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Automation & the Future of Work: When Artificial Intelligence Meets Schumpeterian Innovators*

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Building on the task-based production models augmented with Schumpeterian innovation, we develop a theoretical framework to analyze the labor market impacts of the introduction of artificial intelligence (AI) to the R&D sector. Innovators allocate scientists' time between automation of existing tasks and creation of new varieties of tasks to maximize their profits. The introduction of AI or general-purpose R&D technologies expands the frontier of the automation possibility set to encompass all existing tasks. In this milieu, task innovators prioritize the automation of the most profitable tasks – which depends on task-specific wage, market size, capital productivity, and the innovator's bargaining power. Therefore, unlike the previous waves of automation, new "AI" based automation technologies can pose a significant threat to high-skilled workers. Moreover, the advent of new R&D technologies raises the cost of creating new tasks and slows down the obsolescence of existing ones. Combined with faster task automation, ironically, the dynamics of the R&D sector may eventually decelerate widening income inequality among workers.

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> Although the framework of routine versus nonroutine tasks did a very effective job of describing tasks suitable for the last wave of automation…, simply extrapolating past trends will be misleading, and a new framework is needed. - Brynjolfsson and Mitchell (2017, Science)

I. Introduction

Amid the new waves of technological changes in robotics and artificial intelligence (AI), a growing body of studies has emerged to understand the potential ramifications of production automation on labor market outcomes. They generally predict that modern automation technologies may negatively affect the related labor demand through displacement effects: new automation technologies enable capital to perform tasks previously accomplished by labor (Acemoglu and Restrepo, 2018a, 2020, 2022). However, the adoption of new technology can also have an opposing effect on labor demand through two distinct channels. First, technological advances may allow a more efficient reallocation of labor, which increases the productivity of labor and, therefore, its demand in non-automated tasks. This is called the productivity effect. Second, innovation can create new tasks in which human labor has a comparative advantage. This reinstatement effect shifts the task contents of production in favor of labor (see e.g., Acemoglu and Restrepo, 2019).

These counterbalancing effects notwithstanding, low-skill labor is regarded as highly vulnerable to technological advances. This is because of the ease in writing rules and algorithms to automate manual and routine tasks, which low-skill labor specializes in. By contrast, it has been considered much more difficult to invent software and/or design machines to automate high-skill labor's work as these involve cognitive and nonroutine tasks. Therefore, low-skill labor has been deemed in a more direct competition with "robots" or capital. This view is in conformity with much of the empirical studies based on data since the 1980s and is considered one of the leading explanations of rising income inequality across skill groups (Acemoglu and Restrepo, 2018a, 2022; Krenz et al., 2021; Auto and Dorn, 2013; Autor, 2014; Graetz and Michaels, 2018; Prettner and Strulik, 2020; Frey and Osborne, 2017).

The recent progress in a branch of computer science, in particular, in the areas of machine learning (ML) and artificial intelligence (AI) shows the potential that the frontier of task automation can be extended to many of cognitive and nonroutine tasks. A notable feature of ML and AI is that they are capable of handling highly nonlinear and nonstandard problems. Moreover, in some applications based on technologies such as deep neural networks (DNNs), reinforcement learning, generative models, and large language models, ML-based software has successfully written algorithms to perform tasks that match or surpass human experts in complex and nontrivial settings. Examples that demonstrate its potential are plentiful, including natural language translation (Google Translation, DeepL), gaming (AlphaZero, MuZero), computational biology (AlphaFold), autonomous driving (Waymo, Tesla), computer programming (GitHub Copilot, GPT-Code-Clippy), microchip design (Google, NVIDIA), legal services (Lawgeex, CS Disco, Lex Machina), and visual arts (Midjourney, DALL-E, OpenArt). Undoubtedly, these emerging technologies in AI/ML-related fields are expanding automation to tasks in cognitive, nonroutine, and even creative fields.

In view of such evidence, the socioeconomic impacts of production automation in the near future may not resemble what we know. Our study aspires to fill the gap in our knowledge on this topic. Similar to most studies in this topic, we build on the Schumpeterian task-based framework in which the production of final goods requires a continuum of tasks and new automation technologies are developed endogenously by profit-seeking innovators. Consistent with our discussion above, we deviate from much of the literature by assuming that it is technologically possible to expand the frontier of production automation to *any existing tasks,* which range from the lowest to the highest skill sectors. Our analysis uncovers a novel prediction; in such a milieu, AI/ML-based task automation will be prioritized in a sector where the wage rate is higher, the market size is larger, capital productivity is higher, and the bargaining power of the technology producer is greater. Typically, skill level and wage rates are positively related. Therefore, this result indicates that, unlike the previous generations of automation, other things equal, AI/ML-based automation may also hurt the workers in high-skill sectors. This result is intuitive. The innovator's optimality condition requires that the value of marginal innovation must be equalized across all task sectors. Since the price of unit innovation depends positively on the aforementioned factors, the result follows.[1] Furthermore, the incentive compatibility condition of task producers, and the first order condition of the innovator imply that advancements in automation technologies may stop in the lowest-paying task sectors. Essentially, task producers do not want to adopt automation technologies even if it is technologically feasible when the use of labor is cheaper than the capital. This incentive, in turn, lowers the value of marginal automation and slows down innovation in this task sector.

But we do not predict that high-skill labor will be the only victim of the AI/ML automation. Our results suggest that automation can also progress in low-skill sectors. This advancement would be especially relevant when the size of the task

[1] By incorporating an additional assumption capturing the traits of conventional innovation technologies, our model can be easily extended to replicate the results of conventional literature that high-skill automation is more difficult. We abstract from this important realism because our focus is to understand the economic implications of removing technological restrictions in the R&D sector through the introduction of AI/ML technologies.

market is large. For instance, the hospitality industry accounts for a big portion of labor demand in many developed countries. This increases incentives for the innovator and related task producers to automate these tasks.

Our results contrast with the literature discussed in this section. Leveraging the experience from past waves of automation technologies, the bulk of existing studies essentially build on a set of technologies under which high-skilled workers have a comparative advantage in high-skill tasks and "robots" are better at low-skill tasks. This assumption is consistent with the characteristics of past R&D technologies whereby automation requires manually designed hardware and software to perform every aspect of a task. Therefore, the automation of repetitive and manual tasks has been perceived as easier than that of nonrepetitive and cognitive tasks. A natural complementarity emerges between high-skilled labor and robots, whereas low-skill labor and robots become substitutes.

Reflecting the characteristics of the new waves of automation technologies, we deviate from the literature in two ways. First, we assume that new R&D technologies expand the automation possibility set to include all existing task sectors. A growing body of research supports the view that AI/ML technologies are likely to be the next general-purpose technology (GPT). As discussed above, advances in AI/ML technologies have already successfully automated writing software for many applications, even for tasks where the explicit algorithms are unknown to human researchers. Second, we differentiate each task into subtasks depending on the context and environment in which they are performed. While human workers possessing relevant skills can perform all subtasks that belong to the task, a robot views each subtask as distinct. Thus, the automation of each subtask requires new robot/software. This assumption is motivated by a notable characteristic of workhorse AI/ML techniques: a subtle change in the problem typically requires an entirely new learning process. Automation software can excel at the task it was trained for but often fails at another task that looks very similar to humans.[2] This contrasts with human learning, where ones' existing knowledge of a task accelerates their learning of similar tasks. In this setting, our theory predicts that the direction and scope of automation can be actively expanded in a high-skill and/or large sector. Thus, the new wave of automation may not only affect blue-collar jobs but also white-collar workers and certain experts and professional jobs that require highly cognitive and creative skills.

Our study also offers a novel insight on income inequality. In our framework, incremental automation, the obsolescence of existing tasks, and the creation of new tasks are determined endogenously by Schumpeterian innovators. Our analysis suggests that an increase in the productivity of automation R&D can lower income

[2] This phenomenon is dubbed as catastrophic forgetting in the ML literature. See section 2 for more detailed explanations.

inequality in the long run. This is because fast automation increases the opportunity cost of other types of R&D, namely, the creation of new tasks and the destruction of old ones. Therefore, each task has a longer economic lifespan, and a large proportion of them are fully automated before they retire, leaving only a handful of high-skill sectors available for humans. In a stationary equilibrium, all workers adjust and are employed in the narrow skills of available jobs, contributing to a decrease in income inequality among workers.

II. Related Literature

The literature on technological advancement and its labor market impacts is vast and its exhaustive survey is beyond the scope of this study. This review section aims to restrict its focus to key studies surrounding this area. Much of the debates seek to understand whether or not technological substitution by "robots" would ultimately render human labor redundant. Acemoglu and Restrepo (2018a) provide a comprehensive theoretical analysis of this topic. Building on the task-based production economy, they demonstrate that the effect of technological progress can be decomposed into three parts. An advance in labor-saving technologies suppresses the demand for labor and wages in the affected sector, which they call *the (negative) displacement effect*. At the same time, this process improves the productivity of the overall economy because the process essentially entails the substitution of cheaper capital for expensive labor. This is referred to as *the (positive) productivity effect*. The creation of a new variety of tasks may increase labor demand if the new variety improves the economy's productivity. More important, human labor may have a competitive edge over capital in the production of newly created tasks until the related automation technology is developed, often dubbed as *the (positive) reinstatement effect*. They characterize the technical conditions in which the displacement effect dominates the productivity and reinstatement effect and examine the implications of their theory on income inequality, which Acemoglu and Restrepo (2018b) further investigate. See also Acemoglu and Restrepo (2019) and Prettner and Strulik (2020).

