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The Impact of Industrial Robots on Employment Occupations


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Lilit Marukyan


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# I. Abstract

This thesis examines the impact of industrial robot stock on low- and medium-skill employment across 31 countries between 2004 and 2021, contributing to the ongoing debate on the effects of robot automation on workforce. Drawing on the methodology of Acemoglu and Restrepo (2020), this study employs Pooled OLS, Fixed Effects, and Instrumental Variable (2SLS) regression models to isolate the causal effects of robot adoption and address endogeneity. German robot stock serves as an instrumental variable to account for potential reverse causality and omitted variable bias. Our results reveal no consistent evidence that industrial robots influence employment levels of low- and medium-skilled workers. Pooled OLS results suggest a positive relationship between robots and medium-skill employment. However, these findings reflect the unobserved cross-country differences. Fixed Effects and 2SLS models, which control for country-specific factors and endogeneity, find no statistically significant effects. The weak relationship between German robot stock and robot adoption in the first stage highlights the challenges of identifying robust instruments for robot automation research in a cross-country analysis.

# II. Zussamenfassung

Diese Arbeit untersucht den Einfluss des Bestands industrieller Roboter auf die Beschäftigung von niedrig- und mittelqualifizierten Arbeitskräften in 31 Ländern im Zeitraum von 2004 bis 2021 und leistet damit einen Beitrag zur aktuellen Debatte über die Auswirkungen der Roboterautomatisierung auf die Arbeitsmärkte. Aufbauend auf der Methodik von Acemoglu und Restrepo (2020) werden Pooled OLS-, Fixed Effekts- und Instrumental Variable (2SLS) -Regressionsmodelle verwendet, um die kausalen Effekte der Roboteradoption zu isolieren und Endogenitätsprobleme zu adressieren. Der deutsche Roboterbestand dient als Instrumentalvariable, um potenzielle Rückkopplungseffekte und Verzerrungen durch ausgelassene Variablen zu berücksichtigen.

Die Ergebnisse zeigen keine konsistenten Hinweise darauf, dass industrielle Roboter die Beschäftigungsniveaus von niedrig- und mittelqualifizierten Arbeitskräften beeinflussen. Während die Pooled OLS-Modelle auf eine positive Beziehung zwischen Robotern und mittelqualifizierter Beschäftigung hinweisen, spiegeln diese Ergebnisse vor allem unbeobachtete Unterschiede zwischen den Ländern wider. Im Gegensatz dazu zeigen Fixed Effekts- und 2SLS-Modelle, die länderspezifische Faktoren und Endogenität berücksichtigen, keine statistisch signifikanten Effekte. Die schwache Beziehung zwischen dem deutschen Roboterbestand und der Roboteradoption in der ersten Regressionsstufe verdeutlicht zudem die Herausforderungen bei der Identifikation robuster Instrumente für die Erforschung von Roboterautomatisierung in einer länderübergreifenden Analyse.

# III. Introduction

The integration of industrial robots into various sectors of economy sparks a significant debate about their impact on jobs.[1] As robots grow more agile and capable of performing an array of tasks with great efficiency, they bring potential benefits and challenges to the labor market.[2] The root of this issue lies in robots' ability to perform complex tasks autonomously, which, in turn, can make certain jobs obsolete. A historical example of the Luddite movement in the early 19th century, during which British textile workers strongly opposed the use of automated machinery in the wool industry, supports the fact that workers have long worried about losing their jobs to technology.[3] These concerns are even more prevalent now, since robotics as well as AI technologies have become more advanced and widespread.

Robots introduce a multitude of benefits such as higher productivity, innovation, and are a driver of economic growth. They enable businesses to automate repetitive tasks and enhance precision, as a result, achieving more in less time. This is especially true in production processes, as shown that the implementation of robots increases average labor productivity and annual growth of GDP by 0.36 and 0.37 percentage points across 17 countries in 1993-2007, showcasing their immense global potential to revolutionize industries (Graetz & Michaels, 2015). Moreover, robotic technology empowers companies to maintain their competitiveness both locally and on a global scale, with higher product quality and shorter development deadlines. These benefits are particularly critical for high-cost economies, where automation reduces reliance on low-cost, offshore labor (International Federation of Robotics, 2017).

The rise of robotics has also been linked to job creation through indirect pathways. While some manual jobs may be replaced by robots, new opportunities emerge in areas such as programming or maintenance (Dixon et al., 2018). Robots also contribute to safer workplaces by handling dangerous or physically demanding tasks. For instance, they can handle tasks like welding in car manufacturing, which notably reduces the risks to workers by preventing serious health complications.[4]

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[1] Acemoglu, D., & Restrepo, P. (2017). Robots and Jobs: Evidence from US Labor Markets.
[2] Georgieff, A., & Hyee, R. (2022). Artificial Intelligence and Employment: New Cross-Country Evidence.
[3] Hobsbawm, E. J. (1952). The Machine Breakers. *Past & Present*, *1*(1), 57–70.
[4] Graetz, G., & Michaels, G. (2015). Robots at Work.

While these advances demonstrate how robotic technology can improve worker safety and productivity, their broader effects on employment present a more complex scenario. Particularly, the ability of robots to autonomously carry out tasks once managed by people raises concerns about job redundancy and potential layoffs.[5] Historical moments like the disruption during the First Industrial Revolution shows that the fears about technological displacement have existed for a long time. Today, this anxiety persists, as scholars like Brynjolfsson and McAfee (2014) suggest that automation can undermine job stability. Frey and Osborne's (2017) prediction also suggest that up to 47% of U.S. jobs might be affected by robot automation underscores how significant this disruption could be.

