The Skill Premium Across Countries in the Era of Industrial Robots and Generative AI*

Marcos J Ribeiro†
FEARP/USP

Klaus Prettner‡
Vienna University of Economics and Business

April 28, 2025

Abstract

How do new technologies affect economic growth and the skill premium? To answer this question, we analyze the impact of industrial robots and artificial intelligence (AI) on the wage differential between low-skill and high-skill workers across 52 countries using counterfactual simulations. In so doing, we extend the nested CES production function framework of Bloom et al. (2025) to account for cross-country income heterogeneity. Confirming prior findings, we show that the use of industrial robots tends to increase wage inequality, while the use of AI tends to reduce it. Our contribution lies in documenting substantial heterogeneity across income groups: the inequality-increasing effect of robots and the inequality-reducing effects of AI are particularly strong in high-income countries, while they are less pronounced among middle- and lower-middle income countries. In addition, we show that both technologies boost economic growth. In terms of policy recommendations, our findings suggest that investments in education and skill-upgrading can simultaneously raise average incomes and mitigate the negative effects of automation on wage inequality.

Keywords: Skill Premium; Automation; Industrial Robots; Artificial Inteligence.
JEL: **J31, O14, 033.**

*This study was financed, in part, by the São Paulo Research Foundation (FAPESP), Brasil. Process Number 2024/06763-0.

†Correspondence address: Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto da Universidade de São Paulo, Avenida Bandeirantes, 3900 - Vila Monte Alegre, Ribeirão Preto - SP, 14040-905. Email: mjribeiro@usp.br.

‡Correspondence address: Welthandelsplatz 1, 1020 Vienna, Austria.

1 Introduction

Automation of production processes has risen substantially over the past decade. According to the International Federation of Robotics (IFR), the number of operative industrial robots increased by 689% worldwide between 1993 and 2023. Even more impressive, private investment in artificial intelligence (AI) increased by 1159% between 2013 and 2023.[1] AI models such as ChatGPT are already widely used to translate and write texts, generate computer code, analyze large volumes of data quickly and accurately, diagnose diseases, make accurate predictions that are useful in material science and drug development, and for many other purposes (cf. Prettner and Bloom, 2020; Deng and Lin, 2023).[2]

According to Lankisch et al. (2019), automation by means of industrial robots predominantly replaces low-skill workers in routine tasks and raises the skill premium—the wage differential between high-skill and low-skill workers. By contrast, Bloom et al. (2025) show that the use of AI in production has the potential to reduce the skill premium. We apply the framework suggested by Lankisch et al. (2019) and extended to incorporate AI by Bloom et al. (2025) for assessing how automation in terms of industrial robots and AI affects economic growth and the skill premium across 52 countries.

The framework proposed by Bloom et al. (2025) relies on a nested CES production function with three distinct types of capital (traditional physical capital, industrial robots, and AI) and two types of labor (high-skill and low-skill). In this setting, the impact of industrial robots and generative AI on the skill premium depends on the elasticities of substitution between the different types of capital and the different types of human labor. Our empirical results across countries are in line with their finding that the increase in the use of industrial robots puts upward pressure on the skill premium because it replaces low-skill workers more intensively, while AI puts downward pressure on the skill premium because it replaces tasks of high-skill workers more intensively. Furthermore,

[1] See Figure B1.

[2] While automation involves replacing human workers with machines programmed through some type of software, AI refers to a type of software that can mimic the thinking process of humans and also has the ability to learn from data (Growiec, 2019; Prettner and Bloom, 2020; Deng and Lin, 2023).

we contribute by showing that both technologies have a positive impact on economic growth.

Closely related to our contribution are studies on the impacts of automation on productivity and economic growth. According to Kromann et al. (2020), an increase in the intensity of robot use by one standard deviation raises total factor productivity (TFP) by more than 6.5%. Similarly, Graetz and Michaels (2018) point out that a greater density of robots in industry reduces production costs and improves labor productivity, contributing to an average increase, in seventeen countries, of 0.37 percentage points in economic growth rates over time. In our contribution, we demonstrate that if all countries adopted the same number of industrial robots per worker as observed in South Korea and achieved the same level of investment in AI per worker as recorded in United States—with both countries being the global leaders in the use of the corresponding technology—GDP per worker would increase, on average, by 261% through industrial robot use and by 31% through AI.

As far as wage inequality is concerned, Kunst et al. (2022) identify a U-shaped pattern in the skill premium in several countries, with a decrease between 1950 and 1980, followed by an increase from the 2000s onwards. This dynamic is initially explained by the growth in the supply of educated workers, and later by factors such as the weakening of unions and the increase in the demand for skilled labor, especially as a result of the expansion of trade, skill-biased technological change, and the accumulation of capital that is more complementary to high-skill workers than to low-skill workers (Krusell et al., 2000; Acemoglu, 2002; Fadinger and Mayr, 2014). Additionally, He (2012) shows that demographic change and especially investment-specific technological change (ISTC) are the main drivers of changes in the skill premium in the US economy.[3] Corroborating these analyses, we demonstrate that the increase in the supply of skilled workers does, in fact, contribute to a reduction of the skill premium.

In addition, we show that the number of industrial robots and the level of investment in AI in the different countries also act as important drivers of changes in the skill

[3]Investment-specific technological change (ISTC) refers to advancements in technology that specifically enhance the efficiency and productivity of capital goods (Greenwood et al., 1997).

premium. While industrial robots and AI boost economic growth, they can also have adverse effects on the labor market, such as job displacement and increased wage inequality (Acemoglu and Restrepo, 2020; Dauth et al., 2021). According to Lankisch et al. (2019), automation impacts the real wages of low-skill workers negatively, because it reduces the demand for this type of labor, making low-skill workers replaceable by automation capital. While automation by industrial robots can theoretically also reduce the wages of high-skill workers (especially when their tasks can either also be automated or performed by low-skill workers relatively easily), for realistic parameter values and the observable developments in robot use, Lankisch et al. (2019) show that the skill premium increases with automation.

In our contribution, we show that if countries had the same number of industrial robots per worker as observed in South Korea, the skill premium would increase by an average of 187%. This number is comparatively high and driven by countries that are far from the technological frontier. This rise in the skill premium tends to be more pronounced in countries in which the introduction of industrial robots replaces a greater number of low-skill workers. We also show that the increased use of industrial robots has a stronger impact on wage inequality in high-income countries than in middle-income countries.

As far as the use of AI is concerned, we confirm the findings of Bloom et al. (2025) and show that, in a scenario in which all countries invested the same amount per worker in AI as the United States does, the skill premium would be reduced, on average, by 28%. Furthermore, we show that increasing the share of AI in the production process tends to reduce the skill premium, especially in high-income countries. These results are in line with the theoretical and numerical results of Bloom et al. (2025) suggesting that AI adoption may reduce the relative demand for high-skill workers in some economies. As a consequence, this dynamic may promote greater wage equality among workers.

Finally, Banerjee et al. (2023) examined, among other aspects, the disparities in the skill premium across countries with different levels of economic development. According to them, high-skill individuals tend to earn relatively more in poorer countries than in richer countries. Banerjee et al. (2023) also suggest that a 1% increase in GDP per capita has two distinct effects: a 0.16 percentage point increase in the share of high-skill workers and a 0.54 percentage point reduction in the wage premium for these professionals. These results suggest that as an economy develops, the supply of high-skill workers increases, leading to a reduction in the skill premium. Our simulation results imply that investing in skill-upgrading could reduce the potential adverse effects of technological advances on wage inequality.

Our paper is structured as follows: In Section 2, we revisit the nested CES production function of Bloom et al. (2025) and the associated skill premium. In Section 3, we present the dataset and discuss the parameter values used in our analysis. In Section 4, we present the results of the baseline calibration and the results of the counterfactual exercises we conducted. Section 5 concludes the paper.

2 Model

Bloom et al. (2025) propose the following nested constant elasticity of substitution (CES) production function to analyze the effects of AI on economic outcomes, particularly the skill premium:

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

In this function, Y_t represents the economy's output in period t, K_t corresponds to traditional physical capital (machines, assembly lines, etc.), P_t refers to the stock of industrial robots, and G_t to investment in AI. In addition, $L_{s,t}$ and $L_{u,t}$ denote, respectively, the quantity of high-skill and low-skill workers and the term A_t represents TFP, which we add to the function for calibration purposes.

The remaining parameters are constant, with α being the elasticity of output in relation to physical capital, θ determining the degree of substitutability between low-skill labor and industrial robots, φ determining the degree of substitutability between high-skill labor and AI, and γ determining the degree of substitutability between the combination of low-skill labor and robots, and the combination of high-skill labor and AI. Finally, β_1, β_2, and β_3 represent the weights attributed to low-skill labor, high-skill labor, and the combination of low-skill labor with robots in the production process, respectively.

