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

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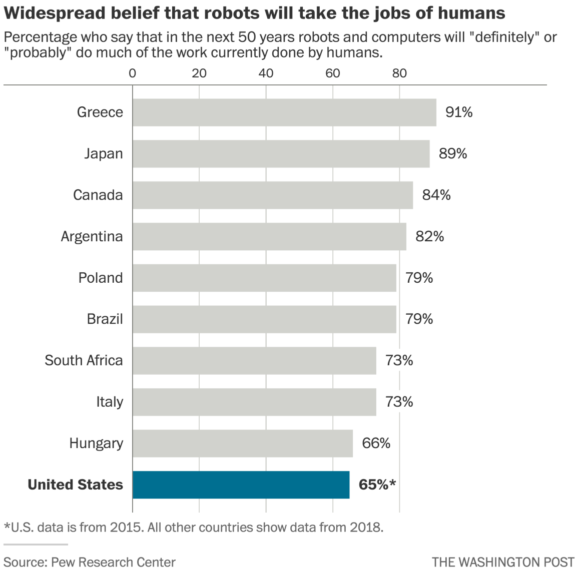
Contents

Robot Fears


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.
0
20
40
60
80
Greece
91%
Japan
89%
Canada
84%
Argentina
82%
Poland
79%
Brazil
79%
South Africa
73%
Italy
73%
Hungary
66%
United States
65%*
*U.S. data is from 2015. All other countries show data from 2018.
Source: Pew Research Center
THE WASHINGTON POST

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

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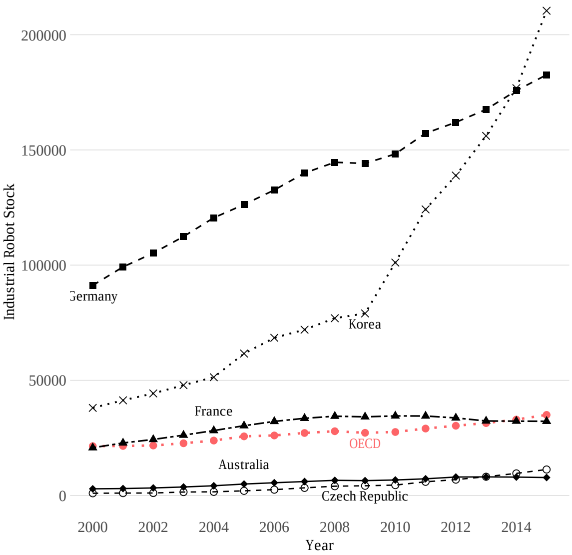
Acemoglu & Restrepo (2018)

- 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

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Simple Model

- 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.**

Basic Setup

- 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 ρ

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

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

$$Y_N = L_O$$

Aggregate Economy

- 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 γ_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 σ as the substitution options between factors (robots, labor) at the task level (as in Acemoglu & Restrepo, 2017)
- I interpret ε as the subtitution possibities between sectors in the economy (as in Graetz & Michaels, 2015)

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- I interpret ε as the subtitution possibities 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

$$R^d \equiv \frac{R}{L} = \left(\frac{1}{\rho}\right)^{\sigma} \left(\frac{\gamma_2}{\gamma_1}\right)^{\frac{\sigma\varepsilon}{\varepsilon-\sigma}} \left(\frac{\ell_y}{\ell_o}\right)^{\frac{\sigma}{\varepsilon-\sigma}} \ell_y \tag{1}$$

- Under the elasticity assumption ($\sigma > \varepsilon$):

1. **Robot density is decreasing in the price of industrial robots, ρ.**
2. **Robot density is increasing in the share of old workers.**
3. **Robot density is increasing in share parameter γ_1 and decreasing in γ_2**

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Data

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

International Federation of Robotics

- 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

- 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

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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

$$\overbrace{\log(R^d_{ct})}^{\text{robot density}} = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct}) + \beta_4 \log(X_{ct}) + \varepsilon_{ct}$$

- I define **robot density** as the number of industrial robots per 10,000 workers

Empirical Specification

$$\log(R^d_{ct}) = \alpha_c + \mu_t + \overbrace{\beta_1 \log(AR_{ct})}^{\text{age ratio}} + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct}) \\ + \beta_4 \log(X_{ct}) + \varepsilon_{ct}$$

