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Artificial intelligence and the skill premium

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ABSTRACT

How will 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.

1. Introduction

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., 2020a; Prettner and Bloom, 2020; Jurkat et al., 2022).[1] 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 created upward pressure on the skill premium (cf. Lankisch et al., 2019; Prettner and Strulik, 2020; Grant and Üngör, 2024).

With the emergence of ChatGPT in the fall of 2022 and, more generally, with the impressive improvements made in artificial intelligence (AI) recently (Igna and Venturini, 2023; Prytkova et al., 2024), the dynamics could move in the opposite direction (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

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[1] This has sparked the development of a strand of literature modeling the effects of automation on economic growth, employment, well-being, offshoring, trade, and inequality. A nonexhaustive list of contributions include Acemoglu and Restrepo (2018b), Prettner (2019), Abeliansky et al. (2020b), Growiec (2019, 2022), Antony and Klarl (2020), Prettner and Strulik (2020), Krenz et al. (2021), Sequeira et al. (2021), Stähler (2021), Guimarães and Mazeda Gil (2022), Hemous and Olsen (2022), Lu (2022), Peralta and Gil (2024), Venturini (2022), Röser et al. (2023), Shimizu and Momoda (2023), Thuemmel (2023), Lu (2024), Grant and Üngör (2024), and Nakamura and Zeira (2024).

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diseases, develop drugs, write reports, code, or simply generate inspiring ideas, e.g., in marketing and research and development. Because these tasks are often nonroutine and performed by high-skill workers, AI may put downward pressure on the wages of high-skill workers and thereby also on the skill premium.

To analyze the corresponding effects of AI formally, 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. We allow for a wide range of different degrees of substitutability between workers with different skill levels on the one hand and robots and AI on the other. This enables us to derive a condition under which the emergence of AI could reduce the skill premium. Afterwards, we illustrate the potential evolution of the skill premium by simulating the framework for such a parameter setting.

There are two strands of related 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 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 in this setting raises the marginal product of labor such that the wages of low-skill and high-skill workers will not decrease due to skill-biased technological change.[2] In our case, by contrast, a decrease in wages is possible in the case of a high elasticity of substitution between a certain 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; Grant and Üngör, 2024), 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. Our contribution extends the analysis by allowing for three conceptually different types of capital, which all intuitively suggest a specific structure for the elasticities of substitution with the different types of labor. Traditional capital (machines, assembly lines) requires workers for production such that a certain degree of complementarity 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 nonroutine 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 rich results regarding the evolution of the skill premium in response to the accumulation of the different forms of capital.

2. AI and the skill premium: theoretical considerations

Because automation in the form of industrial robots predominantly affects low-skill workers performing routine tasks, whereas automation in terms of AI predominantly affects high-skill workers, we propose the following nested CES production function to analyze the differential effects of industrial robots and AI on wages:

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

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 $\gamma, \theta, \varphi \in (0,1]$.[3]

Using this production function,[4] 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 w_s, respectively) as the marginal product of the corresponding production factor:

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

[2] A notable exception is the study by Marczak et al. (2022), who combine skill-biased technological change with endogenous task allocation and equilibrium unemployment that follows from wage setting by labor unions. They show that skill-biased technological change can reduce the wages of low-skill workers under certain conditions.

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

[4] 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.

and

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

Dividing w_s by w_u yields the skill premium, that is, 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

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

Because $L_{u,t} > 0$, $L_{s,t} > 0$, $P_t > 0$, 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

3.1. Parameter values and initial conditions

To illustrate the effects of AI on wage inequality, we simulate the evolution of the skill premium for an increase in G_t. To this end, 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.

3.2. Varying the use of AI

Table 1 shows the simulation results for different AI use values as reflected in G_t.[5] 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.

Our numerical illustrations show that, indeed, AI could reduce the skill premium. However, three cautionary notes are in order. First, the result depends on the difference between φ and γ. If the values of these parameters are close to each other, the skill

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

Table 1
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

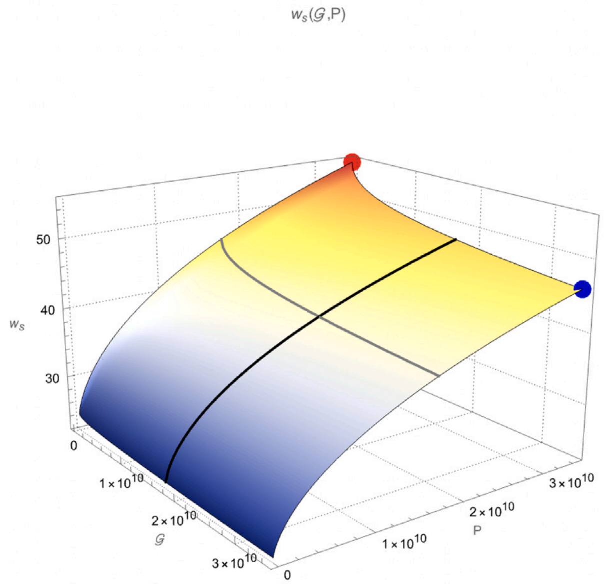

Fig. 1. High-skill wages (w_s) for various levels of AI and industrial robots.

