Competing with Robots: Firm-Level Evidence from France

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Automation substitutes capital for tasks previously performed by labor, reducing the labor share of value added and increasing value added per worker in the process. While the higher productivity from automation tends to increase labor demand, its displacement effect may outweigh this positive impact and may lead to an overall decline in employment and wages (Acemoglu and Restrepo, 2019a). Acemoglu and Restrepo (2019b) estimate negative effects from the introduction of one of the leading examples of automation technology, industrial robots, across US local labor markets, suggesting that the displacement effects could be significantly larger than the productivity effect.[1] Firm-level evidence is also useful for understanding how automation is impacting the production process and productivity.[2] But its interpretation is made complicated by the fact that firms adopting automation technologies and reduce their costs may expand at the expense of their competitors.

In this paper, we study firm-level changes associated with robot adoption using data from France between 2010 and 2015. Consistent with our theoretical expectations (which are developed further in the Appendix), we find that firm-level adoption of robots coincides with declines in labor shares, increases in value added and productivity, and declines in the share of production workers. In contrast to their market-level effects, however, overall employment increases faster in firms adopting robots.

This positive employment effect may reflect the fact that firms with greater growth potential are more likely to adopt robots, generating a classic omitted variable bias. Equally important, this positive effect may be a consequence of reallocation of output and labor towards firms that reduce their costs relative to their competitors. We show that such reallocation accounts for the positive firm-level impact of robots. Firms whose competitors adopt robots experience significant declines in value added and employment.[3] In fact, the overall impact of robot adoption (combining own and spillover effects) is negative and implies that a 20 percentage point increase in robot adoption in an industry (the average in our sample) is associated with a 1.6% decline in that industry's employment.

Finally, we use our firm-level data to show that the "superstar effect" identified in Autor et al. (2019)—where output is reallocated towards firms with lower and declining labor share—is present in French manufacturing as well. In our data, this pattern is explained not so much because expanding firms have higher or rising markups, but because they are experiencing (relative) declines in their labor shares and are gaining market share as they are automating.

I. Data on French Robots

Our sample includes 55,390 firms that were active from 2010 to 2015 in the French manufacturing sector. For these firms, we have data on sales, value added, employment (total hours of work), share of production workers, and wages (and can estimate total factor productivity). For firms that export, we also have data on export prices and quantities by detailed product. Further information on the data and the sample are provided in the (online) Appendix.

We identified 598 manufacturing firms that purchased industrial robots during this period using several sources, including a survey by the

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[1] Graetz and Michaels (2018) use variation across industries and countries and find lower labor share and higher productivity from robots, but negative effects only for unskilled workers. Aghion et al. (2019) find negative regional employment effects in France, while Dauth et al. (2019) estimate employment declines in manufacturing, but not overall, across German regions.

[2] For other recent papers using firm-level data on robot adoption, see Dinlersoz and Wolf (2018), Bessen et al. (2019), Dixen et al. (2019), Bonfiglioli et al. (2019), Humlum (2019), and Koch et al. (2019).

[3] This aligns with Koch et al.'s (2019) findings from Spain.

French Ministry of Industry, information provided by French robot suppliers about their list of clients, customs data on imports of industrial robots by firm, and fiscal files including information on accelerated depreciation allowances for the purchase of industrial robots. Although only 1% of our firms purchased robots in 2010-2015, these firms account for 20% of total manufacturing employment. Table A.1 in the Appendix describes our sample.

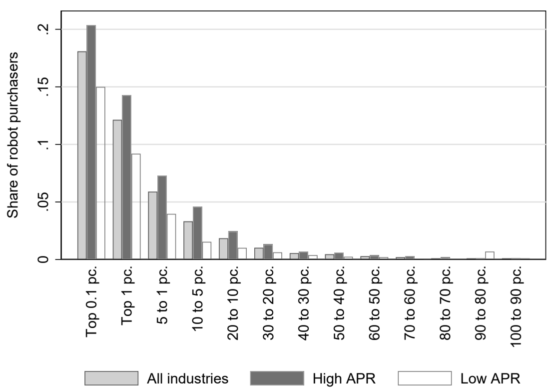

FIGURE 1: Share of robot adopters among firms at different percentiles of the sales distribution within 4-digit industries. The data are shown for all industries, industries with high *APR*, and industries with low *APR*.

Figure 1 presents information on robot adopters. These tend to be the larger firms as shown by the higher rates of adoption at top percentiles of the size distribution within the 258 4-digit industries in our sample. For example, 13% of firms in the top 1% of the industry sales distribution adopted robots, while there is almost no robot adoption among firms below the 20th percentile of the sales distribution. Robot adopters are also likely to be in industries where there are more major advances in robotics technology and more rapid spread of robots in other industrialized economies. In particular, the figure shows that adoption rates are about 50% higher in industries with greater *adjusted penetration of robots (APR)* in other European countries (shown in darker color).[4]

II. Firm-Level Changes

We first study firm-level changes in value added, productivity, the labor share, employment and wages associated with robot adoption. Specifically, we estimate the following regression model by OLS across firms, denoted by f:

$$(1) \qquad \Delta \ln y_f = \beta \cdot \text{Robot}_f + \gamma \cdot X_f + \alpha_{i(f)} + \delta_{c(f)} + \varepsilon_f .$$

On the right-hand side we use the change in the log of several firm-level outcomes between 2010 and 2015. The main regressor is Robot_f, a dummy for whether the firm adopted robots in 2010-2015. We control for baseline firm characteristics that are likely to be correlated with subsequent changes in our variables of interest (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), 4-digit industry-fixed effects for the main industry in which each firm operates, $\alpha_{i(f)}$, and fixed effects for the commuting zone that houses each firm's largest establishment, $\delta_{c(f)}$. We report standard errors that are robust to heteroskedasticity and cross-firm correlation within 4-digit industries.

