 2: Decomposition of productivity effects, industry shifts, direct displacement effects and ripple effects

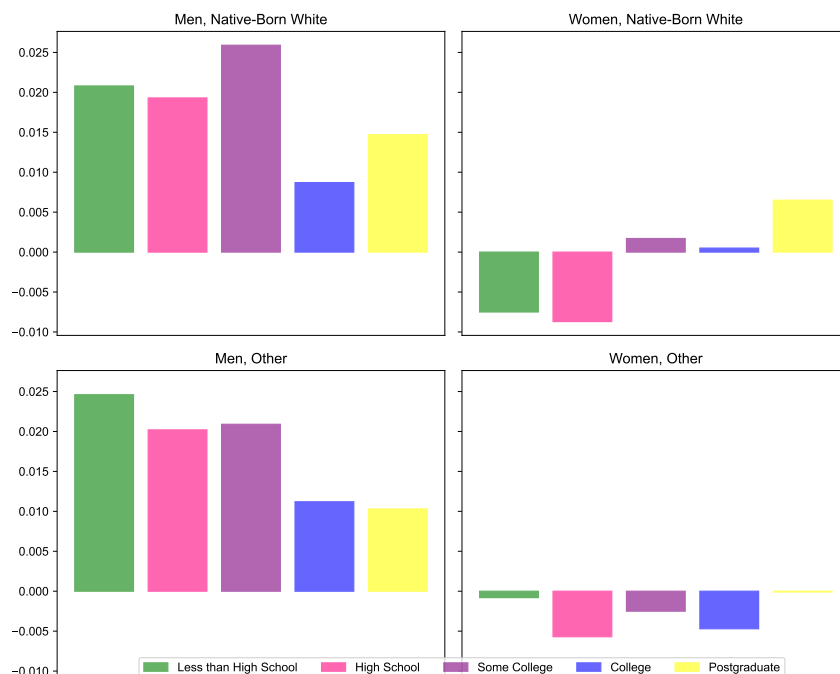


Notes: This figure is based on the estimates of the propagation matrix from Acemoglu and Restrepo (2022) and combines this with the measure of exposure to easy and hard AI tasks in this paper. The first panel includes just the productivity effect. The second panel adds the industry shifts induced by AI exposure. The third panel incorporates the direct displacement effect, while the final panel adds the ripple effects. The horizontal axis gives the average hourly wage for the relevant demographic group between 2018 and 2022, computed from the five-year American Community Survey sample. Marker sizes are proportional to the average 2018-2022 employment level of each group and different colors indicate the education level of the group. See text for details.

Finally, row 7 presents the estimate of the impact on GDP, taking into account the equilibrium increase in the capital stock implied by the model. This is under the assumption that all of the capital stock adjustment will take place within 10 years (while in practice it may take longer) and that the required rate of return on capital investments does not change (whereas with a sizable investment, we may expect an increase). This leads to an upper bound GDP impact of 1.4% in column 7, when I distinguish between easy and hard tasks (or 1.56% in column 3 when this distinction is not drawn). GDP therefore increases substantially more than average wages, and as a result, the capital share of national income increases by about 0.31 percentage points. This confirms that inequality between capital and labor is likely to rise as a result of the rollout of AI.³² Figure 2 performs the same

³²Recall, however, that it is the TFP gains that are the relevant numbers for consumer welfare, since the additional investment comes out of consumption and may involve additional heavy energy use, as remarked in footnote 6.