- I define **age ratio** as the ratio of young workers (ℓ_Y) to old workers (ℓ_O)

Empirical Specification

$$\log(R_{ct}^{d}) = \alpha_c + \mu_t + \overbrace{\beta_1 \log(AR_{ct})}^{\text{age ratio}} + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct}) + \beta_4 \log(X_{ct}) + \varepsilon_{ct}$$

- I define **age ratio** as the ratio of young workers (ℓ_Y) to old workers (ℓ_O)
- I define young workers as those aged 15-54 and old workers as those aged 55+

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- I define **age ratio** as the ratio of young workers (ℓ_Y) to old workers (ℓ_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

$$\log(R^d_{ct}) = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \overbrace{\beta_2 \log(UNION_{ct})}^{\text{union share}} + \beta_3 \log(IVA_{ct}) \\ + \beta_4 \log(X_{ct}) + \varepsilon_{ct}$$

- I define the **union share** as the share of workers in a labor union

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- 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

$$\log(R^d_{ct}) = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \overbrace{\beta_3 \log(IVA_{ct})}^{\text{automation reliance}} + \beta_4 \log(X_{ct}) + \varepsilon_{ct}$$

- 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

$$\frac{\gamma_1}{\gamma_2} \approx \overbrace{VA_R}^{\substack{\text{value added}\\ \text{robot sector}}} \Big/ \underbrace{VA_N}_{\substack{\text{value added}\\ \text{non-robot sector}}}$$

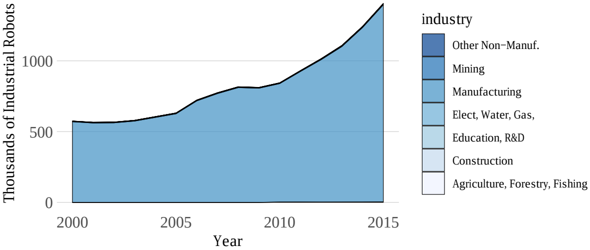
- This appears in the model as the ratio of share paramters γ_i

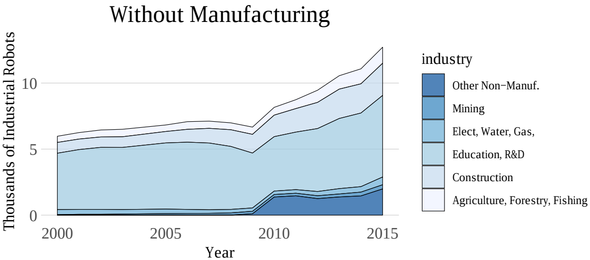
Empirical Specification

$$\log(R^d_{ct}) = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \overbrace{\beta_3 \log(IVA_{ct})}^{\text{automation reliance}}$$
$$+ \beta_4 \log(X_{ct}) + \varepsilon_{ct}$$

- 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.

Industrial Robots by Industry





Empirical Specification

$$\log(R^d_{ct}) = \alpha_c + \mu_t + \beta_1 \log(AR_{ct}) + \beta_2 \log(UNION_{ct}) + \beta_3 \log(IVA_{ct}) + \underbrace{\beta_4 \log(X_{ct})}_{\text{controls}} + \varepsilon_{ct}$$

- I include a set of additional controls for total population and GDP per capita

Contents

	$\log(1+R^d)$			
	(1)	(2)	(3)	(4)
$\log(y)$			0.138	0.294
			(0.412)	(0.497)
$\log(IVA)$	1.174**	0.235	−0.072	−0.207
	(0.471)	(0.266)	(0.256)	(0.313)
$\log(UNION)$			−0.802**	−0.841***
			(0.260)	(0.289)
$\log(AR)$	−3.046***	−3.035***	−1.899**	−2.141***
	(0.345)	(0.527)	(0.574)	(0.588)
$\log(P)$	0.378***	0.977	1.151	1.491
	(0.082)	(0.838)	(0.907)	(1.155)
Observations	534	534	482	482
Adjusted R^2	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.

Robustness

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

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- I get similar results when I define young and old workers as:
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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

Naïve Predictions

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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

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Concluding Remarks

- 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

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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

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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)