Competing with Robots: Firm-Level Evidence from France

D. Acemoglu, C. Lelarge & P. Restrepo

American Economic Association Papers & Proceedings, May 2020

Introduction

Introduction

- Sectoral and regional analyses examine the market-level effects of automation.
- Evidence about market-level effects of automation on labor demand is mixed.
- These market-level effects include direct and all indirect effects of automation.
- To make progress, look at the impact of robot adoption by French manufacturing firms on firm-level outcomes.

Preview of results

1. Wages: No robust impact on hourly wages.
2. Employment:
   - *Firm-level*: $\uparrow$ (and share of production workers $\downarrow$)
   - *Industry-level*: $\downarrow$ because employment at non-adopters $\downarrow$
3. Productivity: VA per hour $\uparrow$
4. Labor share: $\downarrow$

Table of Contents

I. Data on French Robots

Data

- Sample of 55,390 French manufacturing firms active during 2010-2015.
- Robots: 598 firms (accounting for 20% of total manufacturing employment) are identified that purchased industrial robots using several data sources (incl. robot imports).
- Firm-level outcomes: Average hourly wage, employment (in hours), share of production workers; sales, value added; 258 4-digit industries.

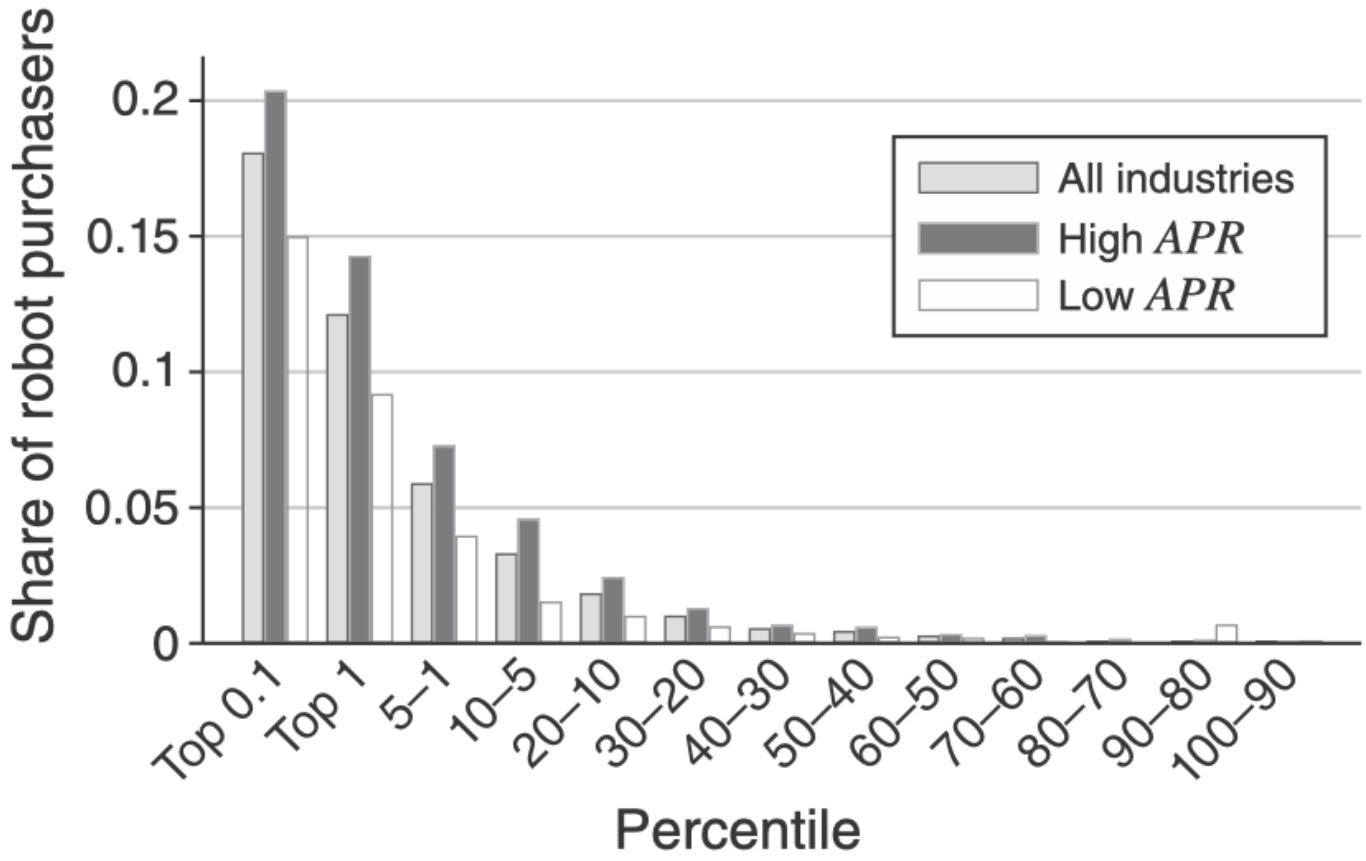

FIGURE 1. SHARE OF ROBOT ADOPTERS AMONG FIRMS IN DIFFERENT PERCENTILES OF THE SALES DISTRIBUTION WITHIN FOUR-DIGIT INDUSTRIES; SHOWN FOR ALL INDUSTRIES AND FOR INDUSTRIES WITH HIGH AND LOW *APR*

II. Firm-Level Changes

Firm-level changes

For a cross-section of firms f, estimate by OLS:

$$\Delta \ln y_f = \beta \text{Robot}_f + \gamma X_f + \alpha_{i(f)} + \delta_{c(f)} + \epsilon_f \tag{1}$$

with:

- $\Delta \ln y_f$ the change between 2010-2015
- Robot_f a dummy for whether f adopted robots
- X_f employment and value added per worker in 2010
- $\alpha_{i(f)}$ 258 4-digit industry fixed-effects
- $\delta_{c(f)}$ fixed-effects for f's commuting zone
- ϵ_f robust error term

TABLE 1—ESTIMATES OF EFFECTS OF ROBOT ADOPTION ON FIRM-LEVEL OUTCOMES

	Δ log value added (1)	Δ labor share (2)	Δ production employment share (3)	Δ log value added per hour (4)	Δ log revenue TFP (5)	Δ log employment (in hours) (6)	Δ log mean hourly wage (7)
