# Online Appendix for "Competing with Robots: Firm-level Evidence from France"

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## A. Data Description

*Data on robot adopters:* Our data sources and sample structure are summarized in Table A.1.

TABLE A.1—SAMPLE DESCRIPTION

| | | Robot adopters | | | Sources of robot purchases data | | |
|---|---|---|---|---|---|---|---|
| Size bins (emp. 2010) | All firms | Total number | Share of adopters in bin | Share hours among adopters | DGE survey | Customs data | SYMOP and fiscal files |
| $>$ 5,000 workers | 21 | 12 | 57.1% | 78.0% | $<5$ | 9 | 8 |
| 250 to 5,000 workers | 1,114 | 169 | 15.2% | 21.3% | 8 | 95 | 82 |
| 10 to 250 workers | 19,975 | 380 | 1.9% | 4.2% | 100 | 158 | 180 |
| $\leq$ 10 workers | 34,280 | 37 | 0.1% | 0.2% | 11 | 13 | 20 |
| Total | 55,390 | 598 | 1.1% | 19.8% | . | 275 | 290 |

*Notes*—The table reports the composition of our sample for firms of different sizes. The Appendix describes the sources used.

Data on purchases of robots for 2010–2015 are assembled from the following sources:

- SYMOP—the French Association of Producers and Importers of Industrial Machinery—we obtained an extract of a subset of the firms who purchased domestically produced or imported industrial robots from SYMOP.
- A survey collected by the French Ministry of Industry (Direction Générale des Entreprises, or DGE), which includes information on robot purchases among small and medium enterprises. This survey sampled firms recognized as clients of SYMOP members.
- From French customs data, we obtained firm imports of industrial robots, which are coded under the NC8 product code 84798950. All imports of industrial robots sourced from outside of the European Union are reported. Imports of robots from other countries in the European Union are not recorded at the transaction level. Instead, firms that imported at least 460,000 Euros worth of intermediate inputs and capital goods (including industrial robots) during that year from all sources in the European Union must report their purchases. The 460,000 Euros threshold is the cost of approximately four or five industrial robots. Thus, the customs' data miss firms that imported three or fewer robots from other European Union countries and small amounts of intermediate inputs (so as not to exceed the combined 460,000 Euros threshold), as well as firms that buy imported robots through subsidiaries of foreign robot producers.
- From French fiscal files, we identified firms that used an accelerated amortization scheme dedicated to industrial robots. Eligibility was restricted to small and medium enterprises and to transactions occurring between October 2013 and December 2015. We also incorporated public information on 40 small and medium enterprises which benefited from a subsidy program entitled "Robot Start PME" that was in effect between 2013 and 2016.

*Firm accounting information:* We obtained detailed accounting information for the firms in our sample from French fiscal files. In particular, we made use of two different files: the BRN (Bénéfices Réels Normaux) and the RSI (Régime Simplifié d'Imposition). The BRN contains the balance sheet of all firms in manufacturing with sales above 730,000 Euros. The RSI is the counterpart of the BRN for firms with sales below 730,000 Euros. Their union covers nearly the entire universe of French manufacturing firms.

*Corporate groups:* In our regressions, we control for a dummy for firms that belong to larger corporate groups. We obtained data on the ownership structure of firms from the LIFI files (Liaisons Financières Entre Sociétés) supplied by INSEE. This survey is complemented with information on ownership structure available from the DIANE (BvDEP) files, which are constructed using the annual mandatory reports to commercial courts and the register of French firms. Using these data, we constructed dummies for firms that are affiliates of larger corporate groups. In regressions we also control for a dummy that indicates when observations in the fiscal files are an aggregate of several affiliates of a corporate group.

*Detailed sales information:* The data on sales by firm across 4-digit industries used in the construction of the measure of adoption of robots by competitors come from these French fiscal files as well. In particular, we use the FARE files (Fichier Approché des Résultats d'Esane), which contain sales by firm and industry for over 85% of the sales in our sample. The FARE does not break down sales by industry for small firms, and so we assume that small firms only sell in their assigned 4-digit industry. The FARE also contain data on total sales by industry, which we use to compute the weights $s_{if'}$ used in our formula for adoption among competitors.

*Data on firm exports and prices:* We have detailed data on firm exports by totals and unit values for each NC8 product category. The data come from the French Customs and cover every transaction between a French firm and a foreign importer located in the European Union.

