Robot Imports and Firm-level Outcomes: Evidence from French Firms

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Machines and Jobs

- machines have been transforming the workplace
  - from steam-powered mechanized cotton spinning
  - to industrial robots
- in 2015:
  - an estimated 1.63 million industrial robots performing activities such as welding, painting, assembly, packaging and labeling
  - the number is expected to double by 2020
- the future is uncertain
  - growth of computing power, AI, machine learning
  - Frey & Osborne (2017): half of U.S. employment is at risk of being automated over the next two decades

Early Automation

- in 1913 Ford introduces the integrated moving assembly line
  - man hours of final assembly dropped from more than 12 to fewer than 3

Automation: Today

- where are the workers?

Not only Manufacturing

What We Do

- key questions
  - how do robots affect jobs and efficiency of production at the firm level?
- main challenge: measure robot adoption
- this paper:
  - proxy for robot adoption: French firm-level imports of industrial robots
  - effect on employment
    - productivity vs displacement
  - heterogeneity across workers by skill level
  - effect on other firm-level outcomes
    - sales, labor productivity
- compare OLS vs IV

What We Find

- robot adopters are bigger and more productive
- robot adoption accompanied by firm's scaling up
  - employment, sales and efficiency increase
- yet, net of demand shocks
  - employment *falls* with robot intensity
  - efficiency *increases*
- who gains/loses?
  - higher demand for high-skill workers (engineers, managers)

Literature on Robots and Jobs

- theory:
  - Acemoglu & Restrepo (2017), Hemous & Olsen (2018), Zeira (1998)...
- empirics:
  - cross-industry studies:
    - Graetz & Michaels (2018): IFR, 17 countries, higher productivity, no job loss
    - Acemoglu & Restrepo (2017): IFR, US CZs, job loss
    - Mann & Puttman (2017): patent data, US CZs, job loss in Mnf gain in Srv
  - firm-level survey data:
    - European Commission (2015, 7 countries); Koch, Manuylov & Smolka (2019, Spain); Cheng et al. (2019, China)
    - descriptive: robot dummy correlates with higher employment
    - Bessen et al. (2019, Netherlands): third-party automation services increase separations
- firm-level data needed to test micro-level adjustment!

A Simple Model

- consider a firm facing CES demand:

$$y = Ap^{-\sigma},\ \sigma > 1$$

  - produce with labor (l) and capital (k) performing a unit measure of tasks
  - share κ of tasks are automated: can be performed by k
    - ★ assume $r < w$

$$y = \varphi \exp \left(\int_0^1 \ln x(z) dz \right) = \varphi \left(\frac{k}{\kappa} \right)^{\kappa} \left(\frac{l}{1-\kappa} \right)^{1-\kappa}$$

    - ★ $\varphi =$ firm productivity

- profit:

$$\pi = py - rk - wl - hf(\kappa)$$

  - $f =$ fixed cost, non-production workers, wage h

Demand for Production Workers

- first-order conditions
  - for capital:

$$rk = \left(1 - \frac{1}{\sigma}\right) A^{1/\sigma} y^{1-1/\sigma} \kappa$$

    - capital increases with automation
  - for labor:

$$wl = \left(1 - \frac{1}{\sigma}\right) A^{1/\sigma} y^{1-1/\sigma} \cdot (1-\kappa)$$