The risk also extends beyond manual or low-skilled labor, since adopting robots changes the makeup of the workforce and shifts roles that require higher cognitive skills.[6] However, now, managerial positions, previously thought to be safeguarded by their cognitive demands, are also vulnerable.[7] Investments in robotics have been linked to reduced hiring for managerial roles (Autor et al., 2003; David & Dorn, 2013). This pattern highlights a significant transformation in the nature of work, propelled by the advanced capabilities of robots that exceed mere mechanisation.

Additionally, there is a potential danger of exacerbating socio-economic inequalities. Research by Karabarbounis and Neiman (2014) and Elsby, Hobijn, and Sahin (2013) points to a decline in the share of national income going to labor. Moreover, the resulting benefits of using robotic technology are not always distributed evenly, since the benefits are inclined to concentrate wealth among capital owners, potentially exacerbating the income disparity between high-earning professionals and low-skilled workers, who experience increased job insecurity.[8]

On a global scale, the growing dependence on industrial robotics is transforming the dynamics of international trade. Nations that make substantial investments in robotics frequently maintain their competitive edge in high-value manufacturing industries, even in the face of increasing labour costs.[9]

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[5] Frey, C. B., & Osborne, M. A. (2017). The Future of Employment.
[6] Felten, E., Raj, M., & Seamans, R. (2019). The Occupational Impact of Artificial Intelligence: Labor, Skills, and Polarization.
[7] Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change.
[8] Acemoglu, D., & Restrepo, P. (2018). *Robots and Jobs: Evidence from US Labor Markets*.
[9] Carbonero, F., Ernst, E., & Weber, E. (2018). *Robots Worldwide: The Impact of Automation on Employment and Trade*. International Labour Office.

## i. Definitions and Scope

To ensure clarity of our research, our thesis focuses primarily on industrial robots and their impact on low- and medium-skill employment. According to International Federation of Robotics, *an industrial robot* is "automatically controlled, reprogrammable, multipurpose, manipulator…designed for and typically utilised in industrial automation applications[10] ". These robots operate autonomously within a physical environment and are integral to processes that involve manipulation, motion, and repetitive task execution.

In contrast, *artificial intelligence (AI)* refers to software systems that simulate human intelligence, such as natural language processing models (e.g., GPTs), computer vision, or image recognition tools (Manning, 2020).

While AI can play a role in automation, our thesis excludes discussions of software-only automation systems and focuses strictly on physical robotic automation of tasks in the manufacturing industry. Clarifying this distinction is important to ensure automation by industrial robots is not confused with broader AI technologies that are outside the scope of our study.

## ii. Research Question and Hypotheses

In this paper, we examine the effects of industrial robots on employment levels across different occupational categories in the manufacturing industry, to understand which employment levels are most influenced by this technological advancement. For that, we formulate the following research question:

*"In what manner do industrial robots influence employment levels across diverse occupational categories?"*

Our research question arises from the current debate in economic literature around skilled-biased technological change (STBC). The SBTC theory highlights that technology improvements such robotics disproportionately impact different employment levels. Low-skill occupations, where regular and manual duties are in place, are more exposed to robot automation, whereas medium-skill

[10] International Federation of Robotics. (2017). The Impact of Robots on Productivity, Employment and Jobs.

employment occupations require problem-solving, creativity or human supervision of automated systems and may gain from this technological change.[11]

We formulate the following hypotheses in our research:

*I.* *Hypothesis 1 (H1): Robot automation has a negative impact on low-skill employment.*

Our first hypothesis assumes that industrial robots have a negative impact on low-skill employment occupations, since industrial robots perform routine tasks, particularly in low-skilled manufacturing and assembly-line operations, and, due to the repetitive nature of the manual labor involved, these low-skill positions are susceptible to robot automation.

*II.* *Hypothesis 2 (H2): Robot automation has a positive impact on medium-skill employment.*

Our second hypothesis suggests that, since medium-skilled workers (engineers, robot technicians, and managers, who conduct inspections), who perform non-routine, cognitive tasks that are more challenging to automate, may see an increase in demand for their skills as robot adoption rises. Since robots are used more in manufacturing, the demand for skilled workers who can program, maintain, and monitor these machines is likely to grow. Therefore, medium-skill workers, such as industrial designers or production managers, who are involved in decision-making and problem-solving, may find their roles to be complemented by robot automation rather than replaced.

We examine the impact of industrial robots on low- and medium-skill employment occupations by isolating the effect of robots to understand, first, if there is a significant impact of robots on the employment levels of different worker occupations, and second, to reveal interesting insights about the broader implications for workforce dynamics. Our research aims to contribute to the ongoing discussion on how robot adoption reshapes employment across different worker occupations. It also emphasizes the importance of balancing technological progress with proactive economic strategies that foster workforce adaptation to evolving labor market demands.

[11] The Race against the Robots and the Fallacy of the Giant Cheesecake: Immediate and Imagined Impacts of Artificial Intelligence. (2019).

### iii. Structure of thesis

Our paper starts with the introduction to the current literature. This section presents empirical evidence about robot adoption, its implications for the future of employment, highlighting potential benefits and challenges. Then, we describe our data, descriptive statistics and methodology. Next, we present our regression results on the impact of robots on employment of low and medium-skilled workers. We also use German robot data as an instrumental variable to analyse the impact on robot adoption in our sample, hence, these results are also presented. Finally, we discuss our findings in the scope of our research hypotheses, highlight the limitations of our study and consider the broader implications of our findings for future research.

# IV. Literature

The influence of industrial robots on different employment occupations is a primary topic in recent studies. Traditionally, robotic technologies predominantly impacted low- and medium-skilled workers, who are engaged in repetitive tasks.[12] In recent decades, employment in manufacturing sector of various member countries has decreased as industrial robots are increasingly displacing low-skilled labour (OECD, 2021). If previously robots aided higher-skilled individuals, current advances in robotics create certain challenges already for workers with various skill levels (Autor et al., 2003; Goos et al., 2009).