As in Bloom et al. (2025), the ratio of the marginal product of high-skill workers to that of low-skill workers yields the skill premium

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

The closer this measure is to unity, the more equal the wages are between high-skill workers and low-skill workers, that is, the lower is the skill premium. From this expression, Bloom et al. (2025) derive the following effects that we simulate across countries in the empirical part of the paper:

- **Effects of AI on the skill premium:** The increasing use of AI, ceteris paribus, reduces the wage gap between high-skill and low-skill workers as long as the degree of substitutability between skilled labor and AI (φ), is greater than the degree of substitutability between low-skill and high-skill intensive production tasks (γ).

- **Effects of industrial robots on the skill premium:** The increasing use of industrial robots, ceteris paribus, increases the wage gap between high-skill and low-skill workers, as long as the degree of substitutability between low-skill labor and industrial robots (θ) is greater than the degree of substitutability between low- and high-skill intensive production tasks (γ).

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

$$\begin{aligned}\frac{\partial(w_s/w_u)}{\partial G_t} = {} & \frac{\left(\frac{\gamma}{\varphi}-1\right)\varphi\beta_2(1-\beta_2)(1-\beta_3)}{\beta_1\beta_3} G_t^{\varphi-1} L_{s,t}^{\varphi-1} L_{u,t}^{1-\varphi} \\ & \times \left[(1-\beta_1)P_t^{\theta} + \beta_1 L_{u,t}^{\theta}\right]^{1-\frac{\gamma}{\theta}} \left[(1-\beta_2)G_t^{\varphi} + \beta_2 L_{s,t}^{\varphi}\right]^{\frac{\gamma}{\varphi}-2}.\end{aligned} \tag{3}$$

Since we assume that all variables and parameters are greater than zero for all $t \geq 0$, the sign of Equation (3) depends only on the term $\left(\frac{\gamma}{\varphi}-1\right)$. Therefore, the skill premium w_s/w_u is decreasing in G_t if and only if $\varphi>\gamma$ (Bloom et al., 2025).

Second, we compute the derivative of the skill premium with respect to the use of industrial robots as

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

Since we assume that all variables and parameters are greater than zero for all $t\geq 0$, the sign of Equation (4) depends only on the term $\left(1-\frac{\gamma}{\theta}\right)$. Therefore, the skill premium w_s/w_u is increasing in P_t if and only if $\theta>\gamma$.

Finally, when observing the production function (1), it is clear that increases in robot use (higher P_t) and increases in AI use (higher G_t) will both raise income per capita and labor productivity as measured by output per worker. However, the extent to which these increases materialize depends on the underlying country characteristics and the extent of the changes in P_t and G_t. Next we will use the information of different countries to assess the extent to which per capita income, productivity, and the skill premium change across countries when robot and AI use change.

3 Dataset and Parameters

To examine the effects of industrial robots and AI on economic growth and the skill premium, we use Equation (2) in a cross-country analysis. The sources of variables and parameter values are described in Table 1. Our sample is composed of data from 2019 and covers 52 countries for which data were available at that time. According to the World Bank income classification (World Bank, 2025), 34 of the countries are considered as high-income, 12 are upper-middle income and 6 are lower-middle income. The reasons why we do not include low-income countries are that industrial robot use and AI investment tend to be very low in these countries and that, generally, data on these variables for low-income countries tend to be un-available. The country names and codes of our sample are displayed in Table A1 of Appendix A.

Capital K was obtained from the International Monetary Fund (2025) database. The stock of industrial robots P was sourced from the International Federation of Robotics (2023), where we set the price of robots according to the information in Klump et al. (2021), who estimated the average price of industrial robots in a set of countries. For our analysis, we used the estimated average price for the United States in 2019, which is US$52,810. For the variable associated with AI, G, we used investment in AI technologies as a proxy, with data from the Center for Security and Emerging Technology and the U.S. Bureau of Labor Statistics, processed by the platform Our World in Data (Roser et al., 2025). Variables related to low-skill and high-skill labor, L_u and L_s, were obtained from the International Labour Organization (2025)[4]

We calibrated TFP (A) for 52 countries in the sample with data from 2019. Our calibration strategy consists of selecting values for A such that the GDP implied by the model coincides with the values in the data. To this end, we define the following objective function for the i countries:

$$D = \sum_{i=1}^{N} \left(\frac{GDP_i^M - GDP_i^T}{GDP_i^T} \right)^2 . \tag{5}$$

The superscripts M and T indicate the model and target statistics. The model fits well with the empirical data, resulting in $D = 0.0002$.

Regarding the parameters of Equation (1), θ was set to $3/4$, based on Jurkat et al. (2022). The values of α and γ were both set to $1/3$, based on Acemoglu (2002, 2009). The parameter φ was defined as $1/2$, respecting the condition $0 < \varphi < \theta \leq 1$ as in Bloom et al. (2025). Our parameter ranges regarding the elasticities imply that industrial robots are a better substitute for low-skill workers than AI is for high-skill workers. This assumption is highly plausible because industrial robots are already widely used along assembly lines without the need for any human labor input in the tasks that they are performing (which implies that the elasticity of substitution is rather high, as also estimated by Jurkat

[4]In Table B1 of Appendix B, we provide the ILO methodology for classifying workers as high, medium- and low -skill. We emphasize that we consider medium-skill workers as low-skill workers for the sake of tractability.

et al., 2022). By contrast, tasks for which AI is used intensively comprise programming, where AI is very often still incapable of producing an error-free code such that human intervention and oversight are needed; diagnosing diseases, where it is required that a medical doctor interprets the results in the end; material science and drug development, where it is still the human scientists who interpret the results and allegedly write the research articles. In addition, our parameters also imply that it is easier to perform the tasks of high-skill workers by AI than by low-skill workers. Again, this is highly plausible because the tasks of high-skill workers that are preformed by AI such as translating texts, writing computer code, diagnosing diseases, combing through large amounts of data, etc. are close to impossible to do for low-skill workers. Overall, however, we provide robustness analyses with respect to the elasticites of substitution.

Finally, the parameters β_1, β_2, and β_3 were assigned the values 0.9, 0.95, and 0.66, respectively, according to Bloom et al. (2025), who demonstrate robustness to variations in their magnitudes in the baseline results.

Table 1: Data source and parameters values

Parameter	**Value**	**Source**
K	–	International Monetary Fund
P	–	International Federation of Robotics; Klump et al. (2021)
G	–	Center for Security and Emerging Technology; U.S. Bureau of Labor Statistics – processed by Our World in Data
L_u	–	International Labour Organization
L_s	–	International Labour Organization
A	–	We calibrated using Equation (5)
θ	0.75	Jurkat et al. (2022)
α	0.33	Acemoglu (2009)
γ	0.33	Acemoglu (2002)
φ	0.5	Chosen such that $0 < \varphi < \theta \leq 1$
β_1	0.9	Bloom et al. (2025)
β_2	0.95	Bloom et al. (2025)
β_3	0.66	Bloom et al. (2025)

4 Results

In this section, we investigate the relationship between industrial robots and AI on the one hand, and economic growth and the skill premium on the other, in 52 countries categorized by income level. In subsection 4.1, we present descriptive statistics of the skill premium, and explore the relationship between this measure and variables such as the stock of industrial robots, investment in AI, GDP, the share of high-skill workers, and TFP.

In subsection 4.2 we present the counterfactuals exercises. To conduct these analyses we consider output per worker. Dividing Equation (1) by L and rearranging the terms, we obtain

$$\begin{aligned}\frac{Y}{L} = A\left(\frac{K}{L}\right)^{\alpha}\Bigg[(1-\beta_3)\left(\left(\frac{G}{L}\right)^{\varphi}(1-\beta_2)+\left(\frac{L_s}{L}\right)^{\varphi}\beta_2\right)^{\frac{\gamma}{\varphi}} \\ +\beta_3\left(\left(\frac{P}{L}\right)^{\theta}(1-\beta_1)+\left(\frac{L_u}{L}\right)^{\theta}\beta_1\right)^{\frac{\gamma}{\theta}}\Bigg]^{\frac{1-\alpha}{\gamma}}.\end{aligned} \tag{6}$$

We can rewrite this expression in a more compact form as

$$y_t = A_t k_t^{\alpha}\left[\beta_3\left(l_{u,t}^{\theta}\beta_1+(1-\beta_1)p_t^{\theta}\right)^{\frac{\gamma}{\theta}}+(1-\beta_3)\left(l_{s,t}^{\varphi}\beta_2+(1-\beta_2)g_t^{\varphi}\right)^{\frac{\gamma}{\varphi}}\right]^{\frac{1-\alpha}{\gamma}}, \tag{7}$$

where the terms k_t, $l_{s,t}$, $l_{u,t}$, p_t, and g_t represent, respectively, capital, high-skill labor, low-skill labor, industrial robots, and AI investment, each measured per worker. This adjustment ensures consistency with the CES production function and facilitates comparison across economies.