Panel A. Unweighted estimates							
Robot adopter	0.204	−0.043	−0.016	0.095	0.024	0.109	0.009
	(0.030)	(0.009)	(0.007)	(0.018)	(0.007)	(0.020)	(0.004)
R^2	0.083	0.161	0.014	0.222	0.196	0.093	0.024
Panel B. Employment-weighted estimates							
Robot adopter	0.094	−0.027	−0.006	0.040	−0.011	0.054	−0.008
	(0.025)	(0.012)	(0.006)	(0.029)	(0.013)	(0.017)	(0.008)
R^2	0.216	0.274	0.080	0.323	0.298	0.188	0.139

Notes: The sample consists of 55,390 firms, of which 598 are robot adopters. Panel A presents unweighted estimates. Panel B presents estimates weighting each firm by its employment (in hours) in 2010. All specifications control for baseline firm characteristics (log employment and log value added per worker in 2010, as well as dummies for whether the firm is affiliated with a larger corporate group), four-digit industry fixed effects for the main industry in which each firm operates, and fixed effects for the commuting zone that houses each firm's largest establishment. The online Appendix describes the construction of all variables used as outcomes. Standard errors robust to heteroskedasticity and correlation within four-digit industries are in parentheses.

III. Market-Level Spillovers

Spillovers between adopters and non-adopters

- Firms adopting robots increase employment and sales.
- These effects could be associated with a decrease in employment and sales for non-adoptors.
- Market-level effects could even be negative.
- To examine spillovers and market-level effects, analyze the impact on firm f of robot adoption by competitors $f' \neq f$.

Measuring robot adoption by competitors

- Define a measure of a firm's competitors' robot adoption as:

$$\text{Adoption by competitors}_f = \sum_i m_{fi} \sum_{f' \neq f} s_{if'} \text{Robot}_{f'}$$

  with m_{fi} the share of sales by f to industry i and $s_{if'}$ the share of industry i's sales by firm $f' \neq f$.

- Add this to (1) which includes $\alpha_{i(f)}$.

- Spillovers are identified from comparing firms in the same industry but selling different proportions across industries with varying degrees of competition from robot adopters.

