

What Is the Impact of Automation on Employment? New Evidence from France

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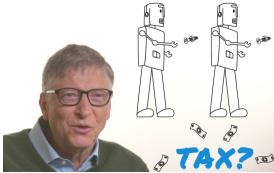
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The Robots Are Coming



Will They Take All Our Jobs?



Bill Gates



Andrew Yang



Ned Ludd

Aren't Machines Already Everywhere?



Introduction

- Will automation lead to “technological unemployment” (Keynes 1930, Leontief 1952)?
 - ▶ Automation can be defined as *“class of electro-mechanical devices that are relatively self-operating after they have been set in motion on the basis of predetermined instructions or procedures”* (Encyclopaedia Britannica, 2015)
- By definition automation is labor-saving at the task level
 - ▶ But could induce productivity gains and need for implementing new tasks (e.g., quality control)
 - ▶ Could be labor-augmenting and promote employment/wages at plant level, firm level, industry level or economy-wide

This Paper

- Despite extensive research, employment effects of automation remain debated
 - ▶ Industrial robots: Acemoglu-Restrepo 2019, Chiacchio et al. 2019 vs. Michaels and Graetz 2018, Dauth et al. 2019. Koch et al. 2019
 - ▶ Automation patents: Webb 2019 vs. Mann and Puttmann 2019
- Industry-level variation in automation makes causal identification challenging

This Paper

- Study automation at plant and firm levels
 - ▶ Primary measure exploits fact that common automation technologies operate with electric motors (e.g., robots or conveyors)
 - ▶ Linked employer-employee data set covers population of French firms in manufacturing sectors (1994-2015)
- Two research design for causal identification:
 - ▶ Event studies exploiting precise timing of adoption of automation technologies across plants (in same firm)
 - ▶ Shift-share research design exploiting changes in the productivity of foreign suppliers of machines
- Estimates indicate that increased automation leads to:
 - ▶ **Increased plant-level and firm-level employment**, with elasticities of about **0.3** after 3 years
 - ▶ Increased sales, and **stable wages and labor share**

Roadmap

- ① **Data and Stylized Facts**
- ② **Event Study**
- ③ **Shift-Share IV**
- ④ **Extensions**

Data

- Ideal data set would provide detailed information on
 - ① Workers: wages, occupation, tasks
 - ② Firms and plants: sales, industry, balance sheet
 - ③ Automation: technology, tasks performed, efficiency, intensity of utilization for each firm/plant

Worker/Firm Data

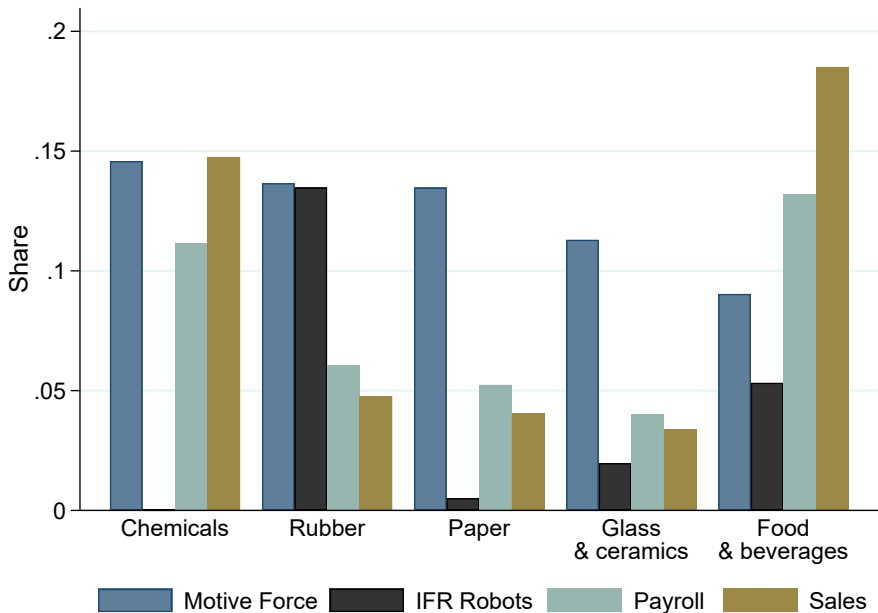
- Detailed information on workers and firms available from French administrative data (DADS and INSEE databases)
 - ▶ Matched employer-employee data covering all plants in private sector from 1994 to 2015

