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?

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, TFP
- causality: 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 adoption and 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:

$$y_i = A_i p_i^{-\sigma}, \ \sigma > 1$$

  - produce with labor (l_i) and capital (k_i) performing a unit measure of tasks
  - share κ_i of tasks are automated: can be performed by k_i
    - ⋆ firm-specific price of capital r_i, assume $r_i < w$

$$y_i = \varphi \exp\left(\int_0^1 \ln x_i(z) dz\right) = \varphi \left(\frac{k_i}{\kappa_i}\right)^{\kappa_i} \left(\frac{l_i}{1-\kappa_i}\right)^{1-\kappa_i}$$

    - ⋆ $\varphi_i =$ firm productivity

- profit:

$$\pi_i = p_i y_i - r_i k_i - w l_i - h f(\kappa_i)$$

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

Demand for Production Workers

- first-order conditions
  - for capital:

$$r_i k_i = \left(1 - \frac{1}{\sigma}\right) A_i^{1/\sigma} y_i^{1-1/\sigma} \kappa_i$$

    - capital increases with automation intensity κ_i
  - for labor:

$$w l_i = \left(1 - \frac{1}{\sigma}\right) A_i^{1/\sigma} y_i^{1-1/\sigma} \cdot (1 - \kappa_i)$$

- combining both

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

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

Endogenous Robot Adoption

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

$$hf\left(\kappa_i\right) = h\frac{\kappa_i^{\delta}}{\rho_i \delta}, \qquad \delta > 1$$

  - ρ_i: firm-specific replaceability of tasks by robots
  - FOC for κ:

$$\left(1 - \frac{1}{\sigma}\right)^{\sigma} A_i \left(\frac{\varphi_i}{w}\right)^{(\sigma-1)} \left(\frac{w}{r_i}\right)^{\kappa_i(\sigma-1)} \ln\left(\frac{w}{r_i}\right) = \frac{h\kappa_i^{\delta-1}}{\rho_i}.$$

- automation κ_i:
  - increasing in demand A_i
  - increasing in productivity φ_i
  - increasing in cost-saving (w/r_i)
  - increasing in replaceability ρ_i

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: robot intensity= measure of automation net of demand shocks
  - from the FOC of k_i and κ_i :

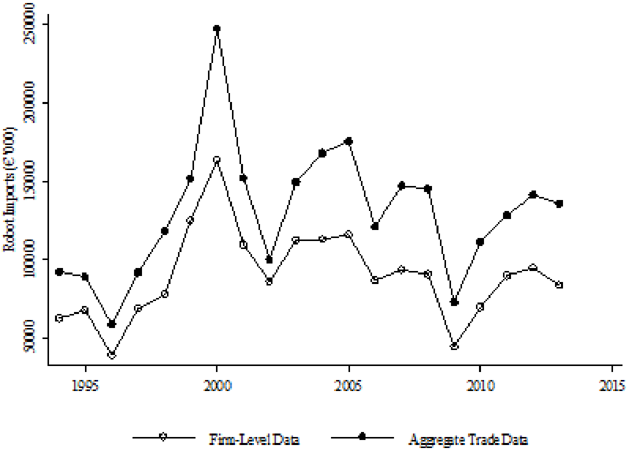
$$\frac{h\kappa_i^{\delta}}{\rho_i \delta r_i k_i} = \frac{1}{\delta} \ln\left(\frac{w}{r_i}\right)$$

    = 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 that proxies for firm-specific cost/benefit ratio of robot adoption: firm-specific replaceability× industry-level robot suitability

The Data

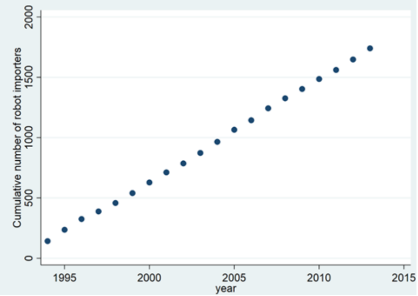
- near universe of French firms from 1994-2013
  - around 1.3 million firms, all economic activities except government
  - manufacturing, services, primary
- imports and exports (value and unit values) at the firm level
  - by 8 digit CN code, by origin country from customs (DOUANES)
- balance-sheet 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 more than 10 employees

