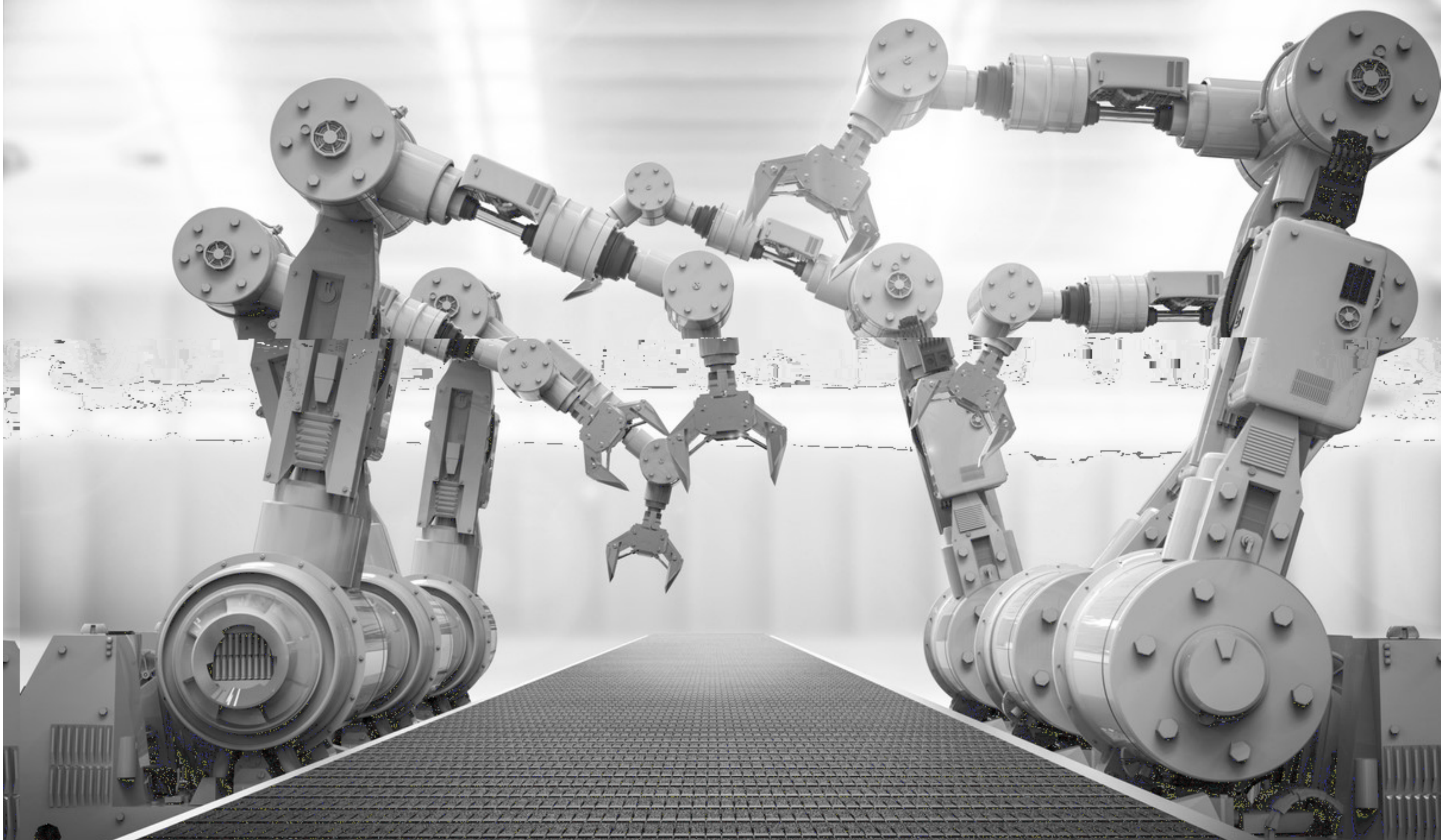

# Robots and the Economy

## The Role of Automation in Driving Productivity Growth

2020

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## INTRODUCTION

Innovation in manufacturing, such as automation, is key to industry global competitiveness. Global multinational companies have consistently selected the United States as a destination for their manufacturing operations. Foreign direct investment (FDI) in manufacturing in the United States represents 40.1 percent of all FDI in the United States, and automation plays a key role in attracting that investment and creating jobs.[1]

Automation is a form of technology that reduces the need for human assistance, such as a self-checkout stand at the grocery store or an automated teller machine. This can include partial automation where workers are adding value alongside robots. It is important to study automation and its impact on the workplace to understand if, and how, this type of technological change shifts the labor market. This report explores automation across industries, specifically analyzing the relationship between industrial robots and productivity. It also identifies industries that most frequently adopt industrial robots and how adoption ultimately impacts industrial competitiveness through productivity growth, value added, and the number of hours worked.

Industrial robots play a significant role in increasing productivity across industries, as seen in the following findings:

- In 2017, the industry with the highest industrial robot density in the world was the automotive and other transportation manufacturing industry, with 29.3 industrial robots per million hours worked. The industry with the second-highest density was the chemical manufacturing industry, with 6.0 industrial robots per million hours worked.

- From 2003 to 2017, the largest change in industrial robot density occurred in the automotive and other transportation manufacturing industry, with an increase of 15.1 industrial robots per million hours worked. The mining and quarrying industry saw the largest increase in productivity during this timeframe despite its low deployment of industrial robots.

- For all industries, **there was a positive relationship between industrial robot density and productivity**. An increase in industrial robot density of one percent correlated with an increase in productivity of 0.8 percent, all else equal. Specifically, for the industries that were slower robot adopters, a one percent increase in industrial robot density simultaneously occurred with a 5.1 percent increase in productivity, all else equal.

- There was an inverse relationship between industrial robot density and hours worked, meaning that **as industrial robot density increased, hours worked simultaneously decreased**. A one percent increase in industrial robot density was associated with a one percent decrease in hours worked, all else equal. The change was much greater for the industries slower to adopt industrial robots. Among observations in that group, a one percent increase in industrial robot density correlated with a 2.7 percent decrease in hours worked, all else equal. This means that industries slower to industrial robot adoption saw larger decreases in hours worked by employees.

