Robots, Unions, and Aging
Determinants of Industrial Robot Adoption: Evidence from OECD Countries

Donato Onorato

University of Pennsylvania

October 13, 2018
Widespread belief that robots will take the jobs of humans

Percentage who say that in the next 50 years robots and computers will "definitely" or "probably" do much of the work currently done by humans.

<table>
<thead>
<tr>
<th>Country</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Greece</td>
<td>91%</td>
</tr>
<tr>
<td>Japan</td>
<td>89%</td>
</tr>
<tr>
<td>Canada</td>
<td>84%</td>
</tr>
<tr>
<td>Argentina</td>
<td>82%</td>
</tr>
<tr>
<td>Poland</td>
<td>79%</td>
</tr>
<tr>
<td>Brazil</td>
<td>79%</td>
</tr>
<tr>
<td>South Africa</td>
<td>73%</td>
</tr>
<tr>
<td>Italy</td>
<td>73%</td>
</tr>
<tr>
<td>Hungary</td>
<td>66%</td>
</tr>
<tr>
<td><strong>United States</strong></td>
<td><strong>65%</strong></td>
</tr>
</tbody>
</table>

*U.S. data is from 2015. All other countries show data from 2018.

Source: Pew Research Center
Graetz & Michaels (2015)

- Examine effects of robot adoption on wages and employment
- Find that robots increase productivity, wages, growth rate of economies studied
Previous Literature

Graetz & Michaels (2015)
- Examine effects of robot adoption on wages and employment
- Find that robots increase productivity, wages, growth rate of economies studied

Acemoglu & Restrepo (2017)
- Examine effect of industrial robots within commuting zones in U.S.
- Develop a task based model of robot substitution for labor
- Find that an additional robot per worker reduces employment and wages in each commuting zone
Previous Literature

Graetz & Michaels (2015)
- Examine effects of robot adoption on wages and employment
- Find that robots increase productivity, wages, growth rate of economies studied

Acemoglu & Restrepo (2017)
- Examine effect of industrial robots within commuting zones in U.S.
- Develop a task based model of robot substitution for labor
- Find that an additional robot per worker reduces employment and wages in each commuting zone

Acemoglu & Restrepo (2018)
- Use small sample cross section data to examine effect of aging on robot usage
- Find that older countries adopt more robots and develop robot technologies more intensively
OECD Industrial Robot Stock 2000-2015
Research Question

What economic and demographic features characterize industrial robot adoption?

- Can variation in observable characteristics explain some of the differential adoption of robots we observe?

- Specifically, focus on how population aging affects equilibrium industrial robot stocks.

- I also include union share, income levels, population, and reliance on robot-using industries as features that may partially characterize robot usage rates.
Contents

1 Introduction

2 Model

3 Data

4 Empirical Specification

5 Results

6 Conclusion
To motivate my focus on aging and the empirical specification I build a simple two sector model with two types of labor (young and old).

The model incorporates ideas from Acemoglu & Restrepo (2017) and Graetz & Michaels (2015) in a simplified setting.

Main idea: Some industries require young labor and when this type labor is scarce firms can substitute with robots. How often this happens depends on the share of the economy that can be automated and the relative price of robots.
I consider a static, frictionless economy.

Total labor in the economy is fixed at $L$ and there are two types of workers: young workers ($L_Y$) and old workers ($L_O$).

There are two sectors in the economy: robot using sector ($Y_R$) and the non-robot using sector ($Y_N$).

Robots are exogenously supplied at price $\rho$. 
For simplicity, the robot using sector combines only young labor and robots in a CES production function to produce $Y_R$

$$Y_R = \left[ R^{\frac{\sigma - 1}{\sigma}} + L^{\frac{\sigma - 1}{\sigma}} \right]^{\frac{\sigma}{\sigma - 1}}$$

Here $\sigma > 0$ represents the elasticity of substitution between robots and labor in the robot using sector.