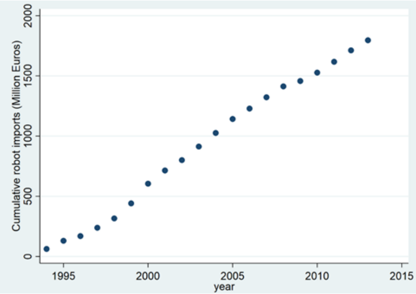
The Data: Robot Imports, HS847950



Aggregate Facts

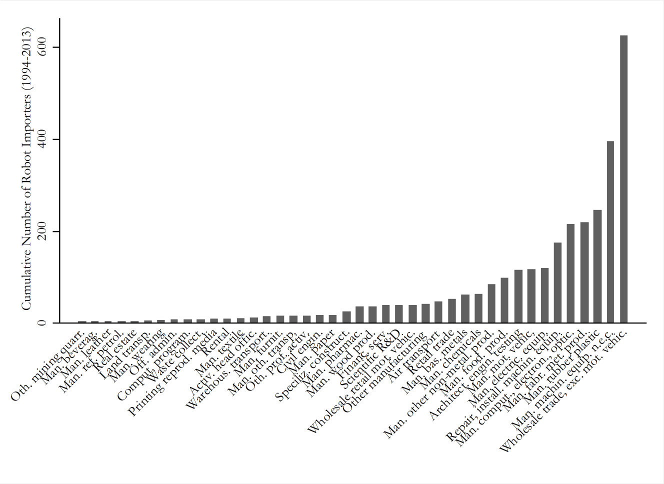
- cumulative number of French robot adopters and cumulative value of robot imports





Aggregate Facts

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



Descriptives: Robot Adopters vs. Non Robot Adopters

	Obs.	No. Firms	Mean	Median	Std. Dev.	Mean Δ (annualized)
Robot Adopters						
Robot adopter	6,003	746	1	1	1	0
Robot intensity	6,003	746	0.108	0.005	0.635	0.190
No. of employees	6,003	746	838	184	3,107	-0.017
Empl. sh. high skill	6,003	746	0.157	0.111	0.142	0.006
Sales (€'000)	6,003	746	758,388	42,911	6,965,072	-0.073
Sales per worker (€'000)	6,003	746	2,002	221	108,120	-0.058
VA per worker (€'000)	5,855	742	183	164	2,802	-0.069
TFP	5,848	741	422	164	2,702	-0.066
Importer	6,003	746	0.973	1	0.163	0.001
Exporter	6,003	746	0.950	1	0.218	0.002
Replaceability	513	513	0.372	0.403	0.185	-
Non Robot Adopters						
Robot adopter	616,798	64,014	0	0	0	0
Robot intensity	604,409	64,014	0	0	0	0
No. of employees	616,798	64,014	77	27	309.54	-0.029
Empl. sh. high skill	616,798	64,014	0.082	0.056	0.107	0.003
Sales (€'000)	616,794	64,014	53,465	7,385	673,610	-0.091
Sales per worker (€'000)	616,794	64,014	653	223	11,554	-0.063
VA per worker (€'000)	604,960	63,307	187	69	1,945	-0.066
TFP	593,795	62,571	287	128	1,343	-0.071
Importer	616,798	64,014	0.560	1	0.4963	0.001
Exporter	616,798	64,014	0.554	1	0.4971	0.004
Replaceability	36,459	36,459	0.356	0.358	0.190	-

The Non-Causal Effect of Robots: DiD

$$Y_{fit} = \alpha_f + \alpha_{it} + \beta \cdot Rob\_Adoption_{fit} + \mathbf{X}'_{fit} \cdot \gamma + \varepsilon_{fit},$$

- α_f = firm fixed effects
- α_{it} = 5-digit-industry-year fixed effects
- $t = 0$: 1st year of robot imports
- $Rob\_Adoption_{fit} = \begin{cases} 0 & t < 0 \\ 1 & t \geq 0 \end{cases}$
- Y_{ift}: sales, employment, sales per worker, VA per worker, TFP (all in logs), high-skill employment share
- $\mathbf{X}_{ift}$: controls for firm characteristics (log sales, import, export status) measured at initial year $\times$ year dummies
- cluster standard errors by firm