## AUTOMATION TRENDS AND PREVIOUS LITERATURE

Historically, the adoption of automated technology has been challenging to measure. The International Monetary Fund, the World Bank, the Organization for Economic Co-operation and Development (OECD), and the U.S. government do not currently offer indicators on robots or other automation practices. The U.S. Bureau of Labor Statistics was tasked by the U.S. Congress to measure the effects of new technologies on the workforce in fiscal year 2020.[2] However, it has not been disclosed when this dataset will be available. Previous studies have used data from the International Federation of Robots (IFR) to better understand automation trends. For example, a 2015 report estimated that an increase in the use of industrial robots raised select countries' gross domestic product (GDP) growth rates by 0.37 percentage points between 1993 and 2007.[3]

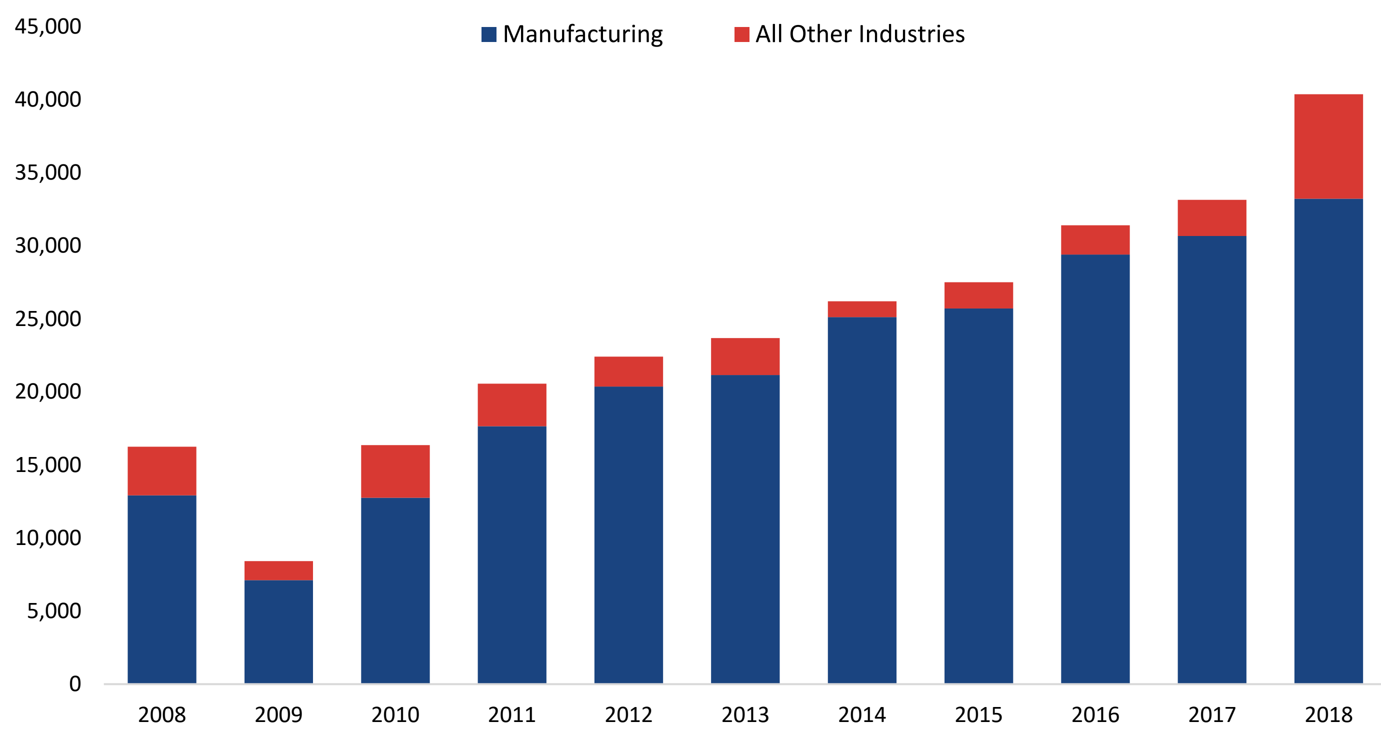
There has been a recent increase in automation worldwide. As indicated in Figure 1, within the United States, industrial robot installations have increased at a 10.28 percent compound annual growth rate (CAGR) in the past decade, from 15,170 in 2008 to 40,373 in 2018. In general, automation most often occurs in the manufacturing industry, but also impacts other industries, such as agriculture, mining, and construction.

In 2018, the manufacturing sector represented 82.3 percent of industrial robot installations across all U.S. industries.

Economists anticipate that the technological change of increased automation will significantly impact the labor market.[4] Automation is specifically expected to increase labor productivity, which would boost economic growth and ultimately create more jobs and improve living standards. However, automation also introduces challenges for both workers and communities, including job displacement, disruptions to local economies, changing skill needs, and rising inequality.[5] In one recent report, economists predicted that 47 percent of U.S. occupation categories may be automated over the next couple decades.[6] Another report estimated that 45 percent of work activities in the United States can be automated, which represents approximately $2 trillion in annual wages.[7]

While these previous studies analyze the relationship between automation, workers, and wages, little research examines how industrial robots impact indicators of significance to businesses: productivity, value added, and hours worked by industry. To address this gap, this report analyzes the impact of increases in industrial robot density on productivity.

FIGURE 1: INDUSTRIAL ROBOT INSTALLATIONS IN THE UNITED STATES BY SECTOR, 2008 TO 2018




*Source: International Federation of Robots, World Robotics 2019, Accessed February 12, 2020, https://ifr.org*.

## METHODOLOGY

This paper follows the approach outlined in a paper by Graetz and Michaels (2015), which analyzed the economic impact of industrial robots using panel data of industries in 17 countries between 1993 and 2007, including the United States.[8] This report similarly conducts three separate ordinary least squares (OLS) estimation tests to understand if increasing industrial robot density simultaneously increases with productivity and value added, and decreases with hours worked. This report is most focused on productivity, specifically the correlation between increases in robot density and increases in production. In other words, this report explores the question: if nothing else changes, do automation and productivity increase together?

The main independent variable of interest is industrial robot density, which is the number of industrial robots per million hours worked. This means that with increases in industrial robot density, productivity is expected to increase. The data are sourced from the International Federation of Robotics (IFR), which compiles data on single industrial robot installations and industrial robot stock by industry and country from 1993 to 2018.[9] The main dependent variables (productivity, value added, and hours worked) are sourced from the European Union Capital, Labor, Energy, Materials and Services (EUKLEMS) database, which is provided by the Vienna Institute for International Economic Studies.[10] The dataset, updated in November 2019, aggregates capital and labor data at the country-industry level. This means that each of the 277 observations represents one industry in one country, for example, chemical manufacturing in the United States.

"Value added" measures an industry's contribution to a country's GDP. It is calculated by taking the difference between an industry's gross output and the cost of its inputs. It is reported in current prices in units of local currency in the EUKLEMS data and converted to U.S. dollars using the Morningstar exchange rate on March 9, 2020. It was adjusted for inflation and is the "real value added" but is referred to as "value added" in this report. "Hours worked" is recorded in millions of hours worked by employees per year. The last dependent variable of interest, productivity, measures the output per unit of labor. It is calculated by taking the ratio of growth in value added to growth in hours. Consequently, and in order to analyze the percent change of the variable, productivity growth is equal to the difference between growth in value added and growth in hours from 2003 to 2017.

To offer robust conclusions across industries, this report categorizes country-industry pairs into thirds based on the percentile change in robot density: top robot adopters, middle robot adopters, and bottom robot adopters. The top robot adopters had the largest increase in the change in robot concentration from 2003 to 2017 and were faster in adopting robots, while the bottom robot adopters had the smallest increase, and in some cases, largest decrease in the change in robot concentration from 2003 to 2017. They were the slower to adopt industrial robots. See Appendix I for the full technical methodology.