Empirical studies document evidence broadly in line with this theoretical framework. They report that a higher exposure to automation technologies such as computers and robots tend to suppress employment and wages, suggesting that the so-called displacement effect dominates (Autor et al., 2003; Autor and Dorn, 2013; Graetz and Michaels, 2018; Blanas et al., 2019; Bessen et al., 2019; Acemoglu and Restrepo, 2020; Krenz et al., 2021; Dauth et al., 2021; Acemoglu and Restrepo, 2022). They generally agree that its negative impact has been disproportionate in tasks based on codifiable explicit rules while favoring workers in nonroutine tasks. This is accepted as a leading explanation for the rise in income inequality.

Massive progress in computer science and machine learning in recent years, however, poses a serious challenge to whether it would remain a valid theory in the age of artificial intelligence. Its applications, such as generative AI services (e.g., ChatGPT, Gemini, DALL·E), have generated hype by demonstrating impressive potentials in various tasks, such as writing a new bedtime short story for kids, helping with computer coding, translating foreign languages, summarizing discussions, and drawing artistic paintings, just to name a few. Academics and practitioners are actively seeking its further applications, which include medicine (Google Health, Neuralink, Hanover Project), chemical engineering (GNoME), and semiconductor design (Synopsis.ai). According to the literature surveyed in this section, these are typically classified as nonroutine cognitive tasks and deemed safe and complementary with automation.

To the best of our knowledge, few attempts have been made to offer a comprehensive micro-founded theoretical framework which analyzes and predicts the impact of AI-like R&D technologies as we define in this study. Our approach is closely related to a series of contributions made by Acemoglu and Restrepo surveyed in this section. They rely on a technical restriction that new automation replaces low-skilled tasks before they can move on to high-skilled ones. This assumption has been taken with little doubt because of its intuitive appeal and perceived wisdom that new technologies are substitutes for low-skilled workers. It is consistent with the conventional theoretical framework of comparing repetitive vs. nonrepetitive, and manual vs. cognitive tasks (e.g., Frey and Osborne, 2017; Acemoglu and Autor, 2011). It has also been successful in providing accounts for historical automation experiences (Acemoglu and Restrepo, 2020, 2022; Dauth et al., 2021; Krenz et al., 2021; Blanas et al., 2019; Autor et al., 2003).

Drawing on insights from recent studies concerning AIs (e.g., Brynjolfsson and Mitchell, 2017; Brynjolfsson et al., 2018; Goldfarb et al., 2023), we depart from this restrictive assumption. We hypothesize that AI is a general-purpose R&D technology, which can be applied to develop substitute for any human task. We further differentiate each task in terms of the degree to which it is automated. This allows us to characterize the general equilibrium economy in the face of such a transformative technology, analyze its labor market impacts, and predict its direction.

Our analysis reveals that, with the emergence of AI-like general-purpose technologies, Schumpeterian innovation will likely prioritize automation in high-skill tasks because it is more cost-effective. This idea goes as far back as Hicks (1932, as cited in Aghion and Howitt, 2008). In fact, the entire economics discipline builds on such incentives. However, this possibility has been largely overlooked in debates in the economics literature concerning technological changes and labor.

Despite their long history in computer science, the practical applications of deep learning and ML have become available only recently. Yet there are already a few empirical studies favoring our theoretical predictions. Using Dutch administrative microdata from 2000 to 2016, Bessen et al. (2019) show that the probability of leaving a job after automation is larger for high-wage workers. Vom Lehn (2018) also documents evidence that the accelerated decline in labor share since 2000 comes largely from the automation of routine components of high-skill tasks. Using Korean firm-level data, Lee and Park (2023) find that the introduction of new technologies in the fields of AI, data, network, and virtual/augmented reality has suppressed the wages of high-skilled workers disproportionately. Kwon and Yi (2020) report similar findings, noting that high-skill groups with low routine intensity lost employment most in Korea amid the recent wave of automation. These are closely aligned with our theory. We expect more empirical evidence to emerge as new relevant data become available.

We also contribute to the ongoing debate on the implications of the "race against the machine" on income inequality. The dominant view is that automation is likely to increase income inequality (see e.g., Prettner and Strulik, 2020) because it displaces low-skilled workers disproportionately. Our analysis offers nuanced counterpoints. First, when GPT-like technologies lift conventional barriers in R&D, innovators are inclined to prioritize the automation of high-skill tasks, which would place more downward pressure on high-skill wages in the short run. Second, wage distribution and income inequality depend crucially on the interplay of the automation of existing tasks and the creation of new ones. In our framework, rapid automation is accompanied by a slow obsolescence of existing tasks. This can lead to the full automation of old, low-skill tasks, potentially leaving only high-skill jobs for humans. In stationary equilibrium, workers adapt to the new labor market conditions, thereby reducing income inequality. It remains for academic and policy makers to understand how this transition can be achieved with minimal pain and disruption.

The rest of the paper is organized as follows. Section 3 presents our theoretical framework. Section 4 describes the model's equilibrium. Section 5 offers the analysis. Finally, section 6 concludes with remarks.

III. The Model

3.1. Final Goods Producers

Final goods producers combine the continuum of individual tasks $y(i)$ to produce the final goods Y using the constant elasticity of substitution (CES) technology as follows (Zeira, 1998):

$$Y = \left(\int_{n-1}^{n} y(i)^{\frac{\sigma-1}{\sigma}} \mathrm{d}i \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where $\sigma \in (1,\infty)$ denotes the elasticity of substitution between tasks, and n refers to the index of the latest task. Following Acemoglu and Restrepo (2018a), we assume that a new task at n replaces the lowest task at $n-1$ immediately, which is reflected in the limit of integration. This means the mass of available tasks always remains one.

Final goods are traded in a perfectly competitive market. The demand for individual task is derived from the standard cost minimization problem below:

$$\min_{\{y(i)\}} \int p(i) y(i) di \tag{2}$$

subject to eq. (1) where $p(i)$ signifies the price of task i. The corresponding task demand schedule is given by:

$$y(i) = p(i)^{-\sigma} \cdot Y \tag{3}$$

where the price of the final goods is normalized to unity as the numeraire of this economy.

3.2. Tasks and Subtasks

a. Subtask producers' problem

A task indicates a specific work activity required in the production of final goods. Each task consists of subtasks differentiated by the context and the environment they are executed. While all subtasks in a task are regarded homogenous to human workers, i.e., perfect substitutes, they are deemed distinct to robots or automation software. For instance, an autonomous delivery truck primarily operating within a busy city cannot successfully run on the software developed for an autonomous interstate-highway truck.

This modelling assumption reflects one of the prominent features of deep neural networks (DNNs) and the related variants, which are workhorse techniques in cutting-edge ML research. AI models trained for one subject tend to forget what they already learned when they are trained for a similar task sequentially.[3] This

[3] With the risk of oversimplification, the DNN approach can be seen as a gradient descent, a nonlinear numerical optimization technique which many computational economists are familiar with. A DNN-based AI model attempts to find a local minimum of its loss function based on a complex

contrasts with the learning process of humans, whereby the understanding of one topic helps learning in the related subjects. Our approach is also consistent with a survey-based measure which indicates that there exists a substantial variation of machine learnability within a task (Brynjolfsson et al., 2018). This finding necessitates a finer categorization of each task according to its susceptibility to automation.

Formally, within each task, there exists a continuum of subtask j in the unit interval, $[0,1]$. To produce a task, a task producer must combine relevant subtasks using the production technology shown below:

$$y(i) = \left(\int_0^1 x(i,j)^{\frac{\rho-1}{\rho}} dj \right)^{\frac{\rho}{\rho-1}} \tag{4}$$

where $x(i,j)$ signifies the quantity of subtask j used to produce task i. The parameter ρ indicates the elasticity of substitution between subtasks. Without loss of generality, the indices for subtasks are rearranged so that a higher value of j is associated with a subtask that is more difficult to automate. Regarding the possible range of ρ, we make the following assumption.

ASSUMPTION 1. (Elasticity of substitution: tasks vs. subtasks) $\sigma \le \rho$.

Conventional task-based approaches such as Acemoglu and Restrepo (2018a) essentially treat every subtask within a task homogenous, thereby, making an implicit assumption that $\rho = \infty$. Assumption 1 is our generalization which reflects heterogeneity in automation susceptibility within a task (i.e., subtask).

Regardless of the availability of the automation technology, each subtask can always be produced by labor based on the production technology given below:

$$x(i,j) = \gamma(i) L(i,j) \tag{5}$$

where $L(i,j)$ denotes the raw labor hours used for the production of subtask

nonlinear model consisting of many hidden layers, by adjusting the numerous parameters which discipline the activation functions. Once the model is successfully trained for one task and sequentially retrained for another task, the model forgets how to solve the first task, even if the two tasks look similar to humans. In the literature, this is called catastrophic forgetting (Kirkpatrick et al., 2017). Some suggest that this is, in part, a manifestation of the curse of dimensionality. In an extremely high-dimensional space over which ML models are optimized, the ratio between the distance between the two nearest points and farthest points approaches to one. This may reflect the difficulty for an AI-model to distinguish between similar and different tasks due to the perceived high-dimensionality of the problem (Domingos, 2012).

$x(i,j)$, and $\gamma(i)$ is the (average) productivity associated with $L(i,j)$. Furthermore, workers are homogenous within each task sector.[4] Taken together, $\gamma(i)L(i,j)$ signifies the *effective man-hours* required to produce $x(i,j)$. Following the literature, we sort i so that $\gamma(i)$ is non-decreasing.