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 the following subsection shows. 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.

3.3. 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 three-dimensional plots in Figs. 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.

Fig. 1 reveals that the wages of high-skill workers, as represented by w_s are at their 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 Fig. 2, tends to be highest in environments with minimal industrial robot use but intensive use of AI. At the red point, which indicates 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 Fig. 3), we observe that 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 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.

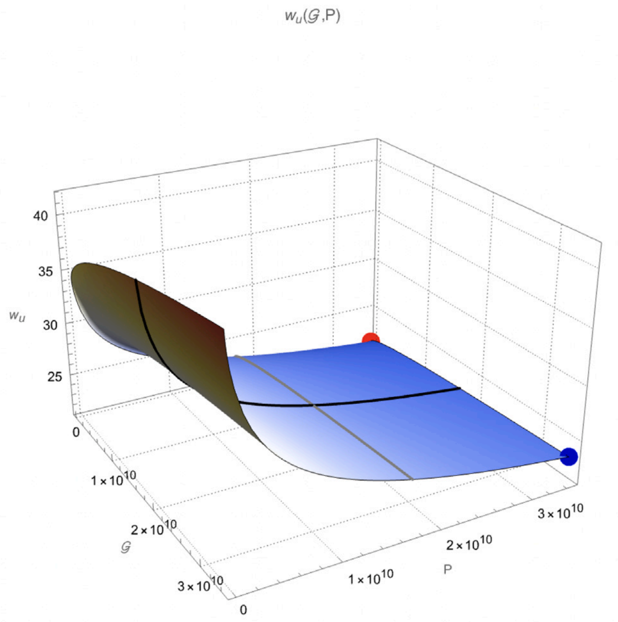

Fig. 2. Low-skill wages (w_u) for various levels of AI and industrial robots.

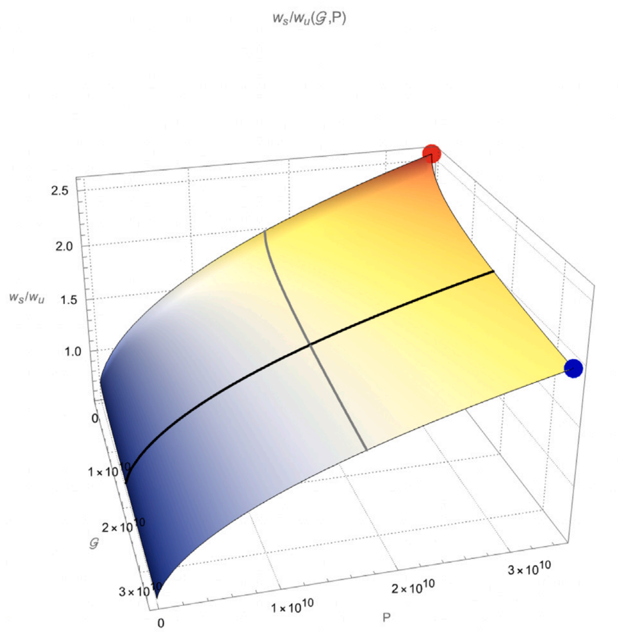

Fig. 3. Skill premium (w_s/w_u) for various levels of AI and industrial robots.

4. Conclusions

To explore the effects of AI on the skill premium, we propose 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 can reduce the skill premium and thereby mitigate or even reverse increases in inequality that have been observed in recent decades.

The production function approach proposed in this paper has a number of limitations. First, we provide a very stylized and aggregate picture that does not do justice to the more nuanced effects that industrial robots and AI have at a disaggregated task-based level. For example, there are low-skill intensive tasks that can be performed by AI and high-skill intensive tasks that can be performed by industrial robots. Thus, we view our approach not as a substitute to a task-based approach but as a complement that focuses more at the aggregate level and the different types of capital. Both approaches would then be able to inform on important aspects at different levels of aggregation, where the share of tasks that can be automated by a certain type of capital would eventually determine the elasticities of substitution at the aggregate level.

Second, our approach is a static, partial-equilibrium analysis and more informative of what may happen to the skill premium in the short run than in the long run. Hence, if anything, the implications for the skill premium derived in the paper will be short-lived. While going beyond the scope of this short paper, introducing the production structure with robots as low-skill automation and AI as high-skill automation into full-fledged general equilibrium models to analyze the effects of AI on economic growth, employment, and welfare (cf. Prettner and Strulik, 2020; Cords and Prettner, 2022; Venturini, 2022) would be a worthwhile topic for future research. 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; (iii) the evolution of social welfare subject to different welfare functions from egalitarian (Rawlsian) to utilitarian (Benthamite or Millian); and (iv) the use of AI in innovation as a determinant of technological progress and economic growth, which would then have feedback effects on the skill premium.