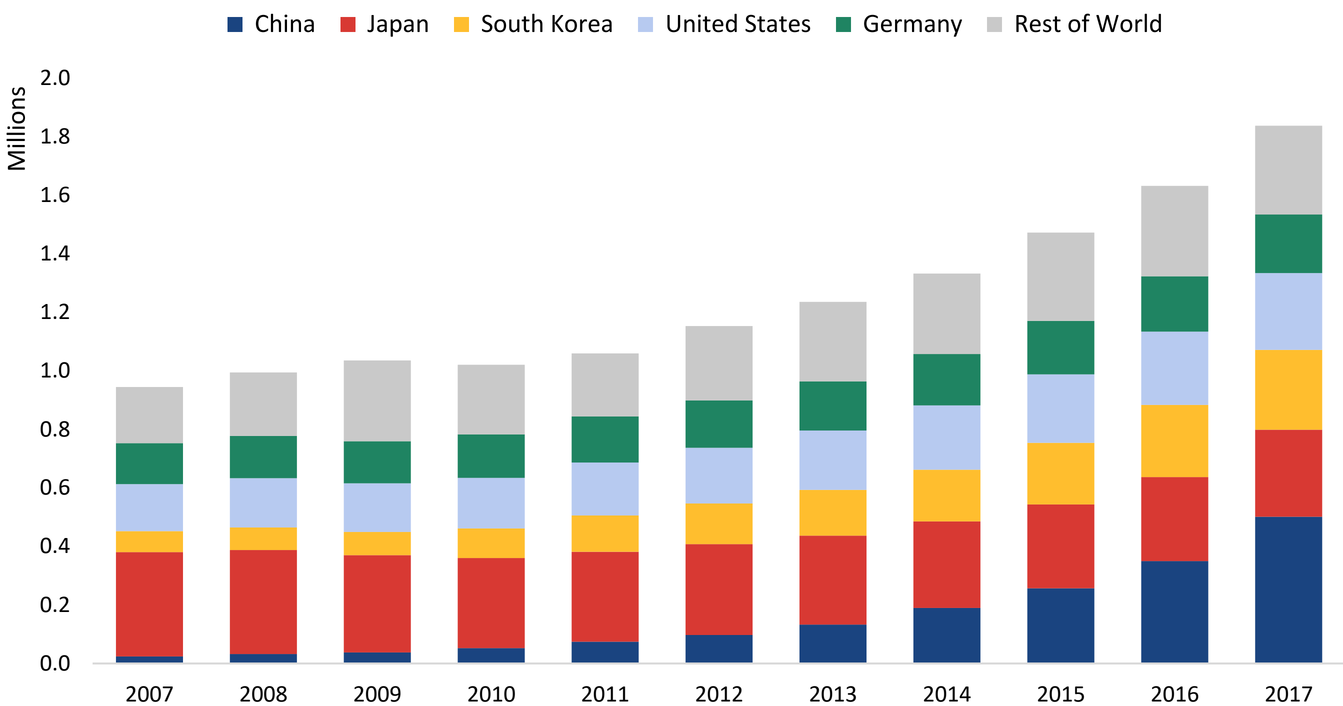
## THE EFFECTS OF AUTOMATION

### Global Statistics

Figure 2 highlights the top five countries by industrial robot installations compared to the rest of the world. In 2017, China installed 501,185 industrial robots, more than any other country in the world. Rounding out the top five, Japan installed 297,215 industrial robots, South Korea installed 273,146, the United States installed 262,058, and Germany installed 200,497. In 2017, these five countries accounted for more than 72 percent of industrial robot installations in the world.

According to the IFR's calculation for robot density, which is measured by the number of industrial robots per 10,000 manufacturing employees in 2017, China ranks 21$^{st}$ in the world, despite leading in the total number of industrial robots installed. Instead, South Korea has the highest robot density, followed by Singapore (which has the second-highest robot density), Germany (third), Japan (fourth), and Sweden (fifth). The United States is seventh in the world for robot density.[11]

## FIGURE 2: GLOBAL INDUSTRIAL ROBOT INSTALLATIONS BY COUNTRY, 2007 TO 2017




*Source: International Federation of Robots, World Robotics 2019, Accessed May 26, 2020, https://ifr.org*

## INDUSTRY STATISTICS

### 2003 Trends

Across all industries globally in 2003, the average value added was $764 billion and average hours worked was 661 million. Additionally, the average robot density was 2.0 industrial robots per million hours worked.

The industry with the highest industrial robot density was the automotive and other transportation manufacturing industry, which deployed significantly more industrial robots (14.2 industrial robots per million hours worked) than the other industries analyzed. However, despite this high industrial robot density, this industry added $705 billion in value, lower than average. The industry with the second-highest industrial robot density, the chemical manufacturing industry, deployed an average of 3.0 industrial robots per million hours worked with a relatively high value added of $1.1 trillion.

Neither of these industries were the most productive in 2003. Instead, the mining and quarrying industry was the most productive, despite having a relatively low industrial robot density of 0.3 industrial robots per million hours worked. Although the industry is not highly automated, it is still highly mechanized or capital intensive. This means that the industry requires a high percentage of capital in the production process compared to labor. The full list of averaged summary statistics by industry in 2003 can be found in Figure 3.

### 2017 Trends

Across all industries globally in 2017, the average value added was $764 billion and average hours worked was 686 million. Productivity decreased by 0.1 percent from 2003. Additionally, the average robot density was 4.0 industrial robots per million hours worked.

The automotive and other transportation manufacturing industry remained the industry with the highest industrial robot density, with an average of 29.3 industrial robots per million hours worked. This industry also had a value added of $854 billion, which was slightly above average compared to other industries. The other top industries by industrial robot density were chemical manufacturing (6.0 industrial robots per million hours worked); metal and electrical/electronic manufacturing

(4.7 industrial robots per million hours worked); food and beverage manufacturing (3.1 industrial robots per million hours worked); and wood and paper manufacturing (1.0 industrial robots per million hours worked). Only a few of the industries had high levels of value added as well as high amounts of hours worked. The top three industries by value added were the metal and electrical/electronic manufacturing industry ($2.2 trillion), the construction industry ($1.3 trillion), and the chemical manufacturing industry ($1.2 trillion). Meanwhile, the industry with the lowest density of deployed industrial robots was the utilities industry with 0.1 industrial robots per million hours worked.

Consistent with the 2003 statistics, the most productive industry in 2017 was the mining and quarrying industry. Despite the low value added of $33 billion, the industry exhibited high productivity due to the few hours worked (105 million). The full list of 2017 averaged summary statistics by industry can be found in Figure 3.

### Change in Trends From 2003 To 2017

From 2003 to 2017, the average change in robot density was an increase of 2.0 industrial robots per million hours worked. The value added across industries increased by four percent (real change of $700 billion), with no significant change to the number of hours worked. When looking at industries, the largest industrial robot density change was in the automotive and other transportation manufacturing industry, which saw a positive increase of 15.1 industrial robots per million hours worked. However, the largest change in productivity was in the mining and quarrying industry, which saw an increase in industrial robot density and value added, and a decrease in hours worked. The full list of summary statistics for average changes by industry between 2003 and 2017 can be found in Figure 4.