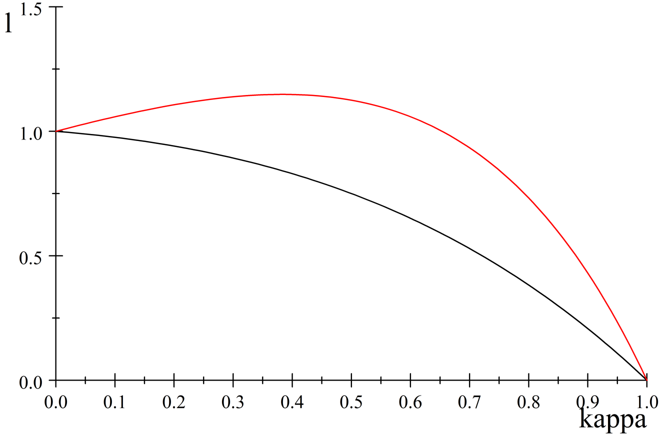
- combining both

$$\frac{dl/l}{d\kappa} = \overbrace{(\sigma - 1)\ln\left(\frac{w}{r}\right)}^{productivity} - \overbrace{\frac{1}{1-\kappa}}^{displace}$$

  - effect of $\uparrow \kappa$: $\begin{cases} \text{1. productivity effect: } \frac{\partial y}{\partial \kappa} > 0 \\ \text{2. displacement effect (-)} \end{cases}$
  - may be positive for κ sufficiently low

Demand for Production Workers: Graph

- Productivity vs. displacement effect on demand for production workers (red: high demand elasticity, black: low demand elasticity)



Endogenous Robot Adoption

- firms choose the degree of automation κ
  - assume convex cost of automation in terms of non-production workers

$$hf(\kappa) = h\left(\lambda + \frac{\kappa^{\delta}}{\delta}\right), \qquad \delta > 1$$

  - FOC for κ:

$$h\kappa^{\delta-1} = \left(1 - \frac{1}{\sigma}\right) A^{1/\sigma} y^{1-1/\sigma} \ln\left(\frac{w}{r}\right)$$

- automation κ:
  - increasing in demand A
  - increasing in cost-saving (w/r)
  - decreasing in cost of nonproduction workers h

Identifying the Effect of Automation on Employment

- threat to identification:
  - demand shocks (A) affect l both directly and through κ
    - regress l on $\kappa \rightarrow$ upward bias
- Strategy 1: measure of automation net of demand shocks
  - from the FOC of k and κ :

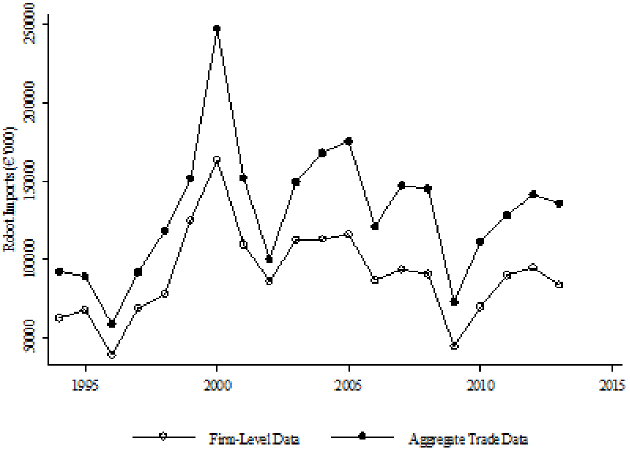
$$\frac{h\kappa^{\delta}}{\delta rk} = \frac{1}{\delta} \ln\left(\frac{w}{r}\right)$$

    $=$ robot cost over capital expenditure
  - "robot intensity" solely driven by the cost-saving effect of automation
    - demand shocks affect robot cost and capital expenditure equally
- Strategy 2: IV – construct exogenous firm-level measure of exposure to automation (cost of robot adoption)