Third, while wage inequality may decrease with AI, our framework is silent on wealth inequality. Since AI models are currently still typically operated by large companies, the prospective income generated through these models would mainly flow to the owners of these firms, which may raise wealth inequality.

Finally, while estimating the effects of AI on wages and inequality is difficult due to issues of measuring the stock of AI, recent advances in constructing exposure indices to emerging digital technologies by Prytkova et al. (2024) could be very useful for empirical work in this area.

CRediT authorship contribution statement

David E. Bloom: Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Klaus Prettner:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization. **Jamel Saadaoui:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization. **Mario Veruete:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

References

Abeliansky, A.L., Algur, E., Bloom, D.E., Prettner, K., 2020a. The future of work: Meeting the global challenges of demographic change and automation. Int. Labour Rev. 159 (3), 285–306.
Abeliansky, A., Martinez-Zarzoso, I., Prettner, K., 2020b. 3D printing, international trade, and FDI. Econ. Model. 85 (2020), 288–306.
Acemoglu, D., 1998. Why do new technologies complement skills? directed technical change and wage inequality. Q. J. Econ. 113, 1055–1090.
Acemoglu, D., 2002. Directed technical change. Rev. Econ. Stud. 69 (4), 781–809.
Acemoglu, D., 2009. Introduction to Modern Economic Growth. Princeton University Press, NJ, USA, Princeton.
Acemoglu, D., 2024. The simple macroeconomics of AI. URL: https://tinyurl.com/dzv4s53. (Accessed on 22 April 2024).
Acemoglu, D., Restrepo, P., 2018a. Low-skill and high-skill automation. J. Hum. Cap. 12 (2), 204–232.
Acemoglu, D., Restrepo, P., 2018b. The race between man and machine: implications of technology for growth, factor shares and employment. Am. Econ. Rev. 108 (6), 1488–1542.
Acemoglu, D., Restrepo, P., 2020. Robots and jobs: Evidence from US labor markets. J. Political Econ. 128 (6), 2188–2244.
Antony, J., Klarl, T., 2020. The implications of automation for economic growth when investment decisions are irreversible. Econom. Lett. 186 (2020), 108757.
Autor, D., 2024. Applying AI to rebuild middle class jobs. NBER Working Paper 32140. https://www.nber.org/papers/w32140. (Accessed on 22 April 2024).
Cords, D., Prettner, K., 2022. Technological unemployment revisited: Automation in a search and matching framework. Oxf. Econ. Pap. 74 (1), 115–135.
Dauth, W., Findeisen, S., Suedekum, J., Woessner, N., 2021. The adjustment of labor markets to robots. J. Eur. Econ. Assoc. 19 (6), 3104–3153.
Duffy, J., Papageorgiou, C., Perez-Sebastian, F., 2004. Capital-skill complementarity? Evidence from a panel of countries. Rev. Econ. Stat. 86 (1), 327–344.
Fadinger, H., Mayr, K., 2014. Skill-biased technological change, unemployment, and brain drain. J. Eur. Econ. Assoc. 12 (2), 397–431.