TABLE 2—ESTIMATES OF EFFECTS OF ROBOT ADOPTION ON COMPETITORS

	Δ log employment (in hours) (1)	Δ log value added (2)	Δ labor share (3)	Δ log employment (in hours) (4)	Δ log value added (5)	Δ labor share (6)
	Unweighted estimates			Employment-weighted estimates		
Robot adoption by competitors	−0.105	−0.100	0.002	−0.250	−0.209	−0.008
	(0.047)	(0.051)	(0.015)	(0.107)	(0.159)	(0.040)
Robot adopter	0.106	0.201	−0.043	0.035	0.078	−0.027
	(0.020)	(0.030)	(0.009)	(0.022)	(0.029)	(0.012)
R^2	0.093	0.083	0.161	0.190	0.217	0.274

Notes: The sample consists of 55,388 firms, of which 598 are robot adopters. Columns 1–3 present unweighted estimates. Columns 4–6 present estimates weighting each firm by its employment (in hours) in 2010. All specifications control for baseline firm characteristics (log employment and log value added per worker in 2010, as well as dummies for whether the firm is affiliated with a larger corporate group), four-digit industry fixed effects for the main industry in which each firm operates, and fixed effects for the commuting zone that houses each firm's largest establishment. The online Appendix describes the construction of all variables used as outcomes. Standard errors robust to heteroskedasticity and correlation within four-digit industries are in parentheses.

Market-level employment effects

- The sum of the direct and spillover effects in Table 2 is *not* the market-level effect.
- Consider a variation of (1):

$$\Delta \ln l_{if} = \beta_c \text{Robot adoption}_i + \beta_o \text{Robot adopter}_f + \epsilon_{if} \quad \text{(A4)}$$

  with Robot adoption$_i$ the employment-weighted share for firms adopting robots in industry i.
- If f is small and only competes with firms in i, the market-level impact of robots on employment is given by $\beta_c + \beta_o = -0.082 < 0$; $\beta_c = -0.117$, $\beta_o = 0.035$.

TABLE A.6—ADDITIONAL ESTIMATES OF SPILLOVERS ON EMPLOYMENT OF OTHER FIRMS.

	Dependent variable: Δ log employment (hours)							
	Adoption among competitors defined as in the main text		Adoption among competitors defined as employment-weighted average among firms in the same 4-digit industry			Adoption among competitors defined as employment-weighted average among firms in the same 3-digit industry		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot adoption by competitors	-0.250	-0.110	-0.117	-0.075	-0.061	-0.128	-0.102	-0.083
	(0.107)	(0.046)	(0.081)	(0.042)	(0.034)	(0.088)	(0.052)	(0.046)
Robot adopter	0.035	0.046	0.035	0.035	0.054	0.033	0.034	0.052
	(0.022)	(0.017)	(0.020)	(0.020)	(0.016)	(0.021)	(0.019)	(0.016)
R^2	0.190	0.155	0.005	0.007	0.154	0.006	0.008	0.152
Covariates:								
Firm covariates	✓	✓			✓			✓
4-digit industry fixed effects	✓							
2-digit industry fixed effects		✓		✓	✓		✓	✓

Notes—The sample consists of $N = 55,388$ firms, of which 598 are robot adopters. All models weight firms by their employment (in hours) in 2010. Columns 3–5 present estimates for the adoption of robots by firms in the same 4-digit industry. Columns 6–8 present estimates for the adoption of robots by firms in all the 3-digit industries in which a firm sells some of its products (weighted by share sales). The set of industry-fixed effects used in each specification is indicated at the bottom rows. Additional covariates in column 1–2, 5 and 8 include: baseline firm characteristics (log employment and log value added per worker in 2010, as well as dummies for whether the firm is affiliated to a larger corporate group), and fixed effects for the commuting zone that houses each firm's largest establishment. Standard errors robust to heteroskedasticity and correlation within 4-digit (and 3-digit industries in columns 6–8) industries are in parentheses.

Market-level employment effects

- The change in industry employment is:

$$\Delta \ln l_i = \sum_f s_{if}^l \Delta \ln l_{if}$$

with s_{if}^l firm f's employment share in industry i.

- Substituting (A4) into this expression:

$$\begin{aligned}\Delta \ln l_i &= \sum_f s_{if}^l \left[\beta_c \text{Robot adoption}_i + \beta_o \text{Robot adopter}_f + \epsilon_{if}\right] \\ &= \beta_c \text{Robot adoption}_i + \beta_o \sum_f s_{if}^l \text{Robot adopter}_f + \sum_f s_{if}^l \epsilon_{if} \\ &= [\beta_c + \beta_o] \text{Robot adoption}_i + \epsilon_i\end{aligned}$$

IV. Superstar Effects and the Labor Share

Decomposing changes in the labor share

- Autor et al. [19] decompose the change in the labor share of industry i as:

$$\Delta\lambda_i^l = \Delta\bar{\lambda}_i^l + \Delta\sum_f [\lambda_f^l - \bar{\lambda}_i^l][s_{if}^v - \bar{s}_i^v] \tag{A5}$$

  with λ_f^l the labor share in firm f, s_{if}^v the share of f in industry VA, and $\bar{\lambda}_i^l$ and $\bar{s}_i^v$ their unweighted averages in i.