Let $a(i)$ denote the automation technology available to task producer i. It allows the substitution of labor for capital for any subtask $j \in [0, a(i)]$. One unit of capital in sector i is equivalent to $\phi(i) > 0$ units of human labor. To summarize, the subtask production technology can be fully characterized by $a(i)$ as below:

$$x(i,j) = \begin{cases} \gamma(i)L(i,j) & \text{if } j > a(i) \\ \gamma(i)[L(i,j) + \phi(i)K(i,j)] & \text{otherwise} \end{cases} \tag{6}$$

where $K(i,j)$ represent the amounts of capital used to produce $x(i,j)$. The production technology in eq. (6) implies that $\phi(i)$ denotes the capital productivity relative to labor in task sector i.

The markets for subtasks and factors of production are perfectly competitive. Subtask producers take the rental rate of capital, R, and the wage rate of labor possessing skill i, denoted by $w(i)$, as given.[5] Therefore, given the frontier automation technology $a(i)$, the optimal production of subtasks can be described entirely by the cost minimization rule as provided below:

$$x(i,j) = \begin{cases} \gamma(i)L(i,j) & \text{if } \quad j > a(i) \\ \gamma(i)\phi(i)K(i,j) & \text{if } \quad j \le a(i),\ w(i)/(R/\phi(i)) \ge 1 \\ \gamma(i)L(i,j) & \text{if } \quad j \le a(i),\ w(i)/(R/\phi(i)) < 1 \end{cases} \tag{7}$$

To understand this result, consider a subtask $j > a(i)$ where automation is technologically infeasible under the current technological frontier. Its production can only be achieved by labor regardless of the relative wage (line 1 of eq. 7). By contrast, subtasks $j < a(i)$ can be potentially produced either by capital or labor. When the wage rate for skill i is greater than the *task-specific effective rental rate* $R(i) \equiv R/\phi(i)$, the use of the capital-only technology is optimal as it minimizes the production costs (line 2). If $w(i) < R/\phi(i)$, then the use of the labor-only technology minimizes the production costs even if the related automation technology is available (line 3).

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[4] We start by analyzing the short-run version of an economy in which workers cannot leave their initial task sector.

[5] By the definitions of the task and subtask, a worker capable of performing a subtask $x(i,j)$ within a task sector i can do any other subtask within the same task sector with the same productivity $\gamma(i)$ (See eq. (6)). Hence, the wage rate must equalize across all subtasks in each task sector to prevent wage arbitrage.

b. Task producer's problem

For each task sector, there is one task producer who is the sole platform operator in the task sector and a monopolistic competitor against platform operators in other task sectors. The state-of-the-art technology from the previous generation becomes the generic technology and is available freely to all people in the economy.[6] Hence the status of task monopoly requires exclusive access to the state-of-the-art automation technology, which ensures cost advantages against potential entrants armed with the generic technology. As a simplification, we further assume that the monopoly is given to a random person in the economy when the existing task monopoly fails to maintain its technological superiority by adopting new cutting-edge technologies. The task producer makes the state-of-the-art technology available to subtask producers, which forms the basis of the production technology shown in eq. (6). In return, subtask producers make an exclusive contract with the task producer. Without loss of generality, we assume this contract is strictly enforceable.[7]

The cost function of a task producer is obtained by solving the cost minimization problem shown below:

$$\min_{\{x(i,j)\}_j} \int p(i,j)x(i,j)dj \tag{8}$$

subject to eqs. (4) and (7). Based on eq. (7) and the market structure, the price of subtask, $p(i,j)$ is

$$p(i,j) = \begin{cases} w(i)/\gamma(i) & \text{if } \; j > a(i) \\ R/(\phi(i)\gamma(i)) & \text{otherwise.} \end{cases} \tag{9}$$

Subtask indexed by $j > a(i)$ must be produced by the labor-only technologies as the relevant automation technology is currently unavailable. The corresponding marginal cost is $w(i)/\gamma(i)$. Similarly, for $j \le a(i)$, automation is technologically feasible. When the capital-only technology is used, the unit production cost is $R/(\phi(i)\gamma(i))$.[8] Since the subtask markets are perfectly competitive, subtask prices

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[6] Although our model is essentially static, this part resembles an element of dynamic models typical to Schumpeterian growth models. Accordingly, the equilibrium in our model can be considered a steady state in a dynamic model.

[7] If such a contract is not enforceable, instead of outsourcing the production of subtasks, task producers can set up their own divisions to produce subtasks internally. Since factor markets are perfectly competitive, the optimality condition concerning the production of subtasks shown in eq. (7) is unaffected.

[8] There exists another possibility of $j \le a(i)$ and $R/\phi(i) > w(i)$ where only labor is used despite

compensate exactly the marginal production costs as shown in eq. (9). This result allows us to simplify and rewrite the task production function (4) as follows:

$$y(i)=\gamma(i)\left(\Gamma_K(i)K(i)^{\frac{\rho-1}{\rho}}+\Gamma_L(i)L(i)^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}} \tag{10}$$

where $\Gamma_K(i)=a(i)^{1/\rho}\phi(i)^{\frac{\rho-1}{\rho}}$ and $\Gamma_L(i)=(1-a(i))^{1/\rho}$ and

$$L(i)=\int L(i,j)dj \quad \text{and} \quad K(i)=\int K(i,j)dj. \tag{11}$$

Eq. (10) represents the task production as a standard CES function of capital and task-specific labor. The parameter ρ has the interpretation of not only the elasticity among subtasks as in eq. (4) but also the elasticity of substitution between capital and labor. In this equation, $\Gamma_K(i)$ and $\Gamma_L(i)$ represent the relative importance of capital and labor, respectively, in the production of task i.

Based on eq. (10), the cost minimization problem of a task producer simplifies to the standard optimization with two input factors shown below:

$$\min_{\{L(i),K(i)\}} c(i)=RK(i)+w(i)L(i). \tag{12}$$

The related first-order necessary conditions can be summarized by

$$\frac{w(i)}{R}=\left[\frac{1-a(i)}{a(i)\phi(i)^{\rho-1}}\right]^{\frac{1}{\rho}}\left[\frac{K(i)}{L(i)}\right]^{\frac{1}{\rho}}. \tag{13}$$

Given eqs. (10) and (13), we can define the marginal cost, $\kappa(i)$, of producing task i as follows:

$$\kappa(i)=\kappa_K(i)R+\kappa_L(i)w(i) \tag{14}$$

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the availability of the automation technology to produce this subtask. However, such a situation is difficult to sustain in the market equilibrium in the long run. The subtask producers in this sector will behave as if the production automation technologies are unavailable, which creates an oversupply of such technologies. This, in turn, suspends innovation in this sector as the innovator finds it unprofitable to invent new state-of-the-art technology for them. Furthermore, workers may also migrate into other skill sectors with higher wages, thereby reducing the labor supply and driving up the wage. The key implications of our model remain unaffected even when the economy has a nontrivial measure of skill sectors that correspond to the last case in eq. (7). For the sake of simplicity, we focus on the first two cases in eq. (7) to analyze the economy, which yields eq. (9).

where

$$\kappa_K(i) = a(i)\left[\frac{\gamma(i)}{\phi(i)}\right]^{\rho-1}\left[\frac{\kappa(i)}{R}\right]^{\rho} \quad \text{and} \quad \kappa_L(i) = [1-a(i)]\gamma(i)^{\rho-1}\left[\frac{\kappa(i)}{w(i)}\right]^{\rho}. \tag{15}$$

Utilizing eqs. (14)-(15), we can simplify the task-specific marginal cost function, $\kappa(i)$, as follows:

$$\kappa(i) = \kappa_{\varnothing}(i) / \gamma(i) \tag{16}$$

The variable $\kappa_{\varnothing}(i)$ denotes the cost of hiring a "hybrid factor" consisting of capital and labor, of which shares are determined endogenously by the level of the state-of-the-art technology $a(i)$, and is defined as below:

$$\kappa_{\varnothing}(i) = [a(i)\phi(i)^{\rho-1}R^{1-\rho} + (1-a(i))w(i)^{1-\rho}]^{1/(1-\rho)} \tag{17}$$

The corresponding cost function of task i is given by:

$$c_i(y(i)) = \kappa(i)y(i) \tag{18}$$

Applying Shephard's lemma, the Hicksian demand functions for capital and labor in task sector i are given, respectively, by:

$$K(i) = \kappa_K(i)y(i) \text{ and } L(i) = \kappa_L(i)y(i). \tag{19}$$

From eq. (19), we can derive the capital–labor ratio as below:

$$\frac{K(i)}{L(i)} = \frac{\kappa_K(i)}{\kappa_L(i)} = \left[\frac{w(i)}{R}\right]^{\rho}\frac{a(i)\phi(i)^{\rho-1}}{1-a(i)}.$$

Given the demand function (3) and the cost function (18), task producer i can set up the profit maximization problem as follows:

$$\max_{\{y(i)\}} \quad \pi(i) = \underbrace{[y(i)/Y]^{-\frac{1}{\sigma}}}_{p(i)} y(i) - \underbrace{\kappa(i)y(i)}_{c_i(y(i))}. \tag{20}$$

Based on the first-order condition, the profit-maximizing output $y(i)$ can be written as:

$$y(i) = (\mu\kappa(i))^{-\sigma} Y \tag{21}$$

and the optimal price is given by

$$p(i) = \mu\kappa(i) \tag{22}$$

where $\mu = \sigma/(\sigma-1) > 0$ represents the gross markup over the marginal cost $\kappa(i)$. Using eqs. (20)–(22), we get the maximized profit of task producer given by:

$$\pi(i) = (\mu-1)\kappa(i)y(i). \tag{23}$$

3.3. R&D sector

Two R&D sectors exist in the economy. The first type involves the incremental automation of a task, which we call *process innovation*. The second type involves the creation of new tasks, which we call *task innovation*.

a. Task innovation

Task innovation requires the R&D time of scientists as its sole input. Let N and ζ denote the mass of new tasks and the number of scientists hired for it, respectively. The production technology is given by

$$N = h(\zeta)$$

where $h \geq 0, h' > 0$, and $h'' \leq 0$. Note that $n = n_0 + N$ where n_0 signifies the last period's state-of-the-art task. To facilitate our analysis, we make the following assumptions.

