# Robots: How bad could it be globally?

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**Abstract**

We show empirically that the global impact of robotization and similar technologies is heterogeneous at the aggregate level. Benefits are mostly concentrated in high-income countries. In contrast, robotization would have negative effects in middle- and high-income countries. We conclude that this could be a new argument to explain the future gap between these two types of countries and argue for appropriate human capital policies to incorporate these technologies in emerging economies.

**JEL Codes: O30; O40; O57.**

**Keywords:** Robots, macroeconomic impact, labor market impact, cross-country comparison, development and economic growth.

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# Introduction

The contribution of our study to the literature is to quantify the impact of robots on the economy at the global level, considering separately the effects on high, upper-middle, and lower-middle income countries. It is to be expected that there will be also significant variations in the way robots will impact different countries. From a medium-term perspective, there are significant obstacles to human capital development in the last two groups of countries mentioned, for example, there is literature that shows that a key aspect in the development of this capital (Hanushek (2016)), and subsequent performance in the labor market (Heckman et al. (2006)), is cognitive skills. In this regard, Hanushek (2013) shows that the gap in these skills between developed countries and other countries is still wide, basically due to the quality of education at different levels.

In fact, although there is abundant literature pointing to a negative impact on labor and distributional variables in high-income countries[1], innovation in robotic production techniques and other related technologies (artificial intelligence, for example) can produce significant positive effects in these countries both directly (reduction in marginal production costs) and indirectly through learning-by-doing process to produce these technologies.

Instead, García (2020) argue, first, that emerging countries will adopt robots by directly importing machines instead of producing them due to the lack of human capital for their use in less automated sectors, such as industry and agriculture, losing all the benefits of learning-by-doing. Therefore, these economies are expected to experience more severe employment effects because new technologies are characterized by replacing jobs rather than creating them, resulting in an economic contraction. They also argue that exports from these countries will compete in the markets of high-income countries and require high-quality services that can be replaced by robots, such as distribution, transportation, and advertising,

[1]Employment Acemoğlu and Restrepo (2020), inequality Acemoğlu and Restrepo (2022); Prettner and Strulik (2020); and Berg et al. (2018), unemployment Cords and Prettner (2018), and wages Bergholt et al. (2022); and Leduc and Liu (2020)

activities that require a lot of skilled labor.

However, such a sharp separation between countries may have important caveats. Indeed, in lower-middle and low income countries, with economies oriented to the production of basic goods with very low-paid jobs, the likelihood of introducing robots may be reduced. Thus, it could be that the impact of robots at the global level would have an effect similar to an unbalanced "U": little impact in lower-middle income countries, negative in upper-middle income countries, and positive in high-income countries.

We explore this last hypothesis in section 2, using an empirical methodology explained in section 1, and close with the conclusions and implications in section 3.

# 1 Methodology

The methodology used for this study was the local projection method (LPM)(Jorda (2005)) to estimate impulse response functions. The LPM allows us to recover the dynamics of the dependent variable after a shock, and it has been widely used in empirical macroeconomics, (see for example Auerbach and Gorodnichenko (2012); Ramey and Zubairy (2018); and Alesina et al. (2020)).

The LPM method is based on the predictions of a panel of $VAR$ or $PVAR(p)$ data over a $h$ horizon with $p$ lags. Thus the model becomes a $VARMA$, in that through simple linear estimation, the LPM (Hansen (2022), page 537) reduces the risks of misspecification of the data generating process (Jorda (2005)), from other alternatives, for example, using a priori a VAR model that imposes the linearity restriction and in which the impulse response functions are recovered with short-run, sign, or long-run assumptions on the parameters, which in our particular case it is not obvious to impose any of these restrictions. The benchmark regression is specified as follows:

$$y_{i,t+h} - y_{i,t-1} = \alpha_i + \beta \Delta P_{i,t} + \nu X_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where, $y_{i,t+h}$ is the outcome variable of interest —GDP, private consumption, labor share, hours worked, and productivity— for country $i$ at time $t+h$ (i.e., the prediction horizon is $h$.), $\alpha_i$ is country fixed effect to control for unobserved cross-country heterogeneity, $\Delta P_{i,t}$ is the change in a proxy for the price of robots, $v$ is a vector of nuisance coefficients, $X_{i,t}$ is a vector of control variables, which includes the changes in the dependent variable, and the other variables: output, private consumption, labor share, hours worked, and productivity, and $\varepsilon$ is an unexplained error.

The most relevant coefficient is $\beta$, the impulse responses of the variables of interest to changes in the laws of motion in another variable of interest. The impulse responses were constructed by plotting directly the $\beta$ coefficient for five predictive regressions, i.e., from $h = 1$ to $h = 4$, of equation (1) with four lags $p = 4$ for the following yearly sample: 1990-2018. Then, confidence bands were based on the respective estimated standard errors. Finally, the countries were selected according to criteria defined by the International Monetary Fund (IMF).