*Worker-level information:* We incorporate information from the French matched employer-employee administrative dataset (Déclarations Annuelles des Données Sociales, DADS) to retrieve worker-level information on occupation, wages, and hours worked.

*Variable definitions:* We constructed value added at the firm level as sales minus expenditure on intermediates. For employment, we have data on the count of employees, total hours of work, and full-time equivalent workers. In the main text we focus on total hours of work as our main measure of employment, value added per hour worked as our main measure of labor productivity, and mean hourly wage for the average wage rate at the firm. To measure wages, we use the wage bill of the firm, which accounts for all wage paymentsd to workers. We obtained very similar results using total compensation, which also includes payroll taxes and other benefits.

We define production workers using the DADS data as those employed in unskilled industrial jobs (categories 67 and 68 in the INSEE classification of professions).

We measure changes in (revenue) TFP for the 2010–2015 period as

$$\Delta \ln \mathrm{TFP}_f = \Delta \ln y_f - \lambda_f^\ell \cdot \Delta \ln \ell_f - \lambda_f^m \cdot \Delta \ln m_f - (1 - \lambda_f^\ell - \lambda_f^m) \cdot \Delta \ln k_f.$$

Here, $\lambda_f^\ell$ and $\lambda_f^m$ denote the shares of wages and intermediates in revenue, respectively. These shares are measured for each firm in 2010. Alternative measures using detailed industry shares instead of firm-level ones yield very similar results. In addition, $\Delta \ln y_f$ is the percent change in sales, $\Delta \ln \ell_f$ is the percent change in hours, $\Delta \ln m_f$ is the percent change in materials, and $\Delta \ln k_f$ denotes the percent change in the capital stock during 2010–2015. Since we do not have data on material prices, we assume that these are common across firms.

For exporting firms, we also have information on prices, which enables us to investigate whether productivity changes are related to price changes or changes in physical productivity. In particular, we construct a price index for an exporting firm as follows:

$$\Delta \ln p_f = \sum_\omega e_{f\omega} \cdot \Delta \ln p_{\omega f},$$

where the sum is taken over all NC8 product categories $\omega$, $e_{f\omega}$ denotes the export share of $\omega$ in firm $f$, and $\Delta \ln p_{\omega f}$ is the observed change in unit values of the exports of firm $f$ in product category $\omega$.

### *B. Robustness Checks*

This section provides additional own-firm estimates of robot adoption and robustness checks for the estimates in the main text. Table A.2 presents estimates for additional outcomes, including log sales and the share of wages in sales. These results show that the results on Table 1 in the main text hold when we focus on sales rather than value added. Columns 3–5 present results for additional measures of labor productivity, including sales per hour, sales per worker, and value added per worker (as opposed to the per hour measure in the main text). Finally, columns 6 and 7 present results for the percent change in the number of employees (not hours) and the number of production workers (as opposed to their share).

TABLE A.2—ESTIMATES OF ROBOT ADOPTION ON ADDITIONAL FIRM-LEVEL OUTCOMES.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Δ log sales | Δ labor share in sales | Δ log sales per hour | Δ log sales per worker | Δ log value added per worker | Δ log employment (in total employees) | Δ log employment production workers |
| | | | *Panel A—Unweighted estimates* | | | | |
| Robot adopter | 0.142 | -0.007 | 0.032 | 0.062 | 0.123 | 0.078 | 0.046 |
| | (0.021) | (0.002) | (0.012) | (0.018) | (0.025) | (0.012) | (0.032) |
| $R^2$ | 0.064 | 0.092 | 0.142 | 0.079 | 0.130 | 0.058 | 0.024 |
| | | | *Panel B—Employment-weighted estimates* | | | | |
| Robot adopter | 0.121 | -0.012 | 0.066 | 0.077 | 0.050 | 0.044 | -0.084 |
| | (0.019) | (0.003) | (0.021) | (0.021) | (0.028) | (0.014) | (0.090) |
| $R^2$ | 0.196 | 0.164 | 0.237 | 0.202 | 0.277 | 0.174 | 0.144 |

*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, and dummies for whether the firm belongs to a larger corporate group), 4-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 Appendix describes the construction of all variables used as outcomes. Standard errors robust to heteroskedasticity and correlation within 4-digit industries are in parentheses.