Measuring Automation

- Common automation technologies typically based on electro-motive force, i.e. set in motion using electric motors
 - ▶ Automation technologies require motive force / motor action
 - ▶ *“class of electro-mechanical devices that are relatively self-operating after they have been set in motion on the basis of predetermined instructions or procedures”* (Encyclopaedia Britannica, 2015)
- Use detailed records of electricity consumption for motors directly used in production process
 - ▶ Assembled by INSEE since 1983; distinguishes between motive power, thermic/thermodynamic uses, and other uses (electrolysis)
 - ▶ Focus on motive power to exclude heating, cooling, servers
- Supplement with firm-level data on industrial equipment/machines

Measuring Automation

- Measuring (changes in) automation using consumption of electricity for motive power has several potential advantages and limitations
- Advantages:
 - ▶ Covers broad set of automation technologies
 - ▶ Available at plant level
 - ▶ Possible to measure using intensity of usage, rather than stock of machines
- Limitations:
 - ▶ Due to variation in efficiency, difficult to draw comparisons across industries and over time $\Rightarrow$ analysis with industry/time fixed effects
 - ▶ Blends different vintages of automation technologies $\Rightarrow$ can focus on subset of industries where modern robots account for large share of motive power (e.g. automobile)



Chemicals



Rubber



Paper

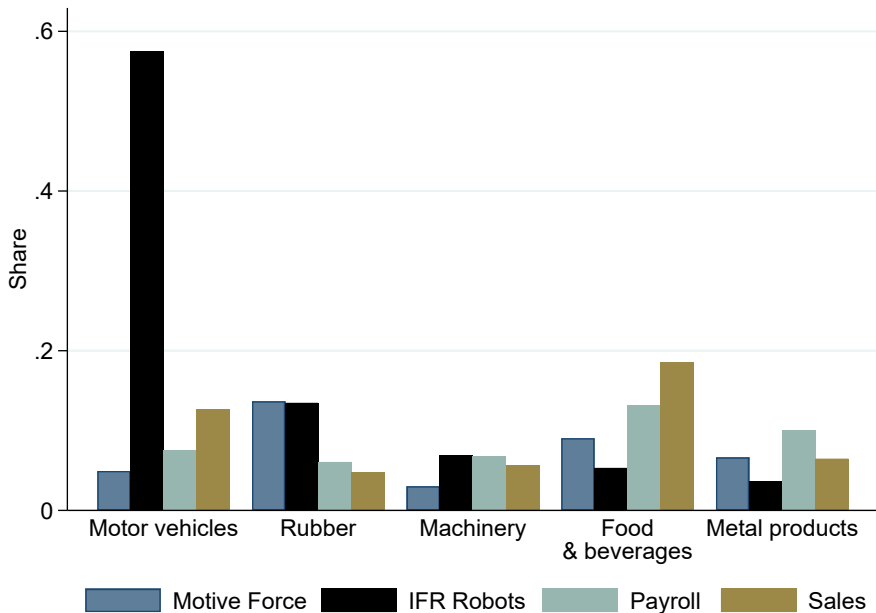


Glass and Ceramics



Food

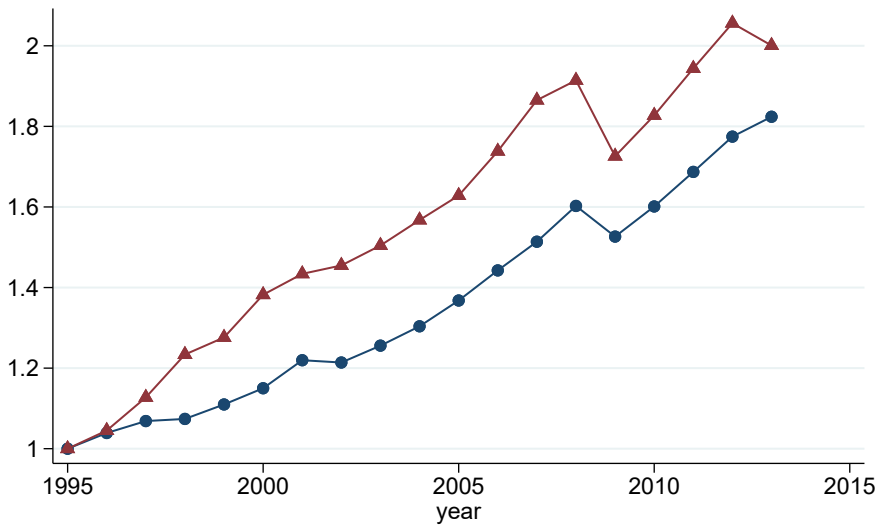




Stylized Facts

- As a preliminary descriptive exercise, compare path of sales, employment and labor share in plants that increase faster their consumption of electricity for motive power
 - ▶ Top 50% vs. bottom 50%