The Data

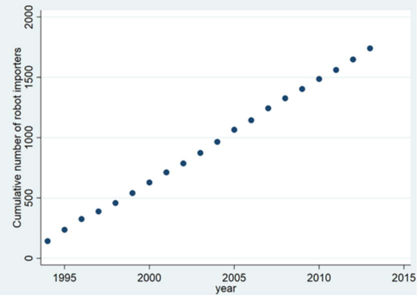
- near universe of French firms from 1994-2013
  - around 1.3 million firms, all economic activities except government
  - manufacturing, services, primary
- imports and exports (value and unit values) at the firm level
  - by 8 digit CN code, by origin country from customs (DOUANES)
- balance-sheet data from BRN and FARE
  - sales, materials, capital stock (value of physical assets), employment
- full-time employment at the plant level by 2-digit occupation code for 5 occupation categories from DADS etablissement aggregated at the firm level
  - 1: firm owners receiving a wage
  - 2:**high-skill professions: scientists, managers and engineers**
  - 3: intermediate-skill professions (teachers, admin., technicians)
  - 4: white-collar workers (low-skill)
  - 5: blue-collar workers
- **Sample**: focus on manufacturing firms with at least 5 employees

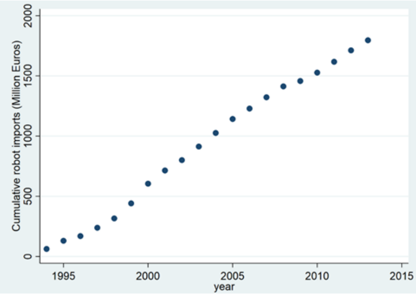
The Data: Robot Imports, HS847950



Aggregate Facts

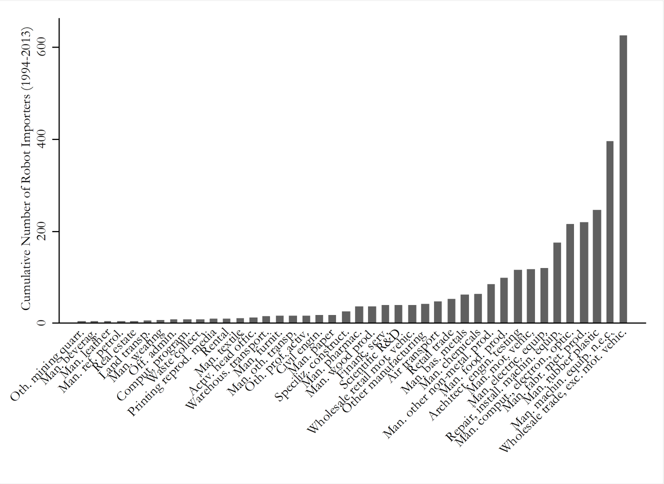
- cumulative number of French robot adopters and cumulative value of robot imports





Aggregate Facts

- number of French robot adopters by sector (1994-2013)



Descriptives: all manufacturing firms vs. robot adopters

Table 1 - Descriptive Statistics

	Obs.	Mean	Median	Std. Dev.	Δ Mean (annualized)
	Whole Sample				
Robot adopter	955851	0.008	0.00	0.089	0.009
Robot intensity	955851	0.0003	0.00	0.018	0.0004
No. of employees	955851	60	16	368796	-0.047
Empl. sh. high skill	955581	0.079	0.045	0.114	0.029
Sales (€'000)	955851	41694	4222	78503	-0.076
Capital (€'000)	955851	15872	946	384474	-0.027
Sales per worker (€'000)	955841	591	205	12704	-0.030
Capital per worker (€'000)	955841	184	55	10366	0.013
Importer	955841	0.446	0.00	0.497	0.0015
Exporter	955841	0.449	0.00	0.497	0.005
Replaceability	624124	0.331	0.318	0.189	
	Robot Adopters				
Robot adopter	7629	1.00	1.00	0.00	0.00
Robot intensity	7629	0.041	0.002	0.200	0.002
No. of employees	7629	800	165	2928	-0.105
Empl. sh. high skill	7629	0.159	0.111	0.151	0.015
Sales (€'000)	7629	723215	38029	6321703	-0.126
Capital (€'000)	7629	280170	17282	2545417	-0.070
Sales per worker (€'000)	7629	1703	225	95911	-0.039
Capital per worker (€'000)	7629	248	106	1623	-0.039
Importer	7629	0.959	1.00	0.198	-0.012
Exporter	7629	0.931	1.00	0.253	-0.003
Replaceability	5011	0.370	0.387	0.181	