We can also rewrite the skill premium in per worker terms:[5]

$$\frac{w_s}{w_u} = \frac{\beta_2(1-\beta_3)}{\beta_1\beta_3} l_{s,t}^{\varphi-1} l_{u,t}^{1-\theta} \times \left[\beta_1 l_{u,t}^{\theta}+(1-\beta_1)p_t^{\theta}\right]^{1-\frac{\gamma}{\theta}}\left[\beta_2 l_{s,t}^{\varphi}+(1-\beta_2)g_t^{\varphi}\right]^{\frac{\gamma}{\varphi}-1}. \tag{8}$$

In subsection 4.2.1, we perform counterfactual exercises in which we equalize, in dif-

[5]The skill premium in Equation (8) is identical to that in Equation (2). We choose to rewrite it in per worker terms just to simplify the implementation of the counterfactual exercises.

ferent scenarios, the composition of the labor force, the stock of robots per worker, and investment in AI per worker to the "best-practice" country with the highest level of the corresponding variables. We then compare GDP per capita and the skill premium before and after the counterfactual. In the case of the fraction of high-skill workers, the counterfactual refers to Sweden, in the case of the stock of robots per worker, the counterfactual is given by South Korea, and for investment in AI per worker, the counterfactual is represented by the United States. Furthermore, in subsection 4.2.2, we simulate gradual increases in the number of robots and in AI per worker, individually and together, to analyze the effects on the skill premium in countries with different income levels.

Finally, in subsection 4.3, we conduct robustness tests in which we vary the model parameters θ, φ, β_1, and β_2, and calculate the variations in the skill premium across scenarios with an increase in robots and AI, to verify the consistency of the results.

4.1 Baseline Calibration

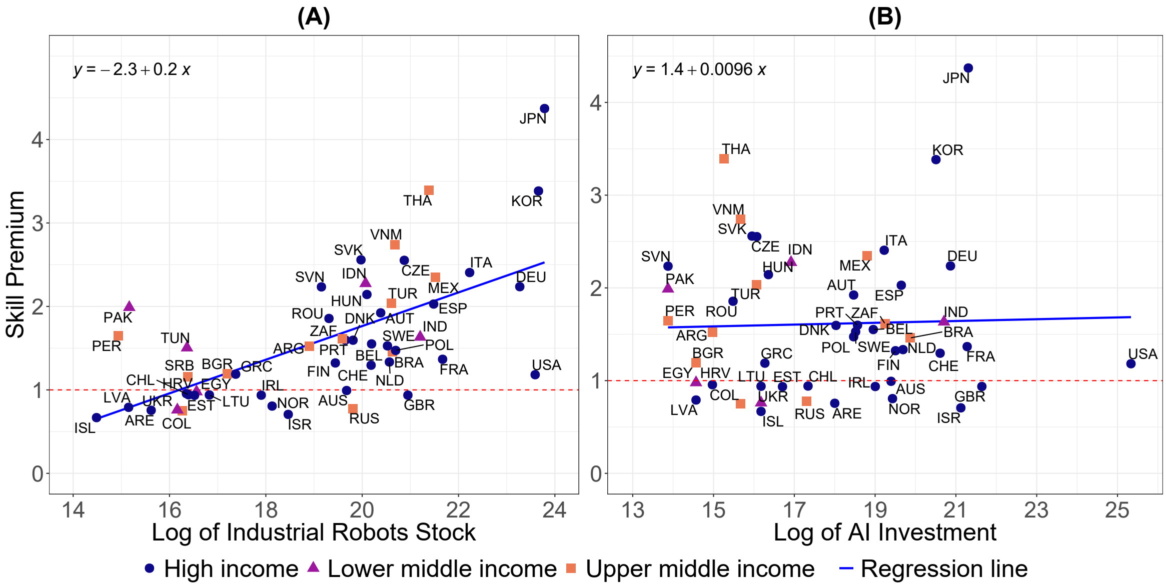
In Table 2, we present model simulations of the skill premium in the 52 countries of our sample. The average value of the skill premium is 1.60, close to the one in Denmark (DNK). The lowest estimated value is 0.67 in Iceland (ISL), while the highest value, 4.37, is observed in Japan (JPN). These differences may be related to the level of industrial robots and investment in AI in each country. Japan, for example, has a high number of industrial robots and significant investments in AI, while Iceland has a relatively limited amount of these technologies.

Table 2: Descriptive statistics of skill premium - 2019

Statistic	**Value**	**Country**	**Code**
Average	1.60	Denmark	DNK
Minimum	0.67	Iceland	ISL
Maximum	4.37	Japan	JPN
Median	1.50	Tunisia	TUN
Standard Deviation	0.78	–	–

In Figure 1, we present the relationship between the skill premium (vertical axis) and two variables: industrial robots (Figure 1 (A)) and AI (Figure 1 (B)). The countries in the sample were categorized by income level: high-income countries (blue circles), upper-middle income countries (orange squares), and lower-middle income countries (purple triangles).[6] We also added a regression line to indicate the general trend of the variables. Figure 1 (A) suggests a positive correlation, indicating that countries with a greater stock of robots tend to have a higher skill premium, especially in high-income economies. This suggests that the number of industrial robots present in the production process may play an important role in the relative valuation of skills on the labor market. On the other hand, in Figure 1 (B), we notice that there is no correlation between the skill premium and AI investments.

Figure 1: Skill premium, stock of robots, and AI investments



In Figure 2, we present the relationship between the skill premium (vertical axis) and three variables: the logarithm of GDP (Figure 2 (A)), the share of high-skill labor (Figure 2 (B)), and the logarithm of TFP (Figure 2 (C)). The dashed horizontal lines refer to the average of the skill premium. While the dashed vertical line represents the average of the logarithm of GDP (Figure A), the average of the share of high-skill labor (Figure

[6]We used the income classification of the World Bank (2025), which divides countries according to their Gross National Income (GNI) per capita. Low-income countries have GNIs below US\$996, lower-middle income countries have GNIs between US\$996 and US\$3,895, upper-middle income countries have GNIs between US\$3,896 and US\$12,055, and high-income countries have GNIs above that amount. It should be noted that there are no low-income countries in our sample. See: https://blogs.worldbank.org.