Empirical studies provide diverse perspectives on macroeconomic impact of industrial robots. Acemoglu and Restrepo (2020) apply U.S. country-level data to demonstrate that an increase in robot density adversely impacted local employment and wages. Specifically, each additional robot per 1,000 workers reduces the employment-to-population ratio by roughly 0.2 percentage points and wages by about 0.42%.[13] On the contrary, Dauth et al. (2017) states that, although robot automation results in job losses in manufacturing sector, it simultaneously fosters job development in the service sector, consequently stabilising overall employment outcomes.

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[12] IFR Statistical Department. (2021). World Robotics Industrial Robots.
[13] Acemoglu, D., & Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets.

Productivity and wage implications of robot automation are also important areas of focus. Research by Graetz and Michaels (2018) demonstrates that, while robot adoption boosts productivity, the consequent wage increases are more modest, thus, the economic benefits of increased productivity do not uniformly translate to higher wages.[14] Acemoglu and Restrepo (2018) further explore that robot automation reduces the labor share size, especially during economic recovery phases. Mainly, if there is no robot automation, wages are likely to be higher, although with slower productivity growth. In their work, they also discussed mechanisms like productivity boosts and capital investments, which can offset job losses by encouraging the formation of new job roles.[15] Additionally, robot automation leads to job polarization, meaning that while middle-skill jobs decrease, positions at both the high-skill and low-skill ends grow. This occurs since robots perform routine, standardized tasks more frequently, which leads to the creation of new jobs[16].

As mentioned earlier, robot automation yields mixed results on employment. For instance, Graetz and Michaels (2018) does not find a clear link between robot adoption and employment in developed nations[17], while De Backer et al. (2018) highlights that enterprises that integrate robots often see positive employment outcomes. These findings point out that many factors, such as government policies, the state of the economy, and the way industries adopt robots, are crucial in shaping the net effect on employment.

Data limitations can also obscure the real impact of robots. The International Federation of Robotics (IFR) acknowledges that data does not fully reflect changes in technology quality over time, which can skew how we interpret advancements in robot capabilities[18]. The IFR also counts robots simply as units without considering improvements in their functions, hence it can overlook the nuanced effects of technological advancements[19].

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[14] Graetz, G., & Michaels, G. (2018). Robots at Work.
[15] Acemoglu, D., Restrepo, P., & National Bureau of Economic Research. (2017). *Robots and Jobs: Evidence from US Labor Markets (No. 23285)*.
[16] Frey, C. B., & Osborne, M. A. (2013). *The Future of Employment: How Susceptible are Jobs to Computerisation*. Working Paper, Oxford Martin School.
[17] Graetz, G., & Michaels, G. (2015). *Robots at Work*. IZA Discussion Paper Series (No. 8938).
[18] Klump, R., Jurkat, A., & Schneider, F. (2021). *Tracking the Rise of Robots: A Survey of the IFR Database and its Applications*. Goethe University Frankfurt.
[19] International Federation of Robotics. (2017). *The Impact of Robots on Productivity, Employment and Jobs*.

While the increase in the adoption of industrial robots changes the labor landscape (boosting productivity and automating many tasks), its impact on jobs is diverse. On one side, there is a displacement of routine jobs and growing job polarization, on the other side, there are also opportunities in productivity gains and the creation of new job types. Another key aspect to consider is the presence of regional and industry-specific factors. Particularly, the economic impact of robotic automation is contingent upon the structural characteristics of specific regions or sectors. For example, economies that rely heavily on manufacturing are likely to experience workforce displacement in contrast to service-oriented economies.[20] Furthermore, robotic automation also affects the educational landscape. As robot automation transforms job requirements, there is an increasing demand for hybrid skill sets that integrate both technical competencies with creative thinking. Nevertheless, the transition to skill-based systems frequently fails to keep pace with the rapid progression of technological advancements, thereby creating a mismatch between the labor market demands and workforce skills.

In terms of research question and methodology, the most relevant research to our study is Acemoglu and Restrepo's (2020) evaluation the robot effect on employment, however, their analysis was based solely on US data and, consequently, the estimated relationship between robots and employment pertains only to the US economy. In our research, we utilize panel data, consisting of multiple countries from different continents and with varying sizes of economy. On the contrast to Acemoglu and Restrepo's work (2020), where the robot effect on employment is evaluated in general, our study estimates the impact of robots separately - on both low-skilled and medium-skilled employment.

[20] Dauth, W., Findeisen, S., & Woessner, N. (2017). *Adjusting to Robots: Worker-Level Evidence*. Economic Journal.

# V. Data and Methodology

## i. Data

The robot data is received from International Federation of Robotics (IFR). It includes data on the operational stock of industrial robots across different countries for years 2004-2021. Our dataset is limited, since many countries have missing figures for multiple years. Therefore, we include 31 countries for analysis to have a balanced panel data.

The dataset also does provide any classification of robots, meaning that it can include electrical robots, metal and machinery robots, food robots or other.

## ii. Descriptive Statistics

*Table I: Summary of variables*

| Variable | Description | Unit | Source |
|---|---|---|---|
| emp1 | Employment by occupation skill level 1 (low) | thousands | ILOSTAT |
| emp2 | Employment by occupation skill level 2 (medium) | thousands | ILOSTAT |
| robots | Operational stock of industrial robots | number | IFR |

Table I provides summary and description of our variables. The dataset includes three variables:

1) employment level of low-skilled workers,
2) employment level of medium-skilled workers,
3) operational stock of industrial robots.

