Pillars – Pathways to Inclusive Labour Markets

Report

# The Effect of Robotization in OECD Countries on Latin American Labor Markets

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# The Effect of Robotization in OECD Countries on Latin American Labor Markets*

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**Abstract**

The rise of robots has raised a controversial discussion about their disruptive impacts on domestic labor markets. Robot adoption, which is largely concentrated in a few high-income countries, might also affect labor markets of trade partners through global value chain linkages. This effect could be even more pronounced in developing countries due to the predominance of routine tasks and labor-intensive activities. Using data on global value chain linkages between countries and sectors, we evaluate the impact of robot adoption in OECD countries on labor markets in Latin American countries. We show that the rise of robots in OECD countries is associated with an *increase* in employment in the production of intermediate goods in Latin America, whereas no effect is found for final demand.

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# 1 Introduction

Recent decades have witnessed an acceleration in the adoption of industrial robots, which has been particularly pronounced in high-income countries. According to the International Federation of Robotics (IFR), more than 3 million industrial robots were in use in factories worldwide in 2020; the stock of industrial robots increased by a factor of 5 between 1993 and 2015 in North America, Europe, and Asia (Dauth et al., 2021). The adoption of robots, which has been largely confined to OECD countries, has created a controversial debate on their disruptive impact on domestic labor markets. Moreover, robot adoption in high-income countries might also have an effect on trading partners through global value chain linkages.

Automation affects the (international) sourcing and investment decision of firms and can thereby reshape the international division of labor. On the one hand, automation might put low-skilled and replaceable jobs at risk not only at home, but also abroad due to a change in relative production costs. If robots can take over tasks at lower costs which were originally performed by low-skilled workers in the Global South the current pattern of relative cost advantages might change, and firms might decide to relocate production to high-income and capital intensive countries (i.e. production reshoring). On the other hand, productivity gains for robot-adopting firms in the Global North might also translate into increasing demand for intermediate goods coming from the Global South, with positive implications for labor demand.

We investigate the effect of robotization in OECD countries on labor market outcomes across sectors in Latin America. Using input-output tables, we map automation shocks across countries and sectors along the value chain to evaluate the impact of robotization within global production networks. This allows us to take into account input-output linkages that channel the effects of automation in the Global North to production in the Global South. Our results indicate that the rise of robots in OECD countries is associated with an increase in employment for the production of intermediate goods in Latin America, whereas no effect is found for employment in the production associated with final demand.

# 2 Literature Review

Robotization is often discussed as the third great economic revolution of the modern era (Baldwin and Forslid, 2020). The use of robots has led to a restructuring of production in many industries and has prompted academic research on the economic impact of automation.

Firms have generally benefited from technological advances in robotics. The introduction of robots has reduced production and operating costs for firms, resulting in significant productivity gains (Koch et al., 2021). Several studies have shown, both at the aggregate and firm level that automation increases labor productivity (Graetz and Michaels, 2018), raises value added (Acemoglu et al., 2020), and boosts competitiveness (Bonfiglioli et al., 2020). While there is agreement in the literature on the general benefits of robotization for firms, the impact on workers remains controversial.

There is no consensus regarding the impact of automation on employment and wages in domestic markets, as discussed by Aghion et al. (2022). The first strand of the literature shows that the introduction of robots in production reduces the demand for labor and thus depresses wages at the aggregate level. Even though demand for workers with complementary capabilities might increase over time, it will not offset the job losses which occur for labor-intensive and replaceable jobs. Using data for US manufactures, Acemoglu and Restrepo (2020) find that robot adopters decrease the share of production workers. Furthermore, they provide evidence that even though these firms expand their total employment, this happens through the attraction of employees from their competitors - overall, industry-level employment shrinks. A second strand of the literature suggests that the use of robots allows production to expand, leading to increases in employment. For instance, Hirvonen et al. (2022) show that Finnish firms that introduced advanced technologies were more likely to produce additional new product types than to replace workers with technologies within the same production type. Thus, the introduction of technologies led to an increase in employment and no change in skill composition. In addition, Koch et al. (2021) find evidence of positive employment effects in firms that adopt robots and negative employment effects for firms that do not adopt robots, based on Spanish firm-level data. For the German labor market, Dauth et al. (2021) show a differentiated picture. Here, the displacement effect of automation in the manufacturing sector is completely offset by redistribution effects toward the service sector. In view of these results, the question of whether automation will lead to positive or negative employment effects overall does not yet seem to be settled.