Figure 3: Total wage effect of exposure to AI, by gender



Notes: This figure is based on the estimates of the propagation matrix from Acemoglu and Restrepo (2022) for 1980-2016, and combines this with the measure of exposure to easy and hard AI tasks in this paper. Each panel includes wage effect estimates for five education groups. Reported estimates are weighted averages of the estimates for the more detailed subgroups (using average employment 2018-2022 as weights). The upper left panel is for native-born white men, the lower left is for all other men, the upper right is for native-born white women and the lower right is for all other women.

exercise as Figure 7 in Acemoglu and Restrepo (2022), focusing on the exposure measure that distinguishes between easy and hard tasks. As in that paper, productivity effects are (by construction) uniform across groups, and there is also not much inequality generated by the cross-industry shifts shown in the second panel. The third panel confirms that AI's direct effects are more equally distributed across demographic groups and throughout the wage distribution. In contrast to the findings in Acemoglu and Restrepo (2022), ripple effects do not change the inequality patterns by much, largely because the direct effects are already fairly equally distributed. Figure 2 also indicates that there is a lot of variability in the experience of low-education groups—and this is the reason why the between-group standard deviation of log wages increases, as noted above. Figure ?? explores this issue further by depicting the real wage changes of finer groupings, distinguished by gender, by education and by white and native-born status versus the rest. It reveals that low-education women, especially white, native-born low-education women, are likely to experience declines in real

wages as a result of AI.

Overall, this exercise suggests that the inequality consequences of AI will not be as adverse as pre-AI automation, because AI exposure is more equally distributed across demographic groups. Nevertheless, there is no evidence that AI will reduce inequality, as some are forecasting. Rather, my analysis suggests that it may have a small positive effect on overall (between-group) inequality and reduce the real earnings of low-education women. It will also further widen the gap between capital and labor income.

4 Concluding Remarks and Discussion

Following its release on November 30, 2022, ChatGPT became the fastest spreading tech platform in history, reaching approximately 100 million monthly users within just two months. Its impressive features, and the greater capabilities of the newer version ChatGPT-4, released in March 2023, soon captured imaginations, both among the general public and economic commentators. Forecasts of large productivity gains have now become commonplace.

While there is no question that generative AI models, including ChatGPT, have impressive achievements and have great potential for beneficial economic effects, the extent of their macroeconomic consequences remains an open question.

There are four potential types of macro effects that AI technologies can have in the medium run:

1. They can quickly revolutionize every aspect of the economy, and lead to massive improvements in productivity, even taking us close to “singularity”. While this is a possibility that cannot be completely ruled out, there is so far no evidence of such revolutionary effects (Nordhaus, 2021), and these are not addressed in the current paper.
2. They can have more modest but still notable effects on the macroeconomy by improving productivity and reducing costs in a range of tasks. Some of the forecasts have focused on these types of improvements and still produced relatively large numbers, such as a 1.5 – 3.4 percentage point per annum increase in economic growth within a 10 year horizon.
3. They can impact wages and inequality because of their automation effects, or conversely, lead to large wage increases, especially for lower-pay workers, as forecast by The Economist (2023).

4. They can have macroeconomic effects by producing deepfakes, misinformation, manipulation and other “bads”.

In this paper, I use the task-based framework of Acemoglu and Restrepo (2018, 2019b, 2022) to evaluate the second and the third effects, and I also take some steps to formalize how the fourth set of effects might work out in a task-based macro framework.

I base my approach on existing experimental studies that estimate productivity gains and time savings from the use of generative AI tools in a number of settings. By building on these studies, I am explicitly taking on board the idea that generative AI will lead to productivity improvements. Nevertheless, combining these numbers with estimates of exposed tasks from Eloundou et al. (2023) and Svanberg et al. (2024) leads to much more modest productivity effects than most commentators and economists have claimed so far. These numbers become even smaller once we take into account that many of the tasks for which we have evidence of cost savings are relatively easy for AI, while in several other tasks the integration of AI will face more formidable difficulties—mostly because these are likely to involve more complex interactions between action and context and because they lack clear metrics for success that are observable, and hence necessitate AI models to learn from the (average) behavior of humans previously performing the same tasks.