As in Acemoglu & Restrepo (2017) and Graetz & Michaels (2015) I allow robots and labor to be substituted imperfectly.
Sectors of the Economy

- For simplicity, the robot using sector combines only young labor and robots in a CES production function to produce $Y_R$

$$Y_R = \left[ R \frac{\sigma - 1}{\sigma} + L_y^{\frac{\sigma - 1}{\sigma}} \right]^{\frac{\sigma}{\sigma - 1}}$$

- Here $\sigma > 0$ represents the elasticity of substitution between robots and labor in the robot using sector

- As in Acemoglu & Restrepo (2017) and Graetz & Michaels (2015) I allow robots and labor to be substituted imperfectly

- The non-robot using sector uses old labor to produce $Y_N$

$$Y_N = L_O$$
Suppose that the aggregate production of the economy is also given by a CES aggregate over each sector:

\[ Y = \left[ \gamma_1 Y_R^{\frac{\varepsilon-1}{\varepsilon}} + \gamma_2 Y_N^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \]

Here, \( \varepsilon > 0 \) represents the elasticity of substitution between the outputs of each sector.

The \( \gamma_i \) are share parameters measuring the relative importance of each sector in the economy so that:

\[ \sum_{i} \gamma_i = 1 \]
Elasticity Assumptions

- In this setting I interpret $\sigma$ as the substitution options between factors (robots, labor) at the task level (as in Acemoglu & Restrepo, 2017).

- I interpret $\varepsilon$ as the substitution possibilities between sectors in the economy (as in Graetz & Michaels, 2015).

$\sigma > \varepsilon$
In this setting I interpret $\sigma$ as the substitution options between factors (robots, labor) at the task level (as in Acemoglu & Restrepo, 2017).

I interpret $\varepsilon$ as the substitution possibilities between sectors in the economy (as in Graetz & Michaels, 2015).

I assume that substitution options between industries in aggregate production are more limited than substitution options between robots and labor at the task level:

$$\sigma > \varepsilon$$
Model Predictions

\[ R^d \equiv \frac{R}{L} = \left( \frac{1}{\rho} \right) ^{A} \left( \frac{\gamma_2}{\gamma_1} \right) ^{\frac{A_2}{\bar{A}-A}} \left( \frac{\ell_y}{\ell_o} \right) ^{\frac{A}{\bar{A}-A}} \ell_y \]  

1. **Robot density is decreasing in the price of industrial robots,** \( \rho \).

2. **Robot density is increasing in the share of old workers.**

3. **Robot density is increasing in share parameter** \( \gamma_1 \) **and decreasing in** \( \gamma_2 \).

Under the elasticity assumption \((A > \bar{A})\):
I construct a panel data set of 34 OECD countries during the years 2000-2015 from three major sources:

- International Federation of Robotics (IFR)
- OECD National Account Statistics
- OECD Labor Market Statistics
The IFR compiles data from a comprehensive list of worldwide robot suppliers.

They provide data on the stocks and flows of industrial robots by sector for a large group of countries.

They define an industrial robot as:

“An automatically controlled, re-programmable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications.”
Data on **GDP per capita** and the **share of workers in a union** come from the OECD.

Current **population** data and population forecasts come from the UN Population Division World Population Prospects 2017.

Data on the **share of value added by industry** comes from the World Bank’s World Development Indicators.
Contents

1 Introduction

2 Model

3 Data

4 Empirical Specification

5 Results

6 Conclusion
Empirical Specification

Based on the model I propose the follow log-log functional form:

$$\log(R^d_{ct}) = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct})$$

$$+ \beta_4 \log(X_{ct}) + \varepsilon_{ct}$$
Empirical Specification

\[
\log(R^d_{ct}) = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct}) + \beta_4 \log(X_{ct}) + \varepsilon_{ct}
\]

- I define **robot density** as the number of industrial robots per 10,000 workers
I define **age ratio** as the ratio of young workers ($\ell_Y$) to old workers ($\ell_O$)
Empirical Specification

\[ \log(R^d_{ct}) = \alpha + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct}) + \beta_4 \log(X_{ct}) + \varepsilon_{ct} \]