The impact of robot adoption on labor market outcomes of trade partners and North-South trade has received less attention from the literature. Closest to our work is the paper by Artuc et al. (2020), who investigate the effect of robotization on North-South trade. Using aggregate trade data, they show that a 10% increase in robot density in Northern countries is associated with a 6% increase in their imports from less developed countries, which is mainly driven by exchanges of parts and components. In contrast to their results, we investigate the effect of robot adoption along the value chain using input-output tables, which allow us to evaluate the effect for directly and

indirectly affected industries. Using detailed firm-level data for Spanish firms, Stapleton and Webb (2020) find that the use of robots had a positive effect on their offshoring to lower-income countries. Robot adoption caused firms to expand production and increase labor productivity and TFP. For firms that had not yet offshored production to lower-income countries, robot adoption caused them to start doing so. On the other hand, for companies that had already relocated to lower-income countries the introduction of robots had no consequences on their offshoring. In contrast to this study which is based on firm-level data, Krenz and Strulik (2021) show using industry-level data a strong association between automation and reshoring at the macro-level.

Our results add to additional papers that evaluated the impact of robot adoption in rich countries on labor markets in developing countries. Taking the perspective of a country from the global South, Faber (2020) shows that the use of robots in the U.S. has a robust and substantial negative effect on employment in Mexico by reducing exports to the United States. The impact is strongest for low-skilled machine operators and technicians in highly robotized manufacturing industries and for high-skilled managers and professionals in service industries. Kugler et al. (2020) assess the impact of U.S. automation on the Colombian labor market. They show that U.S. robots reduce employment and earnings of Colombian workers in sectors with high automation potential. Older workers and employees of SMEs are most affected. In a study for Brazil, Stemmler (2019) finds that automation abroad reduces manufacturing employment by reducing demand for final goods exports, while it increases employment in the mining sector by driving up demand for intermediate goods exports. Such development may lead to "premature deindustrialization" in emerging economies. On the other hand, and closest to our work, Artuc et al. (2022) provide support for a strong efficiency channel of automation and argue that in the long run, developing countries will profit from robot adoption in the Global North through an increase in global demand for intermediate and final goods. We contribute to this literature by evaluating the impact of robot adoption on employment along the value chain.

# 3 Data

Our empirical analysis uses a novel combination of databases and focuses on outcomes for seven Latin American countries (Argentina, Brazil, Chile, Colombia, Costa Rica, Peru, and Mexico) for which data is available over the period 1998 to 2018. To evaluate the impact of automation in Northern countries on labor markets in the South, we combine three different databases. First, employment and income statistics for the seven Latin American countries, aggregated at industry level, are provided by the

OECD . Second, data on the adoption of industrial robots are obtained from the International Federation of Robotics (IFR), available for most OECD countries broken down by industry and year of robot adoption. Third, to match employment industries in Latin America with the respective weighted automation shocks in OECD countries, we combine the two databases based inter-country input-output linkages from the OECD (OECD ICIO 2021) which include 66 countries and 45 industries. This creates a novel dataset that maps automation shocks over the entire supply chain, distinguishing between the production of intermediate and final goods. It allows a comparison of whether changes in labor market outcomes are due to the introduction of robots affecting the production of intermediate goods and services or robots competing with the production of final goods.

More formally, we construct for the production of intermediates from industry $r$ in country $i$ the following adjusted foreign stock of robots

$$robots_{irt}^{intermediate} = \sum_{j} \sum_{s} \omega_{ir}^{js} \; robots_{t}^{js}, \tag{1}$$

This measure is a weighted average of foreign robot stocks in year $t$ across all importing countries indexed by $j$ and the respective importing industries indexed by $s$. The weights $\omega_{ir}^{js}$ are allocation coefficients that refer to the share of total sales from country $i$'s industry $r$ which are used as inputs in the production of sector $s$ in country $j$. These weights are constructed based on the ICIO tables for the year 1995 to ensure that we measure linkages that are not endogenous to robotization in the 2000's (Acemoglu et al., 2016; Bown et al., 2020).

With respect to the production of final goods from industry $r$ in country $i$ we construct the following adjusted foreign robot stock:

$$robots_{irt}^{final} = \sum_{j} \pi_{ir}^{j} \; robots_{t}^{jr}, \tag{2}$$

Here, the weights $\pi_{ir}^{j}$ capture the share of total sales from industry $r$ in country $i$ which are sold as final goods to the importing country $j$. Note that in this case $r = s$. Hence, $robots_{irt}^{final}$ is a weighted average of robots stocks across all importing countries (indexed by $j$) in the same industry $r$.