As mentioned in the main text, the increase in labor productivity and TFP (in the unweighted specification) are not driven by price increases among firms adopting robots, but reflect changes in quantities (physical productivity). Table A.3 provides evidence in support of this claim. The table uses the sample of exporters to estimate the association between robot adoption and changes in export prices. We provide estimates using different weighting schemes (unweghted, weighted by employment hours as in the main text, or weighting by firm exports) and controlling for 2-digit or 4-digit industry dummies. The sample now is much smaller, and the estimates are less precise. But overall, we find uniformly negative point estimates, which suggest that firms that adopt robots reduce prices from 1% to 5.7% (using the estimates with 4-digit industry fixed effects in columns 2 and 4).

Finally, Table A.4 shows that the findings in Table 1 in the text are robust to the inclussion of additional covariates. Specifically, we control for dummies for firms in the top 0.1%, top 1%, top 5%, top 10%, top 20% and top 40% of sales in each 4-digit industry as well as log capital stock per worker and the share of production workers in 2010.

TABLE A.3—ROBOT ADOPTION AND FIRM-LEVEL EXPORT PRICES. ESTIMATES FOR THE SUBSET OF EXPORTERS.

| | Dependent variable: Δ log export price index | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | *Unweighted estimates* | | *Employment-weighted* | | *Export-weighted* | |
| Robot adopter | -0.009 | -0.009 | -0.066 | -0.057 | -0.064 | -0.051 |
| | (0.021) | (0.021) | (0.028) | (0.028) | (0.048) | (0.052) |
| $R^2$ | 0.058 | 0.092 | 0.178 | 0.229 | 0.242 | 0.301 |

*Notes*— The sample consists of 6,614 firms for which we have data on export prices, of which 372 are robot adopters. Panel A presents unweighted estimates. Panel B presents estimates weighting each firm by its employment (in hours) in 2010. Panel C presents estimates weighting each firm by its exports in 2010. All specifications control for baseline firm characteristics (log employment and log value added per worker in 2010, dummies for whether the firm belongs to a larger corporate group, the sales percentile of the firm in its main 4-digit industry, the share of production workers, and the log of capital per worker), and fixed effects for the commuting zone that houses each firm's largest establishment. Also, columns 1, 3, 5 control for 2-digit industry-fixed effects; whereas columns 2, 4, 6 control for 4-digit industry-fixed effects. The Appendix describes the construction of all variables used as outcomes. Standard errors robust to heteroskedasticity and correlation within 4-digit industries are in parentheses.

TABLE A.4—ROBUSTNESS CHECKS FOR ESTIMATES OF ROBOT ADOPTION ON FIRM-LEVEL OUTCOMES. INCLUDES ADDITIONAL COVARIATES.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Δ log value added | Δ labor share | Δ production employment share | Δ log value added per hour | Δ log revenue TFP | Δ log employment (in hours) | Δ log mean hourly wage |
| | | | | *Panel A—Unweighted estimates* | | | |
| Robot adopter | 0.168 | -0.035 | -0.014 | 0.079 | 0.012 | 0.089 | 0.008 |
| | (0.024) | (0.008) | (0.006) | (0.017) | (0.006) | (0.017) | (0.004) |
| $R^2$ | 0.094 | 0.166 | 0.236 | 0.224 | 0.207 | 0.101 | 0.031 |
| | | | | *Panel B—Employment-weighted estimates* | | | |
| Robot adopter | 0.086 | -0.023 | -0.004 | 0.029 | -0.016 | 0.057 | -0.010 |
| | (0.026) | (0.011) | (0.005) | (0.027) | (0.014) | (0.017) | (0.007) |
| $R^2$ | 0.226 | 0.285 | 0.231 | 0.333 | 0.307 | 0.192 | 0.141 |

*Notes*— The sample consists of 55,359 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, dummies for whether the firm belongs to a larger corporate group, the sales percentile of the firm in its main 4-digit industry, the share of production workers, and the log of capital per worker), 4-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 Appendix describes the construction of all variables used as outcomes. Standard errors robust to heteroskedasticity and correlation within 4-digit industries are in parentheses.