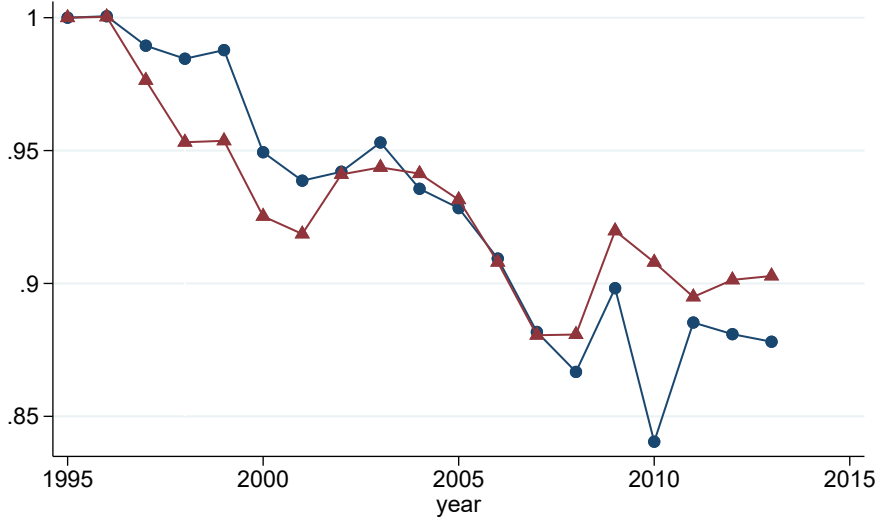
Sales



—●— Bottom 50% by Electric Motor Use

—▲— Top 50%

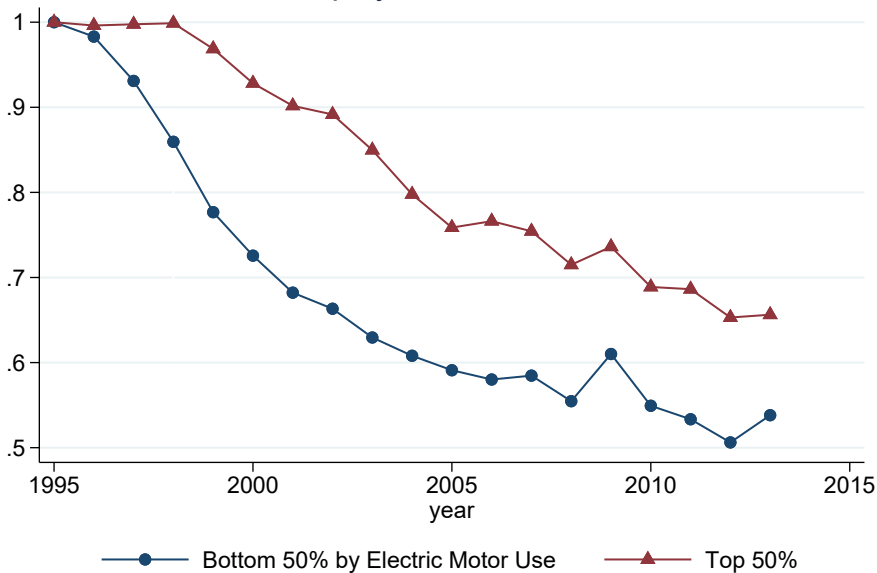
LaborCost/Sales



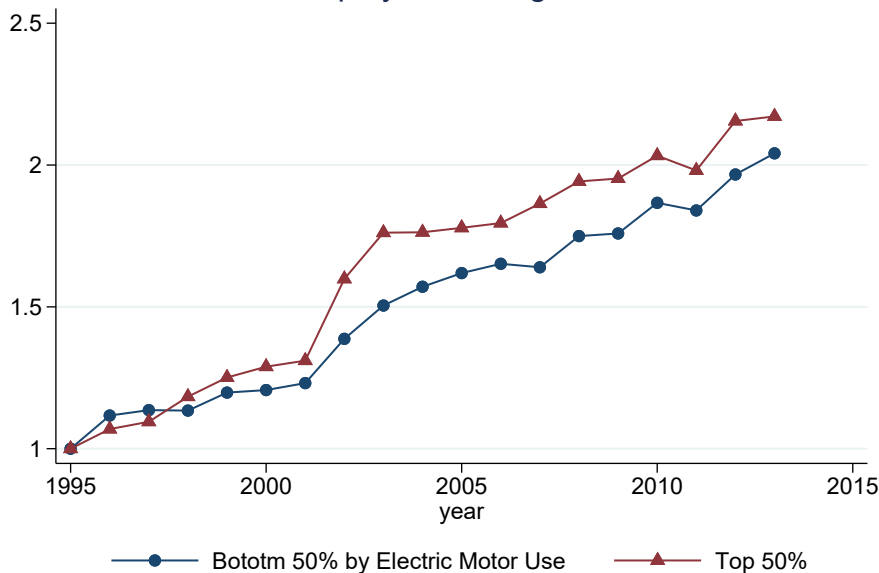
—●— Bottom 50% by Electric Motor Use

—▲— Top 50%

Employment - Low Skill



Employment - High Skill



Roadmap

- ① Data and Stylized Facts
- ② **Event Study**
- ③ Shift-Share IV
- ④ Extensions

Distributed Lead-Lag Model

- How to describe employment dynamics as a firm or plant increases its use of electric motors?
 - ▶ “Extensive margin” event study not possible given that almost all firms/plant use electric motors in all years
 - ▶ Use standard distributed lead-lag model (Stock and Watson 2015)

Distributed Lead-Lag Model