# 4 Empirical Strategy

We estimate the effects based on two long differences (1998-2008 and 2008-2018) to account for lagged effects in robot adoption. Both the weighted robots stock for intermediate goods ($robots_{irt}^{intermediate}$) and the weighted stock for final demand goods ($robots_{irt}^{final}$) are included in the same regression. In this way, the effects of these different robotization developments can be compared. Equation 3 estimates the average levels effect for the sample:

$$ln(Y_{irt}) = \beta_1 asinh(robots_{irt}^{intermediate}) + \beta_2 asinh(robots_{irt}^{final}) + \delta_{it} + \mu_{rt} + \epsilon_{irt} \quad (3)$$

We conduct the analysis for three different outcomes ($Y_{irt}$): $Employment_{irt}$, $Income_{irt}$ and $Income_{irt}/Employee_{irt}$. To rule out the possibility that the results are due to country- or industry-specific changes, several types of fixed effects are included. Our preferred specification, shown in eq. (3), includes country-year ($\delta_{it}$) and industry-year ($\mu_{rt}$) specific effects to account for time-varying characteristics of countries and industries, such as industry-specific innovation shocks, labor market developments, or other country-specific shocks. The standard errors are clustered by industry.

In our main specification, the robot stock is divided by the value added of the respective industry. This normalisation allows for a better comparison of the development of the robot stock in the different industries: If the robot adoption rate of an industry rises faster than the value added of this industry, this indicates a higher robot intensity of the industry. The opposite is true for industries where robot use grows slower than value added. Since our observation period starts in the nineties, we observe a zero robot stock for several industries in some countries during our first observation point in 1998. For this reason, we use the inverse hyperbolic sine transformation instead of logarithms. Applying this transformation, we can include observations with zero stocks, while approaching logarithms for larger values (Burbidge et al., 1988).

# 5 Empirical Results

The results on the impact of robot adoption in OECD countries on $Employment_{irt}$ in the seven Latin American countries are shown in Table 1, whereas results for $Income_{irt}$ and $Income_{irt}/Employee_{irt}$ are shown in Table 2. Column 1 presents results including country-year ($\delta_{it}$) and industry $r$ fixed effects. Column 2 includes industry-year fixed effects ($\pi_{rt}$) and country $i$ fixed effects. Our preferred specification in column 3 includes

**Table 1:** Employment (in Tsd)

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| $asinh(robots_{irt}^{intermediate})$ | 0.197 | 0.371* | 0.365* |
| | (0.129) | (0.0600) | (0.0574) |
| $asinh(robots_{irt}^{final})$ | -0.107 | -0.0466 | 0.0563 |
| | (0.254) | (0.218) | (0.223) |
| Total Observations | 389 | 389 | 389 |
| Industry FE | Yes | | |
| Country FE | | Yes | |
| Country-Year FE | Yes | | Yes |
| Industry-Year FE | | Yes | Yes |

Note: Robust standard errors clustered by Industry in parentheses: *** p<0.01, ** p<0.05, * p<0.1

industry-year and country-year fixed effects. As shown in Table 1, robot adoption in the destination country $j$ in industry $s$ is positively associated with an expansion of employment in the production of intermediate goods in origin country $i$ in industry $r$.Results become even stronger when accounting for country-year and industry-year fixed effects, which account for changes in labor market policy in a country or industry-level shocks.

**Table 2:** Income

| | Income (in Mio. USD) | | | Income/Employee(in Tsd USD) | | |
|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
| $asinh(robots_{irt}^{intermediate})$ | 0.471** | 0.635*** | 0.630*** | 0.179* | 0.0984 | 0.0892 |
| | (0.207) | (0.189) | (0.192) | (0.0925) | (0.115) | (0.118) |
| $asinh(robots_{irt}^{final})$ | -0.0971 | 0.0743 | 0.0934 | 0.0606 | 0.0746 | 0.0851 |
| | (0.209) | (0.201) | (0.209) | (0.109) | (0.140) | (0.141) |
| Total Observation | 458 | 458 | 458 | 389 | 389 | 389 |
| Industry FE | Yes | | | Yes | | |
| Country FE | | Yes | | | Yes | |
| Country-Year FE | Yes | | Yes | Yes | | Yes |
| Industry-Year FE | | Yes | Yes | | Yes | Yes |

Note: Robust standard errors clustered by industry in parentheses: *** p<0.01, ** p<0.05, * p<0.1

The positive relationship between robotization and income is even more pronounced. The changes in aggregate income and income per employee are shown in Table 2. The

results go hand in hand with the findings of Artuc et al. (2020). They likewise suggest that the integration of robots into the production process in the Global North boosts wages and welfare of supplier countries located in the Global South.

# 6 Conclusion

The impact of robotization on labor market outcomes (at home and abroad) remains highly controversial. While some scholars show that workers lose out, especially those who perform labor-intensive and repetitive tasks, other papers suggest that all types of workers benefit due to increased efficiency and expansion of production. We evaluate the impact of robot adoption along the entire value chain on changes in employment and incomes in seven Latin American countries. The results provide compelling evidence that robot adoption in rich countries is associated with a positive employment effect based on intermediate goods production for the robot adopters, whereas no employment effect is found for final goods production.

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