The employment data is taken from ILOSTAT database. We define *employment* as "*all people of working age who are either in paid employment or self-employment for a certain amount of time. In our analysis, we use annual employment data based on economic activity and occupation*[21]." The reason for this is that employment across various economic activity sectors is useful to identify general changes

[21] International Labour Organization. *Employment by economic activity*. ILOSTAT., 2024

in employment trends. Based on that, our employment data is aggregated by *manufacturing* sector, since this is the sector where workers are highly susceptible to robot automation.

Another important aspect of our dataset is *employment occupation*, which provides insights on the range of jobs and tasks an individual can perform or be assigned. In our sample, workers are categorised by occupation based on how they relate to their current position. ILOSTAT provides definitions for each employment skill occupation, starting with elementary occupations (Skill 1) up to advanced, specialized occupations (Skills 3 and 4).

Within the scope of our study, we focus on low-skill (Skill 1) and medium-skill (Skill 2) employment occupations. Low-skill employment occupations cover elementary occupations and include workers in construction, mining, transport, manufacturing, agriculture, food preparation, forestry and others. Medium-skilled occupations include stationary plant and machine operators, handicraft workers, assemblers and others (supplementary data provided in Appendix).

As mentioned in our hypothesis 1 (H1), the proportion of low-skilled occupations will likely decline with the introduction of more robots, while the impact on medium-skilled workers is likely to be positive (H2).

*Table II: Summary of statistics*

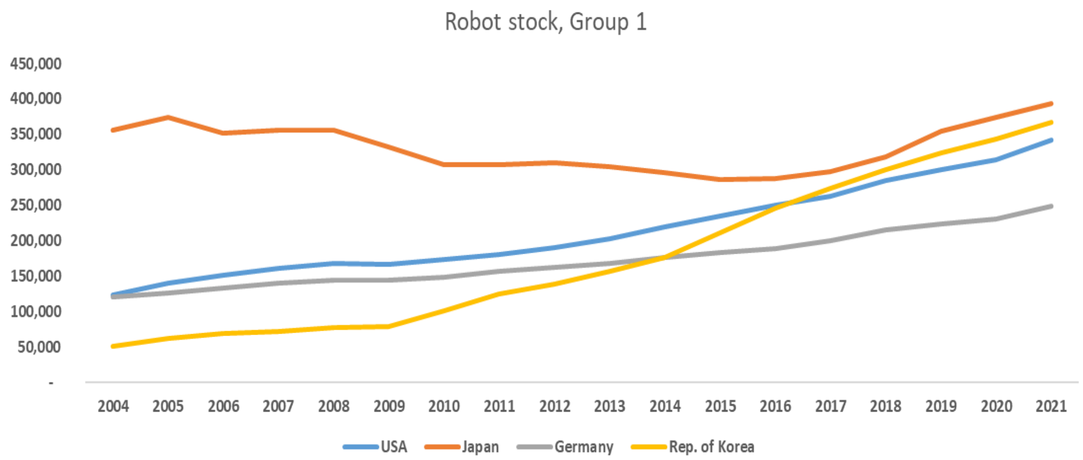
| **Variable** | **Obs** | **Mean** | **Std. dev** | **Min** | **Max** |
|---|---|---|---|---|---|
| emp1 | 558 | 279.2205 | 903.7396 | 1.095 | 8126.84 |
| emp2 | 558 | 1413.212 | 2104.754 | 10.664 | 8981.206 |
| robots | 558 | 36188.31 | 80602.01 | 0 | 393326 |

Table II summarises key statistics. For emp1, the mean value is 279.22, with a standard deviation of 903.74. For emp2, the mean value is at 1413.21, with a bigger standard deviation of 2104.75, indicating more variability. Variable “robots” stands out with the average, at 36,188.31, and a standard deviation of 80,602.01, indicating a lot of variation in robot stock across different observations. The values for robots range from 0 to 393,326, which highlights how unevenly distributed robot adoption is across our dataset. Overall, there is a lot of variability in all three variables.

## iii. Robot Dynamics

In this section, we discuss robot stock dynamics over 2004-2021 years for countries that have the highest robot stock in our sample.

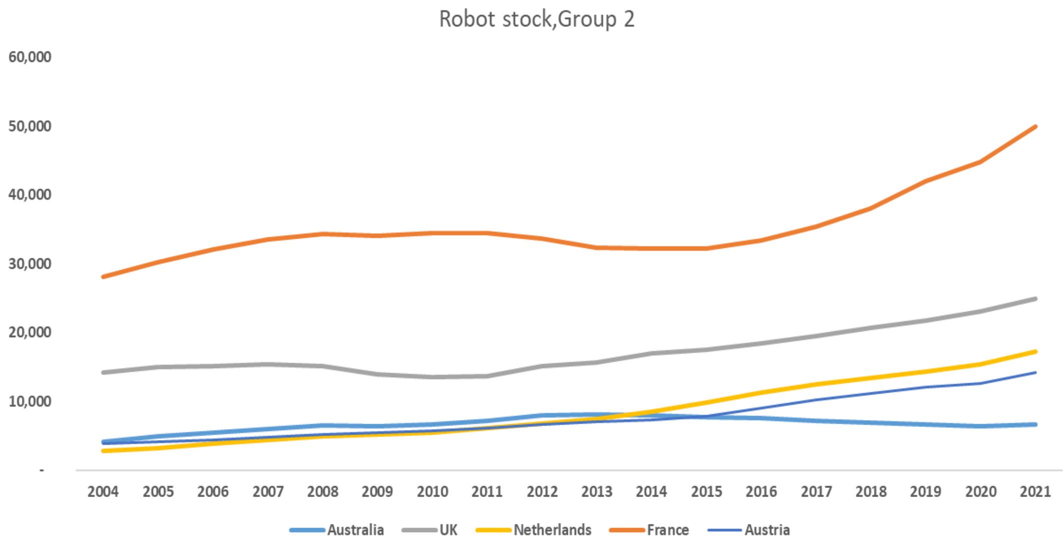
*Graph 1: Robot stock, Group 1 (USA, Japan, Germany, Rep. of Korea)*




Graph 1 demonstrates the industrial stock of robots for major economies - USA, Japan, Germany, and Republic of Korea for years 2004-2021. We notice how robot automation is developing quickly and how the market dynamics is changing in these economies.