*C. Market-Level Effects*

In this section of the Appendix, we aggregate the estimates from Table 2 to obtain market-level effects. Recall that the estimating equation for the models in Table 2 is

$$\Delta \ln \ell_f = \beta_o \cdot \text{Robot}_f + \beta_c \cdot \text{Adoption by competitors}_f + \gamma \cdot X_f + \alpha_{i(f)} + \delta_{c(f)} + \varepsilon_f .$$

We now show that the contribution of robot adoption to overall employment can be approximated (to the first order) as

$$\Delta \ln \ell \approx \beta_o \sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f + \beta_c \sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f \cdot \left( \sum_i m_{fi} \cdot \sum_{f' \neq f} s_{f'i} \cdot \frac{y_f}{\ell_f} \Big/ \frac{y_{f'}}{\ell_{f'}} \right), \tag{A.1}$$

where the sum is taken over all 4-digit industries and $m_{fi}$ is the share of firm $f$'s sales that are in industry $i$, while $s_{if'}$ is the share of industry $i$'s total sales accounted for by firm $f'$. Under the additional assumption that firms have similar baseline labor shares, this expression can be further simplified to

$$\Delta \ln \ell \approx \beta_o \sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f + \beta_c \sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f \cdot \left( \sum_i m_{fi} \cdot (1 - s_{if}) \right). \tag{A.2}$$

The numbers given in the main text are obtained from this equation.

We now provide more details on how these numbers are obtained. With a first-order approximation, the change in manufacturing employment can be expressed as

$$\Delta \ln \ell \approx \sum_f \frac{\ell_f}{\ell} \Delta \ln \ell_f .$$

The contribution of robot adoption to aggregate employment is therefore:[10]

$$\begin{aligned} \sum_f \frac{\ell_f}{\ell} \Delta \ln \ell_f =& \sum_f \frac{\ell_f}{\ell} \left( \beta_o \cdot \text{Robot}_f + \beta_c \cdot \text{Adoption by competitors}_f \right) \\ =& \beta_o \sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f + \beta_c \sum_f \frac{\ell_f}{\ell} \cdot \sum_i m_{fi} \cdot \sum_{f' \neq f} s_{if'} \cdot \text{Robot}_{f'} . \end{aligned}$$

Changing the order of summation, the term multiplying $\beta_c$ can be expressed as

$$\sum_f \text{Robot}_f \cdot \sum_i s_{if} \cdot \sum_{f' \neq f} m_{f'i} \cdot \frac{\ell_{f'}}{\ell} .$$

Multiplying and dividing by $\ell_f$, and then rearranging terms, we obtain

$$\sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f \cdot \sum_i s_{if} \cdot \sum_{f' \neq f} m_{f'i} \cdot \frac{\ell_{f'}}{\ell_f} .$$

[10] Note, however, that this computation ignores any general equilibrium effects from robot adoption that can lead to an expansion or contraction of overall manufacturing employment. Such general equilibrium effects cannot be identified with our methodology (or with other approaches based on cross-industry comparisons). Consequently, the estimate of -1% below should be compared with industry-level estimates of the impact of robot adoption on employment.

Denoting the sales of firm $f$ by $y_f$ and using the definitions of $s_{if}$ and $m_{f'i}$, we can write the previous expression as

$$\sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f \cdot \sum_i \frac{y_{fi}}{y_i} \cdot \sum_{f' \neq f} \frac{y_{f'i}}{y_{f'}} \cdot \frac{\ell_{f'}}{\ell_f}.$$

Dividing and multiplying by $y_f$, this is equivalent to

$$\sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f \cdot \sum_i \frac{y_{fi}}{y_f} \cdot \sum_{f' \neq f} \frac{y_{f'i}}{y_i} \cdot \frac{y_f}{y_{f'}} \cdot \frac{\ell_{f'}}{\ell_f}.$$

Using the definition of $s_{if'}$ and $m_{fi}$ one more time and regrouping terms, we obtain

$$\sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f \cdot \left( \sum_i m_{fi} \cdot \sum_{f' \neq f} s_{f'i} \cdot \frac{y_f}{\ell_f} \Big/ \frac{y_{f'}}{\ell_{f'}} \right).$$

In the special case where firms have similar baseline labor productivity (or equivalently, similar levels of baseline labor shares if wages are common across firms), we would also have $\frac{y_f}{\ell_f} = \frac{y_{f'}}{\ell_{f'}}$, and this expression can be further simplified to the simpler expression used in the main text

$$\sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f \cdot \left( \sum_i m_{fi} \cdot (1 - s_{if}) \right).$$

In our data, we have

$$\sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f = 0.20,$$

and

$$\sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f \cdot \left( \sum_i m_{fi} \cdot (1 - s_{if}) \right) = 0.156.$$

Moreover,

$$\sum_f \frac{\ell_f}{\ell} \cdot \text{Robot}_f \cdot \left( \sum_i m_{fi} \cdot \sum_{f' \neq f} s_{f'i} \cdot \frac{y_f}{\ell_f} \Big/ \frac{y_{f'}}{\ell_{f'}} \right) = 0.193.$$

Using the estimates from the weighted specification for $\beta_o$ and $\beta_c$ (reproduced in column 1 of Table A.6), we estimate aggregate declines in employment associated with robot adoption in the range of 3.2%–4.1%. Alternatively, if we use the specification including 2-digit industry dummies instead of 4-digit industry dummies, the estimates in column 2 of Table A.6 imply somewhat smaller aggregate employment effects, of about -1.2%.