- I define **age ratio** as the ratio of young workers (\(\ell_Y\)) to old workers (\(\ell_O\)).
- I define young workers as those aged 15-54 and old workers as those aged 55+. 
Empirical Specification

\[ \log(R_{ct}^d) = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct}) \\
\quad + \beta_4 \log(X_{ct}) + \varepsilon_{ct} \]

- I define **age ratio** as the ratio of young workers (\(\ell_Y\)) to old workers (\(\ell_O\))
- I define young workers as those aged 15-54 and old workers as those aged 55+
- I test the sensitivity of the results to alternate cutoffs
Empirical Specification

\[ \log(R^d_{ct}) = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct}) + \beta_4 \log(X_{ct}) + \varepsilon_{ct} \]

- I define the **union share** as the share of workers in a labor union.
log($R^d_{ct}$) = $\alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct})$
+ $\beta_4 \log(X_{ct}) + \varepsilon_{ct}$

- I define the **union share** as the share of workers in a labor union
- I use this to proxy the level of labor protections that may prevent firms from automating
Empirical Specification

\[
\log(R^d_{ct}) = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct}) + \beta_4 \log(X_{ct}) + \varepsilon_{ct}
\]

- I measure **reliance on automatable industries** by the ratio of value added from the automation susceptible industries to value added from the remaining industries of the economy

\[
\frac{\gamma_1}{\gamma_2} \approx \frac{VA_R}{VA_N}
\]

- This appears in the model as the ratio of share parameters \( \gamma_i \)
Empirical Specification

\[
\log(R_{ct}^d) = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct}) + \beta_4 \log(X_{ct}) + \epsilon_{ct}
\]

- I proxy automation susceptible industries with the *industry* sector defined by the World Bank
- The *industry* sector is an aggregate of industries including: mining, manufacturing, construction, water, electricity, and gas.
Empirical Specification

\[ \log(R^d_{ct}) = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct}) + \beta_4 \log(X_{ct}) + \varepsilon_{ct} \]

- I include a set of additional controls for total population and GDP per capita
\[
\log(1 + R^d)
\]

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>\log(y)</td>
<td>0.138</td>
<td>0.294</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.412)</td>
<td>(0.497)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>\log(IVA)</td>
<td>1.174**</td>
<td>0.235</td>
<td>−0.072</td>
<td>−0.207</td>
</tr>
<tr>
<td></td>
<td>(0.471)</td>
<td>(0.266)</td>
<td>(0.256)</td>
<td>(0.313)</td>
</tr>
<tr>
<td>\log(UNION)</td>
<td></td>
<td>−0.802**</td>
<td>−0.841***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.260)</td>
<td>(0.289)</td>
<td></td>
</tr>
<tr>
<td>\log(AR)</td>
<td>−3.046***</td>
<td>−3.035***</td>
<td>−1.899**</td>
<td>−2.141***</td>
</tr>
<tr>
<td></td>
<td>(0.345)</td>
<td>(0.527)</td>
<td>(0.574)</td>
<td>(0.588)</td>
</tr>
<tr>
<td>\log(P)</td>
<td>0.378***</td>
<td>0.977</td>
<td>1.151</td>
<td>1.491</td>
</tr>
<tr>
<td></td>
<td>(0.082)</td>
<td>(0.838)</td>
<td>(0.907)</td>
<td>(1.155)</td>
</tr>
</tbody>
</table>

| Observations | 534 | 534 | 482 | 482 |
| Adjusted R²   | 0.555 | 0.573 | 0.622 | 0.160 |
| Country FE     | ✓ | ✓ | ✓ | |
| Time FE        | ✓ |      |      | ✓ |      |