Taking these considerations into account, I estimate that TFP effects from AI advances within the next 10 years will be modest—an upper bound that does not take into account the distinction between hard and easy tasks would be about a 0.66% increase in total within 10 years, or about a 0.064% increase in annual TFP growth. When the presence of hard tasks among those that will be exposed to AI is recognized, this upper bound drops to about 0.53%. GDP effects will be somewhat larger than this because automation and task complementarities will also lead to greater investment. But my calculations suggest that the GDP boost within the next 10 years should also be modest, in the range of 0.93% – 1.16% over 10 years in total, provided that the investment increase resulting from AI is modest, and in the range of 1.4% – 1.56% in total, if there is a large investment boom.

If AI is used to create new tasks and products, these will also add to GDP and can boost productivity growth. Nevertheless, when we incorporate the possibility that new tasks generated by AI may be manipulative, the impact on welfare can be even smaller. Based on numbers from Bursztyn et al. (2023), which pertain to the negative effects of AI-powered social media, I provide an illustrative calculation for social media, digital ads and IT defense-attack spending. These could add to GDP by as much as 2%, but if we apply

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2 the numbers from Bursztyn et al. (2023), their impact on welfare may be -0.72% . This
3 discussion suggests that it is important to consider the potential negative implications of
4 AI-generated new tasks and products on welfare.
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7 Finally, I borrow heavily from the estimates of Acemoglu and Restrepo (2022) on the
8 economy-wide productivity, wage and inequality effects of pre-AI automation technologies
9 to provide some guidance on what the impact of new AI advances will be. Because AI-
10 exposed tasks are more equally distributed within the population than tasks exposed to
11 pre-AI automation, I do not find substantial negative wage effects for any education group.
12 Nevertheless, the estimates do not point to significant reductions in inequality either, and
13 in fact, my findings suggest that low-education women may experience small wage declines,
14 overall between-group inequality may increase slightly, and the gap between capital and
15 labor income is likely to widen further.
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22 These results should not be interpreted as arguing that there are no major benefits from
23 AI. First, an increase of about $0.53 - 0.66\%$ in TFP within 10 years is modest but still far
24 from trivial. Second and more importantly, there may be other ways in which AI can be used
25 to generate much more notable benefits. I have suggested in previous work (Acemoglu, 2021,
26 Acemoglu and Restrepo, 2020b) that if AI is used for generating new tasks for workers, it can
27 have more beneficial productivity, wage and inequality consequences, and it can even increase
28 wages. This may be doubly true for generative AI, which could be used for providing better
29 information to workers and boosting their expertise, as argued in Acemoglu et al. (2023)
30 and explained briefly here.
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37 Many production workers today, including electricians, repair workers, plumbers, nurses,
38 educators, clerical workers, and increasingly many blue-collar workers in factories, are en-
39 gaged in problem-solving tasks. These tasks require real-time, context-dependent and reli-
40 able information. For instance, an electrician dealing with the malfunctioning of advanced
41 equipment or a short-circuit on the electricity grid will be hampered from solving these prob-
42 lems because he or she does not have sufficient expertise and the appropriate information
43 for troubleshooting. Reliable information that can be provided quickly by generative AI
44 tools can lead to significant improvements in productivity. Similarly, generative AI in class-
45 rooms can lead to a major reorganization of how teaching takes place, with greater levels
46 of personalization, as these tools help teachers identify specific aspects of the curriculum
47 with which subgroups of students are having problems and propose new context-dependent
48 teaching strategies. Reliability of AI models will be key for successfully creating such new
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3 tasks and delivering improvements in the quality of education.

4 Productivity improvements from new tasks and new products, which have been impor-
5 tant for previous transformative technologies, such as electricity and the Internet, are not
6 incorporated into my estimates. This is for three reasons. First and most parochially, this is
7 much harder to measure and is not included in the types of exposure considered in Eloundou
8 et al. (2023) and Svanberg et al. (2024). Second, and more importantly, I believe it is right
9 not to include these in the likely macroeconomic effects, because these are not the areas
10 receiving attention from the industry at the moment, as also argued in Acemoglu (2021),
11 Acemoglu and Restrepo (2020b) and Acemoglu and Johnson (2023). Rather, areas of pri-
12 ority for the tech industry appear to be around automation and monetization of personal
13 data, such as through search or social media digital ads. This makes it less likely that many
14 new good tasks will be created quickly. Third, and relatedly, more beneficial outcomes may
15 require new institutions, policies and regulations, as also suggested in Acemoglu and Johnson
16 (2023) and Acemoglu et al. (2023).

