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ABSTRACT

How will the emergence of ChatGPT and other forms of artificial intelligence (AI) affect the skill premium? To address this question, we propose a nested constant elasticity of substitution production function that distinguishes among three types of capital: traditional physical capital (machines, assembly lines), industrial robots, and AI. Following the literature, we assume that industrial robots predominantly substitute for low-skill workers, whereas AI mainly helps to perform the tasks of high-skill workers. We show that AI reduces the skill premium as long as it is more substitutable for high-skill workers than low-skill workers are for high-skill workers.

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1. Introduction

In recent decades, industrial robots have become an increasingly important substitute for workers performing relatively routine mechanical tasks in the manufacturing sector. The worldwide stock of operative industrial robots has increased strongly, particularly since the global economic and financial crisis of 2008–2009 (cf. Abeliansky et al., 2020; Prettner and Bloom, 2020; Jurkat et al., 2022). Recent research indicates that this trend has put downward pressure on the wages of low-skill workers, much more so than on the wages of high-skill workers, which often even increased with automation (cf. Acemoglu and Restrepo, 2018b, 2020; Dauth et al., 2021; Cords and Prettner, 2022). These dynamics create upward pressure on the skill premium (cf. Lankisch et al., 2019; Prettner and Strulik, 2020).

With the emergence of ChatGPT in the fall of 2022 and, more generally, with the impressive improvements made in artificial intelligence (AI) recently, the question arises as to how the future evolution of the skill premium will be affected (cf. Acemoglu and Restrepo, 2018a; Autor, 2024; Acemoglu, 2024). This is because, in contrast to industrial robots, AI predominantly substitutes for tasks performed by high-skill workers. For example, AI-based models and devices are increasingly used to diagnose diseases, develop drugs, write reports, code, or simply generate inspiring ideas in fields such as marketing and research and development. Because these tasks are often nonroutine and performed by high-skill workers, AI may put downward pressure on their wages and thereby also on the skill premium. Autor (2024) even argues that AI can help to rebuild the middle class because tasks that are currently predominantly performed by high-skill experts such as medical care by doctors, legal document production by lawyers, or software coding by computer engineers, come within reach of lower-skill individuals aided by the use of AI.

To analyze the effects of AI on the skill premium at the macroeconomic level, we propose a general nested constant elasticity of substitution (CES) production function that distinguishes among three types of capital: traditional physical capital (machines, assembly lines), industrial robots, and AI. Because industrial robots predominantly substitute for low-skill workers and AI predominantly substitutes for high-skill workers, we allow for imperfect substitutability of workers with different skill levels by robots and AI. This allows us to derive a condition under which the emergence of AI would reduce the skill premium.

There are two strands of related economic literature in this area. The first is the literature on skill-biased technological change, which aims to explain the emergence of wage inequality through differential rates of technological progress for low-skill and high-skill workers (cf. Acemoglu, 1998, 2002; Mortensen and Pissarides, 1999; Fadinger and Mayr, 2014). An increase in the relative size of the high-skill workforce implies a larger market size for technologies that augment high-skill labor. This, in turn, raises the incentives to develop technologies suitable for high-skill workers more strongly than the incentives to develop technologies suitable for low-skill workers. However, technological progress rises for both types of labor such that the wages of low-skill and high-skill workers will never decrease due to skill-biased technological change. In our case, however, such a decrease can happen due to a high elasticity of substitution between a cer-tain type of technology (industrial robots or AI) and the type of labor for which it is a good substitute.

The second strand of literature relates to capital-skill complementarity (cf. Krusell et al., 2000; Duffy et al., 2004), which shows how low-skill workers' wages can decrease with the use of capital if capital is more substitutable for low-skill labor than for high-skill labor. In our case, however, we distinguish among three types of capital, which all have a different and intuitive interpretation suggesting different elasticities of substitution with different types of labor. Traditional capital (machines, assembly lines) requires workers for production such that a certain degree of com-plementarity exists between workers and this type of capital. Industrial robots, by contrast, are designed to substitute for manual and low-skill intensive labor such that the substitutability between low-skill workers and industrial robots is higher than between low-skill workers and traditional capital and also higher than between industrial robots and high-skill workers. By contrast, AI is a technology designed to substitute for non-routine and skill-intensive tasks such that it is a better substitute for high-skill workers than traditional physical capital and a better substitute for high-skill workers than for low-skill workers. This intuitively appealing structure allows for a set of rich results regarding the evolution of the skill premium in response to the accumulation of different forms of capital.