$$L_{it} = \sum_{k=0}^{10} \delta_k^{Lag} \Delta M_{i,t+k} + \sum_{k=-10}^{-1} \delta_k^{Lead} \Delta M_{i,t-k} + \mu_i + \lambda_{st} + \varepsilon_{it}$$

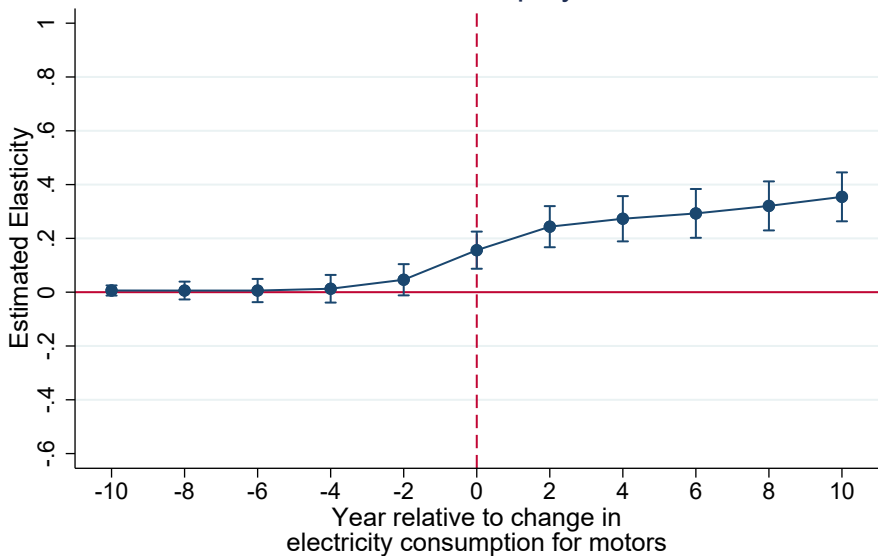
with employment L_{it} , change in electric motor consumption $\Delta M_{i,t}$ and plant F.E. μ_i

- Specification allows for delayed response of employment to increased automation
- Causal interpretation requires $E[\Delta M_{i,t+k} \cdot \varepsilon_{it} | \mu_i, \lambda_{st}] = 0 \ \forall (t, k)$
 - ▶ Leads can be used as a falsification test - but cannot rule out potential demand/supply shocks in contemporaneous period
 - ▶ Mitigate potential correlated shocks with specifications using industry-year or firm-year F.E., λ_{st}