As mentioned above, this report analyzes the degree to which industries have embraced automation. The industries are divided into thirds based on the change in robot adoption from 2003 to 2017, allowing analysis of industries at different levels of automation and the varying impacts of robot adoption. The industries in the top industrial robot adopters, which had the highest levels of positive change in industrial robots, were automotive and other transportation manufacturing, metal and electrical/electronic manufacturing, chemical manufacturing, food and beverage manufacturing, and wood and paper manufacturing. This trend is likely due to the type of work in manufacturing, and the size of firms in these industries. For example, not only can labor easily be automated, but these firms have the financial resources to overcome the cost barriers associated with industrial robot adoption.

The most frequent industries in the bottom and middle robot adopter categories, which had low levels of positive change in industrial robots between 2003 and 2017, included the education; construction; utilities; textile manufacturing; mining and quarrying; and agriculture, forestry, and fishing industries. Unlike manufacturing, these industries face a variety of barriers to industrial robot adoption, such as the inability to automate specific roles, or an industry that is already highly mechanized. In addition, there may be a higher cost than value added benefit in adopting robots for these industries, either due to the high cost of automation or low labor costs. In other words, there is potential to automate work in these sectors, but the return on investment may not be sufficiently high. Figure 5 and Figure 6 display the industries in the categories of top, middle, and bottom robot adopters. As mentioned above, country-industry pairs were split into thirds based on the percentile change in robot density. The top robot adopters were faster to adopt robots, while the bottom robot adopters were slower.

## FIGURE 3: 2003 AND 2017 GLOBAL INDUSTRY SUMMARY STATISTICS

### INDUSTRIAL ROBOT DENSITY, PRODUCTIVITY, VALUE ADDED, AND HOURS WORKED

| Industry | Industrial Robot Density (Per 1 Million Hours) | | Productivity* | | Value added* | | Hours Worked* | |
|---|---|---|---|---|---|---|---|---|
| | 2003 | 2017 | 2003 | 2017 | 2003 | 2017 | 2003 | 2017 |
| Agriculture, forestry, and fishing | 0.1 | 0.2 | (4.7) | (4.8) | $335 Billion (9.3) | $295 Billion (9.5) | 357 Million (5.2) | 379 Million (5.2) |
| Auto and other transportation manufacturing | 14.2 | 29.3 | (5.7) | (5.7) | $705 Billion (8.7) | $854 Billion (9.3)wa | 460 Million (4.7) | 526 Million (4.9) |
| Chemical manufacturing | 3.0 | 6.0 | (4.6) | (4.7) | $1.1 Trillion (9.6) | $1.2 Trillion (10.0) | 660 Million (5.5) | 660 Million (5.5) |
| Construction | 0.0 | 0.1 | (4.0) | (4.0) | $1.4 Trillion (10.0) | $1.3 Trillion (10.4) | 1.6 Trillion (6.3) | 1.7 Trillion (6.4) |
| Education | 0.1 | 0.1 | (3.9) | (3.9) | $879 Billion (9.7) | $918 Billion (10.2) | 981 Million (6.2) | 1.2 Trillion (6.4) |
| Food and beverage manufacturing | 0.9 | 3.1 | (4.5) | (4.6) | $660 Billion (9.2) | $622 Billion (9.6) | 546 Million (5.4) | 609 Million (5.5) |
| Metal and electrical/electronic manufacturing | 2.4 | 4.7 | (4.5) | (4.5) | $2.1 Trillion (9.8) | $2.2 Trillion (10.3) | 1.4 Trillion (6.1) | 1.5 Trillion (6.1) |
| Mining and quarrying | 0.3 | 0.5 | (7.2) | (7.7) | $34 Billion (7.7) | $33 Billion (7.9) | 104 Million (3.5) | 105 Million (3.3) |
| Textile manufacturing | 0.4 | 0.3 | (4.9) | (3.1) | $100 Billion (8.1) | $65 Billion (8.0) | 344 Million (4.9) | 205 Million (4.3) |
| Utilities | 0.0 | 0.1 | (5.2) | (5.5) | $738 Billion (9.2) | $667 Billion (9.7) | 278 Million (4.8) | 302 Million (4.8) |
| Wood and paper manufacturing | 0.7 | 1.0 | (4.9) | (5.1) | $343 Billion (8.7) | $248 Billion (8.9) | 406 Million (5.0) | 323 Million (4.9) |
| **Global Industry Total** | 539.2 | 1,101.8 | (1,361.4) | (1,343.2) | $211.0 Trillion | $211.7 Trillion | 183.1 Billion | 189.9 Billion |

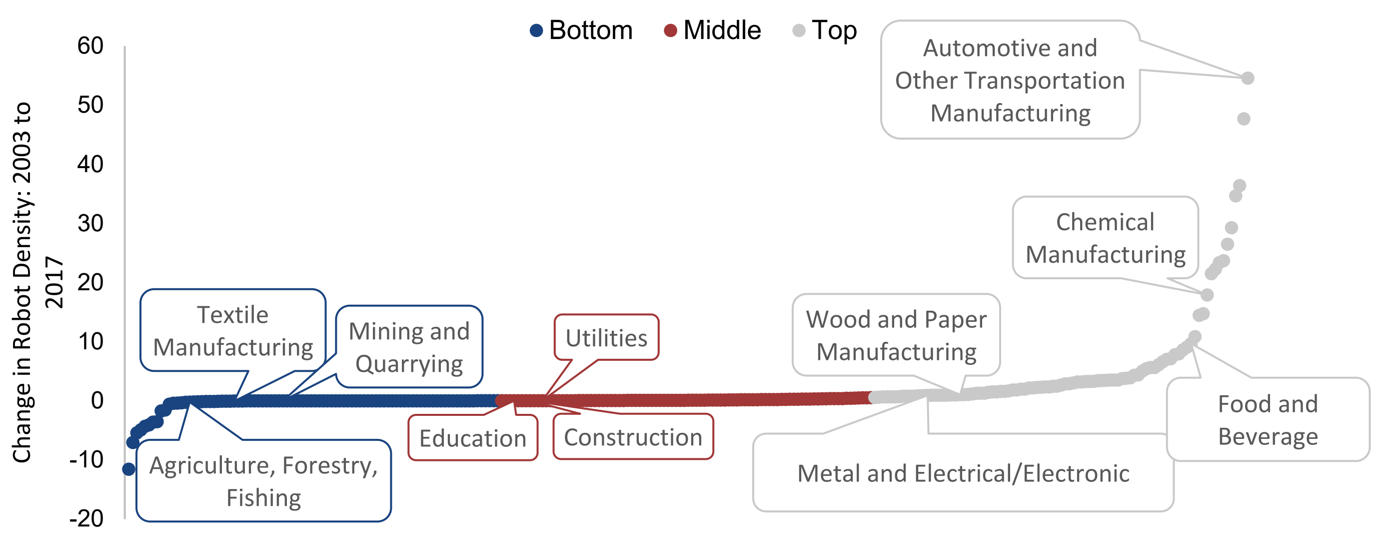
*Note: The values in parentheses are expressed as logarithmic values.*

