Economic Complexity and Robot Adoption*

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Abstract

This paper examines the relationship between economic complexity and industrial robot adoption. Using panel data for 61 countries from 1996 to 2023 and a dynamic panel System GMM approach, we find that higher robot density is significantly associated with greater economic complexity. Notably, this association appears stronger in countries with a larger share of low-skilled workers.

Keywords: Economic Complexity; Industrial Robots; Economic Development.
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1 Introduction

Economic complexity, typically measured by the Economic Complexity Index (ECI), captures the diversity and sophistication of a country's productive capabilities. Higher levels of economic complexity have been associated with higher income levels, faster economic growth and lower income inequality (Hausmann et al., 2014; Hartmann et al., 2017; Hidalgo, 2021). In this paper, we argue that the diffusion of industrial robots contributes to increased economic complexity, as it expands diversification by enabling the production of new goods and increases sophistication by making advanced manufacturing more efficient and precise.

From 1996 to 2023, the global adoption of industrial robots grew by 569%, indicating a strong trend towards automation in recent decades. This technology has been associated with increased productivity, innovation, and quality of intermediate goods, allowing companies to migrate to higher value-added segments in the global value chain (Prettner and Strulik, 2020; Duan et al., 2023; Zheng and Wang, 2025). Furthermore, the use of industrial robots has been associated with improvements in worker health (Liu et al., 2025). According to Le et al. (2024), automation also replaces low-skilled labor in routine tasks, while the creation of new varieties of goods generates new job opportunities for low-skilled workers.

To investigate the relationship between economic complexity and industrial robots adoption, we employ the system Generalized Method of Moments (GMM) approach, utilizing a panel dataset of 61 countries spanning the period 1996–2023. Our results reveal a robust positive association between robot density (robots per worker) and the ECI, indicating that automation provides additional explanatory power for a country's economic complexity beyond its general level of development. Furthermore, our analysis reveals heterogeneity in this effect: the gains in complexity resulting from the adoption of robots are more pronounced in economies with a higher share of low-skilled labor.

Our contribution is threefold. First, we propose a transmission mechanism linking robot adoption to economic complexity, whereby robots enhance productive capabilities through industrial upgrading effects and reinstatement effect. Second, we provide cross-country evidence based on a dynamic panel System GMM approach, which accounts for persistence and endogeneity. Finally, we present policy suggestions for countries to increase the share of automation in their production processes.

2 Econometric Approach and Data

We examine the impact of robot adoption on economic complexity using panel data spanning 61 countries from 1996 to 2023.[1] We specify the following dynamic model:

$$EC_{i,t} = \beta_1 EC_{i,t-1} + \beta_2 RD_{i,t} + \mathbf{X}'_{i,t}\theta + \eta_i + \gamma_t + \epsilon_{i,t}, \tag{1}$$

where i indexes countries and t indexes time. $EC_{i,t}$ denotes economic complexity, $RD_{i,t}$ represents industrial robot density, $\mathbf{X}'_{i,t}$ is a vector of control variables, θ is the associated vector of coefficients and $\epsilon_{i,t}$ is the error term. The model includes country fixed effects (η_i) and time fixed effects (γ_t) to account for unobserved heterogeneity across countries and over time.

As a proxy for economic complexity, we use the economic complexity index from the Atlas of Economic Complexity.[2] We measure robot adoption as the number of industrial robots per 10,000 workers. Data on industrial robots are obtained from the International Federation of Robotics (IFR), while the number of workers comes from the International Labour Organization (ILO).

The variables were selected based on the relevant literature and the availability of data (Lapatinas, 2019; Keneck-Massil and Nvuh-Njoya, 2021; Barros et al., 2022).[3] Specifically, we include the following controls: population density, the logarithm of GDP per capita,

[1]Additional information can be found in the supplementary material.

[2]The Atlas of Economic Complexity provides three versions of the ECI, each calculated based on a different classification system for goods traded in international trade: HS92, HS12, and SITC. In our main regressions, we use the ECI constructed from HS92, which organizes products into more than 5,000 categories using six-digit codes. As a robustness exercise, we also estimate regressions using the ECI based on SITC, and the results remain consistent across the different specifications.