Employment Dynamics: Average

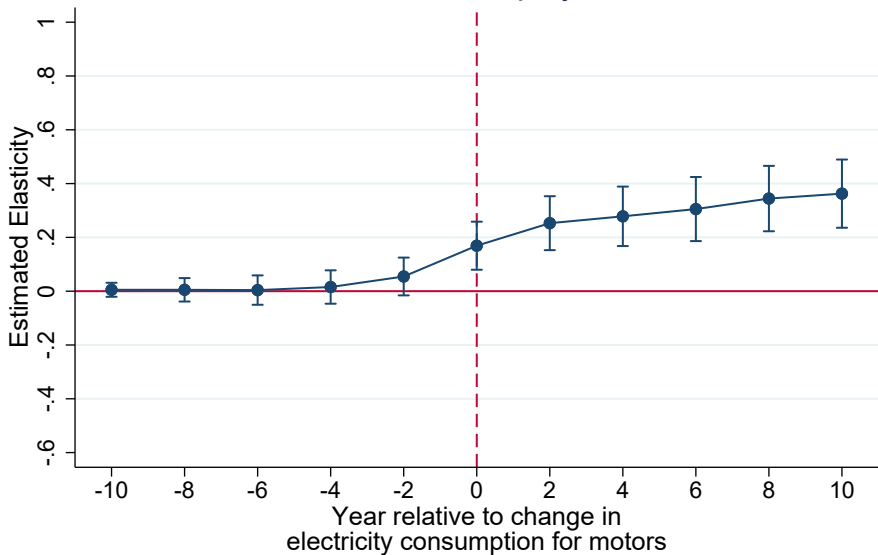
- Start by documenting employment dynamics across all firms
- Find that employment *increases* following increased use of machines
 - ▶ Elasticity of $+0.2$ on impact
 - ▶ Cumulative response increases further over time, with an elasticity of $+0.4$ after 8 years
- No pre-trends and magnitudes robust to changes in industry-year controls
 - ▶ Implies potential confounding factors must have precisely the same timing as automation and have stronger explanatory power than firm-year fixed effects (Oster 2015)

Total Plant Employment



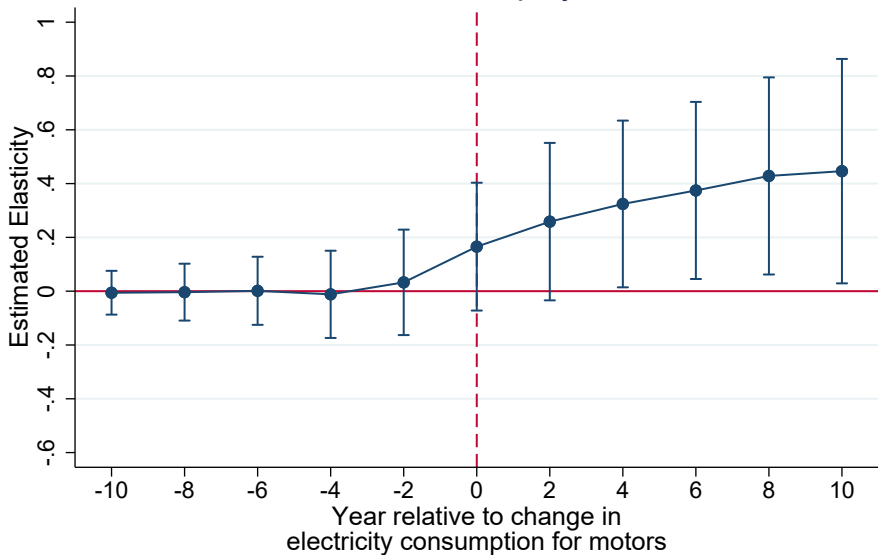
Controlling for 2-digit-industry by year F.E.

Total Plant Employment



Controlling for 4-digit-industry by year F.E.

Total Plant Employment

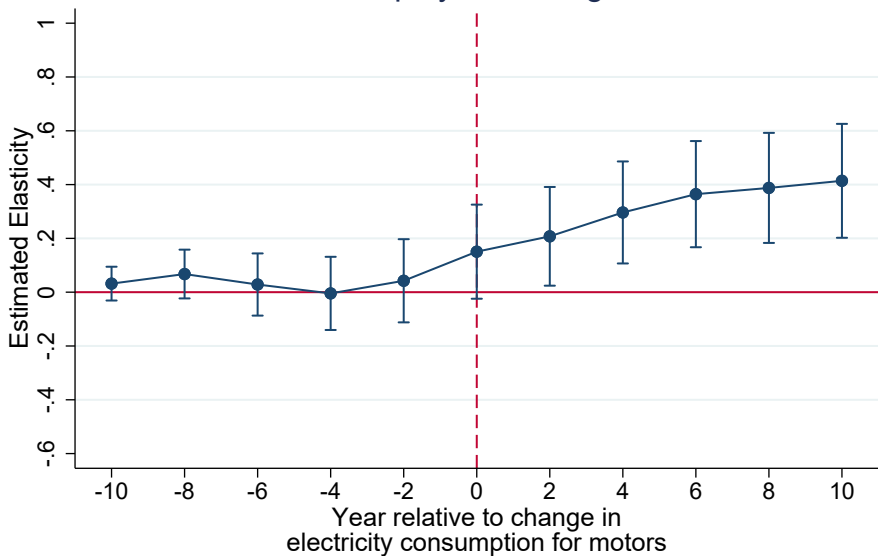


Controlling for firm-by-year F.E.

