Economic Complexity and Robot Adoption*

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June 26, 2025

Abstract

This paper examines the relationship between economic complexity and industrial robot adoption. Using panel data for 61 countries from 1996 to 2022, we find that higher robot density is significantly associated with greater economic complexity. This positive relationship remains robust after controlling for per capita income, human capital, institutional quality, and other relevant factors. Notably, the complexity-enhancing effect of robots is stronger in countries with a larger share of low-skilled workers.

Keywords: Economic Complexiy; Industrial Robots; Economic Development
JEL: **O14, O33, O57**

*This study was financed, in part, by the São Paulo Research Foundation (FAPESP), Brazil. Process Number 2024/06763-0. Fernando Barros Jr thanks CNPq-Brazil for partial financial support. Delalibera acknowledges AGAUR-Generalitat de Catalunya through grant 2021 SGR 00862, and Spanish Ministry of Science, Innovation and Universities through grant PID2022-139468NB-I00.

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1 Introduction

The adoption of industrial robots has surged worldwide. From 1993 to 2023, global adoption grew by 689%, indicating a strong trend toward automation in recent decades (International Federation of Robotics, 2023). Industrial robots can increase productivity in manufacturing, enabling firms and countries to produce more sophisticated goods. Automation may thus facilitate diversification in production processes, a key component of economic complexity. Economic complexity, typically measured by the Economic Complexity Index (ECI), captures the diversity and sophistication of an economy's productive capabilities and has been linked to higher income levels and future growth prospects (Hidalgo and Hausmann, 2009; Hausmann et al., 2014). However, the role of automation in shaping a country's economic complexity remains underexplored.

This paper bridges the economic complexity and automation literatures by investigating whether greater robot adoption is associated with more complex economies. To our knowledge, no prior study has directly examined this nexus. Existing research on economic complexity has emphasized other drivers of productive capabilities, such as digital infrastructure (Lapatinas, 2019) and historical institutions (Keneck-Massil and Nvuh-Njoya, 2021), while studies on industrial robots have focused on productivity growth (Graetz and Michaels, 2018), economic growth (Prettner, 2019; Prettner and Strulik, 2020), and labor market (Acemoglu and Restrepo, 2020; Bloom et al., 2025).

There are reasons to expect a positive relationship between industrial robots and economic complexity. Industrial robots can complement human capital in performing complex or precision tasks, expand the range of producible products, and improve efficiency in manufacturing. By lowering production costs and enabling new high-value industries, automation might help countries diversify their output and climb the technological ladder. Conversely, it is possible that only more advanced (high-ECI) economies possess the necessary skills and infrastructure to deploy robots at scale, suggesting endogeneity between complexity and automation.

We use panel data covering 61 countries from 1996 to 2022 and estimate the relationship between economic complexity and robot adoption, controlling for a comprehensive set of factors typically associated with economic complexity, such as income, human capital, institutional quality, trade openness, and innovation inputs. The results reveal a robust positive association between industrial robot adoption (robots per worker) and the ECI. In economic terms, higher robot penetration corresponds to a more diversified and sophisticated export basket. This relationship holds after accounting for country-fixed effects and global trends, suggesting that automation offers incremental explanatory power for a country's complexity beyond the general development level.

Moreover, our analysis uncovers heterogeneity in this effect: the gains in complexity from robot adoption are more pronounced in economies with a larger share of low-skilled labor. One interpretation is that in labor-abundant countries, robots take over routine tasks and enable reallocation of labor into new productive activities, thereby expanding the set of capabilities without entirely displacing workers. This finding aligns with the view that automation can complement certain labor segments and facilitate structural transformation, rather than uniformly causing job polarization.

2 Econometric Approach and Data

We examine the impact of robot adoption on economic complexity using panel data spanning 61 countries from 1996 to 2022. Following evidence from Barros et al. (2022) and Lapatinas (2019), which indicates that economic complexity exhibits persistence over time, 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 $EC_{i,t}$ denotes the economic complexity for country i in period t; $RD_{i,t}$ represents industrial robots adoption; and $\mathbf{X}_{i,t}$ is a vector of control variables. The model includes fixed effects by country (η_i) and fixed effects by time (γ_t) to account for unobserved heterogeneity between countries and over time, respectively. The error term, $\epsilon_{i,t}$, is assumed to be normally distributed.

As a proxy for economic complexity, we use the economic complexity index (ECI) from the Atlas of Economic Complexity, developed by Hausmann et al. (2014).[1] We measure robot adoption as the number of industrial robots per 10,000 workers. Specifically, it is calculated by multiplying the total number of industrial robots by 10,000 and dividing by the total number of 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).

