### Robot Imports and Firm-Level Outcomes

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Robot Imports and Firms

August 2022 1 / 24

### Machines and Jobs: 1913



• in 1913 Ford introduces the integrated moving assembly line

► man hours of final assembly dropped from more than 12 to fewer than 3

### Machines and Jobs: Today



• where are the workers?

## What We Do

• question:

- how do industrial robots affect jobs and efficiency at the firm level?
- main challenges:
  - measure robot adoption
  - identifying causal effects
- this paper:
  - proxy for robot adoption: French firm-level imports of industrial robots
  - identification: new firm-level exposure to automation
    - ★ available for non-importers too
  - study effect of robots on:
    - employment (across occupations), sales, productivity

## What We Find

- robot adopters are larger, more productive and use more high-skill workers
- robot adoption accompanied by firm's scaling up
  - employment, sales and efficiency increase
- yet, net of demand shocks
  - efficiency increases
  - employment falls with robot adoption
- who gains/loses?
  - higher demand for high-skill workers (engineers & managers)
  - weak effects on total sales (higher profits?)

## A Simple Model

- consider a firm with productivity  $\varphi_i$  facing demand:  $y_i = A_i p_i^{-\sigma}$
- production function:
  - ▶ labor  $(I_i)$  and capital  $(k_i)$  performing a unit measure of tasks

$$y_i = \varphi_i \exp\left(\int_0^1 \ln x_i(z) \mathrm{d}z\right)$$

• problem of the firm:

$$\max_{k_{i},l_{i},\kappa_{i}}\left\{p_{i}y_{i}-rk_{i}-wl_{i}-hf_{i}\left(\kappa_{i}\right)\right\}$$

•  $\kappa_i$  = share of automated tasks  $\rightarrow$  performed by  $k_i$  as  $r_i < w$ 

convex cost of automation:

$$hf_{i}(\kappa_{i}) = h\frac{\rho_{i}}{1-\rho_{i}}\left[(1-\kappa_{i})^{-\frac{1-\rho_{i}}{\rho_{i}}}-1\right]$$

★  $\rho_i \in (0, 1)$ : firm-specific "replaceability" of tasks

### Demand for Labor and Automation

- automation and labor demand
  - combining the FOCs for  $I_i$  and  $k_i$

$$\frac{d\ln l_i}{d\kappa_i} = \overbrace{(\sigma-1)\ln\left(\frac{w}{r_i}\right)}^{productivity} - \overbrace{(1-\kappa_i)^{-1}}^{displacement}$$

- net effect may be positive for low  $\kappa_i$  and high  $\sigma$
- endogenous automation
  - FOC for  $\kappa_i$ :

$$\frac{1}{1-\kappa_i} = \left[ \left( 1 - \frac{1}{\sigma} \right) \frac{p_i y_i}{h} \ln \left( \frac{w}{r} \right) \right]^{\rho_i}$$

- automation κ<sub>i</sub>:
  - increasing in scale (demand and productivity)
  - $\star$  increasing in cost-saving (w/r)
  - $\star$  especially in firms with high replaceability  $\rho_i$

# Identification Strategies

- threat to identification:
  - demand shocks affect employment both directly and through  $\kappa$ 
    - ★ regress / on  $\kappa$  → upward bias
- strategy 1: robot intensity net of demand shocks
  - robot cost over capital expenditure

$$\frac{\kappa_i}{rk_i} = \frac{1}{hf_i'(\kappa_i)} \ln\left(\frac{w}{r}\right)$$

\* demand shocks affect robot cost and capital expenditure equally

- strategy 2: exogenous robot exposure
  - costs savings spur automation more in firms with more replaceable tasks  $\rho_i$

$$\frac{1}{1-\kappa_i} = \left[ \left( 1 - \frac{1}{\sigma} \right) \frac{p_i y_i}{h} \ln \left( \frac{w}{r} \right) \right]^{\rho_i}$$

 $\blacktriangleright$  interact firm-specific replaceability  $\times$  industry-level robot suitability

### The Data

- near universe of French firms from 1994-2013
- balance-sheet data from BRN and FARE
  - sales, materials, capital stock (value of physical assets), employment
- full-time employment
  - at the plant level for 6 occupations from DADS etablissement (aggregated at the firm level)
  - 29 occupations in 1994
- imports and exports at the firm level
  - value and unit values by 8 digit CN code, from French Customs (DOUANES)
  - industrial robot imports: CN 84795000
- final sample:
  - $\blacktriangleright$  64,173 manufacturing firms,  $\geq$  10 employees, 765 robot adopters