## FIGURE 4: PERCENT CHANGE FROM 2003 TO 2017 SUMMARY STATISTICS
### INDUSTRIAL ROBOT DENSITY, PRODUCTIVITY, VALUE ADDED, AND HOURS WORKED

| Industry | Change in Industrial Robot Density | Change in Productivity* | Change in value added* | Change in Hours Worked* |
|---|---|---|---|---|
| Agriculture, forestry, and fishing | 0.0% | 0.1% | 0.3% | 0.0% |
| Auto and other transportation manufacturing | 15.1% | 0.0% | 0.6% | 0.2% |
| Chemical manufacturing | 3.0% | 0.0% | 0.4% | 0.0% |
| Construction | 0.1% | 0.0% | 0.4% | 0.1% |
| Education | 0.0% | -0.0% | 0.5% | 0.2% |
| Food and beverage manufacturing | 2.1% | 0.1% | 0.4% | 0.1% |
| Metal and electrical/electronic manufacturing | 2.3% | -0.1% | 0.5% | 0.1% |
| Mining and quarrying | 0.2% | 0.5% | 0.2% | -0.1% |
| Textile manufacturing | -0.1% | -1.8% | -0.1% | -0.6% |
| Utilities | 0.0% | 0.3% | 0.5% | 0.0% |
| Wood and paper manufacturing | 0.3% | 0.2% | 0.2% | -0.2% |
| Simple Average | 2.0% | -0.1% | 0.4% | -0.0% |

*Note: The values in Figure 4 are expressed as logarithmic values.*

## FIGURE 5: CHANGE IN ROBOT DENSITY BY GLOBAL INDUSTRY
### BY BOTTOM, MIDDLE, AND TOP THIRD PERCENTILE BY CHANGE IN ROBOT DENSITY




*Source: International Federation of Robots, World Robotics 2019, Accessed February 12, 2020, https://ifr.org/ & EUKLEMS, EUKLEMS Data Release 2019, Accessed March 4, 2020, https://euklems.eu/+*

## FIGURE 6: INDUSTRY LIST

### BY BOTTOM, MIDDLE, AND TOP THIRD

| Category | Industries |
|---|---|
| Bottom Third | Agriculture, Forestry, Fishing<br>Mining and Quarrying<br>Textile Manufacturing |
| Middle Third | Construction<br>Education<br>Utilities |
| Top Third | Automotive and Other Transportation Manufacturing<br>Chemical Manufacturing<br>Food and Beverage Manufacturing<br>Metal and Electrical/Electronic Manufacturing<br>Wood and Paper Manufacturing |

### IMPACT OF INDUSTRIAL ROBOT DENSITY GROWTH

Figure 7 includes the full results of the report. The analysis found that **there was a positive and significant relationship between industrial robot density and productivity**. This means that as industry robot density increases, simultaneously productivity increases as well. Specifically, an increase in industrial robot density of one percent correlated with an increase in average expected marginal productivity of 0.8 percent, all else equal. However, for industries that are top robot adopters, the increase in productivity was smaller. These industries – the automotive and other transportation; metal and electrical/electronic; chemical; and food and beverage manufacturing industries – only saw an increase of 0.5 percent with a one percent increase in industrial robot density, all else equal. This increase is relatively small compared to the slow robot adopters.

The industries that were slower to adopt industrial robots saw higher productivity growth. These industries – the education; construction; utilities; textile manufacturing; mining and quarrying; and agriculture, forestry, and fishing – saw the largest change in productivity. For the bottom robot adopters, an increase in industrial robot density by one percent was associated with a 5.1 percent increase in productivity, all else equal, which is the largest of all three groups. There are a few potential reasons that this positive trend was larger for the bottom third of robot adopters compared to the top. For example, the industries in the top third may have already maximized productivity gains from industrial robots. For top industrial robot adopters, installing additional industrial robots therefore did not increase the value added as quickly as when fewer industrial robots were deployed. Alternatively, this finding might indicate that firms who were slower to adopt industrial robots have different investment criteria. Before choosing to automate, companies that did not use robots in the production process may require stronger evidence that industrial robots lead to productivity returns that justify the high investment cost. These findings indicate that while productivity increased with the adoption of industrial robots, the marginal increase in productivity diminished.

When analyzing value added, the results suggest there was an inverse relationship between industrial robot density and value added. When analyzing all categories, an increase in industrial robot density by one percent correlated with a 0.3 percent decrease in value added, all else equal. While this decrease was unexpected, it is relatively small. However, the opposite was true for the industries that were slower to adopt industrial robots. These industries saw a positive relationship between industrial robot density and value added, and a one percent increase in industrial robot density was associated with a 1.5 percent increase in value added, all else equal. Like productivity, the industries in the bottom third saw a higher return in value added with an increase in the percent of robot density.

Lastly, results indicate that an inverse relationship exists between hours worked and industrial robot density. An increase in industrial robot density by one percent correlated with a one percent decrease in hours worked, all else equal. In other words, industrial robot density increases as hours worked decrease. However, for the top robot adopters (automotive and other transportation manufacturing, metal and electrical/electronic manufacturing, chemical manufacturing, and food and beverage manufacturing industries), the decrease in hours worked was much smaller. The report finds that a one percent increase in industrial robot density moved with a 0.3 percent decrease in hours worked, all else equal.

However, consistent with the findings in productivity and value added, the industries that were slower to adopt industrial robots saw the most dramatic change in hours worked: an increase in industrial robot density by one percent is associated with a 2.7 percent decrease in hours worked, all else equal. This means that while hours worked initially decreased with industrial robot adoption, the marginal decrease diminished with more industrial robot adoption.

These findings confirm that a positive relationship exists between industrial robot density and productivity. This productivity growth is even greater for the education; construction; utilities; textile manufacturing; mining and quarrying; and agriculture, forestry, and fishing industries, which were slow to adopt industrial robots.

FIGURE 7: CHANGES IN INDUSTRIAL ROBOT INPUT AND GROWTH IN PRODUCTIVITY, VALUE ADDED, AND HOURS WORKED

| | Δ in Productivity | Δ in value added | Δ in Hours Worked |
|---|---|---|---|
| Δ Industrial Robot Density | 0.0076*** | -0.0032** | -0.0103*** |
| Δ Industrial Robot Density, top robot adopters | 0.0049* | -0.0001 | -0.0031* |
| Δ Industrial Robot Density, middle robot adopters | 0.0084 | -0.0084 | -0.0030 |
| Δ Industrial Robot Density, bottom robot adopters | 0.0510** | 0.0152** | -0.0266** |

*Note: OLS estimation was conducted with fixed effects and controlled for heteroskedasticity. Productivity, Value added, and Hours worked are expressed as logarithmic values. * indicates significance at the 10 percent level, ** indicates significance at the 5 percent level, and *** indicates significance at the 1 percent level.*

## KEY FINDINGS AND CONCLUSION

Industrial robot adoption is a driver of productivity and growth in industries and economies worldwide. This report tested and confirmed that there is a **positive relationship between industrial robot density and productivity**. More precisely, an increase in industrial robot density of one percent was associated with an increase in productivity of 0.8 percent, all else equal. This productivity growth was significantly higher for the education; construction; utilities; textile manufacturing; mining and quarrying; and agriculture, forestry, and fishing industries, where a one percent increase in industrial robot density correlated with a 5.1 percent increase in productivity.