The Non-Causal Effect of Robots: DiD

	(1)	(2)	(3)	(4)
	ln Sales		ln Employment	
Rob_Adoption	0.130***	0.198***	0.093***	0.114***
	[6.113]	[9.546]	[4.622]	[5.664]
Obs.	615,785	614,427	617,229	615,595
R2	0.949	0.95	0.878	0.878
	ln Sales per Worker		Empl. Sh. High Skill	
Rob_Adoption	0.039***	0.087***	0.011***	0.003
	[2.614]	[5.797]	[4.195]	[0.973]
Obs.	615,785	614,427	617,229	615,595
R2	0.89	0.891	0.677	0.679
	ln VA per Worker		ln TFP	
Rob_Adoption	0.011	0.051***	0.030**	0.067***
	[0.707]	[3.155]	[2.042]	[4.492]
Obs.	605,217	603,926	593,996	592,746
R2	0.815	0.815	0.857	0.858
Firm FE	Yes	Yes	Yes	Yes
Industry ×year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

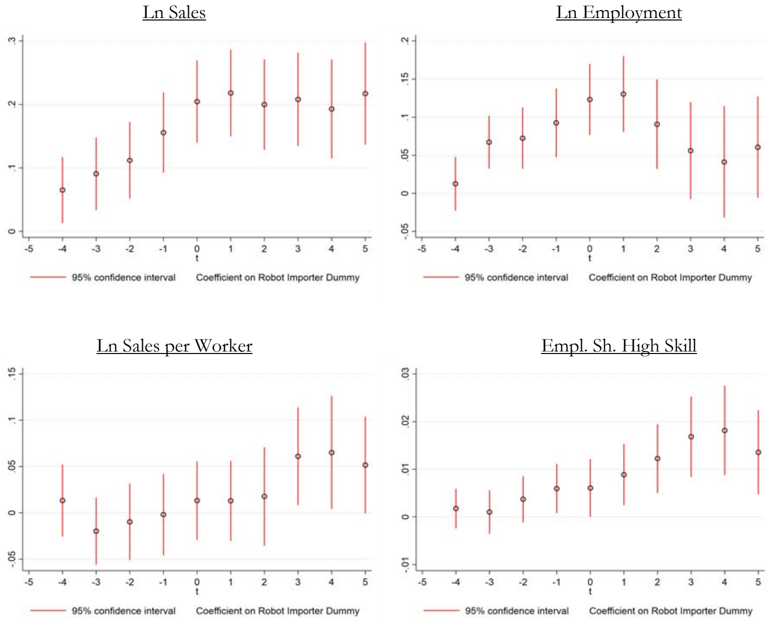
Identifying Pre-Trends: DiD Event Study

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

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

  - 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, VA per worker, TFP (all in logs), high-skill employment share
  - cluster standard errors by firm

Evolution of Outcomes Over Time: DiD Event Study



The Causal Effect of Robots 1: OLS with Robot Itensity

- sample consists of 742 robot adopters
- how do robots affect outcomes (Y_{fit}) *within* the firm once we net out demand shocks?
- specification

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

  - $Rob\_Int_{fit} = \ln(\frac{Rob\_stock_{fit}}{Capitalstock_{fit}}) \rightarrow$ 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
- cluster standard errors by firm

The Causal Effect of Robots 1: OLS with Robot Intensity

	(1)	(2)	(3)	(4)
	ln Sales		ln Employment	
Ln Rob_Intensity	-0.141***	-0.138***	-0.191***	-0.186***
	[-4.396]	[-4.253]	[-5.882]	[-5.661]
Obs.	5,998	5,948	6,003	5,953
R2	0.982	0.982	0.955	0.956
	ln Sales per Worker		Empl. Sh. High Skill	
Ln Rob_Intensity	0.033*	0.029	0.018***	0.018***
	[1.861]	[1.589]	[2.936]	[2.708]
Obs.	5,998	5,948	6,003	5,953
R2	0.885	0.886	0.876	0.877
	ln VA per Worker		Ln TFP	
Ln Rob_Intensity	0.052***	0.056***	0.026*	0.032**
	[3.074]	[3.265]	[1.668]	[2.119]
Obs.	5,823	5,773	5,817	5,767
R2	0.795	0.798	0.883	0.885
Firm FE	Yes	Yes	Yes	Yes
Industry ×year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