Our paper is organized as follows. In Section 2, we propose a production function that includes traditional physical capital in the form of assembly lines and machines; industrial robots that are a comparatively good substitute for low-skill workers; and AI, which is a comparatively good substitute for high-skill workers. We then use this intuitive production structure to derive the wages of low-skill workers, the wages of high-skill workers, and the skill premium analytically. Finally, we derive a condition subject to which the deployment of AI reduces wage inequality. In Section 3, we illustrate our results numerically and we simulate the effects of a contemporaneous rise in the stock of industrial robots and in the stock of AI. In Section 4, we conclude and discuss some promising topics for future research.

2. AI and the skill premium: theoretical considerations

Because automation in the form of industrial robots predominantly affects low-skill workers performing routine mechanical tasks, whereas automation in terms of AI predominantly affects high-skill workers, we develop a nested CES production function to analyze the differential effects of industrial robots and AI on wages. Consider that the aggregate production function is given by

$$Y_t = K_t{}^{\alpha}\left[\beta_3\Big(\beta_1 L_{u,t}{}^{\theta} + (1-\beta_1)P_t{}^{\theta}\Big)^{\frac{\gamma}{\theta}} + (1-\beta_3)\big(\beta_2 L_{s,t}{}^{\varphi} + (1-\beta_2)G_t{}^{\varphi}\big)^{\frac{\gamma}{\varphi}}\right]^{\frac{1-\alpha}{\gamma}}. \tag{1}$$

Here, Y_t is output in period t; β_1, β_2, and β_3 refer to input shares; $L_{u,t}$ is employment of low-skill workers; P_t denotes the stock of operative industrial robots; θ determines the elasticity of substitution between low-skill workers and robots in low-skill intensive production tasks; $L_{s,t}$ denotes employment of high-skill workers; G_t refers to the stock of high-skill-replacing AI; φ determines the elasticity of substitution between high-skill workers and AI in high-skill intensive production tasks; γ determines the elasticity of substitution between low-skill intensive and high-skill intensive production tasks; K_t refers to the traditional physical capital stock (machines, assembly lines); and α is the elasticity of output with respect to traditional capital input. For the attainable values of the parameters, we consider the reasonable range $\alpha, \beta_1, \beta_2, \beta_3, \in (0, 1)$ and $\gamma, \theta, \varphi \in (0, 1]$.[1]

Using this production function,[2] assuming perfect competition, and normalizing the price of final output to unity, allows us to derive the wage rates of low-skill and high-skill workers (w_u and

[1] Hufnagl (2023) analyzes the special case of $\theta = \varphi = 1$.

[2] Steigum (2011), Lankisch et al. (2019), Prettner (2019), Antony and Klarl (2020), Gasteiger and Prettner (2022), and Cords and Prettner (2022) use various production functions that are nested in our general CES production function to analyze the effects of automation on economic growth, wages, the labor income share, and unemployment. However, none of these contributions considers the presence of AI.

w_s, respectively) as the marginal product of the corresponding production factor:

$$\begin{aligned} w_u &= \frac{\partial Y_t}{\partial L_{u,t}} \\ &= (1-\alpha)\beta_1\beta_3 K_t{}^{\alpha} L_{u,t}{}^{\theta-1}\left(\beta_1 L_{u,t}{}^{\theta} + (1-\beta_1)P_t{}^{\theta}\right)^{\frac{\gamma}{\theta}-1} \\ &\times \left[\beta_3\left(\beta_1 L_{u,t}{}^{\theta} + (1-\beta_1)P_t{}^{\theta}\right)^{\frac{\gamma}{\theta}} + (1-\beta_3)\left(\beta_2 L_{s,t}{}^{\varphi} + (1-\beta_2)G_t{}^{\varphi}\right)^{\frac{\gamma}{\varphi}}\right]^{\frac{1-\alpha-\gamma}{\gamma}}, \end{aligned} \tag{2}$$