ASSUMPTION 2A. (New task's initial automation) Upon its entry, a new task comes with the identical initial automation level, $a_m \geq 0$.

ASSUMPTION 2B. (New task's productivity) Each task which made its first appearance at time t has the common task-specific productivity $\gamma_t = e^{At}$ for $A > 0$.

Assumption 2B implies that parameter A can be interpreted as the growth rate of task productivity per period. With Assumption 2, the flow profit for each of new monopoly is as follows:

$$\pi_{m,t} = (\mu-1)\kappa_{m,t} y_{m,t} \tag{24}$$

where $\kappa_{m,t}$ and $y_{m,t}$ are, respectively, the task-specific marginal cost and output at $a(i)=a_m$ and $\gamma(i)=\gamma_t$. Therefore, the flow profit in task innovation is

$$h(\zeta)\pi_{m,t}-w_R\zeta\ .$$

This leads to the interior optimality condition shown below:

$$h'(\zeta)\pi_{m,t}=w_R \tag{25}$$

The left-hand side represents the value of marginal product in the task R&D sector, and the right-hand side shows the marginal cost of hiring a scientist. This is often referred to as the R&D arbitrage condition.

b. Innovation of automation technology

A representative process innovator develops and sells state-of-the-art automation technologies to task producers. The invention of a new state-of-the-art automation technology requires scientists' time and the existing frontier technology. The production function for the automation technology takes the following form:[9]

$$a(i)=a_i^0+g(\eta_i) \tag{26}$$

where $a_i^0\geq 0$ denotes the initial frontier technology level of the previous generation, and η_i is the R&D time of scientists for task sector i's process innovation. This means that the initial technology is common knowledge and freely available to use in R&D. Figure 1 illustrates the environment. We assume that $g_i(0)=0$, and for $z\geq 0$, $g_i(z)\geq 0$, $g_i'(z)>0$, and $g_i''(z)\leq 0$. With these assumptions, we can express the innovation time function based on eq. (26) as follows:

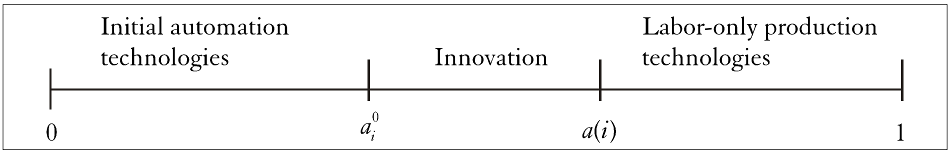
$$\eta_i=\eta(a(i)-a_i^0) \tag{27}$$

where $\eta(z)\equiv g^{-1}(z)\geq 0$ is defined for $z\geq 0$. Our restriction concerning the domain of $\eta(\cdot)$ signifies that the innovator cannot destroy existing technology to create time. The assumptions regarding $g(z)$ implies $\eta(0)=0$, $\eta'>0$, and

[9] In practice, capital is also likely to be a crucial input for innovation whereby the optimal capital intensity differs across task sectors. Our technology production function can be extended to account for heterogeneity in capital requirements, which will enrich our model. By assuming this away, however, our baseline setting can attribute the innovation ultimately to the nonreproducible factor, namely, the innovator's time. Thus, the proper interpretation of our model's results involves the usual caveat of "all else being equal."

$\eta'' \geq 0$.

[Figure 1] Status of automation technologies and innovation



We assume that the innovator and each task producer engage in a Nash bargaining over the total surplus of the task producer $\pi(i)$, where the innovator offers a take-it-or-leave-it deal with a share of $1-B(i)$ proposed to the task producer.[10] The parameter $B(i) \in (0,1]$ reflects the bargaining power of the innovator, which is influenced by various factors such as legal systems, institutions, and government policies.

For simplicity, we assume that the process innovation can start one period after its introduction. Thus, for each $i \in [n-1, n-N]$, the process innovator solves their profit maximization problem as below:

$$\max_{a(i)} B(i)\pi(i) - w_R \eta(a(i) - a_i^0) \tag{28}$$

subject to eq. (23). This contract design forces the innovator to maximize the profits of the task producer. As a result, the process innovation enhances the value-added of task sectors.

To analyze the optimal behavior of the process innovator, let $q(i)$ denote the marginal revenue of innovation of automation technology regarding task i. Considering eqs. (16)–(18) and (28), we can derive $q(i)$, which consists of two components as below:

$$q(i) = B(i)\frac{\partial \pi(i)}{\partial a(i)} = B(i)\left[\underbrace{(\mu-1)\frac{\partial \kappa(i)}{\partial a(i)}y(i)}_{\text{(-)ve markup effect}} + \underbrace{(\mu-1)\kappa(i)\frac{\partial y(i)}{\partial a(i)}}_{\text{(+)ve scale effect}}\right]. \tag{29}$$

Eq. (29) shows that the marginal revenue of innovation consists of two parts. The markup effect reflects the changes in profits of the task producer through the markup. The introduction of new automation technologies, which involves

[10] As discussed in the task producer's problem, task producers face a threat of entries by potential competitors who possess the generic technology. In the absence of a new cutting-edge technology, the incumbents will lose their monopoly. Therefore, accepting the take-it-or-leave-it offer of the innovator weakly dominates the alternative of rejecting it.

replacing more expensive labor with cheaper capital, lowers the marginal cost. Since the task producers charge a fixed net markup $(\mu - 1)$ over their marginal costs, the markup effect is negative. The scale effect captures the effect of automation on demand for the task, which is positive. Although the sign of $q(i)$ appears ambiguous in eq. (29), section 4 demonstrates that $q(i)$ is positive as long as $w(i)/[R\phi(i)] > 1$. This is also the incentive compatibility condition to further automation because, in this case, labor is more expensive than capital.

The first-order necessary condition for the interior optimality of the innovator is given by

$$q(i) = w_R \frac{\partial \eta_i}{\partial a(i)}, \text{ for all } i \in [n-1, n] \tag{30}$$

where w_R signifies the wage rate for scientists.[11]

The supply of total scientists is fixed at η, which is allocated between process and task innovation. Accordingly, the labor market clearing of the R&D sector is given by the following:

$$\eta = \int_{n-1}^{n-N} \eta_i di + \zeta . \tag{31}$$

IV. Market Equilibrium

4.1. Subtask Market

With perfectly competitive markets, the equilibrium prices for subtasks just compensate for the marginal production costs. Given the linear technology and the market structure, subtask prices are the expression shown in eq. (9). This result indicates that the prices of subtasks are influenced by the skill-specific wages, rental rate, and task sector-specific productivity of labor and capital.

The cost-minimizing demand for subtask based on eq. (4) is:

$$x(i, j) = p(i, j)^{-\rho} y(i) . \tag{32}$$

4.2. Task Market

Task producers act as platform operators in monopolistically competitive markets.

[11] Implicitly, we also have Kuhn-Tucker conditions ensuring $\eta_i \geq 0$ and $a(i) \leq 1$.

Eqs. (21)–(22) demonstrate that the quantity and price of individual tasks are determined by the marginal costs defined in eqs. (16)-(17). These costs are influenced by factor prices $\{w(i), R\}$, the task-specific state-of-the-art technology $a(i)$, measures of factor productivity, and elasticity of substitution ρ.

4.3. Labor Market

In the short run, workers cannot change their task sectors. Therefore, the distribution of $\{L^s(i)\}$ is given exogenously. Task-specific labor demand $L(i)$ is obtained by using eqs. (15) and (19):

$$L(i) = [1 - a(i)]\left(\frac{\kappa(i)}{w(i)/\gamma(i)}\right)^{\rho} \frac{y(i)}{\gamma(i)} \tag{33}$$

This expression has three parts. The first component $1 - a(i)$ represents the fraction of unautomated tasks. The second component $(\frac{\kappa(i)}{w(i)/\gamma(i)})^{\rho}$ captures the ratio of marginal cost and the productivity-adjusted task-specific wage. The third part $y(i)/\gamma(i)$ represents the demand for task i relative to labor productivity.

Differentiated labor is supplied inelastically to each task sector, and the equilibrium in the task-specific labor market satisfies the market clearing condition:

$$L^s(i) = L(i) \text{ for all } i \tag{34}$$

where $L^s(i)$ denotes the labor supply for task i. The equilibrium conditions eqs. (33)–(34) implicitly determine $w(i)$ in the short run.