- The first term is the average within-firm change in the labor share and the second term is the change in the covariance between the firm's labor share and value added share.

Decomposing changes in the labor share

- The change in the labor share of industry i is given by:

$$\Delta\lambda_i^l = \Delta\bar{\lambda}_i^l + \Delta\sum_f [\lambda_f^l - \bar{\lambda}_i^l][s_{if}^\nu - \bar{s}_i^\nu] \qquad \text{(A5)}$$

  with λ_f^l the labor share in firm f, s_{if}^ν the share of f in industry VA, and $\bar{\lambda}_i^l$ and $\bar{s}_i^\nu$ their unweighted averages in i.

- For our sample of French manufacturing firms, 2010-2015:
  - $\Delta\lambda_i^l = -0.93$pp (on average across i) (1)
  - $\Delta\bar{\lambda}_i^l = 2.37$pp (2)
  - $\Delta\sum_f [\lambda_f^l - \bar{\lambda}_i^l][s_{if}^\nu - \bar{s}_i^\nu] = -3.29$pp (3)

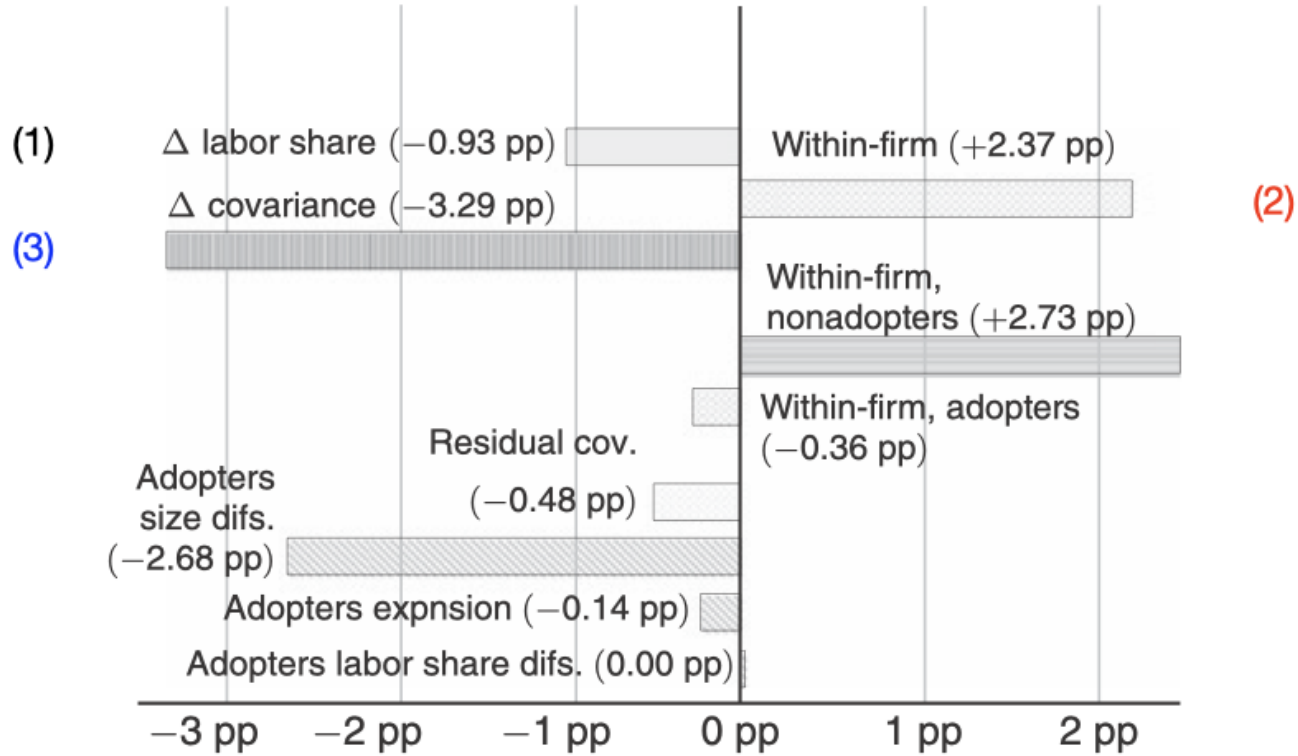

FIGURE 2. CHANGES IN THE LABOR SHARE OF FRENCH MANUFACTURING INDUSTRIES FOR 2010–2015 DECOMPOSED AS IN AUTOR ET AL. (2019); THE DECOMPOSITION IS EXTENDED TO ACCOUNT FOR DIFFERENCES BETWEEN ROBOT ADOPTERS AND NONADOPTERS

Note: PP is percentage points.

Within-firm changes for adopters and non-adopters

- Define F_i as the number of firms in industry i, $\tilde{R}_i$ as the set of R_i robot adopters, and $\tilde{N}_i$ as the set of N_i non-adopters.
- Re-write the within-firm component in (A5) as:

$$\Delta\bar{\lambda}_i^l = \frac{N_i}{F_i}\Delta\bar{\lambda}_{\tilde{N}_i}^l + \frac{R_i}{F_i}\Delta\bar{\lambda}_{\tilde{R}_i}^l$$

  with $\bar{\lambda}_{\tilde{R}_i}^l$ the unweighted average of λ_f^l across robot adopters in $\tilde{R}_i$ (and similarly for $\bar{\lambda}_{\tilde{N}_i}^l$) .