Employment Dynamics: Heterogeneity?

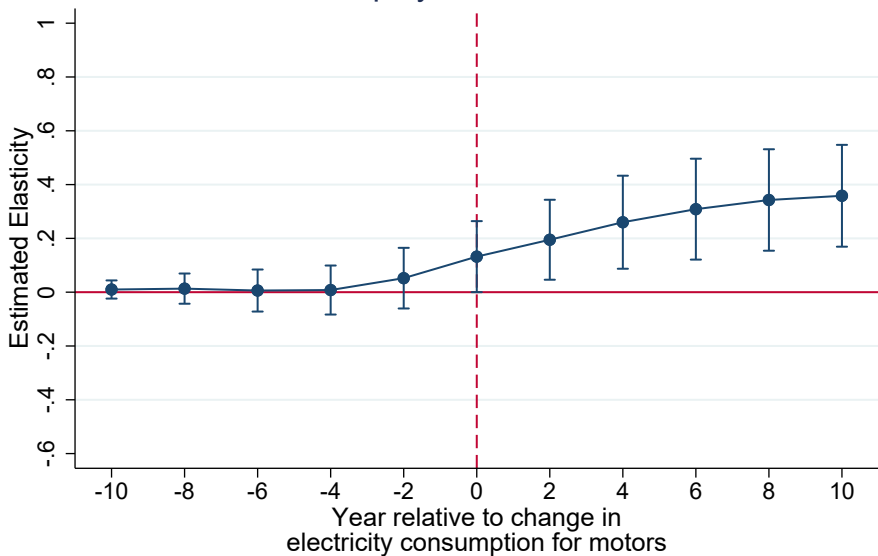
- Are effects different across skill groups?
- Find no heterogeneity across broad skill groups (high/medium/low)
 - ▶ Positive employment response for all, no change in relative wage
 - ▶ Suggests no broad effect on inequality
 - ▶ However heterogeneous effects could arise within skill groups, depending on set of tasks performed (in progress)

Plant Employment - High Skill



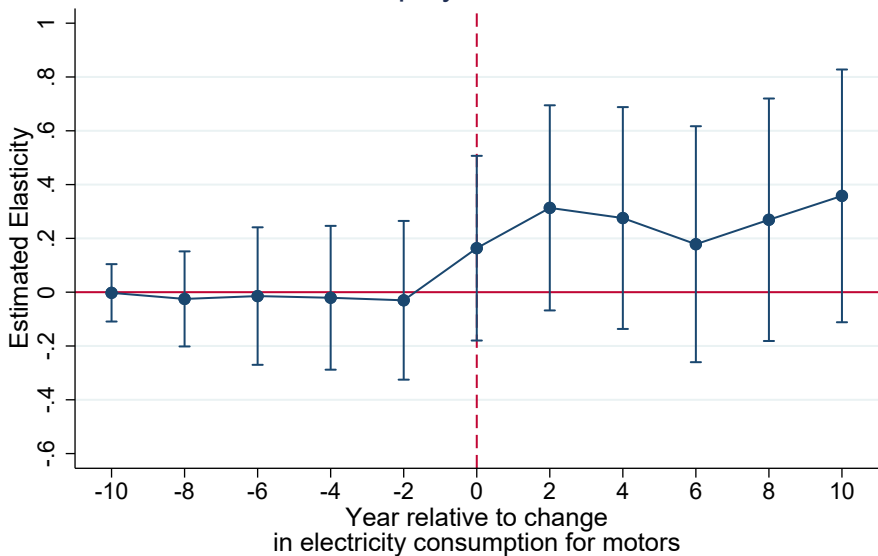
Controlling for 4-digit-industry by year F.E.

Plant Employment - Medium skill



Controlling for 4-digit-industry by year F.E.

Plant Employment - Low Skill



Controlling for 4-digit industry by year F.E.