# Preliminary Evidence: Specifications

- main variables:
  - $Y_{it} = \log$ : sales, employment, VA per worker; share of skilled workers
  - Adoption<sub>it</sub> = 1 since 1st year of robot import, 0 otherwise

► In 
$$RobInt_{it} = ln \frac{RobStock_{it}}{CapStock_{it}} = ln \frac{sum of robot imports over tin}{CapStock_{it}}$$

- specifications:
  - panel OLS:

$$Y_{it} = \alpha_i + \alpha_{jt} + \beta \cdot Adoption_{it} + \mathbf{X}'_{it} \cdot \gamma + \varepsilon_{it}$$

DiD event study:

$$Y_{it} = \alpha_i + \alpha_{jt} + \sum_{s=-5}^{5} \beta_s \cdot Adoption_{it-s} + \varepsilon_{it}$$

- i = firm, j = 5 -digit industry, t = years
- $\mathbf{X}'_{it}$  = initial log sales, importer & exporter status  $\times$  year dummies
- standard errors clustered by firm

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# Preliminary Evidence: Results

	(1)	(2)	(3)	(4)
	Ln Sales	Ln No. of	Ln VA	Empl. Sh.
		Employees	per Worker	High Skill
		a) R	obot Adoption	
Adoption <sub>it</sub>	0.230***	0.106***	0.057***	0.003
	[10.458]	[5.763]	[3.630]	[1.030]
Obs.	596,166	597,282	585,886	597,282
R2	0.95	0.87	0.85	0.70
		b) R	obot Intensity	
Ln RobInt <sub>it</sub>	-0.129***	-0.144***	0.040***	0.015***
	[-4.150]	[-5.427]	[2.654]	[2.815]
Obs.	5,706	5,711	5,542	5,711
R2	0.97	0.93	0.84	0.89

### DiD Event Study



Robot Imports and Firms

August 2022 12 / 24

## Identification: Robot Exposure

• exogenous firm-level exposure to robots:

$$RobExp_i = RobSuit_{j-i} \cdot Repl_i$$

firm-level replaceability of employment:

$$extsf{Repl}_i = \sum_{o=1}^{29} \omega_{oi} \cdot extsf{Repl}_o$$

- *Repl<sub>o</sub>* = replaceability of occupations (from Graetz & Michaels, 2018, mapped to French occupations)
- \*  $\omega_{oi}$  = share of occupation o in firm i's employment in 1994
- industry-level robot suitability:

$$RobSuit_{j-i} = \sinh^{-1}\left(rac{\sum_{i' \neq i \in j} RobStock_{i'}}{\sum_{i' \neq i \in j} CapStock_{i'}}
ight)$$

initial robot intensity of 5-digit industry j (excluding firm i)

# Specification: Long Differences

robot exposure

Iong-differences:

$$\Delta Y_{i} = \alpha_{j} + \beta_{1} \cdot \textit{RobExp}_{i} + \beta_{2} \cdot \textit{RobSuit}_{j-i} + \beta_{3} \cdot \textit{Repl}_{i} + \mathbf{X}_{i}' \cdot \gamma + \varepsilon_{i}$$

- $\Delta Y_i$  = annualized change in firm *i*'s outcome over the sample period
- $\alpha_j = 5$ -digit industry fixed-effects (differential trends across industries)
- $\mathbf{X}'_{i}$  = start-of-period firm characteristics (heterogeneous trends across firms)
- standard errors clustered by firm
- $\beta_1$  identified from differences in the growth of outcomes across sectors and firms (diff-in-diff)

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# Robot Exposure: Main Results

	(1)	(2)	(3)	(4)	(5)		
	Δ Ln Sales	∆ Ln No. of	Δ Ln VA per	Δ Empl. Sh.	Adopter		
		Employees	Worker	High Skill			
		a) Baseline Regressions					
RobExpi	0.148	-0.094**	0.302***	0.006	0.174***		
	[1.343]	[-2.095]	[2.702]	[1.106]	[2.893]		
Obs.	36,301	36,584	35,180	36,584	36,584		
<b>R</b> 2	0.10	0.04	0.07	0.04	0.05		

