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How will Artificial Intelligence Affect the Skill Premium?




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Introduction

Over the 1980s and 1990s, less-educated workers in the US saw a decline in their wages relative to those of more educated workers, with little indication of a subsequent rebound (Katz & Murphy, 1992; Levy & Murnane, 1992; Heathcote et al., 2023). There are many potential explanations for such developments and much empirical effort has been devoted to testing and measuring the contribution of various factors, including variations in immigration and trade flows, changes in the relative supply of less- and more-educated workers, changes in union density, a falling minimum real wage, and technological change. The strongest evidence has favored technological change (Acemoglu, 1998, 2002; Krusell et al., 2000; Duffy et al., 2004) with the advent of new technologies (especially automation) in the 1980s and 1990s (1) displacing routine tasks performed by less-educated workers (Autor et al., 2008; Acemoglu & Restrepo, 2018a, 2022; Acemoglu et al., 2023a) or (2) exhibiting a high degree of complementarity with education, resulting in a rise in the demand for (and, thus, the pay of) the more-educated workers (Bound & Johnson, 1992; Cords and Prettner, 2022).

More recently, Artificial Intelligence (AI) has emerged as a new technology (Agrawal et al., 2019; Acemoglu et al., 2023b; Acemoglu, 2024) and some scholars have argued that the AI revolution may lead to even higher levels of earnings inequality (Korinek & Stiglitz, 2019; Grant and Üngör, 2024). However, other analysts have suggested the opposite (Webb, 2019; Autor, 2024). The main argument is that, in contrast to industrial robots, AI predominantly performs tasks usually accomplished by high-skill workers. For example, AI-based models and devices are increasingly used to diagnose diseases, develop drugs, write and translate texts, code, or simply generate inspiring ideas for employees in the creative industry. Since 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 explains how AI can help rebuild the middle class insofar as complicated tasks come within the reach of lower-skill individuals who use AI.

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A new framework to analyze the effects of AI on the skill premium

To analyze the effects of AI on the skill premium at the macroeconomic level, we propose a general description of the aggregate production process in a modern economy that differentiates between low-skill and high-skill workers as well as among three types of productive capital: traditional physical capital (such as machines and assembly lines), automation capital (such as industrial robots), and AI capital (Bloom et al., 2024). We put particular emphasis on the extent to which these capital stocks are substitutes for different types of skills. Traditional physical capital in the form of assembly lines and machines needs to be operated by humans so that there is a certain degree of complementarity between labor and this type of capital. By contrast, industrial robots are designed to be substitutes predominantly for low-skill routine-intensive workers. Finally, AI predominantly substitutes for high-skill non-routine workers as described above. Overall, this framework allows us to derive conditions subject to which the deployment of industrial robots raises the skill premium, whereas the emergence and increasing use of AI reduces the skill premium.

In our contribution, we investigate the differential effects of industrial robots and AI on the wages of low-skill and high-skill workers as well as on the skill premium. We do so by relying on parameter values from the literature (Jones, 1995; Acemoglu, 2002, 2009; Jurkat et al., 2022; Prettner, 2023) and on data from the U.S. Bureau of Labor Statistics (2020), the International Federation of Robotics (2022), and the Federal Reserve Bank of St. Louis (2023). We simulate the skill premium (w_s/w_u) that our production framework implies for varying levels of the AI capital stock (G) in relation to the stock of automation capital (P) and show the results in Table 1.

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

AI stock (G)	Skill Premium (w_s/w_u)
$G = 0$	2.00
$G = 0.5 * P$	1.70
$G = P$	1.62
$G = 2 * P$	1.52

We observe that the skill premium without the use of any AI is 2.00 – the average wages of high-skill workers are twice the average wages of low-skill workers – and is therefore close to the value observed in the data for the US in the 2000s. This is reassuring insofar as our framework predicts the skill premium correctly for reasonable parameter values and the empirically observed values of labor and capital inputs of the various types.

Next, we investigate what happens if we increase the stock of AI capital to one-half of the traditional automation capital stock (G=0.5*P). We observe that the skill premium decreases to 1.70. Additional reductions occur for further increases in the use of AI, although the rate of decreases in the skill premium diminishes. Overall, our simulated production framework implies that the deployment and increasing use of AI *ceteris paribus* puts downward pressure on the gap between the wages of high-skill workers and low-skill workers.