The whole sample consists of all manufacturing firms with more than five employees

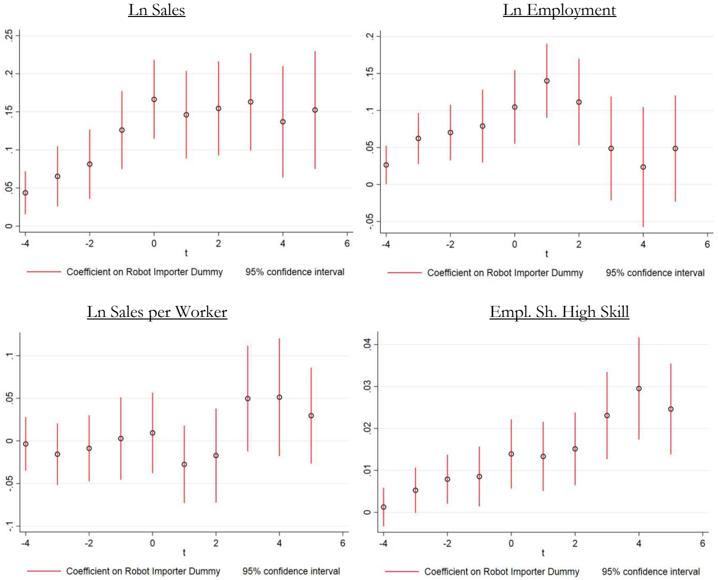
Descriptive Patterns: DiD

- event study DiD specification
- comparison of firm characteristics across robot adopters and non-adopters over time

$$\ln Y_{fit} = \sum_{t=-5}^{5} \beta_t \cdot Treat_{fit} + \alpha_f + \alpha_{it} + \varepsilon_{fit}$$

  - α_f = firm fixed effects
  - α_{it} = 5-digit-industry-year fixed effects
  - $t = 0$: 1st year of robot imports
  - $Treat_{fit} = \begin{cases} 1 & \text{for robot adopters at } t \in [-5, 5] \\ 0 & \text{for robot adopters in other t and other firms in any t} \end{cases}$
  - Y_{ift}: sales, employment, sales per worker, high-skill employment share

Evolution of Outcomes Over Time: DiD



The Causal Effect of Robots – Empirical Strategy 1: OLS

- how do robots affect outcomes (Y_{fit}) within the firm?
- specification

$$\ln Y_{fit} = \beta \cdot Robot_{fit} + \mathbf{X}'_{fit} \cdot \gamma + \alpha_f + \alpha_{it} + \varepsilon_{fit}$$

  - $Robot_{fit}$ = measure of robot adoption
  - $Rob\_Int_{fit} = ln(\frac{Rob\_stock_{fit}}{Capitalstock_{fit}}) \rightarrow$ robot intensity, net of demand shocks (captures within-firm changes in robot intensity)
  - $\mathbf{X}_{fit}$ = controls for firm characteristics (import status, export status, and log sales), measured at initial year $\times$ year dummies

Robots and Firm-Level Outcomes: OLS intensive margin

	(1)	(2)	(3)	(4)
	ln Sales		ln Employment	
Ln Rob_Intensity	-0.090***	-0.087***	-0.124***	-0.117***
	[0.024]	[0.025]	[0.024]	[0.024]
Obs.	6360	6290	6365	6295
R2	0.98	0.98	0.96	0.96
	ln Sales per Worker		Empl. Sh. High Skill	
Ln Rob_Intensity	0.023*	0.018	0.013***	0.012**
	[0.013]	[0.013]	[0.005]	[0.005]
Obs.	6360	6290	6365	6295
R2	0.88	0.88	0.88	0.88
Firm FE	Yes	Yes	Yes	Yes
Industry ×year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

The dependent variables are annual observations of the firm-level outcomes indicated in columns' headings. Ln Rob_Intensity is the log ratio between the cumulative stock of robot capital and the total capital stock of the firm. Industry refers to 5-digit industries. The control variables included in columns (2) and (4) are log sales and dummies for whether the firm is an importer or an exporter, observed in the first year in which the firm appears in the sample and interacted with a full set of year dummies. Standard errors, clustered at the firm level, are reported in squared brackets. ***, **, *: denote significance at the 1, 5 and 10% level, respectively.