[3]To mitigate the influence of extreme observations on the moment conditions of the GMM, all variables were winsorized at the 1st and 99th percentiles. Missing values were limited and were addressed using linear interpolation to preserve the panel structure.

the share of the population using the internet, the human capital index, the share of low-skilled workers, and trade openness (measured as the sum of imports and exports as a percentage of GDP). We obtain these data from the World Bank, the International Labour Organization and the Penn World Table.

To estimate Equation (1), we employed the GMM System estimator. We consider GDP and robots as endogenous, given that both may simultaneously respond to changes in economic complexity.[4] We also report the Arellano-Bond test for second-order autocorrelation and the Hansen test for overidentification restrictions to assess whether the instruments used are exogenous.

3 Results

Table 1 reports the main estimation results, comparing four model specifications. Panel A uses the human capital index as a proxy for human capital, while Panel B relies on the share of low-skilled workers as an inverse measure of human capital. The AR(2) and Hansen tests indicate an absence of autocorrelation and that the instruments are valid.

The coefficient of the lagged economic complexity index (ECI_{t-1}) is positive and statistically significant in all models, corroborating the persistence of economic complexity over time. Industrial robot density is positively associated with economic complexity in most models, indicating that greater automation adoption is linked to higher levels of productive sophistication and diversification.

In Panel A, where human capital is measured by the human capital index, the interaction between robot density and human capital is negative and statistically significant. This suggests that the marginal effect of robot adoption on economic complexity diminishes as human capital increases.

[4] We instrument the endogenous variables using their second lags to ensure orthogonality with the error term and to avoid instrument proliferation, additionally the instrument matrix is collapsed. The results are robust to alternative lag structures.

Table 1: GMM System estimations: Effects of industrial robots, human capital and low-skilled workers on ECI - 1996:2023

	Dependent Variable: ECI			
	Panel A: Human capital index		*Panel B: Share of LSW*	
	Model 1	Model 2	Model 3	Model 4
ECI_{t-1}	0.705***	0.748***	0.770***	0.727***
Robot Density	0.005***	0.032**	0.005***	-0.014*
Log GDP per capita	-0.060	-0.037	-0.129	-0.051
Population Density	0.000	-0.000	-0.000	-0.000
Trade Openness	0.052	0.055	0.059	0.064*
Internet	0.227	0.106	0.419	-0.128
Human Capital	0.237***	0.203***		
Robot D. × Human Cap.		-0.007*		
LSW			-0.748**	-1.745**
Robot Density × LSW				0.035**
Constant	0.069	-0.087	1.832	1.854
AR(2) p-value	0.400	0.386	0.429	0.375
Hansen p-value	0.157	0.278	0.146	0.507
Number of instruments	22	23	22	23
Number of groups	61	61	61	61
Number of observations	1647	1647	1647	1647

Notes: Single (*), double (**) and triple (***) asterisks indicate significance at 10%, 5% and 1% respectively. The AR(2) refers to the Arellano–Bond second-order autocorrelation test (null: no autocorrelation). Hansen test verifies the exogeneity of the instruments (null: instruments are exogenous). Variables: **ECI**: Economic Complexity Index; **Robot Density**: industrial robots per 10,000 workers; **Log GDP per Capita**: logarithm of GDP per capita; **Population Density**: people per sq. km; **Trade Openness**: imports+exports as % of output; **Internet**: individuals using the internet (% of population); **Human Capital**: human capital index; **LSW**: Share of low-skilled workers.