In the long run, workers can freely migrate to different task sectors. To rule out wage-arbitrage across sectors, one unit of effective man-hour must yield the same wage regardless of the task sector, hence, the equation below must be satisfied in the long run:

$$w = w(i)/\gamma(i) = w(j)/\gamma(j) \quad \text{for all } i \text{ and } j. \tag{35}$$

To understand this, note that in order to earn $w(i)$, one must supply $\gamma(i)$ units of effective man-hours (see eq. (5)); thus, one unit of effective labor supplied to task sector i earns $w(i)/\gamma(i)$. Eq. (35) is analogous to Acemoglu and Restropo (2018b). This extra equation together with eq. (33) pins down the distribution of $\{L^s(i)\}$ across different task sectors in the long run, where $\{L(i)\}$ must sum up to the endowed total man-hours as follows:

$$\int_{n-1}^{n} \gamma(i)L(i)\mathrm{d}i = L. \tag{36}$$

The quantity L signifies the total endowment of effective man-hours in the economy.

V. Analysis of the Model

5.1. Task Producers

To close the model and perform analysis, we assume that the supply of capital is perfectly elastic at R.[12] To understand the impact of technological innovation on task producers, we take automation technology and the relative price of factors as exogenously given to task producers and perform comparative static analysis. Using the marginal cost $\kappa(i)$ shown in eq. (16), we can derive the following result:

$$\frac{\partial \kappa(i)}{\partial a(i)} = \frac{1}{\gamma(i)} \frac{1}{\rho - 1} \left(\frac{R}{\phi(i)} \right) \kappa_{\varnothing}(i)^{\rho} \left\{ \left[\frac{w(i)}{R / \phi(i)} \right]^{1-\rho} - 1 \right\} \tag{37}$$

Therefore, in general, the sign of $\partial \kappa(i) / \partial a(i)$ depends on that of $w(i)/(R/\phi(i)) - 1$ as shown below:

$$\frac{\partial \kappa(i)}{\partial a(i)} \lesseqgtr 0 \text{ iff } \frac{w(i)}{R/\phi(i)} \gtreqless 1 . \tag{38}$$

Eq. (38) suggests that the introduction of incremental automation technology to a task sector reduces the marginal cost of producing its task if and only if the task-specific wage rate exceeds the effective rental rate adjusted for capital productivity.

5.2. Direction and Scope of Innovation

a. Process innovation

As a prerequisite, we first examine the sign of the marginal revenue of innovation $q(i)$. Using eqs. (21, (23), and (29), we obtain

[12] By this assumption, we abstract from the explicit modeling of household and the capital market. This approach may be interpreted as a partial equilibrium analysis. Alternatively, it aligns with an open capital market in an otherwise closed small economy. This simplification greatly enhances the clarity of our exposition without compromising the key insights of the model. The authors express their gratitude to an anonymous referee who pointed this out.

$$q(i) = B(i)\frac{d\pi(i)}{da(i)} = -B(i)\frac{\pi(i)}{\kappa(i)}(\sigma-1)\frac{\partial\kappa(i)}{\partial a(i)} \tag{39}$$

Therefore, from eq. (38) and $\sigma > 1$, it follows that

$$q(i) \gtreqless 0 \quad \text{iff} \quad \frac{w(i)}{R/\phi(i)} \gtreqless 1. \tag{40}$$

Eq. (40) shows that the marginal revenue of advancing a task-specific automation technology is positive if and only if the task-specific wage is larger than the related effective rental rate. It is unsurprising that this is also the incentive compatibility condition for the task producer to adopt the new automation technologies.

Having characterized the impact of new automation on $q(i)$, we can now investigate the direction and scope of automation. To this aim, we take arbitrary tasks j and k with $q(j), q(k) > 0$, and use eq. (30) to obtain the following expression:

$$\frac{q(j)}{q(k)} = \frac{\partial\eta_j / \partial a(j)}{\partial\eta_k / \partial a(k)}. \tag{41}$$

The left-hand side of eq. (41) represents the relative marginal benefits of automation R&D in sectors j and k. The right-hand side reflects the marginal rate of technical substitution between the two.

We further expand eq. (41) based on eqs. (23) and (39) as below:

$$\frac{q(j)}{q(k)} = \underbrace{\frac{B(j)}{B(k)}}_{\substack{\text{bargaining}\\ \text{power}}} \underbrace{\frac{y(j)}{y(k)}}_{\substack{\text{rel.}\\ \text{mkt size}}} \underbrace{\frac{\partial\kappa(j)/\partial a(j)}{\partial\kappa(k)/\partial a(k)}}_{\substack{\text{rel. savings}\\ \text{on mg costs}}} = \frac{\partial\eta(a(j)-a_j^0)/\partial a(j)}{\partial\eta(a(k)-a_k^0)/\partial a(k)}. \tag{42}$$

This shows that the progress of task automation $a(j)-a_j^0$ increases with $B(j)$, $y(j)$, and $|\partial\kappa(j)/\partial a(j)|$[13] due to the convexity of research time function η.

LEMMA 1. *(Direction and scope of automation)* All other things being equal, in the presence of general-purpose automation technologies, automation is faster in a task sector with larger values of

[13] Here, we compare two task sectors in which $w(i) > R/\phi(i)$ for $i = j,k$; hence, $\partial\kappa(i)/\partial a(i) < 0$. Otherwise, the incentive compatibility condition of the task producer is violated, and $q(i) < 0$, leading to the corner solution of $a(i) - a_i^0 = 0$.

(a) $w(i)$,
(b) $\phi(i)$,
(c) market size $y(i)$, and/or
(d) bargaining power of innovator $B(i)$.

To understand Lemma 1, observe that the marginal benefit of automation per output $|\partial\kappa(i)/\partial a(i)|$, increases with the task-specific wage rate $w(i)$ and capital productivity $\phi(i)$ as shown in eq. (38). To measure the total value-added of innovation, this must be multiplied by the market size, $y(i)$. Finally, the bargaining power captures the innovator's share of value-added.

b. Creation of new tasks

Since the new task makes the oldest variety obsolete, the size of new tasks N is also a measure of technological obsolescence in our economy. To understand its determinants, we can use task innovator's optimality condition in eq. (25). It suggests that the creation of new tasks is faster when scientist's wage, w_R is lower, and/or the flow profit of new task monopoly is larger. But w_R is proportional to the marginal productivity of alternative R&D, namely, automation research (eq. (30)). Considering eqs. (21)–(22), the flow profit decreases with the marginal cost, κ_m. Therefore, it increases with a_m, ϕ_m and γ_m and decreases with $w(i)$ and R. The results are summarized below.

LEMMA 2. (*Size of new tasks & rate of task obsolescence*) The creation of new tasks is faster when
(a) scientist's wage, w_R is lower, and/or
(b) the flow profit of new task monopoly is larger.

Our discussion suggests that various scenarios may emerge. For instance when the creation of new tasks is slow, many different vintages of tasks can co-exist. In an extreme case, it may be possible that most subtasks are automated before they are replaced by a new task. By contrast, when N is large and technological obsolescence takes place faster, full automation may not happen even at the end of the task's life.

5.3. Short-run Labor Market

We now investigate how the adoption of new automation technology affects factor prices in the short-run labor market where workers cannot migrate to different task sectors. Since $a(i)$ is an endogenous variable, our exercise in this section can be considered as the impact of a higher $a(i)$ sparked by, for instance, an idiosyncratic improvement in sector-specific parameters such as $\gamma(i)$ while holding the quantity and prices of other sectors constant.

The elasticity of task-specific wage rate with respect to the own automation penetration rate is given as follows:

$$\varepsilon_{w(i),a(i)} \propto \underbrace{-\frac{1}{1-a(i)}}_{\substack{\text{(-)ve direct} \\ \text{displacement} \\ \text{effect}}} \underbrace{+\frac{\rho}{\kappa(i)}\frac{\partial \kappa(i)}{\partial a(i)}}_{\substack{\text{(-)ve indirect} \\ \text{displacement} \\ \text{effect}}} \underbrace{+\frac{1}{Y}\frac{\partial Y}{\partial a(i)}}_{\substack{\text{(+)ve direct} \\ \text{scale effect}}} \underbrace{-\frac{\sigma}{\kappa(i)}\frac{\partial \kappa(i)}{\partial a(i)}}_{\substack{\text{(+)ve indirect} \\ \text{scale effect}}}. \tag{43}$$

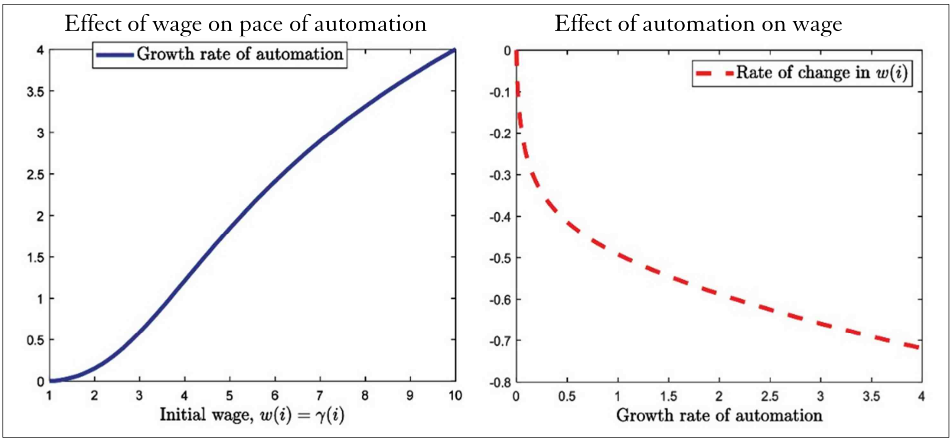
This result suggests that the effect of task-specific automation on the related wage rate can be decomposed into four parts. A brief discussion is in order. The displacement effects signify the replacement of labor for capital in the production of subtasks due to incremental task automation. Progress in the task-specific automation reduces the share of unautomated subtasks. This is the direct displacement effect. The indirect displacement effect reflects the shift in subtask contents of a task – automation of a subtask reduces its price compared to the unautomated subtasks. Otherwise, subtask producers would not automate their production even if it is feasible. This mechanism reduces the skill-specific labor demand and the wage associated with it. This is why the indirect displacement effect is proportional to the elasticity of substitution between subtasks ρ.