To get a broader picture on the evolution of the skill premium when we also allow the stock of automation capital in the form of industrial robots to accumulate, we illustrate the ratio of w_s/w_u in Figure 1 for an increasing stock of robots (P) and an increasing stock of AI (G). The skill premium is greatest at the red point, where no AI is used but a large stock of industrial robots holds down the wages of low-skill workers. However, AI offers a way to narrow this gap. As the blue point suggests, when both AI and the stock of industrial robots are high, the skill premium is still reduced to a substantial degree as compared with the previously described case.

Figure 1. Skill premium (w_s/w_u) for various levels of AI (G) and industrial robots (P)

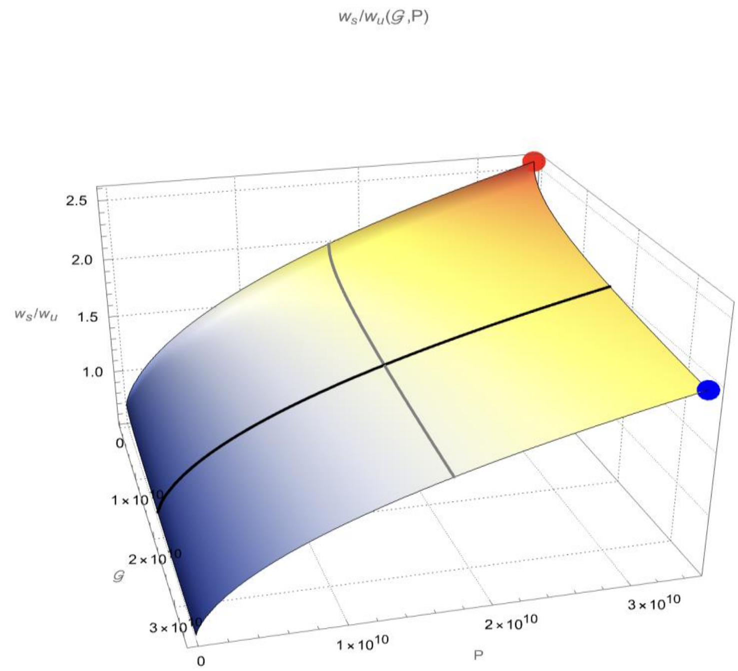


Figure 2 displays the absolute level of the wage rate for low-skill workers and Figure 3 for high-skill workers depending on the stocks of traditional automation capital and of AI. We observe that automation capital in the form of industrial robots puts downward pressure on the wages of low-skill workers and upward pressure on the wages of high-skill workers, whereas the opposite holds true for AI. Overall, the two figures together allow us to arrive at a cautiously optimistic outlook in which the growth of both types of capital, industrial robots and AI, can lead to moderate wage movements for both skill types alike.

Figure 2. Wages of low-skill workers (w_u) for various levels of AI (G) and industrial robots (P)

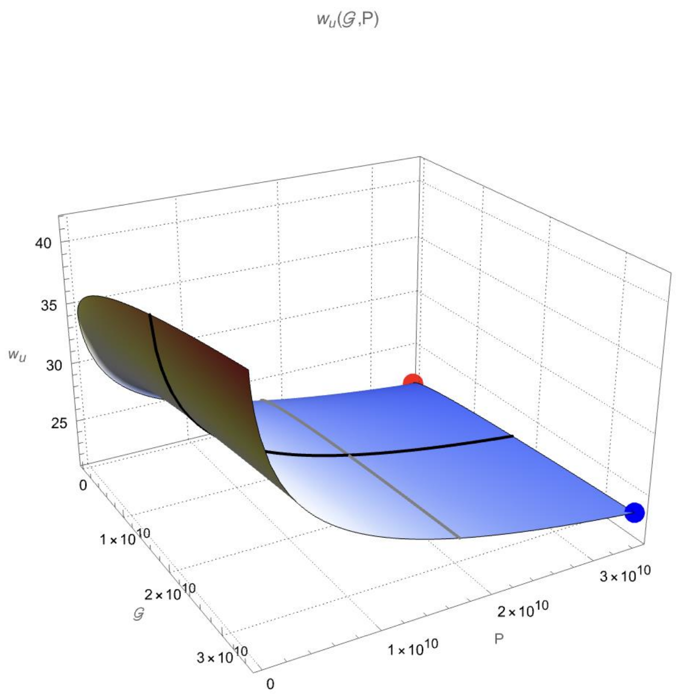
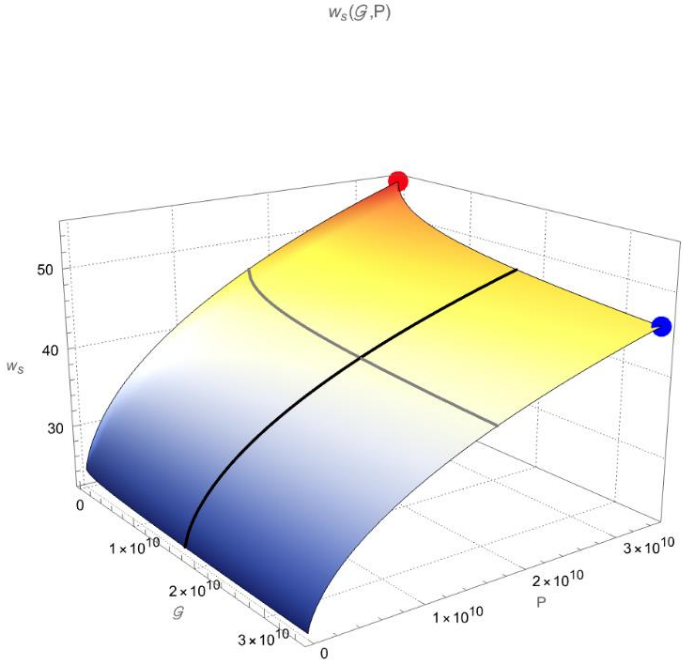