The Causal Effect of Robots 2: IV Long Differences

- identify the causal long-run effects of robots on firm-level outcomes
- sample: manufacturing firms present in 1994, of which 513 start using robots
- specification:

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

  - $\Delta \ln Y_{fi}$ = annualized change in firm f's outcome over sample period
    - employment, sales, sales per worker, value added per worker, TFP, high-skill employment 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 + start-of-period industry characteristics: industry robot stock/capital stock
  - α_i = 3-digit industry fixed-effects (industry-specific growth rates)
  - Cluster standard errors by 5-digit industry

Instrument for Robot Adoption: Robot Exposure

- **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: Robot Exposure

- **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 in initial period

$$Rob\_Suitability_i = \ln\left(\frac{1 + \sum_{f' \neq f} Rob\_stock_{f' \in i}}{\sum_{f' \neq f} Capital\_stock_{f' \in i}}\right)$$

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

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

IV Long Differences - Econometric Identification

- OLS impact of robot adoption is identified as differential in growth rates of outcomes between robot adopters and non-adopters within given 3-digit industry
- robot adoption is endogenous due to unobserved demand shocks
  - demand shocks increase growth and make robot adoption more likely
- shift-share instrument $Rob\_Exposure_{fi}$ picks up variation in growth rate of outcomes due to exogenous variation in firms' technological predisposition to adopt robots
- Reduced form of $Rob\_Exposure_{fi}$ has diff-in-diff interpretation: high vs. low Replaceability firms in high vs. low Suitability sectors

OLS Estimates: Robot Adoption

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ ln Sales	Δ ln Employment	Δ ln Sales per Worker	Δ Empl. Sh. High Skill	Δ ln VA per Worker	Δ ln TFP
Δ Rob_Adoption	0.044***	0.023***	0.021***	0.000	0.017***	0.019***
	[10.565]	[7.145]	[4.572]	[0.303]	[4.091]	[5.277]
Replaceability	-0.021***	-0.021***	0.002	-0.003***	-0.005	-0.013**
	[-3.384]	[-7.179]	[0.325]	[-7.897]	[-0.768]	[-2.099]
ln Initial Robot Intensity	0.249	-0.294	0.649*	0.103***	0.517	0.312
	[0.657]	[-1.634]	[1.772]	[3.497]	[1.077]	[0.689]
ln Initial Sales	-0.015***	-0.000	-0.014***	0.001***	-0.015***	-0.013***
	[-11.563]	[-0.484]	[-10.298]	[10.044]	[-10.621]	[-10.328]
Dummy Initial Importer	0.015***	0.001	0.014***	0.001**	0.015***	0.014***
	[6.449]	[0.819]	[6.910]	[2.509]	[7.063]	[7.225]
Dummy Initial Exporter	0.007***	-0.005***	0.012***	0.001***	0.011***	0.009***
	[3.186]	[-3.530]	[5.779]	[3.844]	[4.950]	[4.964]
Obs.	36,666	36,950	36,666	36,950	35,534	33,964
R2	0.075	0.032	0.055	0.032	0.043	0.050