### *D. Industry-Level Estimates*

An alternative strategy to asses the aggregate implications of robot adoption is to exploit only industry-level variation in robot adoption (and is thus different from the approach used in the main text). In particular, we start by estimating an industry-level variant of equation (1) in the main text:

$$\Delta \ln \ell_i = \beta_m \cdot \text{Robot adoption}_i + \varepsilon_i, \tag{A.3}$$

where Robot adoption$_i$ is the employment-weighted share for firms adopting robots in industry $i$. We focus on industry employment (total hours among the firms in our sample whose main industry is $i$) as the left-hand side variable, and as in the text, on estimates weighted by industry employment, which are more informative about aggregate effects.

Table A.5 shows that robot adoption is associated with a robust decline in employment across industries. Columns 1and 2 present estimates of equation (A.3) for 240 4-digit industries. Column 1 shows the unconditional relationship (without any covariates). The estimate in this column suggests that a 20 percentage point increase in robot adoption in an industry is associated with a 2.56% decline in industry employment. Column 2 controls for 2-digit industry fixed effects and leads to somewhat smaller estimates. Now the same 20 percentage point increase in robot adoption is associated with a decline in industry employment of 1.44%. Finally, columns 3 and 4 reproduce the same estimates but for 95 3-digit industries, and show that a 20 percentage point increase in robot adoption among firms in an industry is associated with a decline in employment of 1.96%.

TABLE A.5—INDUSTRY-LEVEL ESTIMATES OF ROBOT-ADOPTION ON EMPLOYMENT.

| | Dependent variable: Δ log employment (hours) | | | |
|---|---|---|---|---|
| | 4-digit industries | | 3-digit industries | |
| | (1) | (2) | (3) | (4) |
| Robot adoption | -0.128 | -0.072 | -0.144 | -0.098 |
| | (0.081) | (0.042) | (0.088) | (0.058) |
| $R^2$ | 0.121 | 0.559 | 0.178 | 0.713 |
| *Covariates:* | | | | |
| 2-digit industry fixed effects | | ✓ | | ✓ |

*Notes*—The sample consists of $N = 240$ 4-digit industries (columns 1–2) and $N = 88$ 3-digit industries (columns 4–6). All models weight industries by their employment (in hours) in 2010. Columns 2 and 4 control for 2-digit industry fixed effects. Standard errors robust to heteroskedasticity are in parentheses.

We can further decompose these negative industry-level estimates into own-firm and spillover effects by estimating the following variant of equation (1) at the firm level:

$$\Delta \ln \ell_{if} = \beta_o \cdot \text{Robot adopter}_f + \beta_c \cdot \text{Robot adoption}_i + \varepsilon_{if}. \tag{A.4}$$

Here, $\beta_c$ captures spillovers of robot adoption on other firms in the same industry. For this particular specification of spillovers, the estimate of $\beta_c + \beta_o$ corresponds to the industry-level estimate of robots on employment, at least to a first-order approximation.

Columns 3–8 in Table A.6 presents estimates of equation (A.4). Column 3 presents estimates of (A.4) focusing on spillovers among firms in the same 4-digit industry and without any additional covariate. The estimate in column 3 indicates that a 10 percentage point increase in adoption is associated with a 1.17% decline in employment for firms that do not adopt robots and a 0.35% increase in employment at firms that do. The net result is a reduction in employment of 0.82% (s.e.=0.0078), which is similar to the industry-level estimate in Table A.5. Column 4 adds a full set of 2-digit industry dummies as covariates and column 5 further includes the firm-level covariates used

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.

in the main text, which lead to more precise estimates of the spillover effect. Finally, columns 6–8 reproduce the same estimates but focusing on spillovers among firms in the same 3-digit industries.