and

$$\begin{aligned} w_s &= \frac{\partial Y_t}{\partial L_{s,t}} \\ &= (1-\alpha)\beta_2(1-\beta_3) K_t{}^{\alpha}\left(\beta_2 L_{s,t}{}^{\varphi} + (1-\beta_2)G_t{}^{\varphi}\right)^{\frac{\gamma}{\varphi}-1} \\ &\times \left[\beta_3\left(\beta_1 L_{u,t}{}^{\theta} + (1-\beta_1)P_t{}^{\theta}\right)^{\frac{\gamma}{\theta}} + (1-\beta_3)\left(\beta_2 L_{s,t}{}^{\varphi} + (1-\beta_2)G_t{}^{\varphi}\right)^{\frac{\gamma}{\varphi}}\right]^{\frac{1-\alpha-\gamma}{\gamma}}. \end{aligned} \tag{3}$$

Dividing w_s by w_u yields the skill premium, i.e., the factor by which the wages of high-skill workers exceed the wages of low-skill workers:

$$\frac{w_s}{w_u} = \frac{\beta_2(1-\beta_3)}{\beta_1\beta_3} L_{s,t}{}^{\varphi-1} L_{u,t}{}^{1-\theta}\left(\beta_1 L_{u,t}{}^{\theta} + (1-\beta_1)P_t{}^{\theta}\right)^{1-\frac{\gamma}{\theta}} \times \left(\beta_2 L_{s,t}^{\varphi} + (1-\beta_2)G_t{}^{\varphi}\right)^{\frac{\gamma}{\varphi}-1}.$$

The skill premium is an important measure of wage inequality. Its explicit expression allows us to establish the following central and novel result.

Proposition 1. *The growing use of AI, ceteris paribus, reduces wage inequality between high-skill and low-skill workers, as long as AI is more substitutable for high-skill workers than low-skill workers are for high-skill workers.*

Proof. To show this, we compute the derivative of the skill premium with respect to the use of AI as

$$\begin{aligned} \frac{\partial(w_s/w_u)}{\partial G_t} &= \frac{\varphi\beta_2(1-\beta_2)(1-\beta_3)\left(\frac{\gamma}{\varphi}-1\right)}{\beta_1\beta_3} G_t{}^{\varphi-1} L_{s,t}{}^{\varphi-1} L_{u,t}{}^{1-\theta} \\ &\times \left(\beta_1 L_{u,t}{}^{\theta} + (1-\beta_1)P_t{}^{\theta}\right)^{1-\frac{\gamma}{\theta}}\left(\beta_2 L_{s,t}{}^{\varphi} + (1-\beta_2)G_t{}^{\varphi}\right)^{\frac{\gamma}{\varphi}-2}. \end{aligned} \tag{4}$$

Because we assume that $L_{u,t} > 0$, $L_{s,t} > 0$, $P_t > 0$, and $G_t > 0$ hold for any $t \geq 0$, it follows that the sign of $\partial_{G_t}(w_s/w_u)$ is determined by the sign of $\gamma/\varphi - 1$. In particular, w_s/w_u decreases in G_t if and only if $\gamma < \varphi$. ■

The intuition behind this result is that the deployment of AI replaces high-skill workers directly, but it also substitutes for low-skill workers to the extent that high-skill intensive production tasks can substitute for low-skill intensive production tasks according to the CES production structure. As long as substitution between AI and high-skill workers is easier than between low-skill and high-skill workers, the deployment of AI has stronger effects on the wages of high-skill workers than on the wages of low-skill workers. Thus, increasing the use of AI reduces the skill premium. From these results, the following remark follows immediately.