In other words, the adoption of robots increased productivity across industries, but the increase in productivity was particularly large for those adopting industrial robots slower. Additionally, this report found that with the presence of automation, manufacturing industries – specifically the automotive and other transportation manufacturing, metal and electrical/electronic manufacturing, chemical manufacturing, and food and beverage manufacturing – became even more productive.

Based on the findings, economic development organizations and other government development agencies should gain a better understanding of industries with low levels of automation and how that impacts companies' investment decisions. There is also room to develop better strategies to assist companies at various stages of automation. If industries that are slow to adopt industrial robots overcome barriers to automation, this report suggests that they will likely see continued increases in productivity.

However, automation also remains important in industries that have already adopted industrial robots. Not only is automation a major factor in the continued advancement of key U.S. industries, such as the automotive and chemical manufacturing industries, but it is also a major factor in remaining competitive in a global and evolving economy.

Capital investment in the form of industrial robots has already strengthened productivity across industries and furthered the competitiveness of the U.S. economy, and with future investments, it will likely continue to do so. The findings of this report suggest that both domestic and foreign companies, especially those seeking to increase productivity in manufacturing industries, should consider increasing industrial robot adoption. Not only will this increase productivity across firms and industries, but also support a healthy U.S. business ecosystem.

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# APPENDIX I: TECHNICAL METHODOLOGY

This paper follows the approach outlined in a paper by Graetz and Michaels (2015), which analyzed the economic impact of industrial robots using panel data of industries in 17 countries between 1993 and 2007.[1] Similar to their analysis, this report conducts three separate ordinary least squares (OLS) estimation tests to understand if growth in industrial robot density occurs alongside an increase in productivity and value added, as well as a decrease in hours worked. This report is most focused on productivity, specifically the correlation between increases in robot density and increases in production, all else equal.

The primary source of data analyzed for this research is from the International Federation of Robotics (IFR), which compiles data on industrial robot installations and industrial robot stock by industry and country from 1993 to 2018.[7] The organization defines an industrial robot as an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications."[2] This report specifically analyzes industrial robot density. This variable is derived by taking the operational stock of industrial robots per million hours worked. One challenge presented by the IFR data was that data for some industries and countries was unavailable for the early years in the sample. SelectUSA estimated robot density for missing years based on available industry by country data by taking the industry's share in total stock during the years the data was available.

The other source of data for this paper is the European Union Capital, Labor, Energy, Materials and Services (EUKLEMS) database, which is provided by the Vienna Institute for International Economic Studies.[3] The dataset, updated in November 2019, aggregates capital and labor data at the country-industry level.

The IFR and EUKLEMS data use different industry classifications. To ensure consistency, SelectUSA created a concordance system to reconcile the industry classifications between datasets (see Table A1 of the Appendix I). The industries included in this report are agriculture, forestry, and fishing; mining and quarrying; utilities (electricity, gas, water supply); construction; education; food and beverage manufacturing; textile manufacturing; wood and paper manufacturing; chemical manufacturing; metal and electrical/electronic manufacturing; and automotive and other transportation manufacturing. Based on the EUKLEMS 2019 data update, the country observations included in this report include the European Union member states (minus Croatia and Hungary), Japan, and the United States. The countries that make up the country-industry pairs are listed in Table A2 in the Appendix II. A country-industry pair represents one individual industry in a country, for example, the automotive and other transportation manufacturing industry in the United States.

The first year of data analyzed is 2003 and the last year is 2017. The main dependent variables studied are productivity, value added, and hours worked. This report examines how these variables respond with changes in the independent variable: industrial robot density. Value added is the measurement of additional value to an industry's GDP in a country. It is reported in current prices in units of local currency in the EUKLEMS data. In order to compare across countries, value added was converted to U.S. dollars using the Morningstar exchange rate on March 9, 2020. Hours worked was recorded in millions of hours worked by employees per year.

As a strategy to best handle the data, the logarithmic difference of real value added and hours worked between 2003 and 2017 was calculated. The last dependent variable of interest, productivity, measured the output per unit of labor. It was calculated by taking the ratio of growth in value added to growth in hours. In order to analyze the percent change of the variable, productivity growth is equal to the difference between growth in value added and growth in hours from 2003 to 2017.

The main independent variable of interest is industrial robot density, which is the number of industrial robots per million hours worked. Because raw changes in industrial robot density are concentrated at small positive values or zero, this report uses the percentile change in industrial robot density. This is shown in Figure A1, which displays the relationship between the change in industrial robot density and the change in productivity by country-industry pair, and Figure A2, which displays the percentile change in industrial robot density and the change in productivity by country-industry pair. Figure A3 and Figure A4 display the raw values of industrial robot density and productivity in 2003 and 2017, respectively.

We estimate regressions using the form:

$$\Delta Y_{ci} = \beta_0 + \beta_1 \Delta \left( \frac{\#\, robots}{million\ hours} \right) + \beta_2\, controls_{ci} + E_{ci}$$

Where $\Delta Y_{ci}$ is the change in dependent variable of interest (productivity, value added, or hours worked) in industry *i* in country *c* from 2003 to 2017. The *Δ (# robots / million hours)* is the change in the industrial robot density, and $E_{ci}$ is the error in industry *i* in country *c*. Lastly, $controls_{ci}$ accounts for fixed effects, which absorbs trends across industries and countries.

To understand how changes in the industrial robot density impact different industries, the observations are separated into thirds based on percentile change in industrial robot density – top robot adopters, middle robot adopters, and bottom robot adopters. The top robot adopters had the largest increase in the change in robot concentration from 2003 to 2017 and were those faster to adopt robots. Meanwhile, the bottom robot adopters had the smallest increase and, in some cases, the largest decrease in robot concentration from 2003 to 2017. This group was slower to adopt industrial robots.