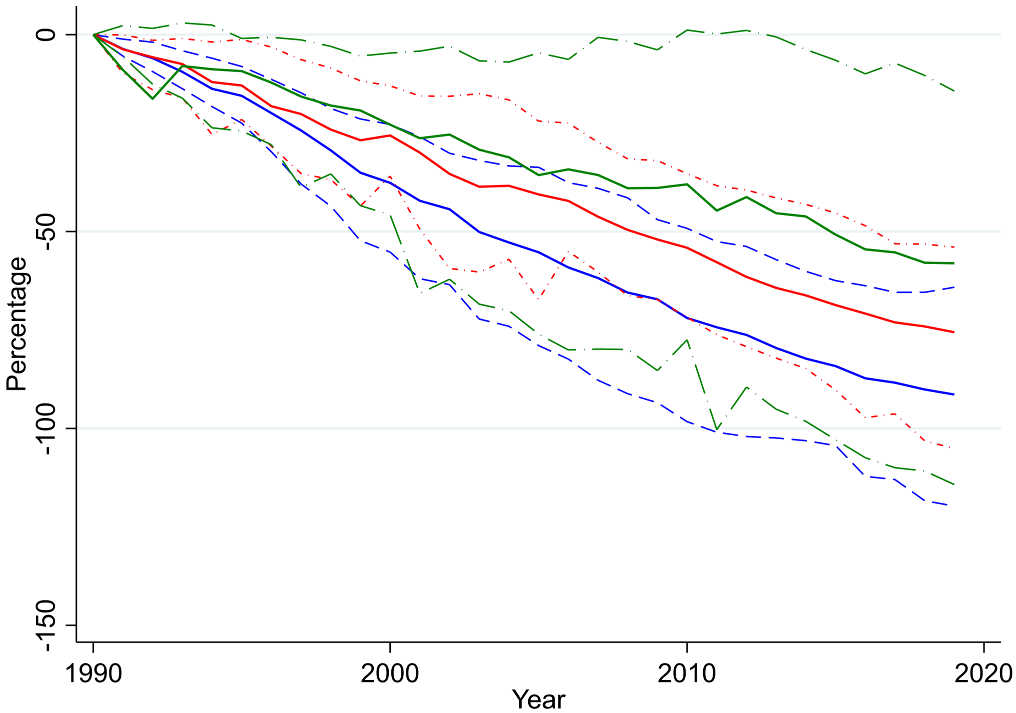
# 2 Results[2]

Figure (2) shows the estimated impulse response functions of the equation (1). An important limitation to measuring the impact of robotization using the price of robots is that while this is an available variable it is not necessarily the appropriate variable to measure this impact. The reason is that, despite the development of robots in recent years, it is not yet a relevant phenomenon in upper-middle, lower-middle, and low-income countries. Even in high-income countries, the real impact of robotization is expected to occur in the next few years.

We therefore looked for a proxy for the price of robots that would have a somewhat similar dynamics and effect to those of robots: the price of capital goods - machinery and equipment, excluding investment in transportation and construction - which in the past has followed a similar trajectory to that of the available robot price series (see Figure (1) and Tilley (2017), Cost of automation figure) and which we also know positively that the fall in the price of capital goods did substitute for labor in recent decades in all country groups.

[2]The Stata code and the database to obtain the results are available online.