Remark 1. *The use of AI is neutral in its impact on the skill premium if $\gamma/\varphi = 1$, which implies that AI is equally substitutable for high-skill workers and low-skill workers.*

3. AI and the skill premium: numerical illustration

To illustrate the effects of AI on the skill premium, we rely on the parameter values and initial conditions summarized in Table 1 and simulate the evolution of the skill premium for an increase in G_t. We take a conventional value $\alpha = 1/3$ for the elasticity of output with respect to physical capital (cf. Jones, 1995; Acemoglu, 2009), set $\gamma = 1/3$ so that the elasticity of substitution between low-skill and high-skill intensive tasks lies comfortably in the range of plausible values (cf. Acemoglu, 2002, 2009), choose $\theta = 3/4$ to get an elasticity of substitution between low-skill workers and industrial robots in low-skill intensive production tasks of 4, and set $\varphi = 1/2$ so that AI is not as good a substitute for high-skill workers in performing high-skill intensive tasks as industrial robots are for low-skill workers in performing low-skill intensive tasks. The value of K_t is taken from the Federal Reserve Bank of St. Louis (2023) for the year 2019, and the value of P_t is constructed for the same year following Prettner (2023) who relies on data from the International Federation of Robotics (2022) for the number of operative industrial robots and a projection of robot prices based on the data reported by Jurkat et al. (2021, 2022). Finally, we take the employment data for L_u and L_s from the U.S. Bureau of Labor Statistics (2020), assuming that high-skill workers are those with a bachelor's degree or higher, while low-skill workers do not have a university degree.

Table 1: Summary of parameter values and initial levels for the simulation

Parameter	Value	Source / Justification
K	69.0 trillion US$	Federal Reserve Bank of St. Louis (2023)
L_u	98.3 million persons	U.S. Bureau of Labor Statistics (2020)
L_s	58.4 million persons	U.S. Bureau of Labor Statistics (2020)
P	17.3 billion US$	International Federation of Robotics (2022); Jurkat et al. (2021, 2022)
α	1/3	Acemoglu (2009); Jones (1995)
γ	1/3	Acemoglu (2002)
θ	3/4	Jurkat et al. (2022)
φ	1/2	Chosen such that $0 < \varphi < \theta \leq 1$
β_1	0.9	The central result is robust to changes in this parameter
β_2	0.95	The central result is robust to changes in this parameter
β_3	2/3	The central result is robust to changes in this parameter

In Table 2, we show the simulation results for different AI use values as reflected in G_t.[3] In the first row, we assume that AI is not yet used in the production process such that $G_t = 0$. This leads to a skill premium of about 2, i.e., wages of high-skill workers are twice the wages of low-skill workers. Increasing the use of AI reduces the skill premium. In the second row, G_t is half the value of P_t and the skill premium decreases to about 1.7. In the third row, the value of G_t is now the same as the value of P_t so that the skill premium shrinks further to 1.62. Finally, in the last row, we assume that the value of AI has exceeded the value of industrial robots by a factor of two, which causes the skill premium to shrink to 1.52.

Table 2: Skill premium for various levels of AI (G_t)

G_t	w_s/w_u
$G_t = 0$	2.00
$G_t = 0.5 \cdot P_t$	1.70
$G_t = P_t$	1.62
$G_t = 2 \cdot P_t$	1.52

Our numerical illustrations show that, indeed, AI has the potential to reduce the skill premium. However, three cautionary notes are in order. First, the result depends on the difference between

[3] We can observe through Equation (4) that Proposition 1 is invariant to the values of β_1, β_2, and β_3.

φ and γ. If the values of these parameters are close to each other, the skill premium is relatively insensitive to increasing AI. This shows the importance of having reliable estimates of the relevant elasticities of substitution at the aggregate level. Second, G_t would not, in reality, change in isolation. Other variables such as P_t, K_t, and the share of high-skill workers can increase at the same time. If P_t increases in addition to G_t, some of the dampening effect of G_t on the skill premium is offset as we show in the following subsection. Finally, labor-augmenting technological progress could occur, which raises the productivity of both low- and high-skill workers. Such changes would obscure the isolated effect of AI on the skill premium in observable data.

3.1. Varying industrial robot use and the use of AI

To address the case in which we increase both types of capital, industrial robots and AI, we illustrate the complex interplay between AI (G_t) and industrial robots (P_t) for wage outcomes by means of 3-dimensional plots in Figures 1, 2, and 3, capturing the surfaces represented by $w_s(G, P)$, $w_u(G, P)$, and the ratio $w_s/w_u(G, P)$. In these graphs, the red points signify high levels of industrial robot use but a complete absence of AI ($G_t = 0$), while the blue points indicate both high AI use and high industrial robot levels.