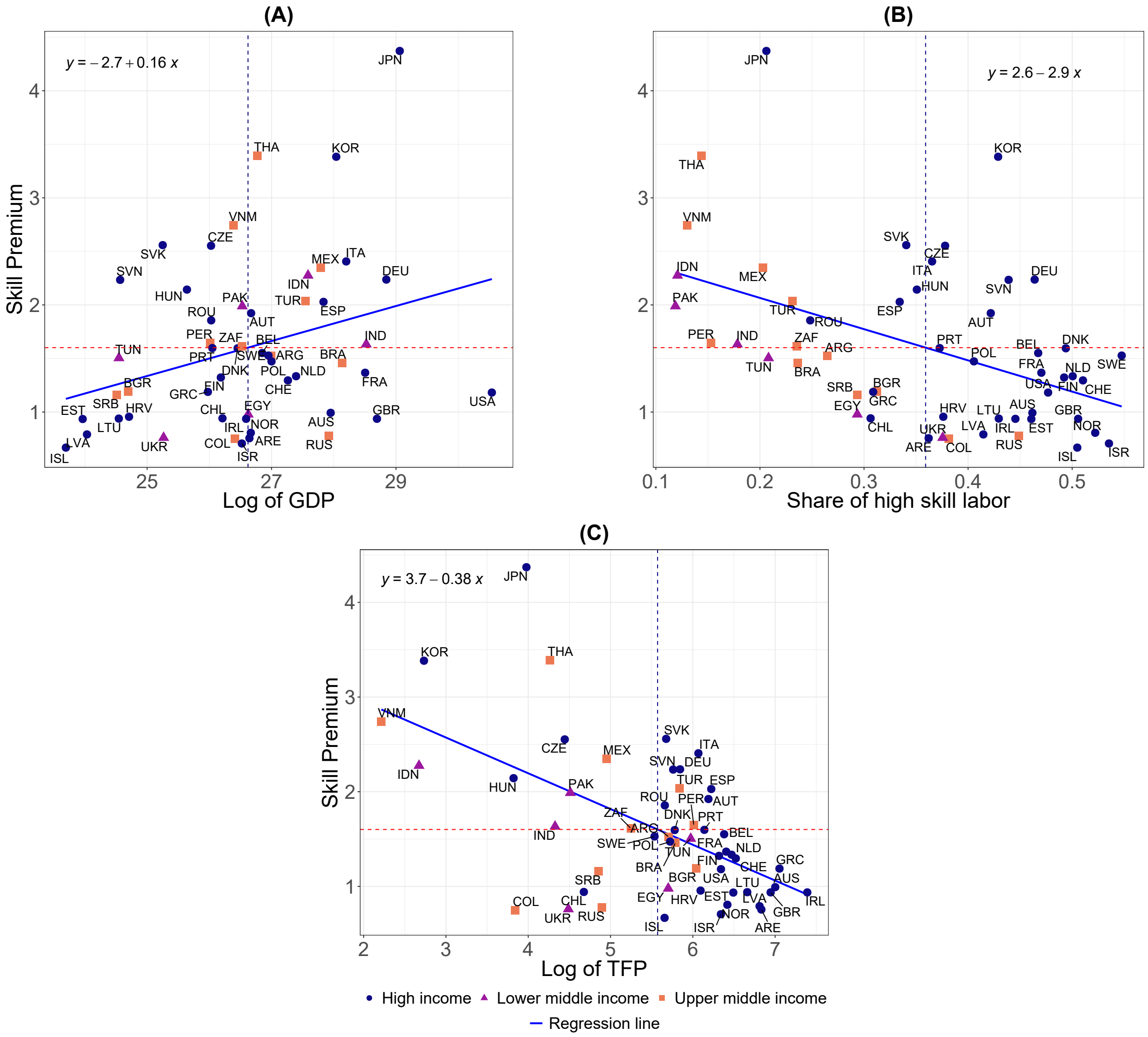
B) or the average of TFP (Figure C).

Figure 2 (A) indicates a positive relationship between the skill premium and GDP, suggesting that economies with higher GDP tend to have a larger wage gap between high- and low-skill workers. Regarding the level of per capita income, the results are rather heterogeneous. High-income countries such as Japan (JPN) and South Korea (KOR) have a high per capita GDP and skill premium, while upper-middle income and lower-middle income countries, for example Thailand (THA), Vietnam (VNM), Mexico (MEX), and Indonesia (IDN) show a similar pattern.

In Figure 2 (B), the relationship between the share of high-skill workers and the skill premium is negative. This indicates that countries with a greater share of high-skill workers tend to have a lower wage gap between different skill levels. High-income countries generally have a greater share of high-skill workers and a lower skill premium, while middle- and low-income economies show greater variability. This effect is expected according to a standard labor market model, because a higher supply of skilled workers reduces the relative scarcity of them, putting upward pressure on their wages and downward pressure on the skill premium. However, it is not in line with the notion of endogenous skill-biased technological change, according to which the skill premium rises further when the supply of high-skill workers rises (Acemoglu, 2002).

Figure 2 (C) reveals a negative correlation between the skill premium and TFP, suggesting that countries with higher productivity tend to have a smaller wage gap between high-skill and low-skill workers. This finding may be associated with the fact that countries with high productivity generally have more developed educational systems, resulting in a higher proportion of the population with higher education or advanced technical training. This pattern can be observed in Figure 2 (B), which shows that most high-income countries have an above-average share of skilled workers. Consequently, as the supply of skilled workers increases, the wage premium for these professionals tends to decrease.

Figure 2: Skill Premium, GDP, share of high skill workers and TFP

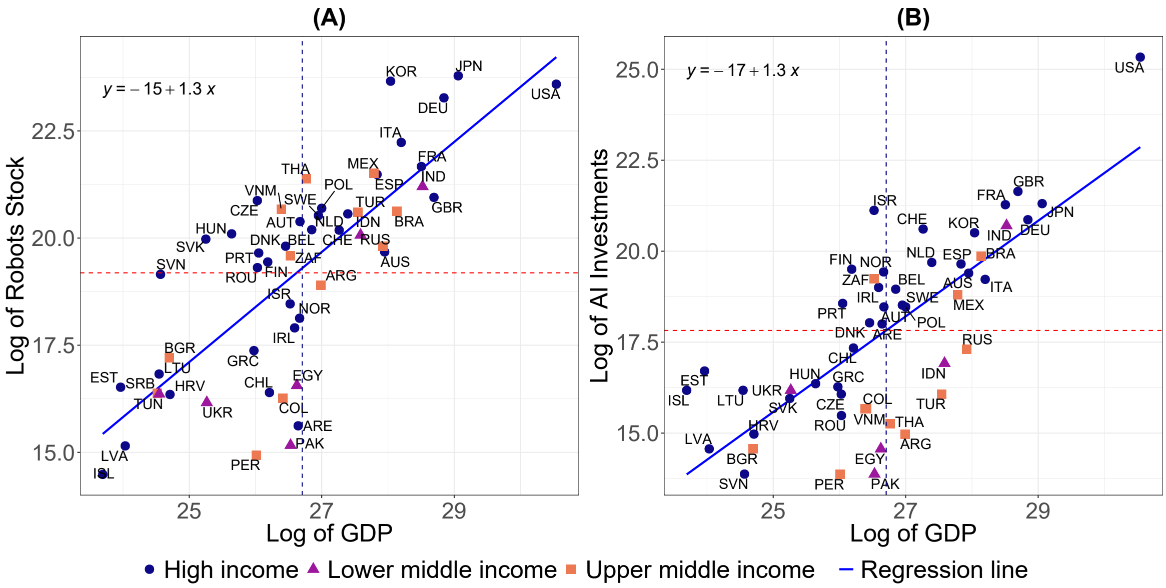


Notes: **(1)** The dashed horizontal lines in graphs (A) and (B) refer to the average of the skill premium. While the dashed vertical line represents the average of the logarithm of GDP and the share of high-skill labor, respectively. **(2)** The average skill premium is 1.6.

In Figure 3, we present the relationship between the logarithm of GDP generated by the model (horizontal axis) and two variables: the logarithm of the stock of robots (Figure 3 (A)) and the logarithm of investment in AI (Figure 3 (B)). In Figure 3 (A), we observe a positive relationship between GDP and the stock of robots, as expected. Countries above the blue line have more robots than would be expected based on their GDP (for example, Germany (DEU), Italy (ITA), Japan (JPN), and South Korea (KOR)), and countries below the line have fewer robots than the size of their economy would predict (for example, Great Britain (GBR), Norway (NOR), and the United States (USA)). Overall, high-income countries are predominantly above the observed average of robots, which is approximately 20. Japan (JPN) and South Korea (KOR) stand out as the countries with the largest stocks of robots, while Iceland (ISL) has a low stock of robots and a low absolute level of GDP because of its small size. There are also upper-middle income countries and lower-middle income countries that have above-average robot stocks, for example, Mexico (MEX), Russia (RUS), Thailand (THA), Indonesia (IDN), and India (IND).

In Figure 3 (B), we also identify a positive relationship between GDP and AI investment. High-income countries lead AI investment, with the United States standing out with values well above the average. In this case, the United States also has much higher investment levels in AI than predicted by the size of its economy. There are upper-middle income and lower-middle income countries that also have above-average AI investment, such as Brazil (BRA), Mexico (MEX), India (IND), and South Africa (ZAF). In contrast, upper-middle income and lower-middle income countries, such as Peru (PER), Bulgaria (BGR), and Pakistan (PAK), have significantly lower investment, falling below the average on both axes.

Figure 3: Industrial Robots, AI investments, and GDP



Note: The dashed horizontal lines in graphs (A) and (B) refer to the averages of the logarithm of the stock of robots and investment in AI, respectively. While the dashed vertical line represents the average of the logarithm of GDP.