To select the vector of control variables, we follow the approach adopted by Barros et al. (2022), Keneck-Massil and Nvuh-Njoya (2021), and Lapatinas (2019). Specifically, we include the following controls: rule of law (as developed by Kaufmann et al. (2011)), population density, the logarithm of GDP per capita, the share of the population using the internet, share of low skill workers, trade openness (measured as the sum of imports and exports as a percentage of GDP), and R&D expenditure (as a share of output). We obtain these data from the World Bank, the International Labor Organization, and the UNESCO Institute for Statistics.

[1]The Atlas of Economic Complexity provides three versions of the Economic Complexity Index (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.

To estimate Equation (1), we employed the GMM System estimator proposed by Blundell and Bond (1998). This estimator is appropriate for models with unobserved individual effects and was developed to deal with specifications in which the lagged dependent variable appears as a regressor. In these circumstances, the presence of the lagged dependent variable generates endogeneity, which makes the use of traditional estimators inappropriate. In addition, we used the Arellano-Bond test for second-order autocorrelation to verify the absence of serial correlation in the error term and the Hansen test for overidentification restrictions to assess whether the instruments used are exogenous.

3 Results

Table 1 presents the results of the analysis, comparing four models with different combinations of control variables and interactions. Initially, the robustness tests indicate that the GMM System model is adequate: the Arellano-Bond test (AR(2)) confirms the absence of second-order autocorrelation, while the Hansen test validates the exogeneity of the instruments used.

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, as pointed out by Barros et al. (2022) and Lapatinas (2019). In Models 1, 2, and 3, the adoption of industrial robots exhibits a positive and significant coefficient, suggesting that increased automation is associated with greater economic complexity. This result indicates that the adoption of robots facilitates the production of more sophisticated goods.

In Model 4, when including the interaction between robot adoption and the proportion of low-skilled workers, the coefficient for robot adoption becomes negative. However, the interaction term is positive and significant, suggesting that the positive effect of automation on economic complexity is more pronounced in countries with a higher proportion of low-skilled workers. In our sample, this share ranges from 0.32 to 0.94. In Figure 1 we present the average marginal effect of robot adoption on economic complexity, considering different levels of the share of low-skill workers. In fact, we can see that the marginal effect is significant only if the share of LSW is above 0.33. This pattern may reflect task complementarity: rather than displacing low-skill workers, robots may assume routine, repetitive tasks, allowing low-skill labor to focus on manual or context-specific functions that remain difficult to automate. Moreover, in more economically complex settings, robot adoption may reallocate skilled workers toward innovation and coordination tasks, while preserving or even expanding auxiliary roles typically held by low-skill workers. As a result, the interaction between automation and a large low-skill labor force can facilitate the diversification of production capabilities, thus enhancing economic complexity.

Regarding the control variables, the proportion of low-skilled workers has a negative and marginally significant effect in Models 1 and 4. On the other hand, R&D investments and trade openness emerge as important determinants of economic complexity. Variables such as per capita income and Internet access show a limited impact on the results.

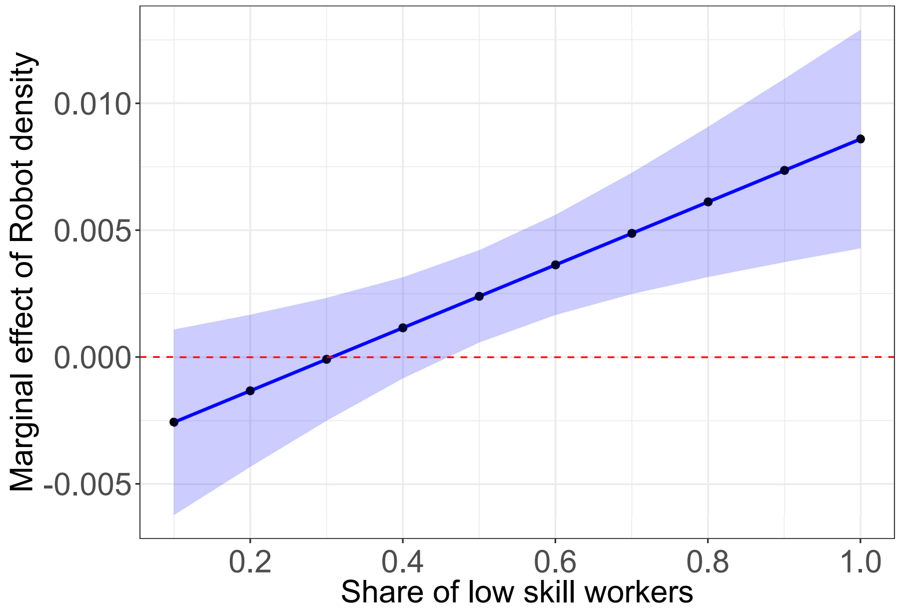
Table 1: GMM system estimation: Effects of industrial robots and share of low skill workers on economic complexity - 1996:2022