For the wages of high-skill workers, as represented by w_s in Figure 1, the graph reveals that the wage is at its peak when AI is at a minimum but the stock of industrial robots is high. An increase in AI use leads to a noticeable decline in w_s, whereas a rise in the use of industrial robots raises the wages of high-skill workers. This underscores the differential impact of different technologies on wages, depending on their substitutability with the corresponding type of labor.

At the other end of the spectrum, the wage rate of low-skill workers, denoted by w_u in Figure 2 tends to be highest in environments with minimal industrial robot use but intensive use of AI. At the red point, indicative of an environment with a high stock of industrial robots but no AI use, low-skill wages are lowest. Yet, there is a silver lining: When AI use and the stock of industrial robots rise in tandem, low-skill workers can witness an increase in their wage rate.

Shifting the focus to the disparity of wages, as represented by the skill premium (the w_s/w_u ratio in Figure 3), the graph paints a vivid picture of the evolving wage dynamics. The skill premium is most pronounced at the red point, where no AI is used but a large stock of industrial robots tips the scale in favor of high-skill workers, amplifying their wage considerably more than those of their low-skill counterparts. But technology also offers a way to narrow this gap. As the

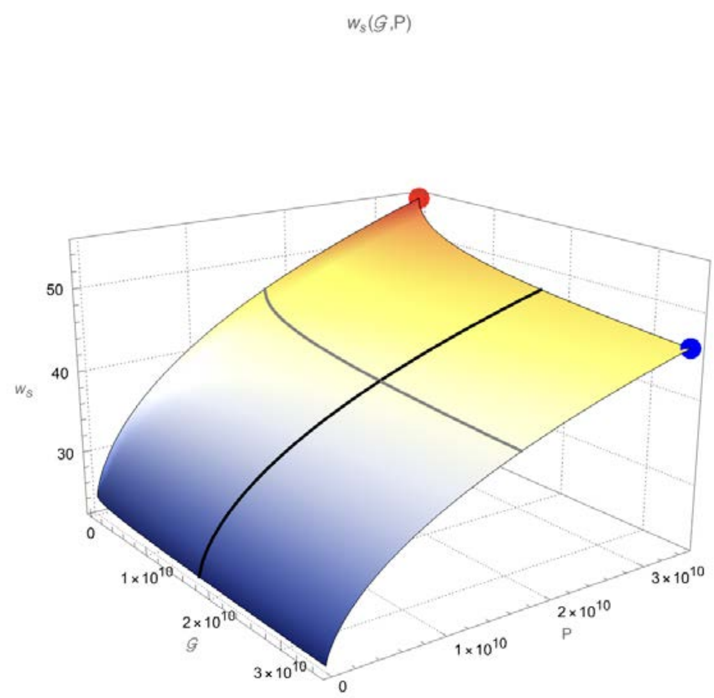

Figure 1: High-skill wages (w_s) for various levels of AI and industrial robots

blue point suggests, when both AI and the stock of industrial robots reach high values, they interact and reduce the high-skill versus low-skill wage disparity.