17 My assessment is that there are indeed much bigger gains to be had from generative AI,
18 which is a promising technology, but these gains will remain elusive unless there is a funda-
19 mental reorientation of the industry, including perhaps a major change in the architecture
20 of the most common generative AI models, such as the LLMs, in order to focus on reliable
21 information that can increase the marginal productivity of different kinds of workers, rather
22 than prioritizing the development of general human-like conversational tools. The general-
23 purpose nature of the current approach to generative AI could be ill-suited for providing
24 such reliable information. To put it simply, it remains an open question whether we need
25 foundation models (or the current kind of LLMs) that can engage in human-like conver-
26 sations and write Shakespearean sonnets if what we want is reliable information useful for
27 educators, healthcare professionals, electricians, plumbers and other craft workers.
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Online Appendix

A-1 Exposed Share of Tasks

Eloundou et al. (2023) present task-level exposures estimates based on O*NET, which lists tasks by occupation at the level of the eight-digit Standard Occupational Classification (SOC). We link these data to the BLS Occupational Employment and Wage Statistics (OEWS) for 2019 to 2022 to calculate the wage bill-weighted share of exposed tasks in the economy. BLS OEWS data are reported at the six-digit SOC level, and we combine these two sources of data as follows:

1. **Six-digit direct matching:** We compute occupational exposures scores at the eight-digit SOC level based on Eloundou et al. (2023). We then aggregate these eight-digit numbers to the six-digit SOC level (with equal weights). This direct match covers 90.8% of the total wage bill in the economy.
2. **Aggregation to five-digit:** In this step, we aggregate the six-digit SOC occupations to five-digits. For five-digit occupations that include both six-digit occupations with exposure estimates and wage bill information in BLS OEWS, we compute the wage bill share-weighted average of the six-digit occupations. This weighting scheme ensures that the information at the six-digit level is preserved when we aggregate up to five-digits. BLS OEWS does not report wage bill information for some small occupations, and as a result, for some five-digit occupations we have no direct match to six-digit occupations with exposure and wage bill data. In such cases, we compute the five-digit exposure by taking the unweighted average of all corresponding six-digit occupations with exposure data. These steps together cover 99.3% of the total wage bill in the economy. The remaining five-digit occupations, which make up 0.7% of the wage bill and have no exposure information in Eloundou et al. (2023), are assumed to have zero exposure. This aggregated occupational exposure score is denoted by Γ_0 .

A-2 Industry Labor Share and Exposure-Adjusted Labor Share

Industry-level exposure to AI, Γ_i , is computed following the strategy used by Eloundou et al. (2023), leveraging industry-level occupation distributions and occupational exposure data.

Specifically:

$$\Gamma_i = \frac{\sum_{o \in O} n_{oi} \Gamma_o}{\sum_{o \in O} n_{oi}},$$

where Γ_o is occupation o 's exposure to AI and n_{oi} are the number of people employed in occupation o in industry i , drawn from the BLS OEWS.

The labor share in non-farm private business income is computed in the usual manner as:

$$s_L = \frac{\sum_{i \in I} s_Y^i s_L^i}{\sum_{i \in I} s_Y^i},$$

where s_Y^i is the share of industry i 's value added in non-farm private sector GDP, and s_L^i is industry i 's labor share of value added. I follow the BLS and Elsby et al. (2013), and impute self-employment income in line with average hourly wage of employees in the same industry according to the number of hours worked of the self-employed. Since the number of hours worked is available only at the level of 14 aggregate NIPA industries, provided in BEA, I use these 14 industries for this exercise.³³ The labor share for 2018-2022 is estimated as 0.576. This number is similar to the estimates provided in Elsby et al. (2013) for the years 2010-2012, when they use the same methodology for imputing self-employment income. They also report a slightly higher labor share of 0.593, leveraging an alternative methodology based on the idea that the implied rate of return to capital used with employees has to be the same as the rate of return to capital used in self employment.