## TABLE A1: INDUSTRY CLASSIFICATIONS

### IFR AND EUKLEMS DATA CROSSWALK

| EUKLEMS Code | IFR Code | SelectUSA Industry |
|---|---|---|
| A | A-B-Agriculture, Forestry, Fishing | Agriculture, Forestry, Fishing |
| B | C-Mining and Quarrying | Mining and Quarrying |
| C10-C12 | D10-D12 Manufacturing: Food and Beverages | Food and Beverage Manufacturing |
| C13-C15 | D13-D15 Manufacturing: Textiles | Textile Manufacturing |
| C16-C18 | D16-D18 Manufacturing: Wood and Furniture; Paper | Wood and Paper Manufacturing |
| C19 | D19 Manufacturing: Pharmaceuticals, Cosmetics | Chemical Manufacturing |
| C20 | D20-D21 Manufacturing: Other Chemical Products | Chemical Manufacturing |
| C21 | D20-D21 Manufacturing: Other Chemical Products | Chemical Manufacturing |
| C22-C23 | D22-D23 Manufacturing: Rubber and Plastic products (Non-Automotive); Glass, Ceramics, Stone, Mineral Products (Non-Automotive) | Chemical Manufacturing |
| C24-C25 | D24-D25 Manufacturing: Basic Metals; Metal Products (Non-Automotive) | Metal and Electrical/Electronic Manufacturing |
| C26 | D26-D27 Manufacturing: Electrical/Electronics | Metal and Electrical/Electronic Manufacturing |
| C27 | D26-D27 Manufacturing: Electrical/Electronics | Metal and Electrical/Electronic Manufacturing |
| C28 | D28: Manufacturing: Industrial Machinery | Metal and Electrical/Electronic Manufacturing |
| C29-C30 | D29-D30 Manufacturing: Automotive and Other Vehicles | Automotive and Other Transportation Manufacturing |
| D | E-Electricity, Gas, Water Supply | Utilities |
| E | E-Electricity, Gas, Water Supply | Utilities |
| F | F-Construction | Construction |
| G – Q | N/A | |
| P | P-Education, Research, Development | Education |
| Q – U | N/A | |

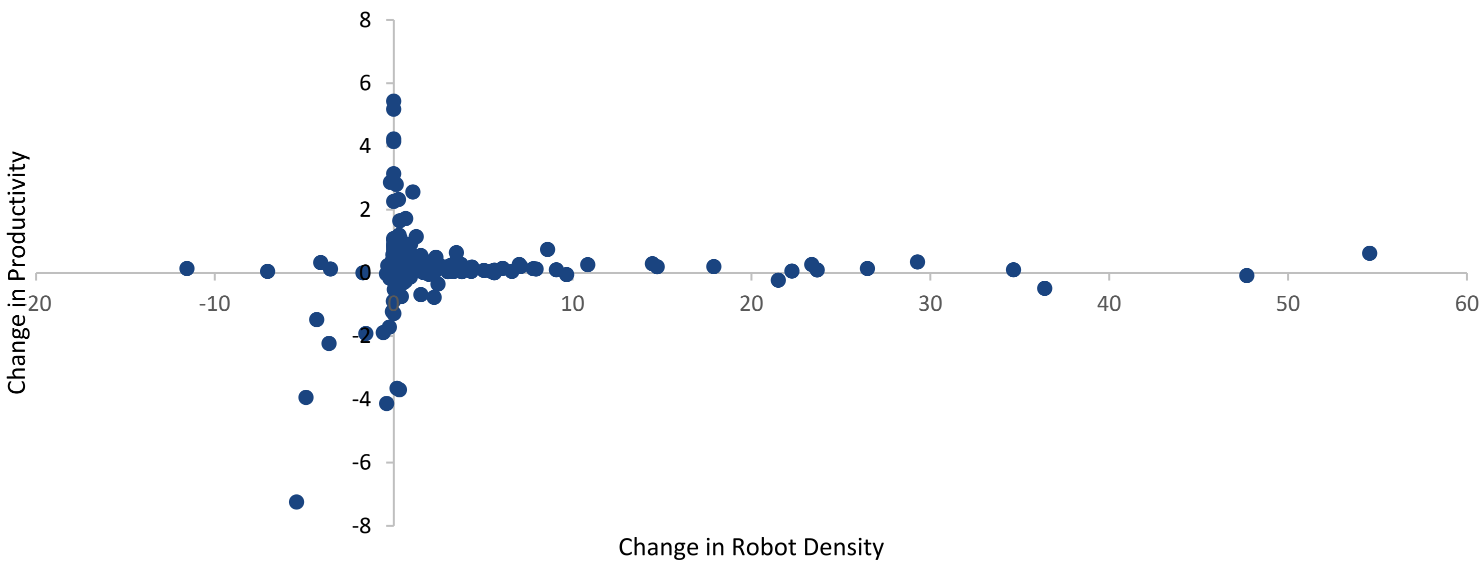
## TABLE A2: COUNTRY LIST

### COUNTRIES INCLUDED IN COUNTRY-INDUSTRY PAIRS

| | | |
|---|---|---|
| Austria | Greece | Portugal |
| Belgium | Ireland | Romania |
| Bulgaria | Italy | Slovakia |
| Czech Republic | Japan | Slovenia |
| Denmark | Latvia | Spain |
| Estonia | Lithuania | Sweden |
| Finland | Malta | United Kingdom |
| France | Netherlands | United States |
| Germany | Poland | |

## FIGURE A1: INDUSTRIAL ROBOT DENSITY AND PRODUCTIVITY CHANGE

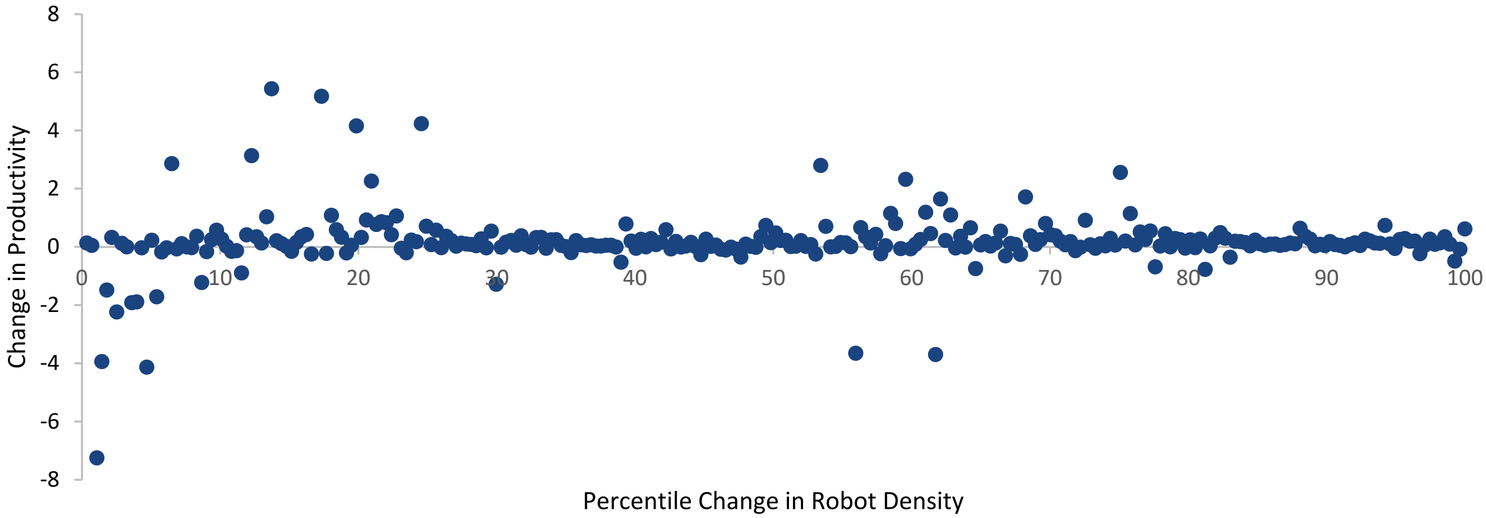
### CHANGE IN INDUSTRIAL ROBOT DENSITY AND CHANGE IN PRODUCTIVITY BY COUNTRY-INDUSTRY PAIR