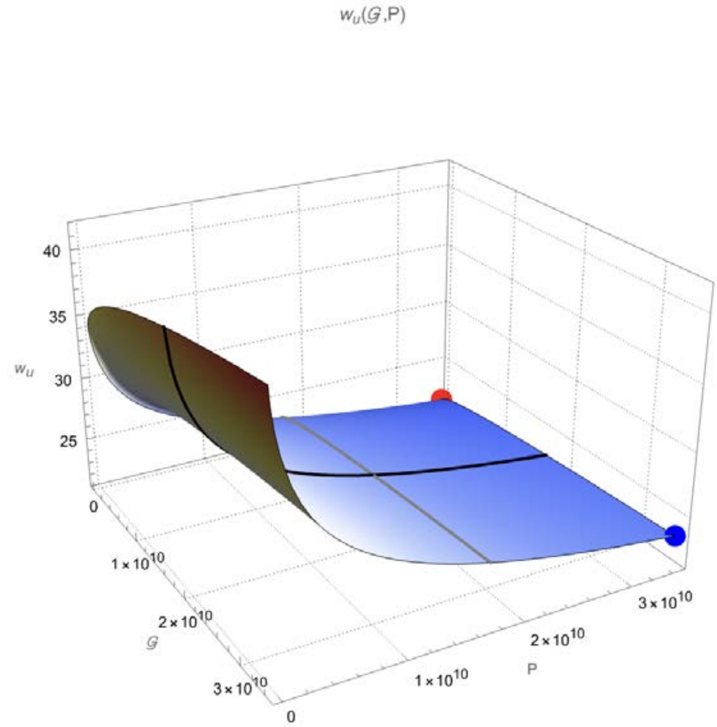

Figure 2: Low-skill wages (w_u) for various levels of AI and industrial robots

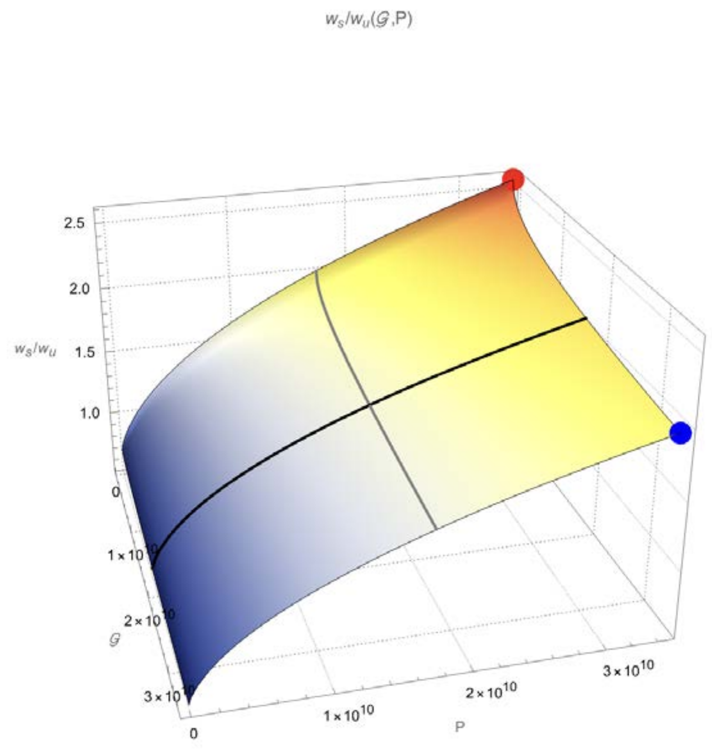

Figure 3: Skill premium (w_s/w_u) for various levels of AI and industrial robots

4. Conclusions

We explore the effects of AI on the skill premium. To this end, we develop a nested CES production function in which industrial robots predominantly substitute for low-skill workers, whereas AI predominantly substitutes for high-skill workers. We show analytically and numerically that AI has the potential to reduce the skill premium and thereby mitigate or even reverse increases in inequality that have been observed in recent decades.

In future research, constructing precise estimates for the relevant elasticities of substitution would be useful for assessing the plausibility of our parameter assumptions. Furthermore, the production structure with robots as low-skill automation and AI as high-skill automation could be introduced into full-fledged general equilibrium models to analyze the effects of AI on economic growth, employment, and welfare (cf. Acemoglu and Restrepo, 2018b; Prettner and Strulik, 2020; Sequeira et al., 2021; Cords and Prettner, 2022; Hemous and Olsen, 2022; Venturini, 2022; Shimizu and Momoda, 2023; Thuemmel, 2023). While doing so is beyond the scope of this paper, such a framework would allow consideration of i) the dynamic effects of the endogenous accumulation of the different capital stocks in the model; ii) an endogenous education decision of whether to stay low-skill or to become high-skill, which would allow for richer dynamics of the skill premium; and iii) the evolution of social welfare subject to different welfare functions from egalitarian (Rawlsian) to utilitarian (Benthamite or Millian).

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