The scale effects refer to the automation's effect on labor demand through task demand. Sector-specific automation improves the production of the sector's tasks, which improves GDP. This is the direct scale effect. As the penetration of task automation $a(i)$ expands, it reduces its price, which in turn increases its demand. The indirect scale effect reflects this channel. Hence, this is proportional to the elasticity of substitution between tasks σ. It turns out that the direct scale effect is found to be $\delta(i)$ times the indirect scale effect, where $\delta(i)=[y(i)/Y]^{1/\mu}$. As an individual sector is infinitesimally small relative to the economy, the magnitude of $\delta(i)$ is tiny. Therefore, the sign of short-run elasticity $\varepsilon_{w(i),a(i)}$ in practice is negative. See Appendix B for details.

Figure 2 depicts the interplay between wage and automation. In Panel A, we plot the relationship between initial wage and the pace of automation as derived from eq. (42). Consistent with Lemma 1(a), automation progresses more rapidly when the initial wage is larger. In Panel B, we present the impact of sector-specific automation on wage changes based on eq. (43). To illustrate the most conservative case, we choose $\rho=\sigma=2$, where the positive impact of the scale effect is maximized. Even under these conditions, we find an inverse relationship between the pace of automation and wage changes. Taken together, these findings suggest that the impact of automation could be more pronounced in high-skill sectors when the conventional restriction on R&D is lifted.

Note that these observations are based on a partial equilibrium analysis, which does not account for the creation of new tasks and market forces that serve to equilibrate markets across task sectors and R&D types. The next section examines the general equilibrium in a stationary economy.

[Figure 2] Interplay of wage and automation, partial equilibrium



Note: To facilitate comparisons, we control for initial conditions. In Panel A, the initial automation level is held fixed. In Panel B, the initial wage is held constant. For initial wages, we impose $w(i) = \gamma(i)$, which is consistent with the no-wage arbitrage condition in eq. (35).

5.4. Stationary Equilibrium

To understand the long-run implications of our model, we restrict our analysis to a symmetric stationary equilibrium in which the distribution of $\{a(i)\}_{i\in[n-1,n]}$ and N is invariant. To this aim, we modify the interpretation of Assumption 2B as below:

ASSUMPTION 2B' (Task productivity) $\gamma_s = e^{As}$, $s = 0,1,2,\ldots,G$ with G being the latest vintage.

In addition, we make the following assumptions to ensure symmetric and stationary equilibrium.

ASSUMPTION 3 (Symmetric and stationary parameters) The distributions of task-specific bargaining power and capital productivity depend on the vintage only, rendering $\{B_s\}$ and $\{\phi_s\}$. Furthermore, the automation level of the new task is time invariant $a_{m,t} = a_m$.

With the danger of abusing notation, the subscript s denotes the vintage from this point forward. This does not mean that varieties belonging to the same vintage are treated as a single entity with a large mass. We maintain the structure of the economy in which each firm is infinitesimally small. In a symmetric stationary equilibrium, however, firms within the same vintage make identical decisions. Therefore, suffice it to index them by their vintages.

Furthermore, we detrend the output of each sector by final goods Y, i.e., $y_s^* = y_s / Y$, so that all variables become stationary, thereby facilitating cross-section comparison. In this case, γ_s can be viewed as the detrended productivity of vintage s. Now we are ready to characterize the stationary equilibrium.

LEMMA 3. (Stationary equilibria) In a stationary equilibrium, $\pi_{m,\tau} / w_R$ and w / R are constant.

In view of eq. (25) and the structure of the economy, it becomes evident that $\pi_{m,\tau} / w_R$ assures a constant mass of each task vintage. Moreover, eqs. (16), (17), (21), (23), and (28) imply that a constant value of w / R, along with Assumptions 2B'-3, guarantees the stationarity of the distributions of $\{y_s\}$ and $\{a_s\}$. Our numerical procedure leverages Lemma 3 for the computation of simulation results.

In a stationary equilibrium, there exists only $G = \lfloor 1/\tilde{N} \rfloor$ vintages of tasks in the economy, where $\tilde{N}$ denotes the value of the mass of new tasks in the stationary equilibrium, and $\lfloor x \rfloor$ represents the floor of x, signifying the largest integer less than or equal to x. In this case, the mass of each vintage is $\tilde{N}$ for $s = 1, 2, \ldots, G$, and the oldest vintage $(s = 0)$ has the mass of $1 - \tilde{N}G$. When $1/\tilde{N}$ is an integer, the mass of the vintage with $s = 0$ becomes zero. To simplify the presentation, without loss of intuition, we focus on the latter case where $\tilde{N}G = 1$. Nevertheless, the reported numerical analysis formally reflects the mass of the oldest vintage. Appendix C provides a full characterization of the stationary equilibrium.

a. Long-run labor demand

The adoption of automation technologies alters relative wage rates across task sectors, creating opportunities for wage-arbitrage. In the long run, workers are free to relocate to seek the highest return for their labor supply. To rule out wage-arbitrage, eq. (36) must be satisfied. As a result, the distribution of effective labor supply across task sectors is determined by the following condition (see Appendix A for its derivation):

$$\frac{\gamma_s L_s}{\gamma_t L_t} = \frac{1 - a_s}{1 - a_t} \left[\frac{\kappa_s}{\kappa_t} \right]^{\rho - \sigma}. \tag{44}$$

LEMMA 4. (*Long-run distribution of labor*) All else being equal, the number of task-specific workers in an efficiency unit is eventually

(a) decreasing (increasing) with the automation penetrate ratio in the own (other) sector and

(b) non-decreasing (non-increasing) with the marginal costs of the own (other) task.

The result in part (a) is intuitive. The implication in (b) may appear surprising. It reflects a combination of two effects. With a higher marginal cost in sector s, the task price rises. This, in turn, substitutes s for less expensive tasks, reducing labor demand in sector s. This is captured by $\kappa_s^{-\sigma}$ where σ is the elasticity of substitution between tasks in the production of final goods. However, κ_s^{ρ} increases labor demand. The marginal cost in sector s, κ_s, is large because its subtasks are produced with more labor. Thus, the elasticity between subtasks ρ appears as well. Ultimately, the net effect of marginal cost on long-run labor supply is non-negative because $\rho \geq \sigma$.

b. Long-run Wage

What are the implications of automation on wages in a stationary equilibrium? Applying Assumptions 2B' and 3, the stationary equilibrium version of the labor market clearing condition in eq. (36) can be expressed as

$$\tilde{N}\sum_{s=1}^{G}\gamma_s L_s = L$$

This condition can be further reduced to the following:

$$\tilde{N}\sum_{s=1}^{G}(1-a_s)\kappa_s^{\rho-\sigma} = w^{\rho}\mu^{\sigma}L \tag{45}$$

See eq. (A3) in Appendix C for the general case with $\tilde{N}G \neq 1$. Note that the task-specific wage can be recovered by the no-wage-arbitrage condition in eq. (35), namely, $w_s = \gamma_s w$. Thus, eq. (45) implicitly determines the relationship among automation, the creation of new tasks, and wage in the stationary long-run equilibrium. Before diving into numerical exercises, we first present some analytical observations about their relationship. First, the size of new tasks $\tilde{N}$ boosts overall wage w. Second, the mass of automated subtasks a_s has negative effects on both the wage in the own sector and in all other sectors in the long run. Finally, as automation reduces marginal costs κ_s, it suppresses w further. To summarize, the effect of task automation and the creation of new tasks on wage work in the opposite directions.

5.5. Numerical Simulation and Discussion

To better understand the stationary equilibria of our model, we perform numerical analysis. Appendix D provides the details regarding its procedure, functional forms, and benchmark parameters. Our investigation focuses on the interplay of automation, creation of new tasks, wages, and employment across different task vintages.

Figure 3 presents the baseline results. In Panel A, the level of automation $\{a_s\}$ and its growth rate across vintages are illustrated. Consistent with Lemma 1, automation R&D is disproportionately directed toward the latest varieties, resulting in the highest growth rate. This is because the latest tasks come with the highest productivity, and thus the wage is also high. Interestingly, the level of automation exhibits an inverse pattern. Specifically, despite its slower growth rate, the older vintages are exposed to more task automation. This appears contradictory to our partial equilibrium analysis depicted in Figure 2. This is because the static partial equilibrium plot is based on the parameterization by which the initial automation levels are set identical across all tasks. By contrast, Figure 3A explicitly takes into account the dynamic structure of the stationary economy whereby each task is introduced with the minimal automation level, and the additional automation level accumulates endogenously over time. Thus, a stationary distribution of $\{a_s\}$ requires that a_s is higher for an older vintage.

Panel B illustrates the distributions of employment $\{L_s\}$ and wage $\{w_s\}$. It indicates that employment is higher for older task vintages in which the extent of task automation is greater. While initially puzzling, this result can be attributed to two opposing forces that influence task-specific employment L_s. On one hand, as task automation advances, more subtasks are produced with capital. This displacement effect generates a negative relationship between vintage and employment. On the other hand, older task varieties have lower productivity, requiring a greater number of workers for production. Given this trade-off, the shape of $\{L_s\}$ ultimately becomes a quantitative issue.