It is evident from analysing the trends that Japan maintained a stable yet dominant position in the robot stock market at first, with relatively high levels in 2004 and a steady climb through 2009. Republic of Korea quickly increased its stock of robots in 2009, surpassing both the United States and Germany, and closed the gap with Japan by the end of the period. This increase demonstrates how Republic of Korea is increasingly focussing on robot automation and technological innovation. The robot stock in the USA and Germany has grown more steadily and gradually over the years. Germany's stable growth is consistent with its position as a highly technologically advanced economy, known for its industrial automation.

*Graph 2: Robot stock, Group 2 (Australia, UK, Netherlands, France, Austria)*




Graph 2 depicts trends for robot stock in a second group of countries—Australia, the UK, the Netherlands, France and Austria.

France emerges as the leader, demonstrating a significant increase in robot stock, especially from around 2014 onward. The Netherlands also showcase a significant growth in robot adoption starting from 2010, which suggests a steady investment in automation, although its total robot stock remains well below that of France. The UK and Austria maintain relatively stable yet low levels of growth throughout the period. Australia displays the lowest level of robot stock among this group.

## iv. Employment growth rates of low and medium-skilled workers, 2004-2022

Graphs below provide insights on employment growth rates in large economies from our sample (USA, France, Germany, Rep. of Korea), assuming that relatively smaller economies will be impacted by larger economies, so the picture will not be deviated in other countries.

*Employment growth rates of low and medium-skilled workers, 2004-2021*


We see that medium-skill employment growth rate is relatively stable, while the low-skill employment dynamic has more volatility, with several notable spikes and dips for selected countries. There is a significant decrease in employment during global crisis periods, particularly in 2008–2009 and 2020, coinciding with the global financial crisis and the COVID-19 pandemic, respectively.

These trends suggest that low-skill employment is more sensitive to economic shocks and external disruptions, while medium-skill employment appears to be more resilient. At the same time, there are country-specific variations, such as the sharp peaks in France's low-skill employment in 2010 and 2022, hinting at local, policy-driven impacts.

## v. Summary of models

We perform our analysis using two estimators: Pooled OLS and Fixed Effects.

I. *Pooled OLS:*

$$emp_{it} = \alpha + \beta \cdot x_{it} + \epsilon_{it},$$

where $emp_{it}$ is the employment level of low-, medium- skilled workers in country $i$ at time $t$, $\alpha$ is the intercept, $x_{it}$ is the robot exposure (in absolute values), $\epsilon_{it}$ is the error term capturing unobserved factors.

II. *Fixed Effects:*

$$emp_{it} = \beta \cdot x_{it} + \delta_i + \epsilon_{it},$$

where $emp_{it}$ is the employment level of low-, medium- skilled workers in country $i$ at time $t$, $\delta_i$ represents individual (country) fixed effects to control for unobserved heterogeneity, $x_{it}$ is the robot exposure (in absolute values), and $\epsilon_{it}$ is the error term capturing unobserved factors.

We implement the models above to explore the relationship between robot exposure and employment levels of low- and medium-skilled workers across countries in our sample. Pooled OLS model assumes a common intercept across countries, offering a baseline estimate of the relationship between robot exposure and employment, and does not account for country-specific characteristics. Pooled OLS is a more straightforward model because it assumes that country-level effects are minimal. On the contrast, FE model incorporates individual country-specific factors ($\delta_i$), to control for unobserved heterogeneity and to isolate the within-country variation over time. FE provides a more nuanced understanding of the data, since it accounts for country-level differences that might influence employment outcomes (e.g. cultural or institutional factors).

We utilize these two models to address the trade-off between maintaining simplicity and accounting for unobserved factors that might shape the observed relationship.

## vi. Instrumental Variable (IV)

To address potential endogeneity in the relationship between robot adoption and employment, we adopt an Instrumental Variable (IV) approach, based on the methodology by Acemoglu and Restrepo, who used European trends to instrument for U.S. exposure to robots. Specifically, we select robot stock of Germany as an instrument, assuming that the German robot stock influences local robot adoption, hence it indirectly affects employment levels only through its impact on local adoption.

We select German robot stock as an instrumental variable, since Germany is one of the most industrially automated countries in Europe, making it a useful reference for studying trends in robot adoption. The idea is that Germany's high levels of automation is likely to influence the adoption of robots in other countries, even if the connection is not guaranteed to be strong. With this approach, we aim to better understand how robot adoption affects employment while addressing potential issues like reverse causality or hidden factors that could influence both robot adoption and employment.

The analysis relies on a two-equation system:

i. *First-Stage Equation:*

$$robots_{i,t} = \beta_0 + \beta_1 Z_{it} + \nu_{it}$$

where $Z_{it}$ is the instrumental variable (German robot stock), $\beta_1$is coefficient indicating how strongly $Z_{it}$ predicts $robots_{it}$, and $\nu_{it}$ is the first-stage error term.

ii. *Second-Stage Equation:*

$$emp_{it} = \beta_0 + \beta_1 \cdot robots_{it} + \epsilon_{it},$$

where $emp_{it}$ is employment levels in country *i* at time *t*, $robots_{it}$ is the robot adoption (endogenous variable) in country *i* at time *t*, and $\epsilon_{it}$ is the error term capturing unobserved factors.