4.2 Counterfactuals

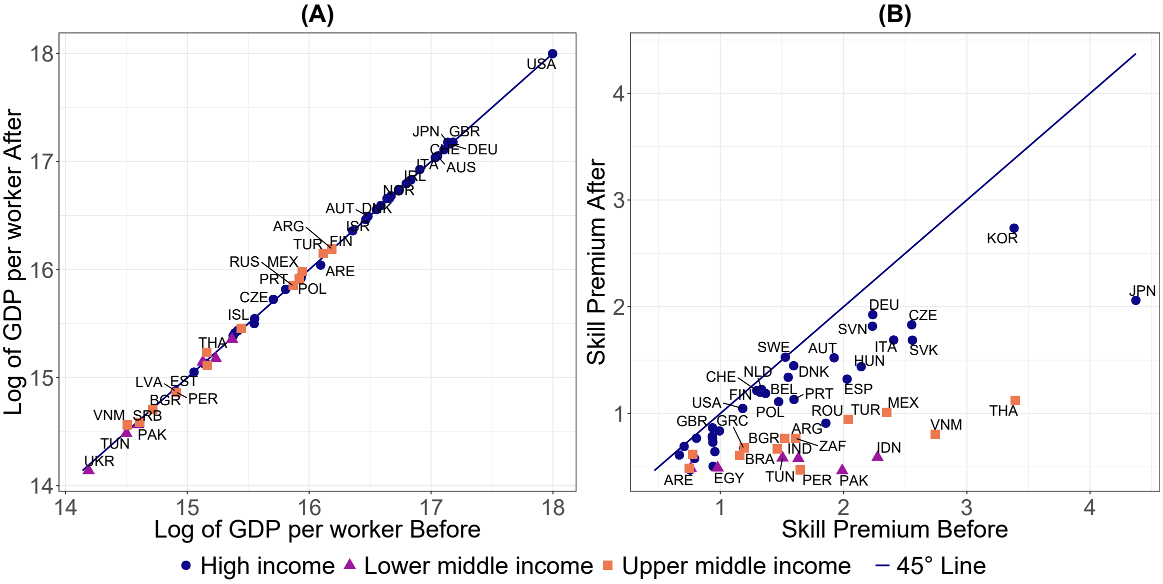
4.2.1 Labor force, robots, and AI

The first counterfactual analysis we conducted is on the impacts of equalizing the workforce composition of different countries (the share of high-skill workers) to that of Sweden (SWE), the country with the greatest share of high-skill workers. The results of this experiment are illustrated in Figure 4. Figure 4 (A) shows GDP per worker before and after the change in workforce composition, while Figure 4 (B) compares the skill premium among high- and low-skill workers before and after the adjustment.

From Figure 4 (A), we note that all countries analyzed showed little or no increase in GDP per worker after adjustment. This increase is evidenced by the concentration of points above, but very close to, the 45° line, suggesting that countries would benefit economically from adopting a workforce structure similar to Sweden's. On average, the increase in output per worker was 0.386%.

In contrast, Figure 4 (B) shows that all points fall below the 45° line, indicating a reduction in the skill premium. The average decline observed was 37.1%. This result suggests that increasing the proportion of high-skill workers in the analyzed economies contributes to reducing wage inequalities between workers with different skill levels.

Figure 4: GDP per worker and the skill premium before and after inserting the share of high-skill workers of Sweden in other countries



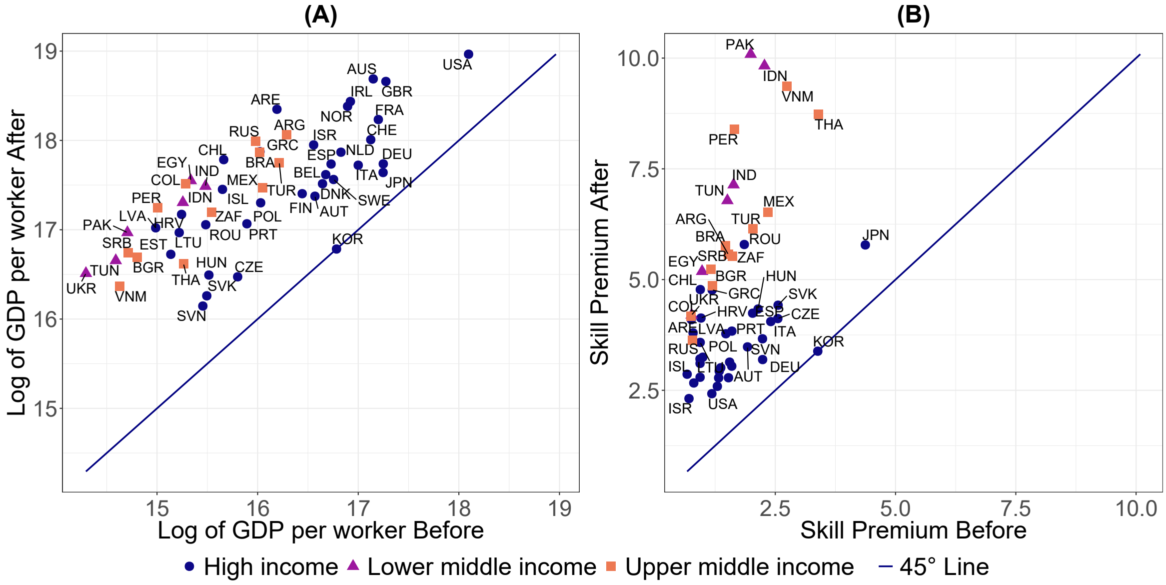
Notes: **(1)** In this counterfactual exercise, we insert into the other countries the share of high-skill workers observed in Sweden. **(2)** Points above (below) the 45° line indicate that the counterfactual exercise increased (decreased) GDP per worker and the skill premium.

The following counterfactual exercise is similar to the previous one, however, we simulate the impact of equalizing the stock of robots per worker in all countries to the stock observed in South Korea (KOR), the country with the greatest stock of robots per worker. In Figure 5 (A), we compare the GDP per worker of the different countries before and after the change in the robot stock. We observe that all of the points are located above the 45° line, indicating that all countries experience a rise in economic output per worker with a robot stock per worker similar to that of South Korea. On average, the observed increase was 261%.

Less developed countries like Pakistan (PAK), Peru (PER), Egypt (EGY), and Colombia (COL) benefit the most from a greater stock of robots per worker. On the other hand, countries closer to the 45° line, for example Japan (JPN) and Germany (DEU), have stocks of robots per worker more similar to South Korea, so the positive effects on GDP per worker are smaller in these countries.

In Figure 5 (B), we compare the skill premium before and after the increase in the robot stock. We note that all points are located above the 45° line, that is, there is a substantial increase in the skill premium, on average by 187%. Countries with the largest changes in the skill premium tend to be those furthest from the technological frontier and where the introduction of robots displaces more low-skill workers, widening the wage gap between high- and low-skill workers.

Figure 5: GDP and skill premium before and after inserting the industrial robots per worker observed in South Korea in other countries

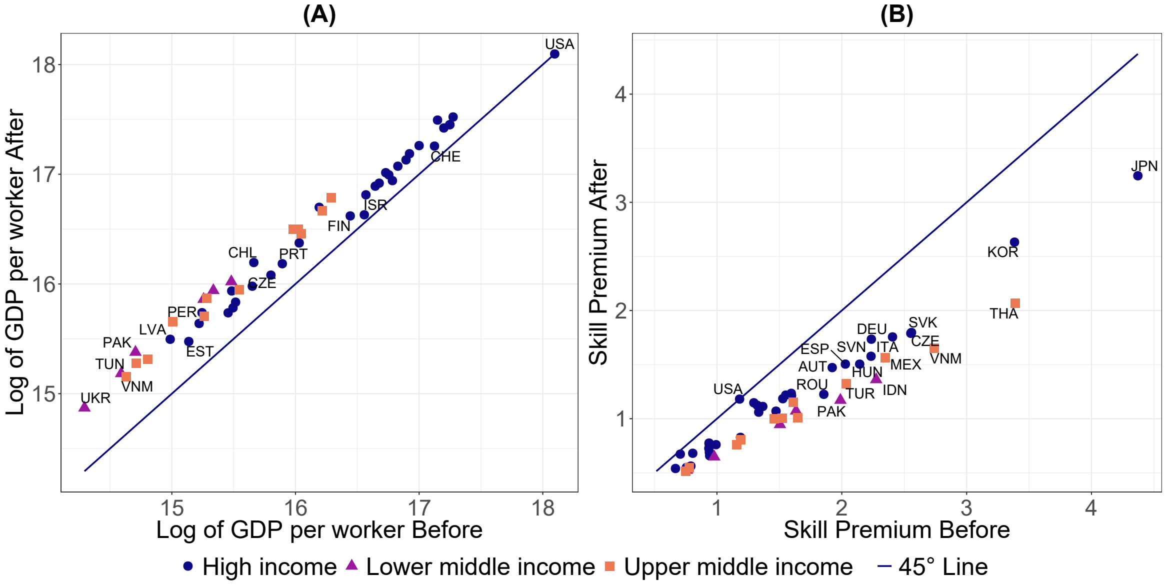


Notes: **(1)** In this counterfactual exercise, we insert into the other countries the robot stock per worker as observed in South Korea. **(2)** Points above (below) the 45-degree line indicate that the counterfactual exercise increased (decreased) GDP per worker and the skill premium.