Figure 4 illustrates the outcomes of an alternative simulation where the productivity of automation R&D is doubled. This question is relevant because AI/ML is often perceived as a catalyst for enhancing R&D productivity with regard to automation. Panel A confirms that Lemma 1's prediction remains valid in this scenario as well, with automation R&D being more active in task sectors with larger productivity.

It also displays a pattern distinct from Figure 3. With increased productivity in automation R&D, the wage of scientists w_R rises. As discussed earlier, this raises the opportunity cost of task innovation and slows down the creation of new tasks $\tilde{N}$. As a result, the pace of technological obsolescence is slower and old tasks stay in the economy longer. Combined with the high productivity of automation R&D

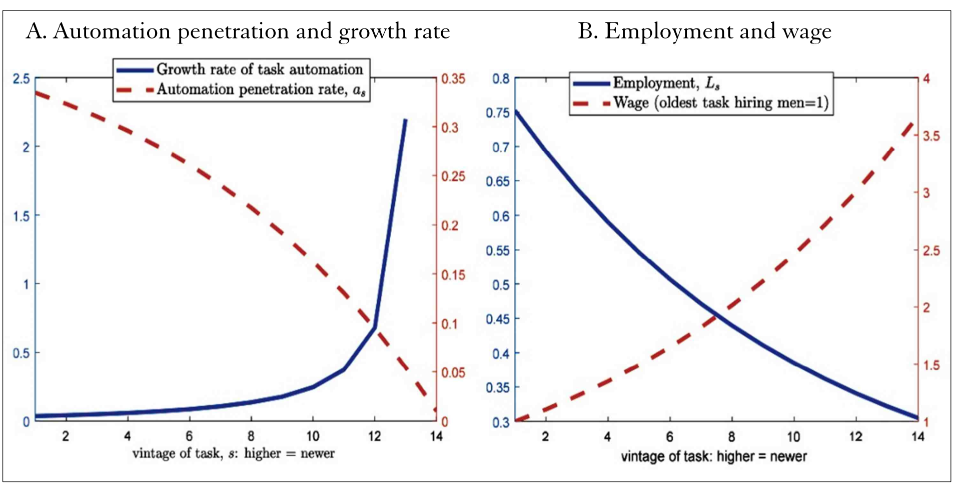
(Figure 4B), old vintages may become fully automated before they retire. Therefore, employment is concentrated in high-skill sectors only.

We conclude this section with a brief discussion on income inequality. In academic and policy debates, automation is often feared due to its potential to widen income inequality. The typical argument is that high-skill sectors are perceived as relatively safe from automation. However, Lemma 1 suggests that this may not necessarily be true. Moreover, our simulation analysis suggests that the interplay of automation and task creation must be carefully considered in this debate.

To make our analysis more concrete, we use two metrics to gauge income inequality. The first one is the ratio of the highest and lowest wages in task sectors that continue to employ workers. The right axis of Figure 3B shows that this metric is slightly below 3.5 times in our benchmark scenario, where automation progress is slow and task creation is fast. In comparison, this ratio is just above 1.2 times in the alternative configuration (Figure 4B), where automation is fast and task creation is slow.

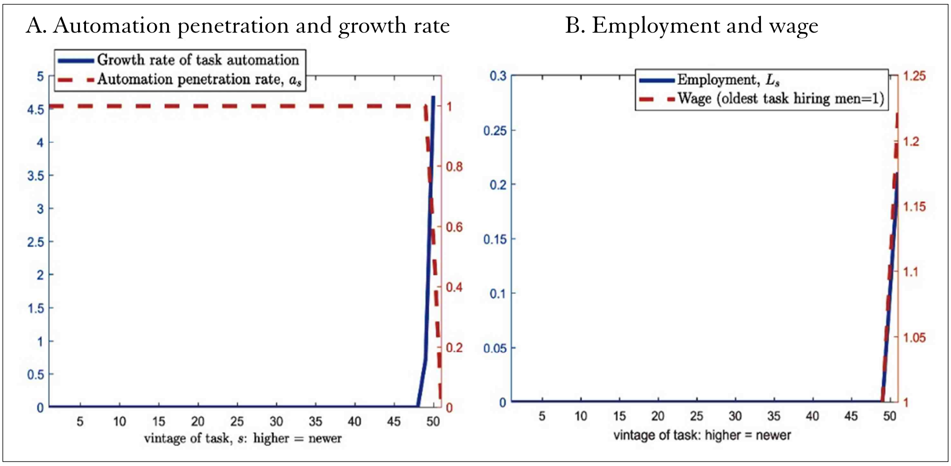
However, this simplistic measure does not account for the number of workers across sectors. To address this issue, we also examine the Gini coefficient. According to this inequality metric, income inequality is significantly worse in the benchmark scenario (0.22) than in the alternative case (0.02). This result is intuitive. Figure 3B (benchmark) shows that workers are hired by all task sectors. By contrast, employment is concentrated in a handful of the most productive sectors in the alternative setting (Figure 4B). Therefore, the weighted inequality as measured by the Gini coefficient becomes more pronounced in the benchmark.

[Figure 3] Numerical simulation: fast task creation, slow automation (benchmark)



Note: See Appendix D for details regarding the simulation.

[Figure 4] Numerical simulation: slow task creation and fast automation



Note: See Appendix D for details regarding the simulation. The only change from Figure 3 is that we set the R&D productivity of automation to $e_1 = 0.030$ from $e_1 = 0.015$.

To summarize, our numerical analysis indicates that the relationship between automation and the wage income inequality among workers depends crucially on the productivity of automation R&D. As this productivity increases, the automation of existing tasks speeds up. This, in turn, increases the opportunity cost of creating new tasks, slowing down the pace of technological obsolescence. In such a milieu, many tasks become fully automated before they become obsolete. As a result, employment is concentrated in the latest variants of tasks, suppressing income inequality among workers.

VI. Concluding remarks

Departing from the conventional assumption that automation must take place sequentially from low-skill to high-skill sectors, we investigate the implications of R&D technology capable of automating a full range of tasks. To facilitate our analysis, we introduce the concept of subtasks within each task and extend a Schumpeterian task-based economic model.

This analysis is particularly relevant in the current landscape marked by the emergence of a new wave of general-purpose technologies (GPTs) such as AI and ML. Contrary to the perceived wisdom in the literature, our findings suggest that the ongoing expansion of automation facilitated by GPT-like R&D technologies may pose a greater threat to high-skill jobs than previously recognized. These include jobs in white-collar and professional domains that rely heavily on creativity and cognitive abilities. However, the predictions of our model extend beyond this.

The new wave of automation may impact not only high-skill jobs but also sectors with a large market size, such as the hospitality and service sectors.

Furthermore, the impact of automation on income inequality is nuanced and multifaceted. A dystopian view often argues that the displacement effect of automation would primarily suppress the wage and employment of low-skilled workers, thereby exacerbating income inequality. However, our study suggests that this issue must be considered with more care. In the short run, AI-driven automation may negatively affect high-skilled workers more seriously. The long-run effect of automation on income inequality depends crucially on the pace of technological obsolescence. When old tasks are rapidly replaced by new ones, automation progresses slowly. In this scenario, income inequality may widen because, in equilibrium, employment spans both in low- and high-skill sectors. When the creation of new tasks is slow, automation accelerates. This results in the full automation of old low-skill tasks. With employment being concentrated in high-skill sectors only, income inequality may be mitigated.

Our study focuses primarily on the short-term or the long-term stationary equilibrium. One limitation is that it does not examine the direct and psychological costs associated with training for labor reallocation across different task sectors nor does it attempt an explicit dynamic analysis. Therefore, we cannot make predictions or policy implications regarding transitions. This topic is left for future research agendas.

Appendix

A. Long-run labor supply across task sectors

Using eqs. (15) and (21), eq. (19) can be re-expressed as below:

$$L(i)=\frac{1-a(i)}{\gamma(i)}\kappa(i)^{\rho-\sigma}\left[\frac{w(i)}{\gamma(i)}\right]^{-\rho}\mu^{-\sigma}Y$$

Taking a ratio of arbitrary j and k task sectors, we have

$$\frac{L(j)}{L(k)}=\frac{1-a(j)}{1-a(k)}\left[\frac{\gamma(j)}{\gamma(k)}\right]^{-1}\left[\frac{\kappa(j)}{\kappa(k)}\right]^{\rho-\sigma}\left[\frac{w(j)/\gamma(j)}{w(k)/\gamma(k)}\right]^{-\rho}$$

In the long run, the wage arbitrage must be ruled out according to Eq. (36). Therefore, the long-run labor supply is pinned down by the following expression:

$$\frac{L(j)}{L(k)}=\frac{1-a(j)}{1-a(k)}\left[\frac{\gamma(j)}{\gamma(k)}\right]^{-1}\left[\frac{\kappa(j)}{\kappa(k)}\right]^{\rho-\sigma}$$

In the text, this expression is presented in terms of vintages. As can be seen from this section, it applies to any two task sectors.