- We get that $2.37(2) = 2.73(4) - 0.36(5)$

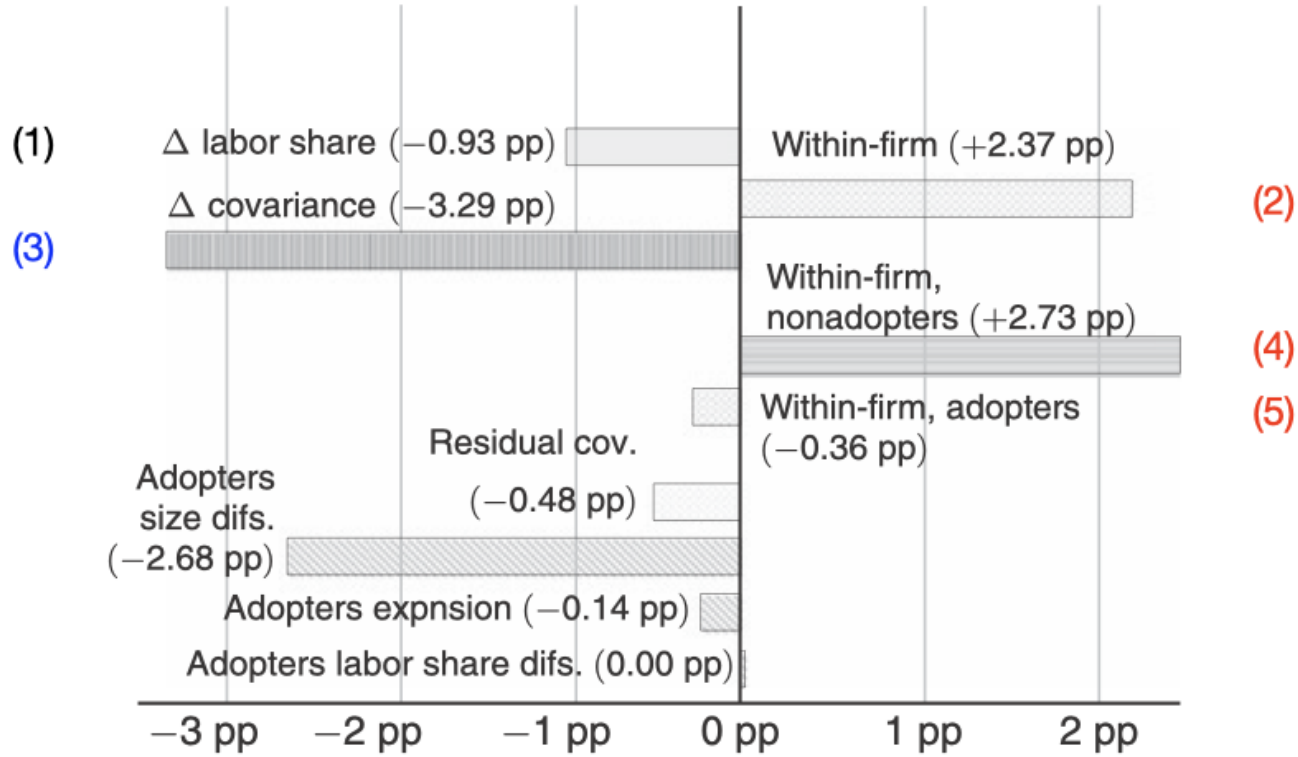

FIGURE 2. CHANGES IN THE LABOR SHARE OF FRENCH MANUFACTURING INDUSTRIES FOR 2010–2015 DECOMPOSED AS IN AUTOR ET AL. (2019); THE DECOMPOSITION IS EXTENDED TO ACCOUNT FOR DIFFERENCES BETWEEN ROBOT ADOPTERS AND NONADOPTERS

Note: PP is percentage points.

Decomposing the change in covariance

Decompose the change in covariance in (A5) as:

$$\Delta \sum_f [\lambda_f^I - \bar{\lambda}_i^I][s_{if}^\nu - \bar{s}_i^\nu] = R_i \Delta [\bar{\lambda}_{\tilde{R}_i}^I - \bar{\lambda}_i^I][\bar{s}_{\tilde{R}_i}^\nu - \bar{s}_i^\nu] \quad (7)$$

$$+ N_i \Delta [\bar{\lambda}_{\tilde{N}_i}^I - \bar{\lambda}_i^I][\bar{s}_{\tilde{N}_i}^\nu - \bar{s}_i^\nu]$$

$$+ \Delta \sum_{f \in \tilde{R}_i} [\lambda_f^I - \bar{\lambda}_{\tilde{R}_i}^I][s_{if}^\nu - \bar{s}_{\tilde{R}_i}^\nu] \quad (6)$$

$$+ \Delta \sum_{f \in \tilde{N}_i} [\lambda_f^I - \bar{\lambda}_{\tilde{N}_i}^I][s_{if}^\nu - \bar{s}_{\tilde{N}_i}^\nu]$$

with (7) capturing differences between adopters and non-adopters (e.g. adopters being larger and expanding while their labor share falls) and (6) residual changes unrelated to automation (e.g. the superstar effect).