In the next counterfactual exercise, we simulate the impact of matching the investment in AI per worker of all countries to that observed in the United States, the country with the highest investment in AI per worker. In Figure 6 (A), where we compare GDP per worker before and after the counterfactual, we observe that all countries are above the 45° line, indicating that if other countries had the same level of investment in AI per worker as the United States, they would experience a rise in output. On average, the observed increase was 31.9%. This suggests that AI adoption can increase productivity, especially in countries with low levels of AI investment.

In Figure 6 (B), where we compare the skill premium before and after the counterfactual, we notice that all points are below the 45° line, indicating a reduction in the skill premium after matching AI investment. The average decline observed was 28.2%. This suggests that AI adoption has a substitution effect, reducing the relative demand for high-skill workers in some economies, which, in turn, induces lower wage inequality among workers.

Figure 6: GDP and the skill premium before and after inserting the value of investment in AI per worker observed in the United States in other countries



Notes: **(1)** In this counterfactual exercise, we insert into the other countries the AI investment per worker as observed in the United States. **(2)** Points above (below) the 45° line indicate that the counterfactual exercise increased (decreased) GDP and the skill premium.

4.2.2 Increase in the Share of Robots and AI per Worker

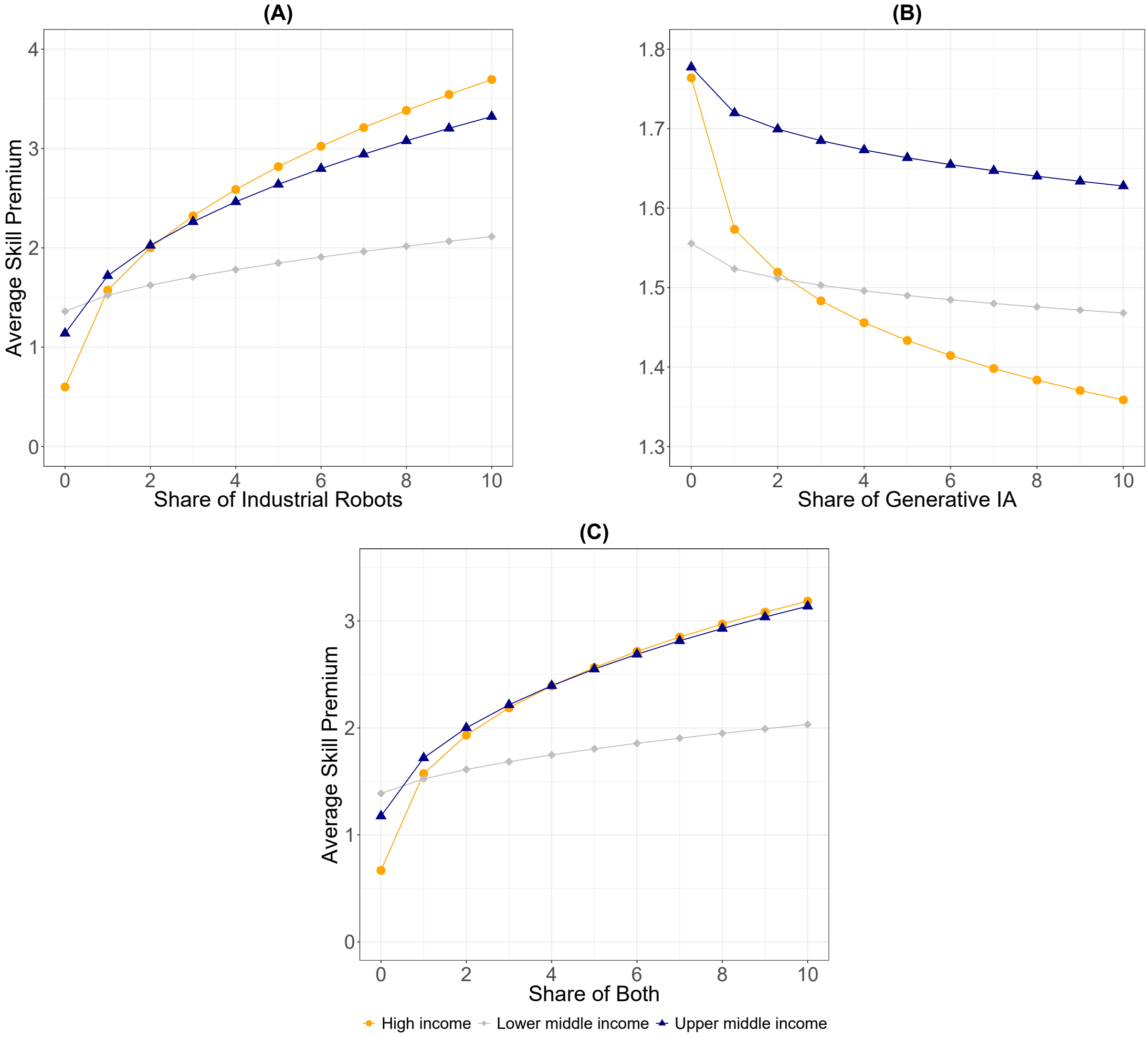
We conducted two counterfactual exercises to assess the differential impacts on the skill premium across countries with different income levels (high, middle, and low). In the first exercise, we multiplied the number of industrial robots per worker by a vector scaled from zero to ten, analyzing the resulting variations. The second exercise followed a similar approach, but we also considered the increase in the share of AI per worker in the production process.

In Figure 7 (A), we observe that for high-income countries (orange), the increase in the share of industrial robots per worker is associated with a steady increase in the skill premium. In upper-middle income countries (blue), the skill premium also increases, but less steeply. For lower-middle income countries (gray), the skill premium is relatively stable, with little variation as the share of robots increases. Thus, the use of industrial robots per worker benefits high-skill workers in high-income countries the most in terms of increasing the skill premium.

In Figure 7 (B), the opposite is true. In high-income countries (orange), the increase in the share of AI per worker is associated with a sharp reduction in the skill premium, suggesting that AI may be replacing high-skill tasks. In upper-middle income countries (blue), the impact of AI on the skill premium is less negative, but there is still a downward trend. In lower-middle income countries (gray), the impact is minimal, with a nearly flat curve. The adoption of AI appears to have a substitution effect in high-income economies, potentially displacing high-skill workers from some roles. In middle-income economies, the impact is more muted, possibly due to differences in the labor market structure.

In Figure 7 (C), we simultaneously increased the share of robots and AI per worker in the production process. This increase led to an increase in the skill premium, driven by the greater number of robots per worker. However, the adverse impacts of this effect were mitigated by the increase in the share of AI per worker. This suggests that, although automation via robots may widen wage inequality by increasing the skill premium, the introduction of AI into the production process may act as a compensating factor as predicted by Bloom et al. (2025).

Figure 7: Increases in the share of industrial robots and AI per worker and the effects on the skill premium



Notes: **(1)** In this counterfactual exercise, we simulate the increase in the share of industrial robots and AI in different economies, considering their effects in isolation (Figures A and B) and combined (Figure C). **(2)** The baseline calibration is where the share of industrial robots and AI is equal to unity.