The Causal Effect of Robots – Empirical Strategy 2: IV Long Differences

- identify the causal long-run effects of robots on firm-level outcomes
- specification:

$$\Delta Y_{fi} = \alpha_i + \Delta Rob\_adoption_{fi} + \mathbf{X}'_{fi} \cdot \gamma + \varepsilon_{fi}$$

  - $\Delta \ln Y_{fi}$ = annualized change in firm f's outcome over sample period
    - employment, sales, sales per worker, high-skill employment share share
  - $\Delta Rob\_adoption_{fi}$ = change in robot adoption by firm f over sample period
    - $\Delta Rob\_adoption_{fi} = 1$ if f started importing robots over sample period, 0 otherwise
  - Use $Rob\_Exposure_{fi}$ as instrument for $\Delta Rob\_adoption_{fi}$.
  - $\mathbf{X}_{fi}$ = start-of-period firm characteristics: import status, export status, log sales, Replaceability
  - α_i = 5-digit industry fixed-effects (industry-specific growth rates)

Instrument for Robot Adoption

- **Step 1:** firm-level measure of replaceability of tasks by robots
- replaceability for 377 US Census occupations (h) from Graetz & Michaels (2018)
  - replaceable occupation: its title corresponds to at least one of the IFR robot application categories (e.g., welding, painting, assembling)
- manually map US Census occupations into 29 French occupations (o) in 1994
  - $Replaceability_o = \frac{\sum_{o \in h} Replaceability_h}{N_{ho}}$
  - $N_{ho} = \#$ of US Census occupations corresponding to French occupation o
- compute firm-level replaceability as

$$Replaceability_f = \sum_{o=1}^{29} \omega_{ofi} \times Replaceability_o,$$

  - ω_{ofi} = share of occupation o in firm f's employment in 1994

Instrument for Robot Adoption

- **Step 2:** industry-level measure of robot suitability
- $Rob\_Suitability_i$ = log ratio between the stock of robots and the total capital stock in each 5-digit industry i, exluding firm f

$$Rob\_Suitability_i = \frac{\sum_{f' \neq f} Rob\_stock_{f' \in i}}{\sum_{f' \neq f} Capital\_stock_{f' \in i}}$$

- **Step 3**: Instrument Rob Exposure$_{fi}$

$$Rob\_Exposure_{fi} = Replaceability_f \times Rob\_Suitability_i$$

IV Long Differences - Econometric Identification

- impact of robot adoption is identified as differential in growth rates of outcomes between robot adopters and other firms within given 5-digit industry
- robot adoption is endogenous due to unobserved demand shocks
  - demand shocks increase growth and make robot adoption more likely
- instrument $Rob\_Exposure_{fi}$ picks up variation in growth rate of outcomes due to exogenous variation in firms' technological predisposition to adopt robots
- control for other observables that might be correlated with variation in growth and robot adoption