**Notes:** All SE are robust to heteroskedasticity and clustered at the country level.  
***Significant at the 1 percent level.  
**Significant at the 5 percent level.  
*Significant at the 10 percent level.
The results are robust to alternate age cutoffs:

- I get similar results when I define young and old workers as:
  - 20-44, 45-69
  - 15-49, 50-69

The results are also robust to alternate time periods:

- I get similar results when I estimate over the following time periods:
  - 2000-2007
  - 2008-2015
  - 2010-2015
The results are robust to alternate age cutoffs:

- I get similar results when I define young and old workers as:
  - 20-44, 45-69
  - 15-49, 50-69

The results are also robust to alternate time periods:

- I get similar results when I estimate over the following time periods:
  - 2000-2007
  - 2008-2015
  - 2010-2015
I use the estimates to see what robot stock would be today had the age ratio remained at its 2010 level.
I use the estimates to see what robot stock would be today had the age ratio remained at its 2010 level

- Age ratio decreased **10%** on average among OECD countries from 2010 to 2015.

Had it remained unchanged over that period there would be **25%** fewer robots per 10,000 workers on average.

I can also use the estimates to predict 2020 values of industrial robot stock by predicting future values of the covariates & UN population projections.

- On average OECD countries will add **9.95** additional robots per 10,000 workers by 2020.
- This represents a **1.7x** increase from 2015 levels and is primarily driven by aging.
Naïve Predictions

I use the estimates to see what robot stock would be today had the age ratio remained at its 2010 level

- Age ratio decreased **10%** on average among OECD countries from 2010 to 2015.
- Had it remained unchanged over that period there would be **25%** fewer robots per 10,000 workers on average

I can also use the estimates to predict 2020 values of industrial robot stock by predicting future values of the covariates & UN population projections

- On average OECD countries will add **9.95** additional robots per 10,000 workers by 2020
- This represents a **1.7x** increase from 2015 levels and is primarily driven by aging
Naïve Predictions

I use the estimates to see what robot stock would be today had the age ratio remained at its 2010 level

- Age ratio decreased 10% on average among OECD countries from 2010 to 2015.
- Had it remained unchanged over that period there would be 25% fewer robots per 10,000 workers on average

I can also use the estimates to predict 2020 values of industrial robot stock by predicting future values of the covariates & UN population projections
Naïve Predictions

I use the estimates to see what robot stock would be today had the age ratio remained at its 2010 level

- Age ratio decreased 10% on average among OECD countries from 2010 to 2015.
- Had it remained unchanged over that period there would be 25% fewer robots per 10,000 workers on average.

I can also use the estimates to predict 2020 values of industrial robot stock by predicting future values of the covariates & UN population projections

- On average OECD countries will add 9.95 additional robots per 10,000 workers by 2020.
Naïve Predictions

I use the estimates to see what robot stock would be today had the age ratio remained at its 2010 level

- Age ratio decreased **10%** on average among OECD countries from 2010 to 2015.
- Had it remained unchanged over that period there would be **25%** fewer robots per 10,000 workers on average

I can also use the estimates to predict 2020 values of industrial robot stock by predicting future values of the covariates & UN population projections

- On average OECD countries will add **9.95** additional robots per 10,000 workers by 2020
- This represents a **1.7x** increase from 2015 levels and is primarily driven by aging
Union rates and the labor force age ratio have significant negative effects on industrial robot stock even after controlling for population, GDP per capita, and reliance on robot-using industries.
Concluding Remarks

Union rates

- Union rates may be a signal of labor protection within a country
- This could produce a barrier for firms that want to switch from human labor to robots

Aging
Concluding Remarks

Union rates

- Union rates may be a signal of labor protection within a country
- This could produce a barrier for firms that want to switch from human labor to robots

Aging

- Some sectors of the economy may require “young” labor
- If labor and robots are easily substituted \((\sigma > \varepsilon)\), aging shocks to the labor force could force firms to adopt more robots
- This aging effect is consistent with previous literature about technological adoption under labor scarcity (see Acemoglu, 2015)