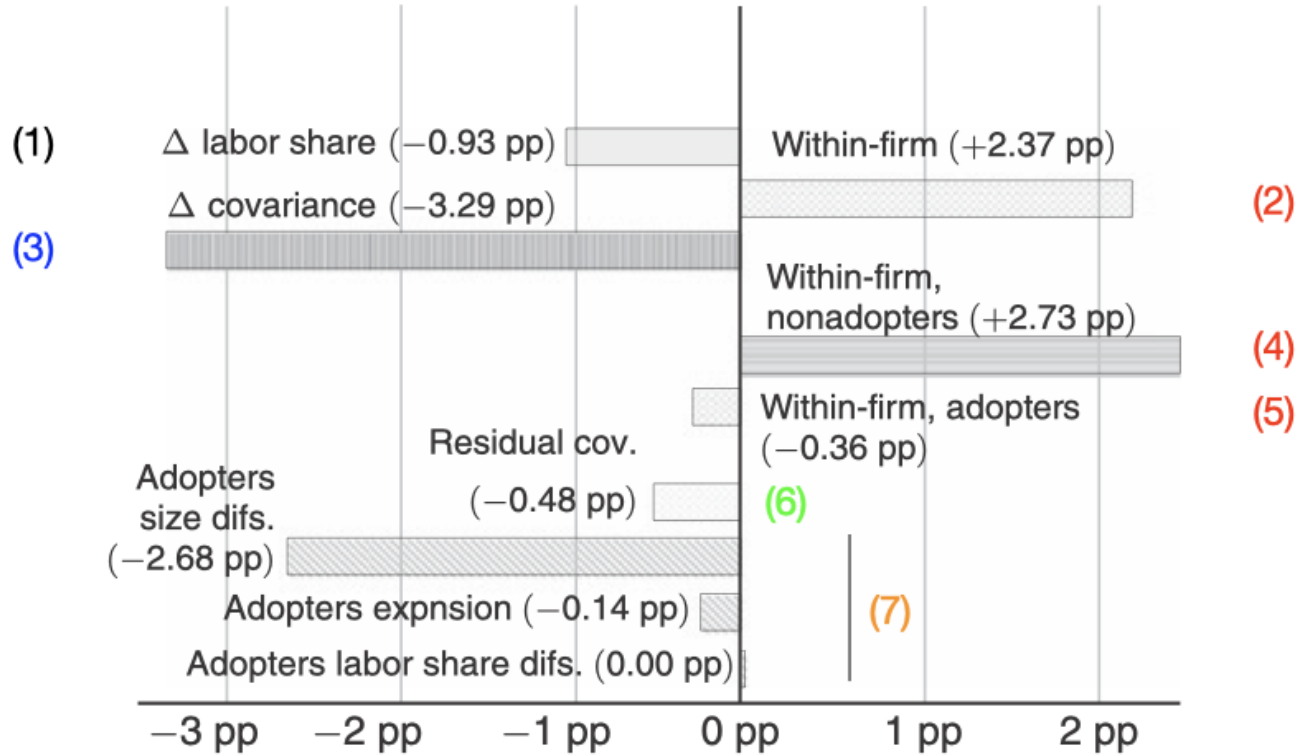

FIGURE 2. CHANGES IN THE LABOR SHARE OF FRENCH MANUFACTURING INDUSTRIES FOR 2010–2015 DECOMPOSED AS IN AUTOR ET AL. (2019); THE DECOMPOSITION IS EXTENDED TO ACCOUNT FOR DIFFERENCES BETWEEN ROBOT ADOPTERS AND NONADOPTERS

Note: PP is percentage points.

The change in covariance due to automation

Further decomposing the difference between adopters and non-adopters gives:

$$R_i \Delta[\bar{\lambda}^I_{\tilde{R}_i} - \bar{\lambda}^I_i][\bar{s}^\nu_{\tilde{R}_i} - \bar{s}^\nu_i] + N_i \Delta[\bar{\lambda}^I_{\tilde{N}_i} - \bar{\lambda}^I_i][\bar{s}^\nu_{\tilde{N}_i} - \bar{s}^\nu_i] =$$

$$\left(s_{\tilde{R}_i} - \frac{R_i}{F_i}\right) \times \Delta[\bar{\lambda}^I_{\tilde{R}_i} - \bar{\lambda}^I_{\tilde{N}_i}] \quad (7a)$$

$$+\Delta[\bar{\lambda}^I_{\tilde{R}_i} - \bar{\lambda}^I_{\tilde{N}_i}] \times \Delta s_{\tilde{R}_i} \quad (7b)$$

$$+[\bar{\lambda}^I_{\tilde{R}_i} - \bar{\lambda}^I_{\tilde{N}_i}] \times \Delta s_{\tilde{R}_i} \quad (7c)$$

with (7a)+(7b) capturing adopters being larger and expanding while decreasing their labor share and (7c) capturing that adopters can have a different labor share at baseline.