4.3 Robustness Check

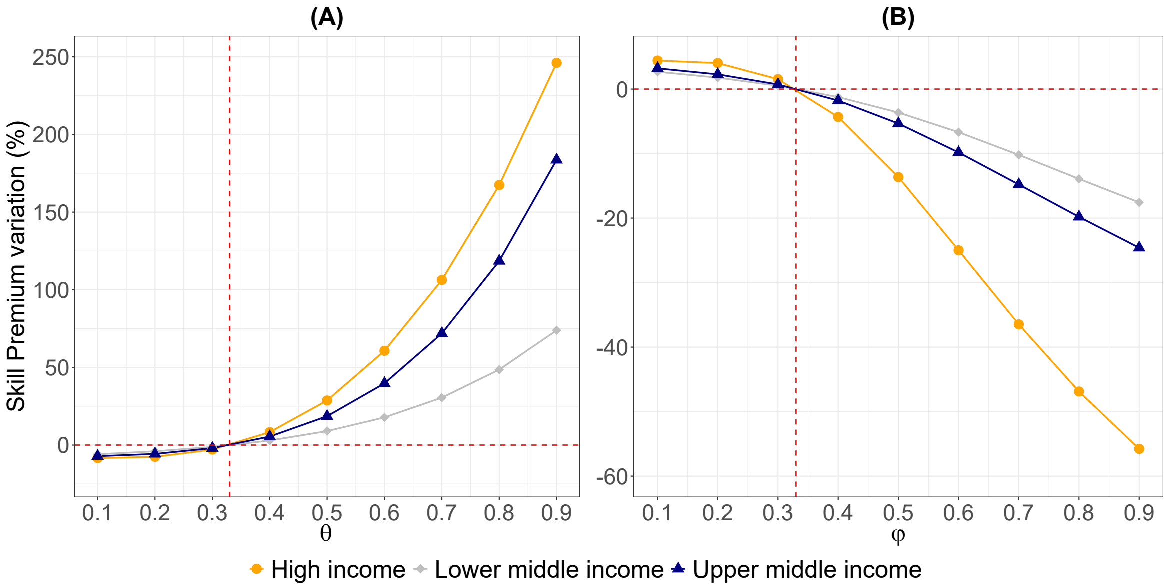
We claim that the increased use of AI reduces the wage gap between high-skill and low-skill workers when the substitutability parameter between AI and high-skill labor (φ) is greater than the substitutability parameter between productive tasks of different skill levels (γ). On the other hand, the increased use of industrial robots increases the wage gap when the substitutability parameter between robots and low-skill labor (θ) exceeds the substitutability parameter between productive tasks of different skill levels (γ). Thus, the impacts of automation on the skill premium depend on the substitution parameters between technology and labor. We therefore conduct a robustness exercise to assess how sensitive our results are to variations in θ and φ.

We present the results of the robustness check in Figure 8. For this analysis, we perform a counterfactual exercise similar to the one in Section 4.2.2, but with one important difference: first, we calculate the skill premium with the initial parameters of the model. Then, the number of industrial robots is increased by a factor of ten, and the skill premium is recalculated based on this new configuration. From these two values, we obtain the percentage change in the skill premium. This procedure is repeated for different values of the parameter θ to analyze the sensitivity of the results. We do the same for AI, however, the procedure is repeated for different values of the parameter φ in this case.

Figure 8 (A) shows the relationship between the variation in the skill premium and the parameter θ (degree of substitutability between low-skill workers and industrial robots). We observe that when θ is between 0.1 and 0.3, the variation in the skill premium is negative, that is, the increase in the share of industrial robots in economies tends to reduce the skill premium. When $\theta = 0.1$, the reductions are 8.4%, 7.2%, and 5.9% for high-income, upper-middle income, and low-income countries, respectively. However, as θ increases, the skill premium also increases, especially for high-income countries. This is in line with economic intuition and suggests that when robots more easily replace low-skill workers, wage inequality between high-skill and low-skill workers increases.

Figure 8 (B) shows the variation of the skill premium as a function of φ (the degree of substitutability between high-skill labor and AI). As long as φ is between 0.1 and 0.3, the effects of increasing the AI share in the skill premium are positive, that is, the higher the AI share, the greater the wage gap between high-skill and low-skill workers. However, the increase is rather modest, being 4.42%, 2.68%, and 3.21% for high-income, lower-middle income and upper-middle income countries, respectively, when $\varphi = 0.1$. From the dashed vertical line, which represents the value of γ, we note that increases in φ reduce the skill premium. This occurs because greater substitutability between AI and high-skill labor tends to reduce the relative demand for high-skill workers, decreasing the wage gap between the two groups.

Figure 8: Percentage changes in the skill premium due to increases in the share of robots and AI per worker, and in θ and φ

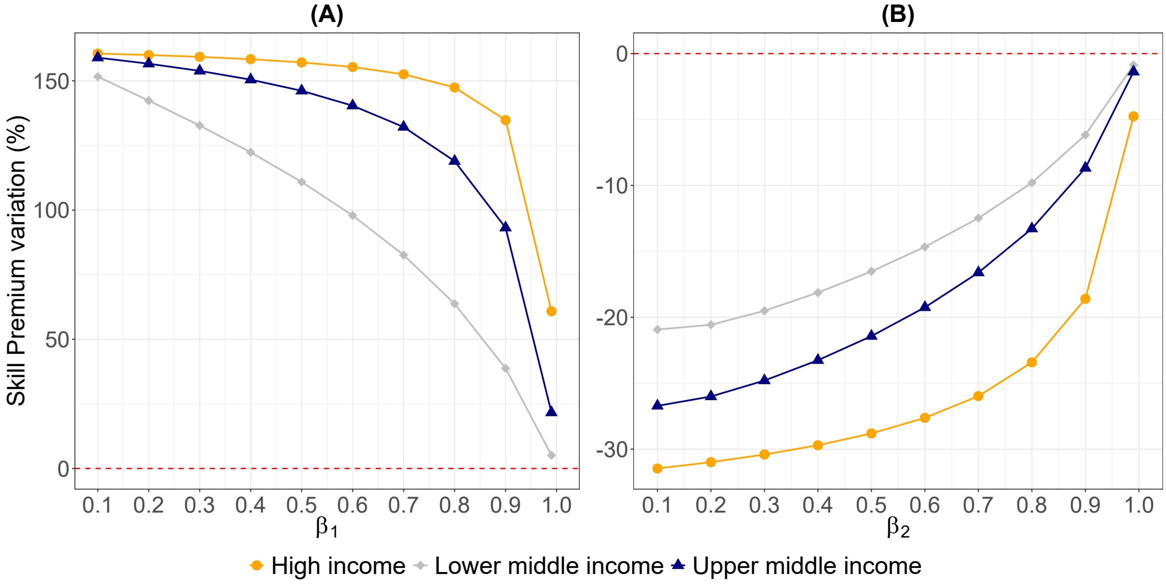


Notes: **(1)** In this counterfactual exercise, we simulate a scenario in which the share of industrial robots and AI are ten times greater than they are in the baseline calibration. In this context, we analyze the percentage variation in the skill premium, considering different values of θ and ϕ. **(2)** The dashed vertical line indicates the value of γ used in the baseline calibration. **(3)** The baseline values are: $\gamma = 0.33$, $\theta = 0.75$, $\varphi = 0.5$, $\beta_1 = 0.9$, $\beta_2 = 0.95$, and $\beta_3 = 0.33$.

Finally, we perform an additional robustness exercise, with a similar structure to the previous one. However, instead of varying the parameters θ and φ, we change the values of β_1 and β_2. We observe that, for different values of β_1, the effect of increasing the number of industrial robots by a factor of ten on the variation of the skill premium remains positive. On the other hand, when varying β_2, we verify that the tenfold increase in investment in AI has a negative effect on the variation of the skill premium.

Regarding β_3, it only adjusts the absolute magnitude of the skill premium, with a higher β_3 reducing the skill premium; however, in the context of these counterfactual exercises, the percentage variation of the skill premium is independent of β_3. All results presented in this section are consistent with the results presented in this paper.

Figure 9: Percentage changes in the skill premium due to increases in the share of robots and AI per worker, and in β_1 and β_2



Notes: **(1)** In this counterfactual exercise, we simulate a scenario in which the share of industrial robots and AI are ten times greater than they are in the baseline calibration. In this context, we analyze the percentage variation in the skill premium, considering different values of β_1 and β_2. **(2)** The baseline values are: $\gamma = 0.33$, $\theta = 0.75$, $\varphi = 0.5$, $\beta_1 = 0.9$, $\beta_2 = 0.95$, and $\beta_3 = 0.33$.

5 Final Remarks

We build on Bloom et al. (2025) to investigate how industrial robots and AI affect the skill premium between high-skill and low-skill workers in 52 countries. Using a nested CES production function, we demonstrate that the impact of these technologies on the skill premium depends on the degree of substitutability between these technologies and human labor.

The empirical results indicate that the increase in the use of industrial robots tends to increase the skill premium by more intensively substituting for low-skill workers. On the other hand, AI can reduce the skill premium by substituting tasks performed by high-skill workers. The results are in line with the findings of Bloom et al. (2025) and with economic intuition. Furthermore, we show that both industrial robots and AI have a positive impact on economic growth.

If adopted in a balanced manner and accompanied by investments in education, the automation of production processes may not only boost economic growth but also potentially reduce wage inequality over time, especially in high-income countries where the substitution of workers by advanced technologies is more pronounced.

References

Acemoglu, D. (2002). Directed technical change. *The Review of Economic Studies*, 69(4):781–809.

Acemoglu, D. (2009). *Introduction to modern economic growth*. Princeton university press.

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

Banerjee, A., Basu, P., and Keller, E. (2023). Cross-country disparities in skill premium and skill acquisition. *Economic Inquiry*, 61(1):179–198.

Bloom, D. E., Prettner, K., Saadaoui, J., and Veruete, M. (2025). Artificial Intelligence and the Skill Premium. *Finance Research Letters*.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association*, 19(6):3104–3153.