Exposure-adjusted labor share income, \hat{s}_L , is then calculated as:

$$\hat{s}_L = \frac{\sum_{i \in I} \Gamma_i s_Y^i s_L^i}{\sum_{i \in I} \Gamma_i s_Y^i}.$$

The only difference from the labor share computer previously, s_L , is the adjustment by the level of industry exposure, Γ_i . This leads to a slightly lower number than s_L , 0.536.

³³Specifically, we averaged data for the years 2018-2022 from Section 6 of NIPA Tables, available through the BEA, [here](#). Data on wages and salaries come from Table 6.2, on value added by in are from Table 6.1, the number of self-employed from Table 6.7, hours worked by employees from Table 6.9 and corporate taxes from Table 6.18. In addition, we follow the BLS and use the Current Population Survey (CPS) to impute weekly hours worked by the self-employed in each of these 14 industries.

The 14 NIPA industries are: (1) agriculture, forestry, fishing, and hunting, (2) mining, (3) utilities, (4) construction, (5) manufacturing, (6) wholesale trade, (7) retail trade, (8) transportation and warehousing, (9) information, (10) finance, insurance, real estate, rental, and leasing, (11) professional and business services, (12) educational services, health care, and social assistance, (13) arts, entertainment, recreation, accommodation, and food services, and (14) other services, except government.

ages word co-occurrence within task statements to determine probabilistic assignment of each task to topic clusters.

We use the output of these three steps with our supervised learning model, which is a gradient boosted classifier (GBC) (Friedman, 2001). GBCs maximize goodness-of-fit over a training set by iteratively generating partitions. We produce the training set by manually classifying 757 of the 4089 exposed tasks. The GBC produces the best fit for these 757 tasks, and we obtain the output of the classifier for the remaining tasks. The inputs into the GBC are: the verb classification, the IWA classification, and probabilities to belonging to each one of the 100 topic clusters from the LDA. In addition, we also feed the GBC the empirical frequencies of each verb being associated with an easy or uncertain task (hard task being the omitted category), and each IWA being associated with an easy task in our training data. This information is useful as it provides an empirical measure of the degree of certainty with which each verb and IWA is classified (analogous to the prior in a Bayesian calculation). When a task has more than one primary verb, we take the average across these.

The goodness-of-fit of the GBC is quite good. It matches 90% of the manual classification on our training data and has an AUC (area under the curve) score of 0.99. As output, we generate the probability of each task being easy-to-learn or hard-to-learn. When calculating the adjusted TFP scores, we weight each task by the degree of exposure (according to Eloundou et al) multiplied by the probability scores, to obtain the share of easy-to-learn tasks in the economy. Further details on the GBC and the training sample are contained in the replication package.

Finally, it is important to note that because the GBC algorithm is trained and tested exclusively on exposed tasks, its output is most meaningful for this sample. For example, for verbs that are absent or rare in this sample, it would not provide a meaningful classification. Therefore, its output should not be directly extrapolated to non-exposed tasks. Moreover, because Eloundou et al's sample is already for exposed tasks, we would expect a higher fraction of these to be easy-to-learn than for the entire set of tasks. Indeed, as reported in the text, about three quarters of the wage bill-weighted exposed tasks are classified as easy-to-learn within this sample.

A-4 Wage and Inequality Calculations

To estimate the general equilibrium impact of AI on wage outcomes, I follow the methodology used in Acemoglu and Restrepo (2022).

We focus on 500 demographic groups defined by age (five age groups), sex, race (white, Black, Asian, Hispanic and other), education (less than high school, with high school degree, some college, Bachelor's degree, and postgraduate degree) and immigration status (native or foreign-born). We use the 2018-2022 five-year American Community Survey data to determine hourly wages for workers and winsorize to deal with outliers as in Acemoglu and Restrepo (2022).