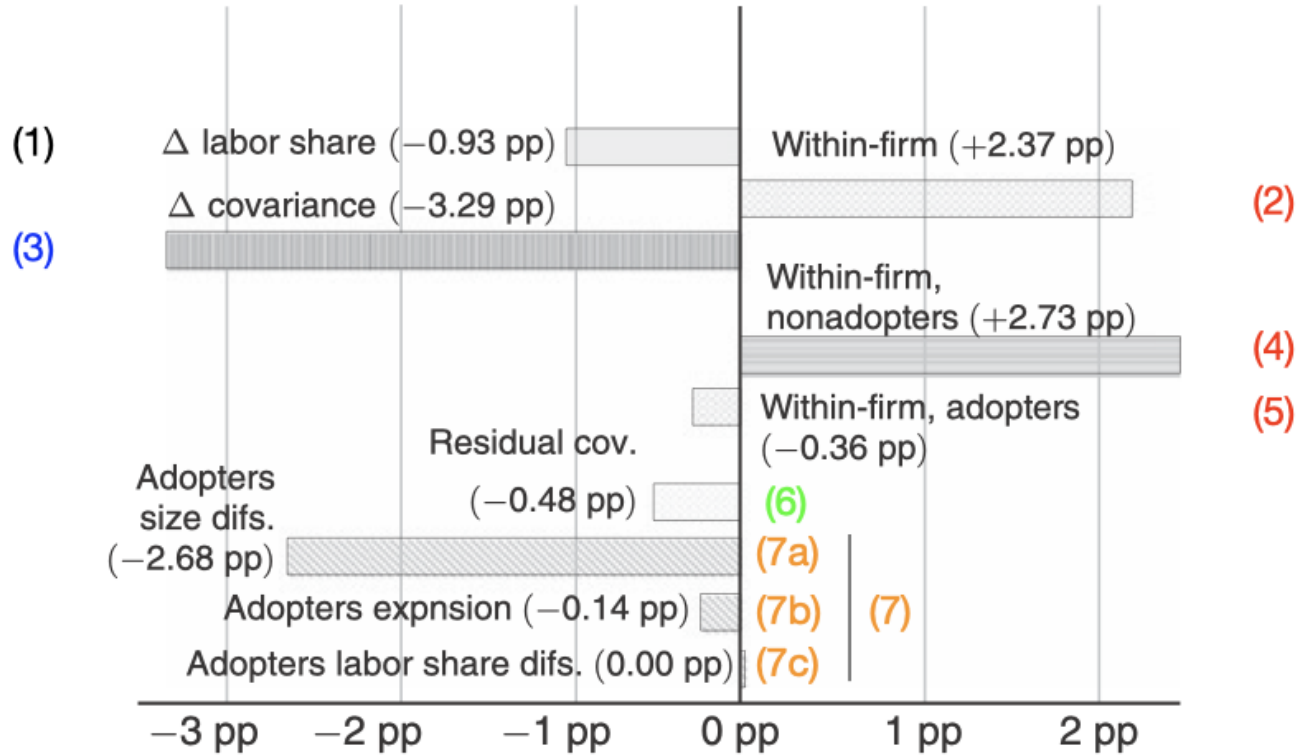

FIGURE 2. CHANGES IN THE LABOR SHARE OF FRENCH MANUFACTURING INDUSTRIES FOR 2010–2015 DECOMPOSED AS IN AUTOR ET AL. (2019); THE DECOMPOSITION IS EXTENDED TO ACCOUNT FOR DIFFERENCES BETWEEN ROBOT ADOPTERS AND NONADOPTERS

Note: PP is percentage points.

Superstar effects?

- Autor et al [19] document a decline in the US labor share driven by a decrease in the covariance term.
- They argue that this is driven by a "superstar effect": Firms with lower labor shares (or higher markups) at baseline expand due to winner-takes-all dynamics.
- Instead, this paper shows that the decrease in the covariance term is driven by adopters being larger and expanding while their labor share falls (and not because expanding firms have lower baseline labor shares, i.e. no superstar effect).

V. Conclusions

Conclusions

- In firms that adopt robots, employment increases and the labor share falls.
- Industry employment falls because employment falls at non-adopters.
- The aggegrate labor share falls because robot adopters are larger and expanding while decreasing their labor share (instead of a superstar effect).

Related Literature

Sectoral and regional analyses