Additional Results

- Similar results on employment with:
 - ▶ Firm-level analysis
 - ▶ Alternative definitions of skill groups
 - ▶ Industries with large share of IFR robots
- Find no significant change in wages or in labor share

Limitation

- Distributed lead-lag model cannot fully address potential correlated demand/supply shocks
 - ▶ When firm grows due to demand or supply shocks unrelated to increased automation, it may decide to increase both employment and automation
 - ▶ Turn to IV research design to address this limitation

Roadmap

- ① Data and Stylized Facts
- ② Event Study
- ③ **Shift-Share IV**
- ④ Extensions

Shift-Share IV

- Ideal experiment would randomly assign purchasing prices for machines/robots across firms
- Approximate with a shift-share research design, leveraging two components:
 - ① Variation in the cost of imported machines/robots over time across international trading partners (“shocks”)
 - ② Variation in pre-existing supplier relationships across French firms (“exposure shares”)
- Intuitively, changes in quality-adjusted price for machines/robots is not observed can be inferred from changes in trade flows
 - ▶ French firms are differentially exposed to changes in sector-specific foreign productivity

Shocks

- “Shocks” across trading partners by sectors:
 - ▶ g_n is aggregate change in imports flows of machines/robots from each trading partners (Germany, Italy, Japan, China, etc.) for each 2-digit industry
 - ▶ Infer from trade flows that some countries do particularly well in machines/robots supply in specific sectors and periods
 - ▶ e.g., Italy for textile in the 1990s, Germany for automobiles in the 2000s, the Netherlands for food products after 2010

Exposure Shares

- “Exposure shares” of French firms:
 - ▶ s_{in} is share of trading partner n in firm i 's total imports of machines and robots
 - ▶ Because of switching costs, French firm more likely to benefit from a trading partner's productivity shock if it has a pre-existing importing relationship with them
 - ▶ Contemporaneous shares liable to reverse causality: use shares lagged by 5 years

Shift-Share IV

- Consider changes in employment ΔL_i and changes in motor consumption ΔM_i over a five-year period across firms indexed by i
- We estimate by 2SLS:

$$\begin{cases} \Delta L_i = \beta \Delta Z_i + \gamma X_i + \varepsilon_i \\ \Delta M_i = \alpha \Delta Z_i + \tilde{\gamma} X_i + \tilde{\varepsilon}_i \end{cases}$$

with Z_i the shift-share instrument constructed from shocks g_n and (lagged) exposure shares $s_{in} \geq 0$,

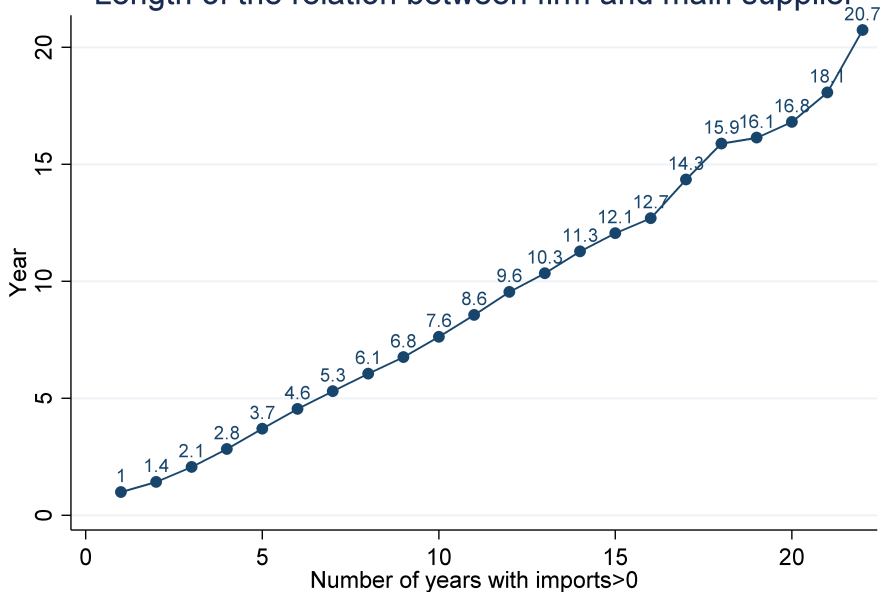
$$Z_i = \sum_{n=1}^N s_{in} g_n$$

- Use panel with 5-year periods, 204 trading partners, and 24 2-digit industries

Identification Assumptions

- Standard shift-share IV identification assumptions apply
- Relevance: need supplier relationships to be sufficiently persistent
 - ▶ Can check power with first-stage F statistic as usual
 - ▶ Can also assess plausibility by documenting stickiness of import relationships

Length of the relation between firm and main supplier



Identification Assumptions

- Exclusion restriction: firms linked to increasingly productive suppliers should not be unobservably different
 - ▶ Run falsification test with lagged outcome variable
 - ▶ Can express exclusion restriction at firm level or in space of shocks:

$$\left(\frac{1}{I} \sum_i z_i \varepsilon_i \rightarrow^p 0 \right) \iff \left(\frac{1}{N} \sum_n \hat{s}_n g_n \bar{\varepsilon}_n \rightarrow^p 0 \right)$$

with $\bar{\varepsilon}_n = (\sum_i s_{in} \varepsilon_i) / \sum_i s_{in}$ and $\hat{s}_n = \frac{1}{I} \sum_i s_{in}$