### *E. Decomposing Changes in the Labor Share*

This section provides the details for the decomposition used in Figure 2. Following Autor et al. (2019), we decompose changes in the labor share of industry $i$ as

$$\Delta \lambda_i^\ell = \Delta \bar{\lambda}_i^\ell + \Delta \sum_f (\lambda_f^\ell - \bar{\lambda}_i^\ell) \cdot (s_{if}^v - \bar{s}_i^v), \tag{A.5}$$

where $\lambda_i^\ell$ is the labor share in industry $i$, $\lambda_f^\ell$ is the labor share in firm $f$, $s_{if}^v$ is the share of value added in industry $i$ accounted for by firm $f$, and $\bar{\lambda}_i^\ell$ and $\bar{s}_i^v$ correspond to unweighted averages of these terms among firms in the industry. The first term in the above decomposition is what Autor et al. (2019) term the *within component* (which is the *unweighted mean* change). The second term is a *covariance term* which accounts for reallocation to firms with lower labor shares, reallocation to firms with declining labor shares, and larger reductions of the labor share among larger firms. We use a balanced panel of firms and ignore entry and exit.

We can explore the contribution to changes in the aggregate labor share arising from robot adoption as follows. Let $\mathcal{R}_i$ be the set of robot adopters in an industry and $\mathcal{N}_i$ be the remaining set of firms. Also, denote the number of adopters by $R_i$, the number of non-adopters by $N_i$, and the total number of firms in the industry by $F_i$. Finally, for a set of firms, $\mathcal{X}$, define the following unweighted averages

$$\bar{\lambda}_{\mathcal{X}}^\ell = \frac{1}{|\mathcal{X}|} \sum_{f \in \mathcal{X}} \lambda_f^\ell \qquad\qquad \bar{s}_{\mathcal{X}}^v = \frac{1}{|\mathcal{X}|} \sum_{f \in \mathcal{X}} s_{if}^v.$$

We can decompose the within-firm change component in equation (A.5) as:

$$\Delta \bar{\lambda}_i^\ell = \frac{R_i}{F_i} \Delta \bar{\lambda}_{\mathcal{R}_i}^\ell + \frac{N_i}{F_i} \Delta \bar{\lambda}_{\mathcal{N}_i}^\ell.$$

The first term accounts for the within-firm change in the labor share among adopters. The second term accounts for the within-firm change in the labor share among non-adopters. (Both of those are still unweighted following Autor et al., 2019).

We next decompose the superstar effect in (A.5) as:

$$\begin{aligned}\Delta \sum_f (\lambda_f^\ell - \bar{\lambda}_i^\ell) \cdot (s_{if}^v - \bar{s}_i) = {} & R_i \cdot \Delta(\bar{\lambda}_{\mathcal{R}_i}^\ell - \bar{\lambda}_i^\ell) \cdot (\bar{s}_{\mathcal{R}_i}^v - \bar{s}_i^v) + N_i \cdot \Delta(\bar{\lambda}_{\mathcal{N}_i}^\ell - \bar{\lambda}_i^\ell) \cdot (\bar{s}_{\mathcal{N}_i}^v - \bar{s}_i^v) \\ & + \Delta \sum_{f \in \mathcal{R}_i} (\lambda_f^\ell - \bar{\lambda}_{\mathcal{R}_i}^\ell) \cdot (s_{if}^v - \bar{s}_{\mathcal{R}_i}^v) + \Delta \sum_{f \in \mathcal{N}_i} (\lambda_f^\ell - \bar{\lambda}_{\mathcal{N}_i}^\ell) \cdot (s_{if}^v - \bar{s}_{\mathcal{N}_i}^v).\end{aligned}$$

The first line in the above equation captures how differences between adopters and non-adopters contribute to changes in the covariance term. The second line captures the residual changes in the covariance term that are unrelated to automation (for example, due to the changes in the allocation of economic activity within robot adopters and separately within non-robot adopters).