This two-stage least squares (2SLS) method helps to solve the problem of simultaneity bias, which can occur when robot adoption and employment levels influence each other, or when there are hidden factors that affect both robot adoption and employment at the same time. We isolate this exogenous variation to, first, analyse the causal impact of robot adoption on employment levels and, second, evaluate whether the lack of significant effects stems from weak instrument performance or inherent absence of relationships.

# I. Results

This section presents the results of our study. The results below demonstrate the scope of impact of industrial robots on employment of low- and medium-skilled workers, revealing key differences between the two model approaches and the regression results using Germany's robot data as an instrumental variable (IV).

*Table 3: Summary of results*

| | (POOLED OLS) | (FE) | (POOLED OLS) | (FE) |
|---|---|---|---|---|
| **VARIABLES** | emp1 | emp1 | emp2 | emp2 |
| robots | 0.00711*** | 0.00279 | 0.0187*** | -0.00427 |
| | (0.00191) | (0.00331) | (0.00346) | (0.00379) |
| Constant | 22.06 | 178.1 | 738.2*** | 1,568*** |
| | (38.88) | (119.8) | (223.4) | (137.2) |
| | | | | |
| Observations | 558 | 558 | 558 | 558 |
| R-squared | 0.402 | 0.011 | 0.510 | 0.032 |
| Number of Country | 31 | 31 | 31 | 31 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3 above summarises results from two models for each employment level (robust standard errors):

*I.* *low-skill (emp1)*: in Pooled OLS model, the coefficient for robots is 0.0071, with a standard error of 0.0019. The result is statistically significant at the 99.9% confidence level (p-value = 0.001), indicating that a 1-unit increase in robot exposure is associated with a 0.0071-unit increase in low-skill employment. The R-squared value is 0.4017, meaning that approximately 40.17% of the variation in low-skill employment is explained by robots.

In FE model, the coefficient for robots is 0.0028, indicating that an increase of 1-unit in robots is associated with 0.0028 unit increase in low-skill employment. However, this coefficient is not statistically significant, with a robust standard error of 0.0033 and p-value is 0.405. The model's R-squared value shows that within-country variation explained by the model is 0.0111, so the model explains only 1 percent variation in the dependent variable. The between-country variation explained is 0.8153, and the overall variation explained is 0.4017. While the model explains a substantial amount of the variation between countries, it explains less of the variation within countries over time.

*II.* *medium-skill (emp2):* in Pooled OLS model, the coefficient for robots is 0.0187 with a robust standard error of 0.0034 and the associated p-value of 0.000, so the coefficient is statistically significant. The 95% confidence interval for the coefficient ranges from 0.0115 to 0.0257, implying that 1 unit increase in the operational stock of robots is associated with an increase of approximately 0.018 units in medium-skill employment. F-statistic for the model is 28.99, with a p-value of 0.000, indicating that the model is statistically significant overall. R-squared value is 0.5102, indicating that 51.02% of the variation in medium-skill employment is explained by the operational stock of robots.

In FE model, the coefficient for robots is -0.0042 with a robust standard error of 0.0038 and associated p-value is 0.269, indicating the relationship between robots and medium-skill employment is not statistically significant (p-value > 0.05). F-statistic is 1.27 with a corresponding p-value of 0.2686, which further confirms that the model is statistically not significant overall.

Our results suggest that there is no significant relationship between the operational stock of industrial robots and medium-skill employment, when controlling for unobserved heterogeneity across countries and using robust standard errors.

## I. 2-stage regression results

This analysis builds upon the foundational framework by Acemoglu and Restrepo (2020), where industrial robot adoption was studied on the U.S. labor market. Following their approach, we utilize an instrumental variable (IV) approach, leveraging German robot stock as an exogenous predictor of robot adoption, to resolve endogeneity in the relationship between robot adoption and employment. For instance, firms adopting robots might simultaneously experience other shocks influencing employment, making direct OLS estimates biased.

German robot stock serves as an exogenous instrument, similar to how Acemoglu and Restrepo utilized trends in European robotics adoption to estimate impacts in U.S. markets. This allows us to isolate the causal effect of robot adoption on employment by addressing reverse causality and omitted variable bias.

Table 4 below presents the results of our two-stage least squares (2SLS) regression.

*Table 4: Summary of 2SLS results*

| | (1) | (2) |
|---|---|---|
| | emp1 | emp2 |
| **VARIABLES** | | |
| robots | -0.0116 | 0.00225 |
| | (0.00992) | (0.0109) |
| Constant | 636.1* | 1,231*** |
| | (345.1) | (349.6) |
| Observations | 540 | 540 |
| R-squared | . | 0.110 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

I. *First-Stage results:* the results indicate a weak relationship between German robot stock and robot adoption, with F-statistic of approximately 4.04 (summary statistics are provided in Appendix). This falls below the commonly accepted threshold of 10, suggesting a weak instrument and implying that the variation in robot adoption explained by the German robot stock is limited, potentially undermining the reliability of the second-stage results (first-stage summary statistics are provided in the Appendix). One reason for this is that our dataset includes countries from different continents, where German robot stock has a weaker effect on robot adoption in countries outside the EU.

II. *Second-Stage results:* the coefficients for robot adoption in the second-stage regression are not statistically significant for either employment metric (emp1, emp2). This aligns with the conclusion that, after accounting for the exogenous variation in robot adoption driven by the German robot stock, there is no causal impact on employment levels in our sample.

The lack of statistical significance implies that, after accounting for the exogenous variation in robot adoption (instrumented by German robots), there is no evidence that robot adoption has a measurable causal impact on employment in our sample. This finding also aligns with our previous results from FE models, which also revealed a weaker relationship, once unobserved heterogeneity was accounted for.