Figure 1: Dynamics of relative price of machinery and equipment



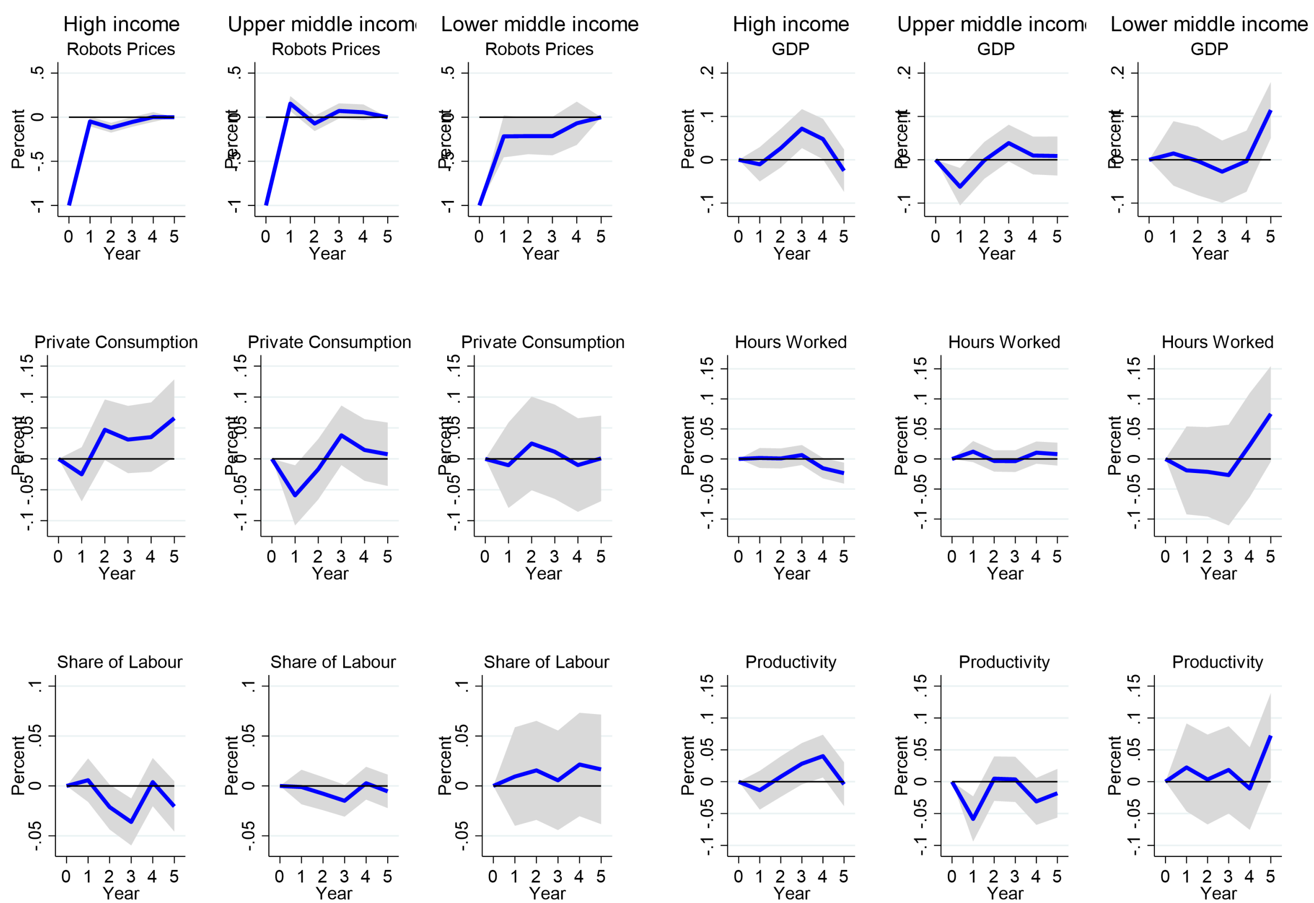

*Source*: Penn World Table, version 10.
*Note*: blue line "high income countries", red line "Upper- middle income countries", and green line "lower-middle income countries". Intervals: 25th and 75th percentiles.

Considering this approximation in the price of robots, we analyze the figure (2). The drop in the price proxy for the price of robots is equal for the three groups of countries considered. The impact on GDP is positive for high-income countries in the medium term (three years), while for high and middle-income countries it is immediately contractionary. There is no statistically significant effect in the case of middle- and low-income countries. This result could partly illustrate the hypothesis raised by García (2020): to the extent that the "learning by doing" effect develops, the impact of robotization ends up being positive.

The effects on other variables follow a similar dynamic: consumption, albeit marginal for high-income countries, and productivity. The result on productivity is particularly interesting because it could be indicating the learning-by-doing effect mentioned above.

Hours worked and labor participation follow a pattern already studied in high-income countries (and which we mentioned in the footnote of the introduction): hours worked decline from the fourth year, but participation also falls. However, in middle- and high-income countries the situation is worse: participation falls and hours worked are not affected. In middle- and low-income countries, there are no statistically significant effects.

Figure 2: Impact of robotization at the aggregate level in different groups of countries




*Source:* Authors' calculations, based on the model presented in section 1.

# 3 Conclusion, limitations, and implications

In this paper we show evidence that the impact of robotization may be heterogeneous at the global level. The positive effects on GDP growth, productivity and private consumption would be concentrated in high-income countries, however, the negative effects on the labor market are confirmed. On the contrary, in the rest of the countries the effects would be negative or marginal. The implications of our results indicate that there would be a major dilemma for middle-high income countries in terms of their human capital policies and initiatives since these are where the negative effects are concentrated.

Although our analysis does not consider an explicit model of economic growth, the stylized facts of this article would indicate that if these countries do not undertake the necessary reforms for the production and incorporation of robots and other similar technologies, their aspirations to reach the income levels of developed countries will again be delayed. Worse, to the extent that these technologies become fundamental pillars of technological progress, upper-middle income countries may end up converging to lower-middle income levels.

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