Finally, we can further decompose the contribution of robot adoption to the change in the covariance term in three terms:

$$\begin{aligned}R_i \cdot \Delta(\bar{\lambda}_{\mathcal{R}_i}^\ell - \bar{\lambda}_i^\ell) \cdot (\bar{s}_{\mathcal{R}_i}^v - \bar{s}_i^v) + N_i \cdot \Delta(\bar{\lambda}_{\mathcal{N}_i}^\ell - \bar{\lambda}_i^\ell) \cdot (\bar{s}_{\mathcal{N}_i}^v - \bar{s}_i^v) = {} & \left(s_{\mathcal{R}_i} - \frac{R_i}{F_i}\right) \times \Delta(\bar{\lambda}_{\mathcal{R}_i}^\ell - \bar{\lambda}_{\mathcal{N}_i}^\ell) \\ & + (\bar{\lambda}_{\mathcal{R}_i}^\ell - \bar{\lambda}_{\mathcal{N}_i}^\ell) \times \Delta s_{\mathcal{R}_i} \\ & + \Delta(\bar{\lambda}_{\mathcal{R}_i}^\ell - \bar{\lambda}_{\mathcal{N}_i}^\ell) \times \Delta s_{\mathcal{R}_i},\end{aligned}$$

where $s_{\mathcal{R}_i}$ denotes the share of value added accounted for by adopters. These terms capture three potential mechanisms via which industrial automation can lower the covariance between value added and labor shares across firms in an industry. The first term accounts for the fact that robot adopters are larger to begin with. Because Autor et al.'s (2019) within component is unweighted, the covariance between value added and the labor share also includes the size difference between adopters and non-adopters. In particular, this covariance declines as adopters automate and reduce their labor share relative to non-adopters. The second term captures the possibility that adopters had a different labor share to begin with. The third term captures the fact that adopters increase their share of value added in their industry as they simultaneously experiencing a reduction in their labor share.

Figure 2 in the main text implements this decomposition using data from French manufacturing firms for 2010–2015. We first obtain the components for each 4-digit industry, and we then aggregate across industries using their average share of value added during this period as weights.

*F. A Model of Automation and Reallocation across Firms*

This section presents a model that builds and extends on Acemoglu and Restrepo (2019b). Our aim is to clarify the conditions under which robot adoption will be associated with increases in own-firm employment but declines in aggregate employment.

Consider an economy with a single industry consisting of multiple firms with imperfectly substitutable products. In particular, industry output is

$$y = \left( \sum_f \alpha_f^{\frac{1}{\sigma}} y_f^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where $y_f$ is the output produced by firm $f$ and $\sigma > 1$ is the elasticity of substitution across firms.

Firm production is given by

$$y_f = A_f \left( \frac{k_f}{\theta_f} \right)^{\theta_f} \left( \frac{\ell_f}{1-\theta_f} \right)^{1-\theta_f},$$

where $\theta_f$ denotes the extent of automation at firm $f$. We think of improvements in industrial automation technologies as generating an increase in $\theta_f$ for the firms that adopt it.

Capital and labor are perfectly mobile across firms. Capital is produced using the final good at a cost $\Gamma_k \cdot k^{1+1/\varepsilon_k}/(1+1/\varepsilon_k)$. Labor is supplied by households, who have quasi-linear preferences and face a disutility from working given by $\Gamma_\ell \cdot \ell^{1+1/\varepsilon_\ell}/(1+1/\varepsilon_\ell)$. These assumptions ensure that a competitive equilibrium maximizes

$$\max_{k,\ell,\{k_f,\ell_f\}_f} \left( \sum_f \alpha^{\frac{1}{\sigma}} y_f^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} - \frac{\Gamma_k}{1+1/\varepsilon_k} k^{1+1/\varepsilon_k} - \frac{\Gamma_\ell}{1+1/\varepsilon_\ell} \ell^{1+1/\varepsilon_\ell}$$

$$\text{subject to: } y_f = A_f \left( \frac{k_f}{\theta_f} \right)^{\theta_f} \left( \frac{\ell_f}{1-\theta_f} \right)^{1-\theta_f}$$

$$\sum_f k_f = k \text{ and } \sum_f \ell_f = \ell.$$

Therefore, an equilibrium is given by factor prices $\{w, r\}$, an allocation $\{k_f, \ell_f\}_f$, and aggregates $\{y, k, \ell\}$ such that:

- the ideal-price index condition holds

$$1 = \sum_f \alpha_f \cdot \left( \frac{r^{\theta_f} w^{1-\theta_f}}{A_f} \right)^{1-\sigma}; \tag{A.6}$$

- aggregate labor demand satisfies

$$w\ell = \sum_f (1-\theta_f) \cdot y \cdot \alpha_f \cdot \left( \frac{r^{\theta_f} w^{1-\theta_f}}{A_f} \right)^{1-\sigma}; \tag{A.7}$$

- aggregate capital demand satisfies

$$rk = \sum_f \theta_f \cdot y \cdot \alpha_f \cdot \left( \frac{r^{\theta_f} w^{1-\theta_f}}{A_f} \right)^{1-\sigma}; \tag{A.8}$$