# II. Discussion

## i. Pooled OLS vs Fixed Effects (emp1)

Our Pooled OLS results indicate a statistically significant, positive relationship between robots and low-skill employment (robot's coefficient = 0.00711, $p < 0.01$). This contradicts with our first hypothesis (H1), where we assume a negative impact of robot automation on low-skill employment. A possible explanation for this can be that robot adoption might not necessarily replace low-skill workers directly. Instead, robots can lead to the creation of complementary tasks for low-skill workers as well (e.g. machine monitoring) or increase productivity in a way that preserves or even increases the number of low-skill jobs. However, Pooled OLS model does not account for unobserved country-specific or time-specific factors, so this positive relationship could have been influenced by external factors such as different industry structures across countries, local labor policies, or other omitted variables.

Fixed Effects model indicates the relationship between robots and low-skill employment is statistically insignificant (robot's coefficient = 0.00279, $p > 0.05$). While controlling for country-specific factors, there is no clear evidence that robot automation impacts low-skill employment within countries in our sample. Results show that our first hypothesis (H1) is not supported by the data. While robot adoption may displace low-skill workers in certain contexts, the overall impact varies, depending on other country-dependent factors.

## ii. Pooled OLS vs Fixed Effects (emp2)

Pooled OLS model shows a statistically significant and positive relationship between robots and medium-skill employment (coefficient = 0.0187, $p < 0.01$). Results support our second hypothesis (H2), which states that robot automation positively impacts medium-skill employment, aligning with the notion that medium-skilled workers, such as technicians, engineers, and managers, play crucial roles in maintaining, programming, and supervising robots. The adoption of robots in industries likely increases the demand for these skills, as companies require more workers to manage and optimize automated systems. Additionally, the higher R-squared value (0.510) in Pooled OLS model for emp2 compared to emp1 indicates that the model explains a larger portion of the variation in medium-skill employment. However, our goal is to isolate the specific effect of robots on employment, hence the OLS results are biased, due to unobserved factors that are not accounted for in the model.

In contrast, the Fixed Effects model shows a statistically insignificant and slightly negative relationship (coefficient = - 0.00427, $p > 0.05$). This model confirms that the positive relationship observed in the Pooled OLS model is influenced by cross-country differences rather than changes occurring within countries over time. For example, countries with advanced industrial sectors may experience growth in medium-skill jobs, while countries lacking these resources might not see the same benefits. FE model results suggest that the positive relationship between robots and medium-skill employment is not universal. Hence, these results partially support our second hypothesis (H2) - while robot automation can create opportunities for medium-skill workers, the impact depends on country-specific factors.

## iii. Model comparison

When comparing Pooled OLS and Fixed Effects models, an important indicator is the within R-squared value in the Fixed Effects model, which estimates the percentage of variation explained over time within each country. The results in Table 3 demonstrate that the R-squared values for both medium-skill employment (emp2) and low-skill employment (emp1) are notably higher in the Pooled OLS models compared to the Fixed Effects models. This indicates that the Pooled OLS models explain a larger proportion of the variation in employment outcomes overall. However, it is critical to interpret these results with caution. While the higher R-squared in the Pooled OLS model suggests that it captures more variation, this also reflects the influence of unobserved, time-invariant country-specific factors that are not accounted for in Pooled OLS. Meanwhile, Fixed Effects model controls for these unobserved factors, which may explain why the coefficients for robot adoption in FE model lacks statistical significance. Hence, the relationship between employment and the operational stock of robots becomes weaker. Thus, although Pooled OLS model yields stronger and more significant results, but this does not necessarily mean it is the more reliable model. The validity of the Pooled OLS estimates assumes that unobserved heterogeneity across countries is uncorrelated with the independent variable (robot adoption). If this assumption holds, the Pooled OLS results can provide useful insights. However, if unobserved factors, such as differences in industrial structure or workforce, are correlated with robot adoption, the Pooled OLS results may suffer from omitted variable bias.

In summary, while the Pooled OLS model suggests a stronger relationship between robot adoption and employment outcomes, the Fixed Effects model provides a more cautious interpretation by controlling for unobserved heterogeneity. The divergence between these models highlights the importance of considering the broader context, including the potential impact of unobserved, time-invariant factors, when interpreting the results.

### iv. 2SLS Regression

Our method mirrors Acemoglu and Restrepo's approach of using robot adoption trends in European economies as instruments to isolate causal effects on the U.S. labor market. However, our findings diverge from their conclusions, highlighting key differences.

The weak relationship between the instrument and robot adoption in first stage, as shown by the low F-statistic, reduces the explanatory power of our instrument and undermines the validity of 2SLS estimates. In the second stage, we find no statistically significant relationship between robot adoption and either employment levels. This suggests that, after accounting for exogenous variation in robot adoption driven by German robot stock, there is no causal effect of robot adoption on employment in our sample.

Our results differ from Acemoglu and Restrepo's findings in the U.S., where robot adoption was associated with significant reductions in employment, particularly in routine-intensive jobs.

Several factors may explain this discrepancy:

1. *Weak Instrument:* the weak, first-stage relationship between German robot stock and robot adoption diminishes the reliability of our second-stage estimates. The variation in robot adoption attributable to German robot stock may not be sufficient to capture meaningful differences in employment outcomes. A stronger instrument would be needed to draw more definitive causal inferences. As discussed before, the reason comes from the fact, that our dataset consists of countries from different continents, hence introducing greater heterogeneity and reducing the strength of the instrument.
2. *Weak or absent relationship between robot adoption and employment*: the link between robot adoption and employment may be context-dependent and rely on structural differences across countries in our sample. For instance, Germany's robot stock may mostly affect countries within the European Union, where trade and industrial integration are stronger. Meanwhile, it may have weaker influence on non-EU countries, such as the U.S., South Korea or Japan, where these countries, being leading robotics producers, rely more on their own capacities for robot adoption
3. *Model misspecification:* the model may be mis-specified, potentially omitting other critical variables that influence employment. For instance, local labor market policies, skill mismatches, demographic changes, or other macroeconomic trends could play an important role, but are not included in the model. Therefore, including additional controls might improve the explanatory power and robustness of our results to capture the nuanced relationship between robot adoption and employment.