Figure 3. Wages of high-skill workers (w_s) for various levels of AI (G) and industrial robots (P)



Conclusion

We propose a general production function framework that incorporates automation in terms of both industrial robots and AI as separate production factors. When simulating the evolution of the skill premium using standard parameter values on the substitutability among different types of capital and labor, we find that the increasing use of AI reduces the skill premium. Thus, AI has the potential to mitigate or even reverse increases in the skill premium that have been observed in the US in the 1980s and 1990s and may be a potential explanation for why the skill premium has not increased as fast in the 2000s and 2010s as it did in the preceding two decades.

Overall, however, our contribution has only focused on wage inequality. It may well be that AI raises inequality in capital income because the expensive training of AI models implies that widespread ownership is not to be expected. This type of inequality needs to be a key focus of policymakers as they seek to understand and guide the future use of AI.

References

Acemoglu, D. (1998). Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality. *Quarterly Journal of Economics*, 113:1055–1090. DOI: https://doi.org/10.1162/003355398555838

Acemoglu, D. (2002). Directed Technical Change. *The Review of Economic Studies*, 69(4):781–809. DOI: https://doi.org/10.1111/1467-937X.00226

Acemoglu, D. (2009). *Introduction to Modern Economic Growth*. Princeton, NJ: Princeton University Press,

Acemoglu, D. (2024). The Simple Macroeconomics of AI. URL: https://tinyurl.com/hkmynrx5 [accessed on April 22, 2024].

Acemoglu, D. and Restrepo, P. (2018a). Low-Skill and High-Skill Automation. *Journal of Human Capital*, 12(2):204–232. DOI: https://doi.org/10.1086/697242

Acemoglu, D. and Restrepo, P. (2018b). The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment. *American Economic Review*, 108(6):1488–1542. DOI: https://doi.org/10.1257/aer.20160696

Acemoglu, D. and Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, 128(6):2188–2244. DOI: https://doi.org/10.1086/705716

Acemoglu, D., & Restrepo, P. (2020). Unpacking Skill Bias: Automation and New Tasks. *AEA Papers and Proceedings*, 110, 356–361. DOI: https://doi.org/10.1257/pandp.20201063

Acemoglu, D., Koster, H., and Ozgen, C. (2023a). Industrial robots on workers: Winners and losers. VoxEU, March 31, 2023 Url: https://cepr.org/voxeu/columns/industrial-robots-workers-winners-and-losers [accessed on June 15, 2024].

Acemoglu, D., Autor, D., and Johnson, S. (2023b). How AI can become pro-worker. VoxEU, October 4, 2023. Url: https://cepr.org/voxeu/columns/how-ai-can-become-pro-worker [accessed on June 15, 2024].

Agrawal, A., Gans, J.S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. Journal of Economic Perspectives, 33(2), 31–50. DOI: https://doi.org/10.1257/jep.33.2.31

Autor, D., Katz, L., & Kearney, M . (2008). Trends in U.S. wage inequality: revising the revisionists. *The Review of Economics and Statistics*, 90(2), 300–323. DOI: https://doi.org/10.1162/rest.90.2.300

Autor, D. (2024). Applying AI to Rebuild Middle Class Jobs. NBER Working Paper 32140. URL: https://www.nber.org/papers/w32140 [accessed on April 22, 2024].