- aggregate labor supply satisfies

$$\ell = (w/\Gamma_\ell)^{\varepsilon_\ell}; \tag{A.9}$$

- aggregate capital supply satisfies

$$k = (r/\Gamma_k)^{\varepsilon_k}; \tag{A.10}$$

Let $w$ be the equilibrium wage and $r$ the rate at which capital is rented to firms. To ensure that automation technologies are adopted, we assume that for all firms we have

$$\pi \equiv \ln\left(\frac{w}{r}\right) > 0.$$

This equation implies that producing automated tasks with industrial automation technologies is cheaper than producing it with labor. Hence, whenever it can, befirm will adopt automation technologies and this would reduce its costs.

PROPOSITION A1: Suppose that $\theta_f = \theta$ and technological improvement increase $\theta_f$ for firm $f$ by $d\theta_f > 0$.

- Own-firm employment changes by

$$d \ln \ell_f = \left( -\frac{1}{1-\theta} + (\sigma - 1) \cdot \pi \right) d\theta_f + m, \tag{A.11}$$

  where $m$ is common to all firms in the industry.

- Aggregate employment changes by

$$d \ln \ell = \frac{\varepsilon_\ell}{\theta\varepsilon_\ell + (1-\theta)\varepsilon_k + 1} \left( -\frac{1}{1-\theta} + (1+\varepsilon_k) \cdot \pi \right) \sum_f s_f^\ell \cdot d\theta_f, \tag{A.12}$$

  where $s_f^\ell$ denotes the share of employment accounted for by firm $f$.

- The labor share of firm $f$ declines by $d\theta_f$ and the labor share of other firms remains constant.
- A necessary and sufficient condition for relative employment in firm $f$ to increase and for industry employment to decline is

$$\frac{1}{(1+\varepsilon_k)\cdot(1-\theta)} > \pi > \frac{1}{(\sigma-1)\cdot(1-\theta)}.$$

PROOF:

First, note that labor demand in firm $f$ satisfies

$$w\ell_f = (1-\theta_f) \cdot y_f \cdot p_f = (1-\theta_f) \cdot y \cdot \alpha_f \cdot \left( \frac{r^{\theta_f} w^{1-\theta_f}}{A_f} \right)^{1-\sigma}.$$

Taking a log derivative of this equation around an equilibrium with $\theta_f = \theta$ yields

$$d \ln \ell_f = \frac{1}{1-\theta} \left(-1 + (\sigma - 1) \cdot (1-\theta) \cdot \pi\right) d\theta_f \underbrace{-d \ln w + d \ln y + (1-\sigma)\theta d \ln r + (1-\sigma)(1-\theta) d \ln w}_{\equiv m},$$

which coincides with the formula in equation (A.11).

For aggregates, we can take a log derivative of (A.6), (A.7),(A.8),(A.9) and (A.10) to obtain a system of equations in $\{d \ln \ell, d \ln k, d \ln w, d \ln r, d \ln y\}$. When $\theta_f = \theta$ the system simplifies to

$$(1-\theta) d \ln w + \theta d \ln r = \pi \sum_f s_f^\ell d\theta_f$$

$$d \ln w + d \ln \ell = d \ln y - \frac{1}{1-\theta} \sum_f s_f^\ell d\theta_f$$

$$d \ln r + d \ln k = d \ln y + \frac{1}{\theta} \sum_f s_f^\ell d\theta_f$$

$$d \ln \ell = \varepsilon_\ell d \ln w$$

$$d \ln k = \varepsilon_k d \ln r$$

Solving this system of equations yields the formula in equation (A.12) and establishes the second part of the proposition.

The third part follows from the fact that labor share in firm $f'$ is simply $\theta_{f'}$, and thus the labor share in firm $f$ declines and there is no impact on the labor shares in other firms.

The fourth part follows readily from equations (A.11) and (A.12). $\square$

The assumption that initially $\theta_f = \theta$ is imposed for simplicity. If, for example, $\theta_f$ and $d\theta_f$ were positively correlated, then economic activity would be reallocated to firms that start with the lower labor share and there would be a larger decline in aggregate employment. As noted above, in French manufacturing, there is little baseline difference in the labor shares of adopters and non-adopters, and thus the equations presented here, where $\theta_f$ and $d\theta_f$ are initially uncorrelated, appear to be a good approximation in this context.