## v. Policy implications

In our analysis, German robot stock is used as an instrument to explain variations in robot adoption across countries, since Germany has one of the highest levels of robot stock globally and is a major economic player in the European Union. German robot stock was intended to serve as a tool for capturing broader trends in robot adoption and addressing issues like endogeneity. However, in this study, the relationship between German robot stock and robot adoption was weak, suggesting that other factors, such as country-specific differences, might play a more significant role in shaping the effects of robot adoption on employment outcomes.

Although our study does not find clear evidence of direct effects on employment, past research, such as Acemoglu and Restrepo's work in the U.S., shows that automation can lead to significant job losses in routine-based roles if proactive steps are not taken. Developing countries face additional challenges when it comes to robot adoption, since they often lack the resources to adapt their labor markets. These economies tend to rely heavily on low-skilled labor, making them more vulnerable to job losses due to robot automation. If there is not enough investment in worker retraining or skill-based, educational programs, rapid robot adoption could worsen unemployment and boost economic inequality. Hence, developing countries, particularly those in Western Europe, should prioritize education and workforce training to prepare for the challenges brought by robot automation.

# III. Limitations

Our research acknowledges several important limitations.

## i. Data Limitations

The dataset used in this analysis comes from the IFR, but it includes gaps, with missing data for numerous countries and across various time periods. As a result, certain countries had to be excluded from the study, which impacts the comprehensiveness of the analysis.

Our data is inherently noisy due to varying conditions across countries - differences in the rate of robot adoption, population growth, or changes in other economic factors, making it challenging to isolate the true effect of robots on employment. For instance, the number of robots might be increasing in some countries, while other structural changes are simultaneously occurring, which complicates the analysis further.

## ii. Different Rates of Robot Adoption and Labor Market Structures

Economies differ significantly in how rapidly they adopt industrial robots. Some countries are quick to embrace automation, while others take a more gradual approach. Additionally, labor market structures, shaped by regulations and the makeup of the workforce, differ widely across nations. These differences can influence how robot automation impacts employment in each country. Since our models cannot fully capture for these variations, some unobserved cross-country disparities may remain, potentially introducing bias into the results.

## iii. Nonlinearities

Our models assume a simple, linear relationship between industrial robots and employment, implying that each additional robot has the same impact on employment. However, this simplification overlooks potential nonlinear effects. For example, adopting robots might initially reduce jobs, but over time, the negative impacts could diminish or even reverse, because industries adapt to labor market conditions as well as continue to innovate and create new employment opportunities.

## iv. Lagged effects

The analysis presumes that changes in robot automation influence employment within the same year. The impact may be delayed, as businesses often require time to reorganize their workforce or for new job opportunities to emerge. By not accounting for these lagged effects, the models could misinterpret or underestimate the true influence of automation on employment.

## v. Exclusion of other independent variables

Finally, on our study, we did not incorporate other economic variables that could have also influenced our results. Factors such as GDP growth, technological investments or education are also key indicators for shaping how robot automation impacts labor markets. The absence of these variables may lead to an incomplete analysis, potentially skewing the perceived impact of automation on employment.

# IV. Conclusion

We studied the impact of industrials robots on different employment occupations, specifically on low- and medium-skill employment levels, based on the framework of Acemoglu and Restrepo (2020). By using Pooled OLS, Fixed Effects, and Instrumental Variable (2SLS) regression models, we analysed the relationship between industrial robots and employment across these two occupational skill groups. We also addressed endogeneity by using German robot stock as an instrument to uncover the causal effects of robot adoption on employment.

Our results show no clear evidence of a consistent impact of robot adoption on employment levels. Mainly, Pooled OLS models indicated a positive relationship, especially for medium-skill jobs, however these findings stem from unobserved differences between countries in our sample. In contrast, Fixed Effects and 2SLS models, which control for country-specific and endogenous factors, find no statistically significant relationship. A weak relationship between the instrument and robot adoption in the 2SLS analysis further complicates efforts to draw definitive conclusions.

Our findings emphasize the importance of country-specific factors (e.g. labor market policies, industrial structures of countries, demographic shifts and other macroeconomic conditions) in shaping how robots influence employment. While robots can enhance productivity and create job opportunities in certain roles, their broader impact depends on localized policies and workforce adaptability. There is also the need for proactive strategies, like education and training programs, to help both low-skill and medium-skilled workers adapt to robot automation changes. For that, policymakers should strike a balance between advancing robotic technology and ensuring inclusive economic outcomes for all workers.

# V. Appendix

*Skill levels*

| Broad skill level | ISCO-08 |
|---|---|
| Skill levels 3 and 4 | 1. Managers |
| | 2. Professionals |
| | 3. Technicians and associate professionals |
| Skill level 2 | 4. Clerical support workers |
| | 5. Service and sales workers |
| | 6. Skilled agricultural, forestry and fishery workers |
| | 7. Craft and related trades workers |
| | 8. Plant and machine operators, and assemblers |
| Skill level 1 | 9. Elementary occupations |
| Armed forces | 0. Armed forces occupations |
| Not elsewhere classified | X. Not elsewhere classified |

Supplementary data about occupation classification and industrial robots can be found at ILOSTAT and IFR online respectively.

*First-stage regression summary statistics*

| model | R-sq. | Adj. R-sq. | Partial R-sq. | Robust F(1,538) | Prob > F |
|---|---|---|---|---|---|
| emp1 | 0.0097 | 0.0079 | 0.0097 | 4.0401 | 0.0449 |
| emp2 | 0.0097 | 0.0079 | 0.0097 | 4.0401 | 0.0449 |

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