Deng, J. and Lin, Y. (2023). The benefits and challenges of ChatGPT: An overview. *Frontiers in Computing and Intelligent Systems*, 2(2):81–83.

Fadinger, H. and Mayr, K. (2014). Skill-Biased Technological Change, Unemployment, and Brain Drain. *Journal of the European Economic Association*, 12(2):397–431.

Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5):753–768.

Greenwood, J., Hercowitz, Z., and Krusell, P. (1997). Long-run implications of investment-specific technological change. *American Economic Review*, pages 342–362.

Growiec, J. (2019). The hardware-software model: A new conceptual framework of production, r&d, and growth with ai.

He, H. (2012). What drives the skill premium: Technological change or demographic variation? *European Economic Review*, 56(8):1546–1572.

International Federation of Robotics (2023). World Robotics. Industrial Robots and Service Robots. URL: https://ifr.org/ifr-press-releases/news/world-robotics-2023-report-asia-ahead-of-europe-and-the-americas [accessed on July 20, 2024].

International Labour Organization (2025). Data and Statistics. Url: https://www.ilo.org/data-and-statistics.

International Monetary Fund (2025). IMF Data. Url: https://www.imf.org/en/Data.

Jurkat, A., Klump, R., and Schneider, F. (2022). Tracking the rise of robots: The IFR database. *Jahrbücher für Nationalökonomie und Statistik*, 242(5-6):669–689.

Klump, R., Jurkat, A., and Schneider, F. (2021). Tracking the rise of robots: A survey of the IFR database and its applications.

Kromann, L., Malchow-Møller, N., Skaksen, J. R., and Sørensen, A. (2020). Automation and productivity—a cross-country, cross-industry comparison. *Industrial and Corporate Change*, 29(2):265–287.

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.

Kunst, D., Freeman, R. B., and Oostendorp, R. (2022). Occupational skill premia around the world: New data, patterns and drivers. *Labour Economics*, 79:102255.

Lankisch, C., Prettner, K., and Prskawetz, A. (2019). How can robots affect wage inequality? *Economic Modelling*, 81:161–169.

Prettner, K. and Bloom, D. E. (2020). *Automation and its macroeconomic consequences: theory, evidence, and social impacts*. Academic Press.

Roser et al. (2025). Our World in Data. Url: https://ourworldindata.org/.

World Bank (2025). New country classifications by income level: 2018-2019. Url: https://blogs.worldbank.org/en/opendata/new-country-classifications-income-level-2018-2019.

Appendix A Cross Country Skill Premium

Table A1: Countries, codes, income classification, and the skill premium

Country	Code	Income Classification	Skill Premium
Argentina	ARG	Upper middle income	1.52
Australia	AUS	High income	0.99
Austria	AUT	High income	1.92
Belgium	BEL	High income	1.55
Brazil	BRA	Upper middle income	1.46
Bulgaria	BGR	Upper middle income	1.19
Chile	CHL	High income	0.94
Colombia	COL	Upper middle income	0.75
Croatia	HRV	High income	0.96
Czech Republic	CZE	High income	2.55
Denmark	DNK	High income	1.60
Egypt	EGY	Lower middle income	0.98
Estonia	EST	High income	0.93
Finland	FIN	High income	1.32
France	FRA	High income	1.37
Germany	DEU	High income	2.24
Greece	GRC	High income	1.19
Hungary	HUN	High income	2.14
Iceland	ISL	High income	0.67
India	IND	Lower middle income	1.63
Indonesia	IDN	Lower middle income	2.28
Ireland	IRL	High income	0.94
Israel	ISR	High income	0.71
Italy	ITA	High income	2.41
Japan	JPN	High income	4.37
Latvia	LVA	High income	0.79
Lithuania	LTU	High income	0.94
Mexico	MEX	Upper middle income	2.35
Netherlands	NLD	High income	1.33
Norway	NOR	High income	0.81
Pakistan	PAK	Lower middle income	1.99
Peru	PER	Upper middle income	1.65
Poland	POL	High income	1.47
Portugal	PRT	High income	1.60
Rep. of Korea	KOR	High income	3.38
Romania	ROU	High income	1.86
Russian Federation	RUS	Upper middle income	0.78
Serbia	SRB	Upper middle income	1.16
Slovakia	SVK	High income	2.56

Continued on next page

Table A1: Countries, codes, income classification, and the skill premium (Continued)

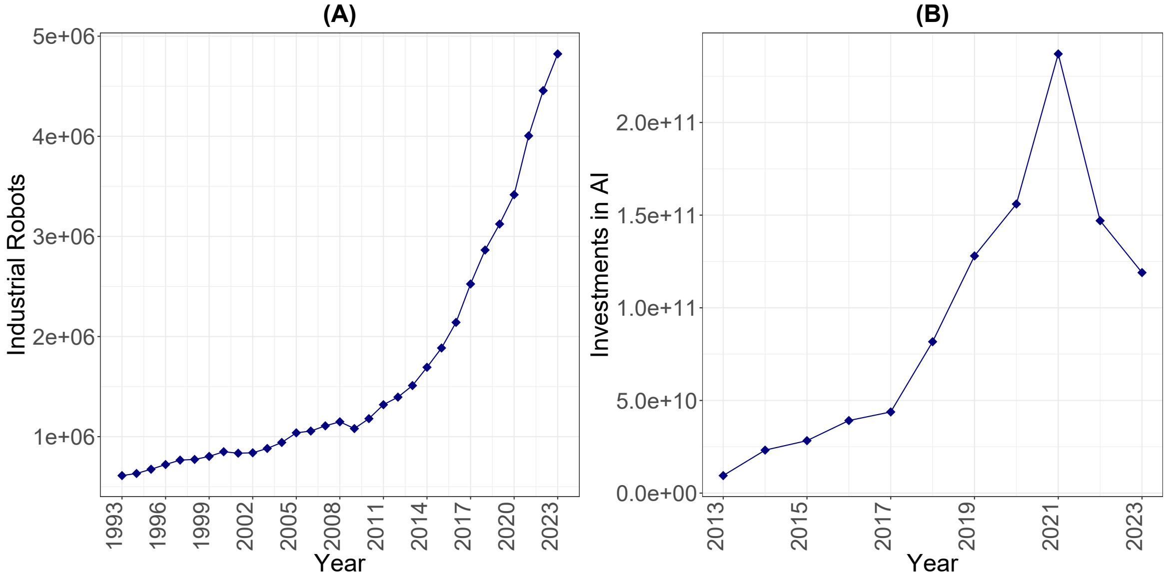
Country	Code	Income Classification	Skill Premium
Slovenia	SVN	High income	2.23
South Africa	ZAF	Upper middle income	1.61
Spain	ESP	High income	2.03
Sweden	SWE	High income	1.53
Switzerland	CHE	High income	1.30
Thailand	THA	Upper middle income	3.39
Tunisia	TUN	Lower middle income	1.50
Turkey	TUR	Upper middle income	2.04
Ukraine	UKR	Lower middle income	0.76
United Arab Emirates	ARE	High income	0.76
United Kingdom	GBR	High income	0.94
United States	USA	High income	1.18
Vietnam	VNM	Upper middle income	2.74

Appendix B Additional Information

B.1 Global Evolution of the Number of Industrial Robots and Private Investment in AI

Figure B1 shows the global evolution of the number of industrial robots (Fig. A) and private investments in AI (Fig. B). In 1993, according to the data, there were 610,925 industrial robots in use globally. Thirty years later, in 2023, this number has reached 4,822,887 units. In percentage terms, the increase was 689%. On the other hand, between 2013 and 2023, private investments in AI totaled approximately 9.45 billion dollars. In 2023, this value reached approximately 119 billion dollars. This represents a rise of 1,159%.

Figure B1: Global evolution of the number of industrial robots and of private investment in AI



Note: Private investment in AI is in 2021 dollars.

B.2 Workers Classification

Table B1: International Standard Classification of Occupation (ISCO-08) by skill level

Skill Level	Occupation
Skill levels 3 and 4 - High Skill	Managers
	Professionals
	Technicians and associate professionals
Skill level 1 and 2 - Low Skill	Clerical support workers
	Service and sales workers
	Skilled agricultural, forestry and fishery workers
	Craft and related trades workers
	Plant and machine operators, and assemblers
	Elementary occupations
Armed forces	Armed forces occupations
Not elsewhere classified	Not elsewhere classified

Notes: **(1)** Adapted from International Labour Organization, see https://ilostat.ilo.org. **(2)** We do not consider workers in the armed forces and those not classified elsewhere.