B. Elasticity of wage with respect to task-specific innovation

Given eqs. (15), (19), (21), and (34), the labor market clearing condition is

$$L(i)=\kappa_L(i)y(i)=\frac{1-a(i)}{\gamma(i)}\left[\frac{\gamma(i)\kappa(i)}{w(i)}\right]^{\rho}(\mu\kappa(i))^{-\sigma}Y$$

Taking the total differentiation of the expression above, we have

$$0=\left[-\frac{1}{1-a(i)}+\frac{(\rho-\sigma)}{\kappa(i)}\frac{\partial\kappa(i)}{\partial a(i)}-\rho\frac{1}{w(i)}\frac{\partial w(i)}{\partial a(i)}+\frac{1}{Y}\frac{\partial Y}{\partial a(i)}\right]L^{s}(i)$$

Rearranging this result yields

$$\varepsilon_{w(i),a(i)} = \frac{\partial w(i)}{\partial a(i)}\frac{a(i)}{w(i)} = \frac{a(i)}{\rho}\left[-\frac{1}{1-a(i)} + \frac{(\rho-\sigma)}{\kappa(i)}\frac{\partial \kappa(i)}{\partial a(i)} + \frac{1}{Y}\frac{\partial Y}{\partial a(i)}\right]$$

The above expression is eq. (43) in the text.

The direct scale effect can be expressed as below:

$$\frac{1}{Y}\frac{\partial Y}{\partial a(i)} = -\frac{\sigma}{\kappa(i)}\left[\frac{y(i)}{Y}\right]^{\frac{\sigma-1}{\sigma}}\frac{\partial \kappa(i)}{\partial a(i)}$$

Therefore, the sum of direct and indirect scale effects is

$$\frac{1}{Y}\frac{\partial Y}{\partial a(i)} - \frac{\sigma}{\kappa(i)}\frac{\partial \kappa(i)}{\partial a(i)} = -\frac{\sigma}{\kappa(i)}(1+\delta(i))\frac{\partial \kappa(i)}{\partial a(i)}$$

where $\delta(i) = [\frac{y(i)}{Y}]^{\frac{\sigma-1}{\sigma}}$.

C. Stationary equilibrium

We present the conditions used for our numerical analysis. As discussed in the text, under Assumptions 2B' and 3, the productivity of each vintage is identical. In a symmetric equilibrium, they make identical decisions. Thus, we index each task sector by their vintage. In a stationary equilibrium, w_R / π_m is constant, and so is the mass of newly created tasks $\tilde{N}$ in each period. Therefore, the total number of vintages that coexist is $G = \lfloor 1/N \rfloor$.

To facilitate the analysis, we normalize y_τ and Y by Y, so that they represent detrended quantities. While avoiding excessive notation, we use y_τ for the normalized variable in this section.

The normalized version of the production technology for final goods are

$$1 = \left[(1-\tilde{N}G)y_0^{\frac{\sigma-1}{\sigma}} + \sum_{s=1}^{G}\tilde{N}(y_s)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{A1}$$

(unknowns: y_s, $\tilde{N}$).

To understand this expression, each task sector that belongs to vintage s produces y_s^*. Each vintage, except for the oldest one, has the mass of $\tilde{N}$. This part is represented by the second term in the bracket. Since the total mass of task is always 1, the oldest vintage accounts for the rest, $1-\tilde{N}G$. The first term in the bracket represents this.

The marginal cost is function of w, R, and automation a_s is as follows:

$$\kappa_s = \frac{R}{\gamma_s}\left[a_s\phi_s + (1-a_s)\left(\frac{w\gamma_s}{R}\right)^{1-\rho}\right]^{1/_{1-\rho}} \tag{A2}$$

where $\gamma_s = e^{As}$ (unknowns: $\tilde{N}$, w, a_s).

Wage is determined by the labor market clearing condition:

$$(1-\tilde{N}G)(1-a_0)\kappa_0^{\rho-\sigma} + \tilde{N}\sum_{s=1}^{G}(1-a_s)\kappa_s^{\rho-\sigma} = w^{\rho}\mu^{\sigma}L^* \tag{A3}$$

with the definition of $a_G = a_m$ (unknowns: $\tilde{N}$, a_s).

Using eqs. (21) and (23), the normalized flow profit function of task producers is given by

$$\pi_s^* = (\mu-1)\mu^{-\sigma}\kappa_s^{1-\sigma} \tag{A4}$$

The optimal automation is satisfied for $s = 0,1,2,\ldots G-1$:

$$B\frac{\partial \pi_s}{\partial a_s} = B(1-\sigma)(\mu-1)\mu^{-\sigma}\kappa_s^{-\sigma}\frac{\partial \kappa_s}{\partial a_s} = w_R\frac{\partial \eta_s}{\partial a_s} \tag{A5}$$

(unknowns: $\tilde{N}$, w_R).

The R&D arbitrage requires the following conditions to hold:

$$\frac{\partial N}{\partial \zeta} = h'(\zeta)\pi_m = w_R \tag{A6}$$

(unknowns: $\tilde{N}$).

Finally, the labor market clearing of R&D scientists is

$$\eta = (1-\tilde{N}(G-1))\eta_0 + \tilde{N}\sum_{s=1}^{G-1}\eta_s + \zeta \tag{A7}$$

Here the oldest vintage accounts for the mass of $1-\tilde{N}(G-1)$ because no automation R&D is performed on the latest vintage. Additionally, observe that ζ is the scientist's time used to create the newest task.

D. Numerical Analysis

a. Algorithm and solution strategies

To implement our simulation exercises based on the stationary equilibrium conditions described in the previous appendix, we use the inner- and outer-loops strategy.

(i) We start by an initial conjecture about the distribution of $\{a_{s0}\}$ and (N_0, w_0, w_{R0}), where the zero subscript represents that they are the initial values used for numerical optimization.

(ii) In the inner loops, we solve for (N, w, w_R) using the market equilibrium conditions (A1), (A3), and (A7) and the conjecture of $\{a_{s0}\}$. Since the optimization procedure cannot manage variable input size, we fix $G_0 = \lfloor 1/N_0 \rfloor$ if G concerns the size of the matrix. If it is about the multiplicative coefficient as in $1-NG$ (the size of the oldest variety), we can safely use the proper definition $G = \lfloor 1/N \rfloor$. The discrepancy disappears as the optimization routine converges.

(iii) The solution from (ii) is treated as the parameters in the outer loop in which we solve for the distribution of $\{a_s\}$. We leverage the structure of the stationary equilibrium, sequentially solve the FOC of the process innovator from vintage G, and obtain a_G, where the initial automation level is a_m. For vintage $G-1$, a_G is used as the initial automation level, etc.

(iv) Check convergence of the loop. We use the following criteria: (a) w_R / π_m and w/R do not vary much across iterations, and (b) the inner and outer loops have found local solutions given the parameters and respect the bounds of $\{a_s\}$. In particular, we ensure the solution does not violate $a_s \geq a_s^0$ (otherwise, automation technology is destroyed to create the scientist's time), and $a_s \leq 1$ for all s. If the process finds nonconvergence, it sets $\{a_{s0}\} = \{a_s\}$ and returns to (ii).

b. Functional forms used

We use the following R&D function for automation:

$$a_s = a_s^0 + c\eta_s^{1/2}, c > 0$$

This leads to the related R&D time:

$$\eta_s = \frac{1}{2e_1}(a_s - a_s^0)^2, e_1 > 0$$

For task creation, we use the functional form below:

$$N = h(\zeta) = e_0\zeta$$

c. Parameters

Parameter	Value	Remarks
L	1	Total effective labor endowment, normalization
A	0.1	Productivity growth across vintages
R	0.1	Rental rate of capital
B_s	0.2	Share of innovators
ϕ_s	1	Productivity of task-specific capital
η	$0.1L$	Size of scientists
σ	2	Elasticity of substitution among task varieties
ρ	2	Elasticity of substitution among subtasks. The negative effect of automation on wage is most conservative when $\rho = \sigma$.
a_m	0.01	Initial level of automation upon entry
e_0	1	R&D productivity regarding creation of new tasks
e_1	0.015	R&D productivity regarding automation

Notes: Parameter A is the only source of economic growth in stationary steady state. Thus, $A = 0.1$ means our one period corresponds roughly to five years with 2% growth rate. We set $R = A$ to ensure that the unmodeled distribution of capital does not affect the income inequality. Parameter B is loosely based on the ratio of business R&D to corporate profits in the US (R&D, https://ncses.nsf.gov/pubs/nsf23350 and corporate profits https://www.bea.gov/data/income-saving/corporate-profits both accessed on 3/30/2024). Parameter η is loosely based on STEM majors in age 25+ population in the US (World Bank). Parameters e_0 and e_1 are carefully selected to represent two different scenarios shown in the text. Specifically, $e_1 = 0.015$ is used for Figure 3 and $e_1 = 0.030$ for Figure 4.

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생산자동화와 직업의 미래: 인공지능이 슘페터식 혁신가를 만날 때*

정 용 훈 ** **· 이 성 훈** *** **· 신 종 국** ****

초 록 슘페터식 기술혁신이론을 직무기반의 생산 모형에 접목하여, 본 연구는 연구개발부문에 인공지능기술 도입이 노동시장에 미치는 영향을 분석한다. 여기서 "인공지능"은 모든 부문의 직무 자동화를 실현 가능하게하는 일반목적 연구기술을 통칭하는 것이다. 혁신가는 기존의 다양한 직무를 자동화하거나 새로운 직무를 창조할 수 있다. 그들의 이익 극대화를 감안하면, 직무 자동화는 임금, 시장 크기, 자본 생산성 및 혁신가의 시장 교섭력이 높은 부문에 우선 진행될 것으로 분석되어 고숙련 노동에 상당한 위협이 될 것으로 보인다. 또한, 인공지능 기반의 자동화 기술은 새로운 직무를 창출하는 연구개발의 기회비용을 높이고 기존 직무의 진부화를 감속시켜, 역설적으로, 소득 불균등의 증가를 완화시키는 방향으로 작용할 수 있는 것으로 분석된다.

핵심 주제어: 자동화, 인공지능, 연구개발, 노동시장, 소득불균등

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