## Robot Exposure: Robustness I

	(1)	(2)	(3)	(4)	(5)		
	$\Delta$ Ln Sales	∆ Ln No. of	Δ Ln VA per	Δ Empl. Sh.	Adopter		
		Employees	Worker	High Skill			
		b) V	Weighted Regre	ssions			
RobExp <sub>i</sub>	0.142	-0.108**	0.310***	0.008	0.224***		
	[1.192]	[-2.230]	[2.629]	[1.396]	[2.666]		
Obs.	36,301	36,584	35,180	36,584	36,584		
<b>R</b> 2	0.10	0.04	0.06	0.05	0.069		
		c) Excluding Manufacturing of Motor Vehicles					
RobExpi	0.148	-0.095**	0.303***	0.005	0.171***		
	[1.329]	[-2.101]	[2.695]	[0.837]	[2.847]		
Obs.	35,759	36,040	34,647	36,040	36,040		
R2	0.10	0.04	0.07	0.04	0.052		
		d) Broader	Definition of F	Robot Imports			
RobExpi	0.127	-0.038	0.187*	0.010**	0.261*		
	[1.314]	[-0.810]	[1.768]	[2.096]	[1.830]		
Obs.	36,301	36,584	35,180	36,584	36,584		
R2	0.10	0.04	0.07	0.04	0.11		

# Robot Exposure: Robustness II

	(1)	(2)	(3)	(4)	(5)	
	$\Delta$ Ln Sales	∆ Ln No. of	Δ Ln VA per	$\Delta$ Empl. Sh.	Adopter	
		Employees	Worker	High Skill		
		e) Interact	ions with Dema	and Elasticity		
RobExp <sub>i</sub>	-0.160	-0.203**	-0.061	0.001	0.065	
	[-0.737]	[-2.020]	[-0.270]	[0.111]	[0.414]	
RobExp <sub>i</sub> x Elast <sub>h</sub>	0.069*	0.023	0.076*	0.002	0.023	
	[1.963]	[1.405]	[1.955]	[0.774]	[0.838]	
Obs.	32,427	32,679	31,365	32,679	32,679	
<b>R</b> 2	0.11	0.04	0.07	0.04	0.05	
	f) Alternative Proxy for Robot Exposure (IFR)					
RobExp <sub>i</sub>	3.331***	0.248	3.537***	0.070**	0.625***	
	[9.669]	[1.043]	[11.543]	[2.537]	[3.469]	
Obs.	36,301	36,584	35,180	36,584	36,584	
<b>R</b> 2	0.10	0.04	0.07	0.04	0.05	

## Robot Exposure: Identification Threats I

	(1)	(2)	(3)	(4)	(5)
	$\Delta$ Ln Sales	$\Delta$ Ln No. of	$\Delta$ Ln VA per	$\Delta$ Empl. Sh.	Adopter
		Employees	Worker	High Skill	
	a) Inte	eraction of Rob	ot Suitability v	with Routine In	ntensity
RobExp <sub>i</sub>	0.151	-0.090**	0.297***	0.006	0.181***
	[1.385]	[-1.994]	[2.676]	[1.005]	[3.055]
RobSuit <sub>i-i</sub> x Routine <sub>i</sub>	-2.934	4.864	9.589	1.193***	2.545
	[-0.129]	[0.829]	[0.433]	[2.781]	[0.355]
Obs.	36,301	36,584	35,180	36,584	36,584
<b>R</b> 2	0.10	0.04	0.07	0.04	0.05
	b) Inter	actions of Rob	ot Suitability w	ith Firm Chara	cteristics
RobExp <sub>i</sub>	0.137	-0.091**	0.283**	0.007	0.167***
	[1.260]	[-2.006]	[2.564]	[1.174]	[2.730]
Obs.	36,301	36,584	35,180	36,584	36,584
<b>R</b> 2	0.10	0.04	0.07	0.04	0.05

# Robot Exposure: Identification Threats II

	(1)	(2)	(3)	(4)	(5)		
	$\Delta$ Ln Sales	$\Delta$ Ln No. of	Δ Ln VA per	$\Delta$ Empl. Sh.	Adopter		
		Employees	Worker	High Skill			
	c) Inte	ractions of Rej	placeability wit	h Firm Charac	teristics		
RobExp <sub>i</sub>	0.148	-0.095**	0.304**	0.008	0.169***		
	[1.245]	[-2.070]	[2.534]	[1.286]	[2.906]		
Obs.	36,301	36,584	35,180	36,584	36,584		
R2	0.10	0.04	0.07	0.04	0.05		
	d) Interactions of Replaceability with Industry Characteristics						
RobExp <sub>i</sub>	0.173	-0.137***	0.399***	0.012*	0.136**		
	[1.591]	[-2.771]	[3.969]	[1.795]	[2.252]		
Obs.	36,254	36,537	35,134	36,537	36,903		
<b>R</b> 2	0.10	0.04	0.07	0.04	0.05		
	e) In	teractions of <b>R</b>	eplaceability w	rith Sector Du	nmies		
RobExp <sub>i</sub>	0.155	-0.089*	0.306***	0.006	0.175***		
	[1.353]	[-1.934]	[2.620]	[0.968]	[2.853]		
Obs.	36,301	36,584	35,180	36,584	36,584		
<b>R</b> 2	0.10	0.04	0.07	0.04	0.05		