*Source: International Federation of Robots, World Robotics 2019, Accessed February 12, 2020, https://ifr.org/ & EUKLEMS, EUKLEMS Data Release 2019, Accessed March 4, 2020, https://euklems.eu/+*

## FIGURE A2: INDUSTRIAL ROBOT DENSITY PERCENTILE CHANGE AND PRODUCTIVITY CHANGE

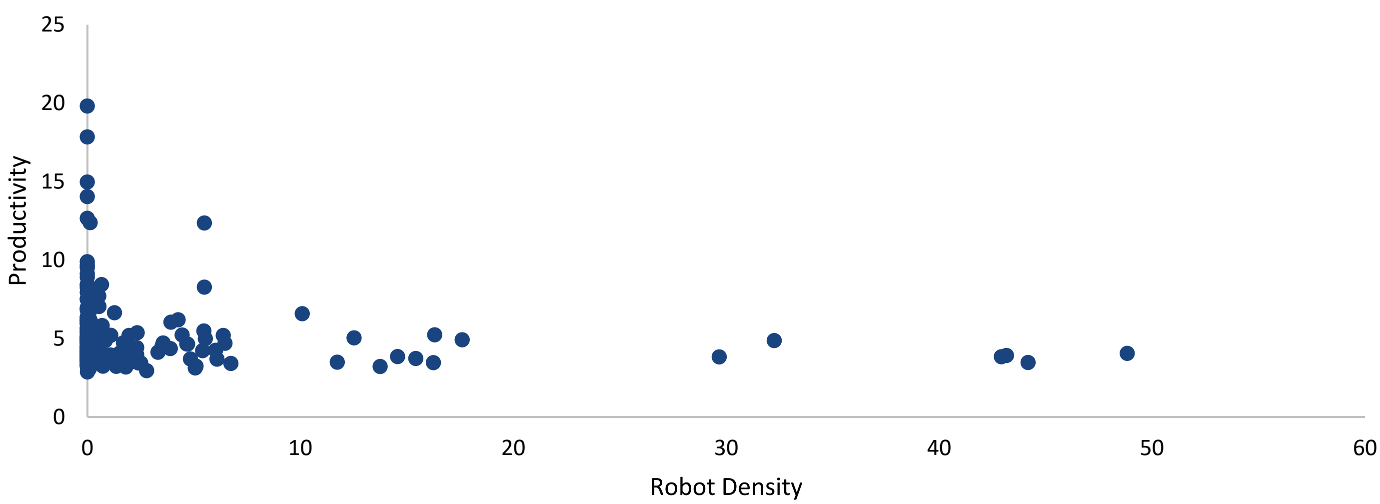
PERCENTILE CHANGE IN INDUSTRIAL ROBOT DENSITY AND CHANGE IN PRODUCTIVITY BY COUNTRY-INDUSTRY PAIR




*Source: International Federation of Robots, World Robotics 2019, Accessed February 12, 2020, https://ifr.org/ & EUKLEMS, EUKLEMS Data Release 2019, Accessed March 4, 2020, https://euklems.eu/*

## FIGURE A3: INDUSTRIAL ROBOT DENSITY AND PRODUCTIVITY IN 2003

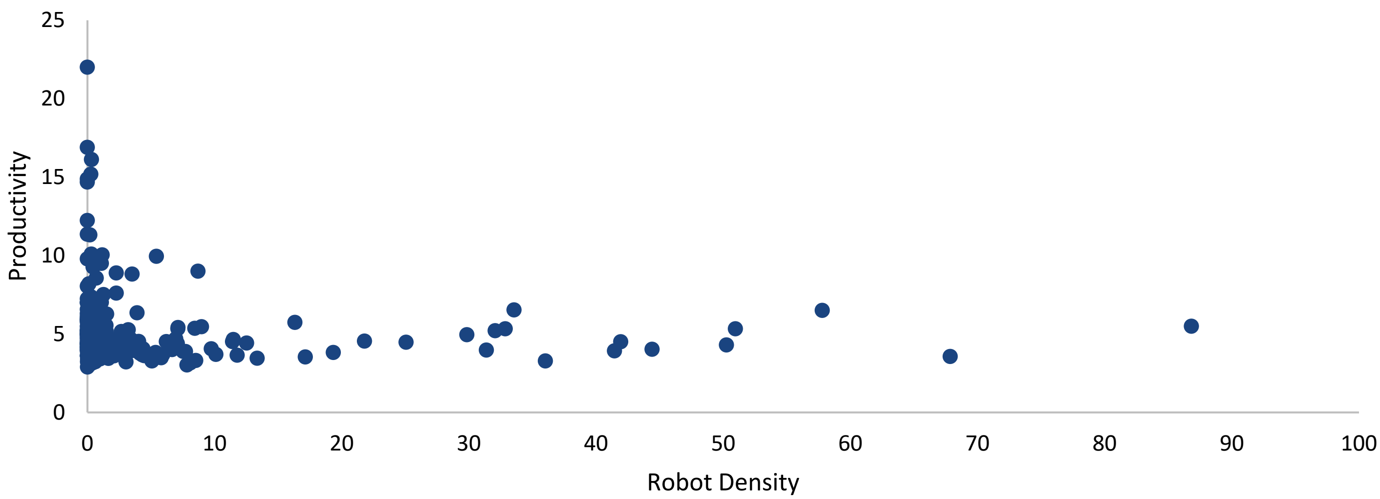
INDUSTRIAL ROBOT DENSITY AND PRODUCTIVITY BY COUNTRY-INDUSTRY PAIR




*Source: International Federation of Robots, World Robotics 2019, Accessed February 12, 2020, https://ifr.org/ & EUKLEMS, EUKLEMS Data Release 2019, Accessed March 4, 2020, https://euklems.eu/*

FIGURE A4: INDUSTRIAL ROBOT DENSITY AND PRODUCTIVITY IN 2017

INDUSTRIAL ROBOT DENSITY AND PRODUCTIVITY BY COUNTRY-INDUSTRY PAIR




*Source: International Federation of Robots, World Robotics 2019, Accessed February 12, 2020, https://ifr.org/ & EUKLEMS, EUKLEMS Data Release 2019, Accessed March 4, 2020, https://euklems.eu/*

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# ABOUT SELECTUSA

SelectUSA is a U.S. government-wide program housed in the International Trade Administration at the United States Department of Commerce. Our mission is to facilitate job-creating business investment into the United States and raise awareness of the critical role that economic development plays in the U.S. economy.

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