IV Results

- Implement shift-share design with baseline set of pre-determined firm controls (turnover, investment, total assets, employment)
- Study sensitivity to additional controls and implement falsification test
- Find positive employment response, with an elasticity of $+0.3$ to $+0.4$ across specifications
- Find positive sales response of similar magnitude and no response of average wage, leaving payroll share unchanged

IV Results: Employment

	Δ_5 Employment				
	(1)	(2)	(3)	(4)	(5)
Δ_5 Motor Cons.	0.341*** (0.121)	0.361*** (0.1276)	0.410** (0.167)	0.276** (0.138)	0.430*** (0.202)
First-Stage F	29.3	26	16.8	20.6	17.9
Industry-year F.E.	✓	✓	✓	✓	✓
Firm Controls		✓	✓	✓	✓
Lagged Motor Cons.			✓		✓
Lagged Machines				✓	
Exports					✓
<i>N</i>	29,109	29,109	29,109	29,109	29,109

Falsification Test

	Lagged Δ_5 Employment				
	(1)	(2)	(3)	(4)	(5)
Δ_5 Motor Cons.	-0.194 (0.185)	-0.0283 (0.177)	-0.156 (0.236)	-0.233 (0.200)	0.120 (0.247)
First-Stage F	25.8	23.8	15.2	20.1	13.1
Industry-year F.E.	✓	✓	✓	✓	✓
Firm Controls		✓	✓	✓	✓
Lagged machines (consumption)			✓		✓
Lagged machines (balanced sheet)				✓	
Exports					✓
<i>N</i>	17,250	16,609	16,609	16,574	15,641

IV Results: Sales

	Δ_5 Sales				
	(1)	(2)	(3)	(4)	(5)
Δ_5 Motor Cons.	0.552*** (0.148)	0.422*** (0.148)	0.498** (0.197)	0.349** (0.164)	0.561*** (0.197)
First-Stage F	29.3	26	16.8	20.6	17.9
Industry-year F.E.	✓	✓	✓	✓	✓
Firm Controls		✓	✓	✓	✓
Lagged Motor Cons.			✓		✓
Lagged Machines				✓	
Exports					✓
<i>N</i>	29,109	29,109	29,109	29,109	29,109

IV Results: Labor Share

	Δ_5 Labor Cost / Sales				
	(1)	(2)	(3)	(4)	(5)
Δ_5 Motor Cons.	-0.134 (0.0944)	-0.00851 (0.0936)	-0.0298 (0.122)	-0.00607 (0.107)	-0.0691 (0.118)
First-Stage F	29.3	26	16.8	20.6	17.9
Industry-year F.E.	✓	✓	✓	✓	✓
Firm Controls		✓	✓	✓	✓
Lagged Motor Cons.			✓		✓
Lagged Machines				✓	
Exports					✓
<i>N</i>	29,109	29,109	29,109	29,109	29,109

Robustness

- Similar results with
 - ▶ Alternative automation measure from balance sheet data
 - ▶ Labor share defined as a share of value added

Roadmap

- ① Data and Stylized Facts
- ② Event Study
- ③ IV Estimates
- ④ **Extensions**

Extensions

- 1 **Heterogeneity** across industries, occupations, and types automation technologies
 - ▶ Characterize which occupations perform routine tasks
 - ▶ Examine differences between robots and other forms of automation
- 2 Effect on **wages** accounting for changes in firm's worker composition
 - ▶ Track long-term wage effects using worker panel identifier
- 3 **Industry-level** impact on concentration and labor share accounting for reallocation/exit
 - ▶ Find that firms that automate more have a lower labor share *ex ante*
- 4 Effect on consumer **prices**

Thank you!

OLS: Employment

	Δ_5 Employment				
	(1)	(2)	(3)	(4)	(5)
Δ_5 Motor Cons.	0.235*** (0.00637)	0.207*** (0.00611)	0.215*** (0.00611)	0.199** (0.00608)	0.211*** (0.00630)
Industry-year F.E.	✓	✓	✓	✓	✓
Firm Controls		✓	✓	✓	✓
Lagged Motor Cons.			✓		✓
Lagged Machines				✓	
Exports					✓
<i>N</i>	30,180	30,180	30,180	30,180	30,180