IV Estimates: Robot Adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Rob_Adoption	Δ ln Sales	Δ ln Employment	Δ ln Sales per Worker	Δ Empl. Sh. High Skill	Δ ln VA per Worker	Δ ln TFP
Δ Rob_Adoption		0.192	-0.557**	1.019**	0.047**	1.188*	0.816
		[0.422]	[-2.006]	[2.100]	[2.024]	[1.864]	[1.521]
Rob_Exposure	0.002***						
	[2.898]						
Replaceability	0.033***	-0.021***	-0.021***	0.002	-0.003***	-0.005	-0.013**
	[2.657]	[-3.423]	[-6.324]	[0.291]	[-7.431]	[-0.666]	[-2.102]
ln Initial Robot Intensity	0.344**	0.196	-0.085	0.289	0.085**	0.244	0.113
	[2.334]	[0.504]	[-0.308]	[0.743]	[2.407]	[0.516]	[0.253]
ln Initial Sales	0.013***	-0.017***	0.007**	-0.027***	0.000	-0.029***	-0.023***
	[7.308]	[-2.665]	[2.111]	[-4.458]	[0.272]	[-3.764]	[-3.260]
Dummy Initial Importer	0.000	0.015***	0.001	0.014***	0.001**	0.015***	0.014***
	[0.127]	[6.561]	[0.787]	[5.704]	[2.380]	[5.365]	[6.172]
Dummy Initial Exporter	0.001	0.006***	-0.004***	0.011***	0.001***	0.009***	0.008***
	[0.724]	[3.124]	[-2.762]	[4.557]	[3.610]	[3.605]	[4.001]
Obs.	36,950	36,666	36,950	36,666	36,950	35,534	33,964
KP F-Statistic		8.745	8.399	8.745	8.399	7.370	7.081

IV Estimates: Robot Adoption - Reduced Form and Robustness

	(1)	(2)	(3)	(4)		
	Δ ln Sales	Δ ln Employment	Δ ln Sales per Worker	Δ Empl. Sh. High Skill	Δ ln VA per Worker	Δ ln TFP
	a) Reduced Form (RF)					
Rob_Exposure	0.0003	-0.001***	0.000**	0.0001**	0.002**	0.001*
	[0.411]	[-2.733]	[2.561]	[2.256]	[2.268]	[1.687]
Obs.	36,666	36,950	36,950	36,950	35,534	33,964
R2	0.074	0.032	0.033	0.033	0.043	0.050
	b) Additional Interactions of Replaceability, IV					
Δ Rob_Adoption	-0.042	-0.713**	0.947*	0.069**	1.231*	0.828
	[-0.071]	[-2.316]	[1.646]	[2.272]	[1.940]	[1.537]
Obs.	36,903	36,903	36,903	36,903	36,903	36,903
KP F-Statistic	8.238	8.238	8.238	8.238	8.238	8.238
	c) Additional Interactions of Replaceability, RF					
Rob_Exposure	-0.00002	-0.001***	0.001*	0.0001***	0.002**	0.001*
	[-0.071]	[-3.029]	[1.806]	[3.137]	[2.358]	[1.676]
Obs.	36,903	36,903	36,903	36,903	36,903	36,903
R2	0.085	0.033	0.068	0.033	0.045	0.042

IV Estimates: Quantification & Decomposition

- OLS coefficient on $\Delta Rob\_Adoption_{ij}$, β_{OLS}, can be decomposed as:

$$\beta_{OLS} = \overbrace{\beta_{IV} \times \frac{\sigma^2_{RA_{IV}}}{\sigma^2_{RA}}}^{exog.\ adoption} + \overbrace{\beta_{RES} \times \frac{\sigma^2_{RA_{RES}}}{\sigma^2_{RA}}}^{demand\ shocks}$$

  - $\beta_{RA_{IV}}$: IV coefficient on $\Delta Rob\_Adoption_{ij}$
  - $\left(\sigma^2_{RA_{IV}}/\sigma^2_{RA}\right)$: fraction of overall variance of $\Delta Rob\_Adoption_{ij}$ explained by first-stage regression (exogenous adoption)
  - $\left(\sigma^2_{RA_{RES}}/\sigma^2_{RA}\right)$: residual fraction due to demand shocks (endogenous adoption)
  - $\left(\sigma^2_{RA_{IV}}/\sigma^2_{RA}\right) = 4.3$ percent $\Rightarrow$ most firms (95.7 percent) adopt robots due to demand shocks.

- $\beta_{OLS} = 0.023 = \overbrace{-0.024}^{exog.\ adoption} + \overbrace{0.047}^{demand\ shocks}$
  - exogenous adoption: average annual fall in employment equal to 2.4 p.p. in robot adopters relative to non robot adopters
  - residual adoption due to demand shocks: average annual increase in employment equal to 4.7 p.p.

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"
- employment effects at the industry level may be even stronger if (as other evidence suggests), adoption has negative effects on competing firms
- estimates correspond to partial-equilbrium analysis. In GE wages would change in response to automation if sufficiently many firms automate.