	Dependent Variable: Economic Complexity Index (ECI)			
	Model 1	Model 2	Model 3	Model 4
ECI (lag)	0.749***	0.744***	0.709***	0.691***
	(0.047)	(0.049)	(0.047)	(0.054)
Robot Adoption	0.003***	0.002***	0.003***	-0.004*
	(0.001)	(0.001)	(0.001)	(0.002)
Rule of Law	0.060*	0.037	0.031	0.037
	(0.033)	(0.032)	(0.034)	(0.035)
Pop. Density	-0.000**	-0.000	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Log of GDP per Capita	0.040	0.044	0.052	0.040
	(0.044)	(0.041)	(0.051)	(0.052)
Internet	0.000	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Shr. LSW	-0.361*	-0.217	-0.134	-0.387*
	(0.214)	(0.196)	(0.218)	(0.231)
R&D		0.063***	0.091***	0.083***
		(0.024)	(0.028)	(0.027)
Trade Openness			0.001***	0.001***
			(0.000)	(0.000)
Robot × Shr. LSW				0.012***
				(0.004)
Constant	-0.114	-0.281	-0.513	-0.167
	(0.528)	(0.482)	(0.599)	(0.632)
Time Fixed Effects	✓	✓	✓	✓
AR(2) p-value	0.639	0.615	0.624	0.606
Hansen p-value	0.326	0.379	0.189	0.335
Num. of Instruments	36	37	38	39
Num. of Groups	61	61	61	61
Observations	1595	1595	1595	1595

Notes: **(1)** Single (*), double (**) and triple (***) asterisks indicate significance at 10%, 5% and 1% respectively. **(2)** Standard errors are in parentheses. **(3)** The (AR(2)) refers to the Arellano-Bond second-order autocorrelation test, the null hypothesis is that there is no autocorrelation. **(4)** Hansen test is to verify the exogeneity of the instruments, the null hypothesis is that the instruments are exogenous. **(5)** Variables: **ECI**: Economic complexity index; **Robots Adoption**: Industrial robots per 10,000 workers; **Rule of Law**: rule of law index of Kaufmann et al. (2011); **Population density**: people per square km of land area; **Log of GDP per capita**: logarithm of real per capita GDP; **Internet**: fraction of population with internet access; **Shr. LSW**: share of low skill workers; **Trade openness**: sum of imports and exports as a percentage of output; **R&D**: the share of output spent on research and development; **FDI**: foreign direct investment.

Our results show that the average marginal effect of robot adoption on economic complexity increases with the share of low-skill workers, which in our sample ranges from 0.32 to 0.94 (see Figure 1). This pattern may reflect task complementarity: rather than displacing low-skill workers, robots may assume routine, repetitive tasks, allowing low-skill labor to focus on manual or context-specific functions that remain difficult to automate. Moreover, in more economically complex settings, robot adoption may reallocate skilled workers toward innovation and coordination tasks, while preserving or even expanding auxiliary roles typically held by low-skill workers. As a result, the interaction between automation and a large low-skill labor force can facilitate the diversification of production capabilities, thus enhancing economic complexity.

Figure 1: Marginal effects of robot adoption on economic complexity - Model 4



4 Final Remarks

These findings carry implications for development policy. By fostering automation, countries—especially those with abundant low-skill labor—may enhance their productive capabilities and advance industrial upgrading. Policies that improve access to technology and support skills development can help ensure that automation complements rather than displaces the existing workforce. While our results do not establish causality, they indicate that robot adoption can accompany gains in economic complexity, especially when supported by conducive labor and innovation environments.

Future work should explore the causal direction of this relationship and its underlying mechanisms. For instance, do robots enable entry into more complex industries, or are they more readily adopted in already sophisticated economies? Research using firm-level data or exogenous variation in automation costs could shed light on this question.

Moreover, as new technologies such as AI and machine learning continue to diffuse, their implications for economic complexity warrant further investigation.

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