Estimates of the propagation matrix, Θ , are directly from Acemoglu and Restrepo (2022) and are for exposure to robots, software and dedicated machinery between 1980 and 2016. I take their estimates of task displacement based on industry labor share declines, reported in column 1 of Table A-X in the Online Appendix of Acemoglu and Restrepo (2022). The propagation matrix calculates the total spillovers between industry, occupation and age-education groups for observed changes between 1980-2016. The only difference from Acemoglu and Restrepo (2022) is that we feed in exposure to AI and its TFP implications, rather than those related to automation between 1980-2016 due to other technologies, as in their paper.

The quantitative implications are then produced using a fixed-point iteration algorithm to solve the following set of equations, as in Proposition 4 of Acemoglu and Restrepo (2022):

$$\begin{aligned}
 d \ln w_g &= \Theta_g \cdot \left(\frac{1}{\sigma} d \ln y + \frac{1}{\sigma} d \ln \zeta - \frac{1}{\sigma} d \ln \Gamma^{AI} \right) \\
 d \ln \zeta_g &= \sum_{i \in I} \omega_{gi} \cdot \left(\frac{\partial \ln s_i^Y(p)}{\partial \ln p} \cdot \ln p + (\sigma - 1) \cdot d \ln p_i \right), \forall g \\
 d \ln p_i &= \sum_{g \in G} s_{gi}^L \cdot (d \ln w_g - d \ln \Gamma_{gi}^{AI} \cdot \pi_{gi}), \forall i \\
 d \ln y &= \frac{1}{1 - s^K} \cdot (d \ln tfp + s^K \cdot d \ln s^K) \\
 d \ln s^K &= -\frac{1}{s^K} \sum_{g \in G} s_g^L \cdot (d \ln w_g - d \ln y).
 \end{aligned}$$

Here w_g is the wage of group g , Θ_g refers to the row in the propagation matrix associated with group g , y is economy-wide GDP, ζ is the vector of industry shares, Γ_g is AI exposure for g , ω_{gi} is the share of wages earned by group g in industry i relative to this group's total wage income, s_i^Y is the income share of industry i , p_i is the price index for industry i , s_{gi}^L is the share of wages earned by members of group g as a fraction of total earnings in industry i , π_{gi} is cost savings in tasks performed by group g in industry i , s^K is the capital share of income. Finally, Acemoglu and Restrepo (2022) provide an equation for $d \ln tfp$ as a

1
2 function of cost savings and industry shares, but rather than using this equation explicitly,
3 I take the change in TFP from my previous computations. All variables (except y) when
4 denoted without a subscript refer to $G \times 1$ vectors.
5

6
7 The variables s_i^Y , s_{gi}^L and ω_{gi} are computed directly from the American Community
8 Survey data, supplemented with industry-level labor share data from the BEA at the level
9 of 49 industries as in Acemoglu and Restrepo (2022). Γ^{AI} is derived from our aforementioned
10 occupation-level exposure numbers. Specifically, we aggregate from the occupation level to
11 the industry-group level by first matching occupations with occupation-level AI exposure,
12 then aggregating this to the industry \times demographic group level. For the baseline exposure
13 results, we set $\pi_{gi} = \bar{\pi} = 0.27$, which is the average of Noy and Zhang (2023) and Brynjolfsson
14 et al. (2023), as explained in the text. Finally, $\frac{\partial \ln s_i^Y(p)}{\partial \ln p}$ is computed as in Acemoglu and
15 Restrepo (2022) by assuming that sectoral outputs are combined in GDP with the constant
16 elasticity of substitution of $\eta = 0.2$ (as explained in the text).
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19 For easy versus hard tasks, I repeat the same procedure, except that I use separate
20 exposure measures for exposure to AI in easy tasks and exposure to AI in hard task for each
21 demographic groups.
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