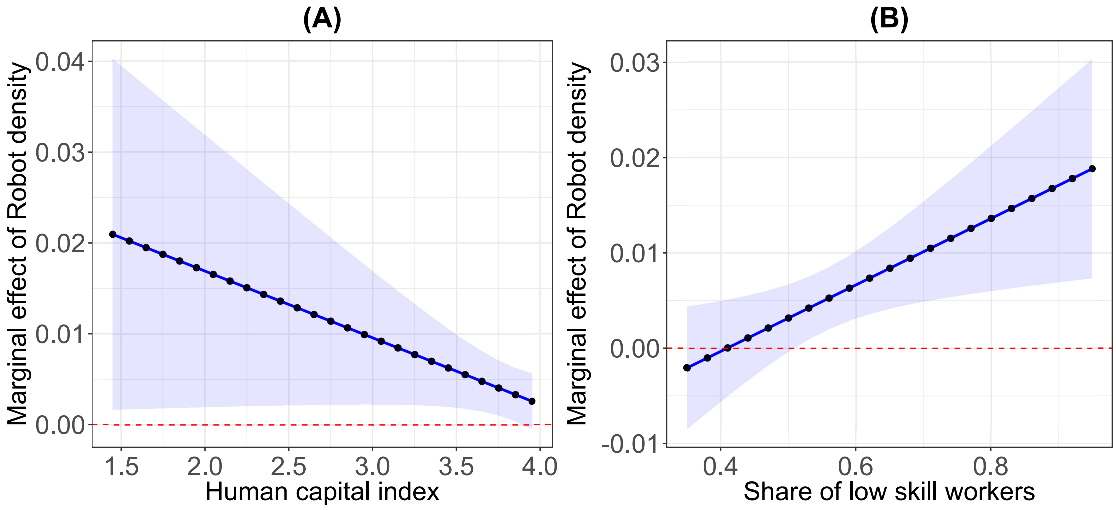
Panel B provides complementary evidence using the share of low-skilled workers as an inverse proxy for human capital. The interaction between robot density and the low-skill share is positive and statistically significant, indicating that the effect of robots on economic complexity is stronger in countries with a higher proportion of low-skilled labor. Control variables display the expected signs in most models, although their statistical significance varies across specifications.[5]

Figure 1 presents the marginal effects of industrial robot adoption on economic complexity for Models 2 and 4, respectively. The results indicate that the average marginal

[5] In the supplementary material, we estimated the same regressions dividing the sample into countries above and below the median income. The results show that the estimated effect of robot adoption on economic complexity is statistically significant only in developed countries. We argue that, in developing countries, robot density is still insufficient to generate gains in diversification and productive sophistication.

effect of robot adoption declines with human capital and increases with the share of low-skilled workers. This implies that the impact of robot adoption on economic complexity is heterogeneous along workforce characteristics.

Figure 1: Marginal effects of robot adoption on ECI - Models 2 and 4



Notes: The shaded areas represent 95% confidence intervals.

4 Discussion

Industrial robots can be seen as a form of industrial upgrading that can affect both the diversification and sophistication of exported goods. Robots affect export diversification because some goods, such as automobiles and advanced semiconductors, are highly dependent on automation. Thus, their introduction expands the range of products that the economy is capable of producing and exporting.

Sophistication, in turn, occurs through two main channels. First, robots make the production of technologically advanced goods viable by enabling levels of precision, reliability, and process control that cannot be achieved with simple production techniques. Second, robots reduce the cost of producing sophisticated goods while increasing productivity and quality.

Industrial robots can also affect economic complexity through the reinstatement effect. By replacing tasks performed by low-skilled labor, the reinstatement effect may, in some contexts, offset displacement effects by creating new tasks that require human intervention. When this condition occurs, countries can diversify their production matrix without entirely replacing workers.

5 Final Remarks

We found that a higher density of industrial robots is associated with greater economic complexity. We also observed that the impact is stronger in economies with a higher proportion of low-skilled workers, indicating that robots tend to facilitate the reallocation of labor to other activities that can broaden the diversification of exported products.

These findings offer insights for development policies. By promoting automation through tax incentives, research investments, and educational programs focused on training in automation, mechatronics, electrical, and software engineering, countries, especially those with an abundance of less-skilled labor, can expand their productive capacity and drive industrial upgrading. While our results do not establish causal relationships, they indicate that the adoption of robots may be associated with gains in economic complexity, particularly when supported by favorable institutional and work environments.

Disclosure statement

No potential conflict of interest was reported by the authors.

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