- Graetz & Michaels [2018, *RESTAT*]
- Acemoglu & Restrepo [2019, *JPE*]
- Aghion, Antonin & Bunel [2019, *Economics & Statistics*]
- Acemoglu & Restrepo [2019, *JEP*]
- Dauth, Findeisen, Suedekum & Woesnner [2021, *JEEA*]
- Acemoglu & Restrepo [2022, *RESTUD*]

Firm-level analyses

- Dinlersoz & Wolf [2018, *CES*]
- Dixon, Hong & Wu [2019]
- Koch, Manuylov & Smolka [2021, *EJ*]
- Humlum [2021]
- Aghion, Antonin, Bunel & Jaravel [2020]
- Bonfiglioli, Crino, Hadinger & Gancia [2021]
- Bessen, Goos, Salomons & van den Berge [2022]

Paper (country studied)	Measure of automation and identification	Employment: *firm-level*	Employment: *sector*	Sales or VA	Sales or VA per worker	TFP	Labor share
Agemoglu et al. (20, AEA P&P) (France, manufacturing, 00-15)	robot use survey, robot imports; FE	+	- non-adopters - overall	+	0/+	0/+	-
Aghion et al. (20) (France, manufacturing, 94-15)	electric motive power, machinery; event study, shift-share IV	+	0 overall but + if exporting	+			0
Bonfiglioli et al. (20) (France, manufacturing, 94-13)	robot imports; event-study, IV	-		0 but + if dem. elast.	+		
Koch et al. (20, R&R EJ) (Spain, manufacturing, 90-16)	robot use survey; propensity score matching	+	- non-adopters	+		+	-