Gasteiger, E., Prettner, K., 2022. Automation, stagnation, and the implications of a robot tax. Macroecon. Dyn. 26 (1), 218–249.
Grant, R., Üngör, M., 2024. The AI revolution with 21st century skills: Implications for the wage inequality and technical change. Scott. J. Political Econ. 71 (5), 731–765.
Growiec, J., 2019. The hardware-software model: A new conceptual framework of production, R & D, and growth with AI. Working Paper 2019-2042, Warsaw School of Economics.
Growiec, J., 2022. Automation, partial, and full. Macroecon. Dyn. 26 (7), 1731–1755.
Guimarães, L., Mazeda Gil, P., 2022. Explaining the labor share: Automation vs labor market institutions. Labour Econ. 75, 102146.
Hemous, D., Olsen, M., 2022. The rise of the machines: automation, horizontal innovation, and income inequality. Am. Econ. J.: Macroecon. 14 (1), 179–223.
Hufnagl, M., 2023. How will automation with artificial intelligence affect wages and inequality? Bachelor thesis submitted at the vienna university of economics and business.
Igna, I., Venturini, F., 2023. The determinants of AI innovation across European firms. Res. Policy 52 (2), 104661.
Jones, C.I., 1995. R & D-based models of economic growth. J. Political Econ. 103 (4), 759–784.
Jurkat, A., Klump, R., Schneider, F., 2021. Tracking the rise of robots: a survey of the IFR database and its applications. Munich Personal RePEc Archive. https://mpra.ub.uni-muenchen.de/107909/. (Accessed on 19 April 2024).
Jurkat, A., Klump, R., Schneider, F., 2022. Tracking the rise of robots: The IFR database. Jahrb. Für Nationalökonomie Stat. 242 (5–6), 669–689.
Krenz, A., Prettner, K., Strulik, H., 2021. Robots, reshoring, and the lot of low-skilled workers. Eur. Econ. Rev. 136, 103744.
Krusell, P., Ohanian, L.E., Ríos-Rull, J.-V., Violante, G.L., 2000. Capital-skill complementarity and inequality: A macroeconomic analysis. Econometrica 68 (5), 1029–1053.
Lankisch, C., Prettner, K., Prskawetz, A., 2019. How can robots affect wage inequality? Econ. Model. 81 (2019), 161–169.
Lu, C.-H., 2022. Artificial intelligence and human jobs. Macroecon. Dyn. 26 (5), 1162–1201.
Lu, C.-H., 2024. Automation, job reallocation, occupational choice, and related government policy. Macroecon. Dyn. 1–30.
Marczak, M., Beissinger, T., Brall, F., 2022. Technical change, task allocation, and labor unions. IZA Discussion Paper 15632. URL: https://docs.iza.org/dp15632.pdf. (Accessed on 14 July 2024).
Mortensen, D.T., Pissarides, C.A., 1999. Unemployment responses to ‘‘skill-biased’’ technology shocks: The role of labour market policy. Econ. J. 109 (455), 242–265.
Nakamura, H., Zeira, J., 2024. Automation and unemployment: Help is on the way. J. Econ. Growth 29 (2), 215–250.
Peralta, C., Gil, P.M., 2024. Automation, education, and population: Dynamic effects in an OLG growth and fertility model. Journal of Economic Behavior & Organization 234, 107002.
Prettner, K., 2019. A note on the implications of automation for economic growth and the labor share. Macroecon. Dyn. 23 (3), 1294–1301.
Prettner, K., 2023. Stagnant wages in the face of rising labor productivity: The potential role of industrial robots. Financ. Res. Lett. 58, 104687.
Prettner, K., Bloom, D., 2020. Automation and Its Macroeconomic Consequences: Theory, Evidence, and Social Impacts. Academic Press, Amsterdam, NL.
Prettner, K., Strulik, H., 2020. Innovation, automation, and inequality: policy challenges in the race against the machine. J. Monet. Econ. 116 (2020), 249–265.
Prytkova, E., Petit, F., Li, D., Chaturvedi, S., Ciarli, T., 2024. The employment impact of emerging digital technologies. cesifo Working Paper 10955. URL: https://www.fabienpetit.com/wp/cesifo_wp10955.pdf. (Accessed on 14 July 2024).
International Federation of Robotics, 2022. World robotics. Industrial robots and service robots. URL: https://ifr.org/worldrobotics/ . (Accessed on 22 April 2023).
Röser, F., Niemann, S., Angelini, D., 2023. Fiscal policy and human capital in the race against the machine. Available at: https://www.econstor.eu/bitstream/10419/277672/1/vfs-2023-pid-87108.pdf. (Accessed on 17 July 2024).
Sequeira, T.N., Garrido, S., Santos, M., 2021. Robots are not always bad for employment and wages. Int. Econ. 167, 108–119.
Shimizu, R., Momoda, S., 2023. Does automation technology increase wage? J. Macroecon. 77, 103541.
Federal Reserve Bank of St. Louis, 2023. Economic data. Federal Reserve Bank of St. Louis. URL: https://fred.stlouisfed.org. (Accessed on 22 April 2023).
Stähler, N., 2021. The impact of aging and automation on the macroeconomy and inequality. J. Macroecon. 67 (2021), 103278.
Steigum, E., 2011. Robotics and growth. In: de la Grandville, O. (Ed.), Frontiers of Economics and Globalization: Economic Growth and Development. Emerald Group, Bingley, UK, pp. 543–557.
Thuemmel, U., 2023. Optimal taxation of robots. J. Eur. Econ. Assoc. 21 (3), 1154–1190.
U.S. Bureau of Labor Statistics, 2020. Job Market Remains Tight in 2019, as the Unemployment Rate Falls to Its Lowest Level Since 1969. Technical Report, https://www.bls.gov/opub/mlr/2020/article/job-market-remains-tight-in-2019-as-the-unemployment-rate-falls-to-its-lowest-level-since-1969.htm. (Accessed on 25 July 2023).
Venturini, F., 2022. Intelligent technologies and productivity spillovers: evidence from the fourth industrial revolution. J. Econ. Behav. Organ. 194, 220–243.