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### Magnitudes

- compare firm with average *Repl<sub>i</sub>* in:
  - manufacture of motor vehicles industry (high  $RobSuit_{i-i}$ )
  - **2** manufacture of wine industry (low  $RobSuit_{i-i}$ )
    - \* 56% higher adoption probability in (1) vs (2)
    - \* 0.30 p.p. per year larger employment fall in (1) vs (2)
- consider average increase in  $RobSuit_{i-i}$  over 1994-2013, and compare:
  - firm at 75th percentile of distribution by Repli
  - Irrm at 25th percentile of distribution by Repl;
    - \* 48% higher adoption probability in (1) vs (2)
    - ★ 0.26 p.p. per year larger employment fall in (1) vs (2)

# Conclusions

- first paper using a firm-level identification strategy to study the effect of robots
  - robot adoption and employment are correlated
  - but exogenous changes in automation lead to job losses
- displacement effect is large
  - important for labor demand and welfare
- automation increases productivity much more than sales
  - ▶ higher profits → excessive automation?

### Literature on Robots and Jobs

- theory:
  - Acemoglu & Restrepo (2018), Hemous & Olsen (2018), Zeira (1998)...
- empirics:
  - cross-industry studies: mixed results
    - \* Acemoglu & Restrepo (2019): IFR, US CZs, job loss
    - ★ Graetz & Michaels (2018): IFR, 17 countries, higher productivity, no job loss
  - firm-level studies: correlations
    - survey data: EC (2015, 7 countries); Koch, Manuylov & Smolka (2019, Spain); Cheng et al. (2019, China), Dinlersoz & Wolf (2018, US)
    - \* import data: Humlum (2019), Dixen, Hong & Wu (2019), Acemoglu, Lelarge & Restrepo (2020)
  - firm-level studies: causality
    - \* Aghion et al. (2020, France): investment in machines and electricity raises employment
    - \* Bessen et al. (2019, Netherlands): third-party automation services increase separations

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#### The Data: Robot Importers



 $\bullet$  robot importers: 1% of all firms, but up to 15% of value added

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# Descriptive Stats: Robot Adopters vs. Non Adopters

	Robot Adopters						
-	Obs.	No. Firms	Mean	Median	Std. Dev.	Mean $\Delta$	
						(annualized)	
Adoption	6,373	765	1	1	1	0	
Robot Intensity	6,373	765	0.078	0.005	0.520	0.182	
No. of Employees	6,373	765	852	191	3,129	-0.016	
Empl. Sh. High Skill	6,373	765	0.153	0.108	0.142	0.006	
Sales (€'000)	6,373	765	761,597	46,050	6,812,860	-0.075	
Sales per Worker (€'000)	6,373	765	1,912	226	104,935	-0.061	
VA per Worker (€'000)	6,225	761	178	65	2,715	-0.070	
TFP	6,218	760	426	170	2,625	-0.066	
Profits (€'000)	6,373	765	19,855	529	223,342	-0.052	
Dummy Importer	6,373	765	0.972	1	0.164	0.001	
Dummy Exporter	6,373	765	0.947	1	0.224	0.002	
Export Price Index	6,039	750	242	22	2,045	0.014	
	Non Robot Adopters						
Adoption	598,925	63,408	0	0	0	0	
Robot Intensity	586,785	63,448	0	0	0	0	
No. of Employees	598,925	63,448	78	27	313	-0.030	
Empl. Sh. High Skill	598,925	63,448	0.081	0.056	0.106	0.003	
Sales (€'000)	598,922	63,448	54,703	7,615	683,130	-0.092	
Sales per Worker (€'000)	598,922	63,448	666	231	11,725	-0.063	
VA per Worker (€'000)	587,342	62,741	190	71	1,973	-0.066	
TFP	576,404	62,005	292	132	1,362	-0.071	
Profits (€'000)	598,925	57,293	1,256	98	36,795	-0.065	
Dummy Importer	598,925	63,448	0.568	1	0.495	0.001	
Dummy Exporter	598,925	63,448	0.561	1	0.496	0.004	
Export Price Index	335,886	42,346	280	14	16,844	0.012	
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