Bloom, D.E., Prettner, K., Saadaoui, J., and Veruete, M. (2024). Artificial Intelligence and the Skill Premium. NBER Working Paper 32430. Url: https://www.nber.org/papers/w32430 [accessed on June 15, 2024].

Bound, J., & Johnson, G. (1992). Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations. *The American Economic Review*, 82(3), 371–392. URL: https://www.jstor.org/stable/2117311 [accessed on September 29, 2024].

Duffy, J., Papageorgiou, C., and Perez-Sebastian, F. (2004). Capital-Skill Complementarity? Evidence from a Panel of Countries. *Review of Economics and Statistics*, 86(1):327–344. URL: https://www.jstor.org/stable/3211676 [accessed on September 29, 2024].

Federal Reserve Bank of St. Louis (2023). Economic Data. Federal Reserve Bank of St. Louis. URL: https://fred.stlouisfed.org [accessed on April 22, 2023].

Grant, R. and Üngör, M. (2024). The AI Revolution with 21st Century Skills: Implications for the Wage Inequality and Technical Change. *Scottish Journal of Political Economy* (Forthcoming). DOI: https://doi.org/10.1111/sjpe.12395

Heathcote, J., Perri, F., Violante, G. L., & Zhang, L. (2023). More unequal we stand? Inequality dynamics in the United States, 1967–2021. *Review of Economic Dynamics*, 50, 235–266. DOI: https://doi.org/10.1016/j.red.2023.07.014

Jones, C. I. (1995). R&D-Based Models of Economic Growth. *Journal of Political Economy*, 103(4):759–784. URL: https://www.jstor.org/stable/2138581 [accessed on September 29, 2024].

Jurkat, A., Klump, R., & Schneider, F. (2022). Tracking the Rise of Robots: The IFR Database. *Jahrbücher für Nationalökonomie und Statistik*, 242(5-6):669–689. DOI: https://doi.org/10.1515/jbnst-2021-0059

Katz, L. F., & Murphy, K. M. (1992). Changes in Relative Wages, 1963–1987: Supply and Demand Factors. *The Quarterly Journal of Economics*, 107(1), 35–78. DOI: https://doi.org/10.2307/2118323

Korinek, A., & Stiglitz, J.E. (2019). Artificial Intelligence and Its Implications for Income Distribution and Unemployment. In Agrawal et al.: *The Economics of Artificial Intelligence: An Agenda*. Chicago, IL: University of Chicago Press.

Krusell, P., Ohanian, L. E., Ríos-Rull, J.-V., and Violante, G. L. (2000). Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica*, 68(5):1029–1053. DOI: https://doi.org/10.1111/1468-0262.00150

Levy, F., & Murnane, R. J. (1992). U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations. *Journal of Economic Literature*, 30(3), 1333–1381. URL: https://www.jstor.org/stable/2728062 [accessed on September 29, 2024].

Prettner, K. (2023). Stagnant Wages in the Face of Rising Labor Productivity: The Potential Role of Industrial Robots. *Finance Research Letters*, 58:104687. DOI: https://doi.org/10.1016/j.frl.2023.104687

Prettner, K. and Bloom, D.E. (2020a). The macroeconomic effects of automation and the role of COVID-19 in reinforcing their dynamics. VoxEU, June 25, 2020. Url: https://cepr.org/voxeu/columns/macroeconomic-effects-automation-and-role-covid-19-reinforcing-their-dynamics [accessed on June 15, 2024].

Prettner, K. and Bloom, D.E. (2020b). *Automation and Its Macroeconomic Consequences. Theory, Evidence, and Social Impacts*, Cambridge, MA: Academic Press.

U.S. Bureau of Labor Statistics (2020). Job Market Remains Tight in 2019, as the Unemployment Rate Falls to Its Lowest Level Since 1969. URL: https://www.bls.gov/opub/mlr/2020/article/jobmarket-remains-tight-in-2019-as-the-unemployment-rate-falls-to-its-lowest-level-since-1969.htm [accessed on July 25, 2023].

Webb, M. (2019). The Impact of Artificial Intelligence on the Labor Market. DOI: http://dx.doi.org/10.2139/ssrn.3482150

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