IV Estimates: Robot Adoption

	(1)	(2)	(3)	(4)	(5)
	Δ Rob_Adoption	Δ ln Sales	Δ ln Employment	Δ ln Sales per Worker	Δ Empl. Sh. High Skill
Δ Rob_Adoption		0.294	-0.462*	0.895***	0.070**
		[0.246]	[0.245]	[0.326]	[0.034]
Rob_Exposure	0.002***				
	[0.0004]				
Replaceability	0.033***	-0.013***	-0.033***	0.022***	-0.002***
	[0.009]	[0.004]	[0.004]	[0.005]	[0.001]
ln Initial Sales	0.010***	-0.020***	0.004	-0.026***	0.000
	[0.001]	[0.002]	[0.002]	[0.003]	[0.000]
Dummy Initial Importer	0.001	0.022***	0.001	0.021***	0.000*
	[0.001]	[0.002]	[0.002]	[0.002]	[0.000]
Dummy Initial Exporter	0.001	0.009***	-0.003*	0.012***	0.001***
	[0.001]	[0.002]	[0.002]	[0.002]	[0.000]
Obs.	55333	55333	55333	55333	55333
KP F-Statistic		29.72	29.72	29.72	29.72

The dependent variables are indicated in columns' headings and are: Δ Rob_Adoption, a dummy equal to 1 for firms that start importing robots over the sample period and equal to 0 for non-importers (column 1); the annualized changes in log sales (column 2), log employment (column 3), log sales per worker (column 4) and the employment share of high-skill professions (column 5). Rob_Exposure is the product between the firm-level employment share of occupations that can be replaced by robots in 1994 (Replaceability) and the log ratio

IV Estimates: Robot Adoption - Robustness Checks

	(1)	(2)	(3)	(4)
	Δ ln Sales	Δ ln Employment	Δ ln Sales per Worker	Δ Empl. Sh. High Skill
	a) Pre-2008			
Δ Rob_Adoption	0.616	-0.734*	1.502**	0.033
	[0.432]	[0.434]	[0.613]	[0.053]
Obs.	54327	54327	54327	54327
KP F-Statistic	15.53	15.53	15.53	15.53
	b) Elasticity of Substitution			
Δ Rob_Adoption	1.899***	0.465	1.812***	0.059
	[0.615]	[0.515]	[0.702]	[0.069]
Δ Rob_Adoption x Low_Ela	-2.062***	-1.191**	-1,179	0.014
	[0.722]	[0.585]	[0.823]	[0.078]
Obs.	55333	55333	55333	55333
KP F-Statistic	14.66	14.66	14.66	14.66
	c) All Firms			
Δ Rob_Adoption	1.385***	-0.476	1.864***	0.049
	[0.414]	[0.298]	[0.519]	[0.042]
Obs.	204450	204450	204450	204450
KP F-Statistic	23.91	23.91	23.91	23.91
	d) Additional Interactions of Replaceability			
Δ Rob_Adoption	-0.065	-0.613***	0.705*	0.096**
	[0.285]	[0.300]	[0.364]	[0.041]
Obs.	55245	55245	55245	55245
KP F-Statistic	22.28	22.28	22.28	22.28

The dependent variables are the annualized changes in the firm-level outcomes indicated in columns'

Discussion

- first paper using a firm-level measure of robot intensity
  - while robot adoption and employment are correlated
  - an increase in robot intensity is followed by job losses
- causal estimates imply that robots
  - displace production workers
  - increase productivity , but potentially also market power (since efficiency gains not translated into higher sales)
  - consistent with concerns of "excessive automation"
- reduced-form estimates correspond to partial-equilbrium analysis. In GE wages would change in response to automation.

Automation and the Covid19 Crisis

- disruption of global supply chains and reshoring:
    - Covid may induce increased reshoring but reshored manufacturing will be automatized due to high labor costs
    - small employment effects of reshored manufacturing, biased towards highly skilled (engineers, managers...)
- digitalization of service tasks:
    - Covid may lead to increased digitalization outside of manufacturing:
    - potentially large negative effects on employment in services, since services ¿80% of employment
    - highly skilled workers will likely to benefit from digitalization, others may lose
- large distributive effects of automation and digitalization: challenges for income distribution and taxation (larger fraction of income goes to (intangible) capital, which is highly mobile).