Table 1 reports our findings using unweighted (in Panel A) and employment-weighted specifications (in Panel B). The results in Panel A show that, consistent with our theoretical expectations, robot adoption is associated with a 20% increase in value added from 2010 to 2015 (s.e.=0.030) as well as a 4.3 percentage point decline in the labor share (s.e.=0.009) and a 1.6 percentage point decline in the production worker share of employment (s.e.= 0.007). Value added per hour and revenue TFP also increase significantly.[5] Column 5 shows that, in contrast to market-level results in previous works, employment (total hours of work) also increases in firms adopting robots — by 10.9% (s.e.= 0.020). Hourly wages rise modestly as well (column 6).

The weighted results in Panel B are similar, except that there are no longer positive effects on

[4]The *APR* measures the common increase in robot use in an industry among advanced economies (excluding France) since 1993 and adjusts for the mechanical effect of industry growth on robot use (see Acemoglu and Restrepo, 2019b). Manufacturing industries with a high *APR* are pharmaceuticals, chemicals, plastics, food and beverages, metal products, primary metals, industrial machinery, and automotive. Industries with a low *APR* are paper and printing, textiles and apparel, electronic appliances, furniture, mineral products, and other transportation vehicles.

[5]The value added per hour and TFP results are not driven by price increases but by higher physical productivity. In the Appendix, we show that, for the sample of exporting firms where we have detailed price data, robot adoption is associated with price declines.

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

	(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	0.204	-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 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.

TFP and hourly wages.[6] The Appendix, documents that these results are robust to controlling for additional covariates in 2010, including sale distribution percentiles, capital intensity and the share of production workers in employment.

III. Market-Level Spillovers

As noted above, firms adopting robots, by reducing their costs, may gain market share at the expense of their competitors. If so, employment gains in these firms may go hand-in-hand with employment losses in other firms, and the market-level effects of automation may be very different than its firm-level impact. To investigate this issue, we estimate a variant of equation (1) including a measure of a firm's competitors' robot adoption. This measure is defined as

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

where the first sum is over all 4-digit industries and m_{fi} is the share of firm f sales made to industry i, while the second is over all firms other than f and $s_{if'}$ is the share of industry i sales accounted for by firm f'. Thus, the measure of adoption by competitors gives the sales overlap across 4-digit industries between a given firm and all robot adopters in the economy. The shares m_{fi} and $s_{if'}$ are constructed using sales data by firm and 4-digit industry from French fiscal files, which cover 85% of sales in our sample. We assume that small firms that are not in the fiscal files only sell in their main 4-digit industry. Because equation (1) includes 4-digit industry fixed effects, the spillovers are identified from the comparison of firms in the same main industry, but selling different proportions of their products across industries with varying degrees of competition by robot adopters.

Table 2 presents estimates for employment, value added, and the labor share. We report both unweighted and employment-weighted estimates, but because our main interest is aggregate effects, we now focus on weighted models. Consistent with the notion that automation leads to expansion at the expense of competitors and the labor share of value added in a firm depends on its own automation decisions, the estimates in columns 4-6 show that a 10 percentage point increase in robot adoption by competitors is associated with a 2.5% decline in employment (s.e.=0.0107) and a 2.1% decline in value added (s.e.=0.0159), while competitors' robot adoption has no impact on a firm's labor share.

These results establish that firm-level effects

[6]Even the positive estimate on hourly wages in Panel A, which implies a pass-through elasticity from output per worker to wages of about 0.1%, is much smaller than estimates in the literature resulting from other sources of productivity increases, such as the impact of obtaining a high-value patent (Kline et al., 2019, and the references therein), which generate a pass-through elasticity of about 0.35. This is as expected since automation substitutes capital for labor.

TABLE 2—ESTIMATES OF ROBOT ADOPTION ON COMPETITORS

	(1) Δ log employment (in hours)	(2) Δ log value added	(3) Δ labor share	(4) Δ log employment (in hours)	(5) Δ log value added	(6) Δ labor share
	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. 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 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.

will not translate into similar market-level impacts because of negative spillovers on competitors. What is then the overall impact of robot adoption on employment? Aggregating the own and the competitors' effects (across 4-digit or 3-digit industries), we find that robots adoption is associated with an overall decline in industry employment. In particular, a 20 percentage point increase in robot adoption in an industry (which is approximately the average robot adoption by competitors in our sample) is associated with a 1.6% decline in employment (see column 1 in Table A.5 in the Appendix, where we estimate a regression only including competitors' robot adoption, which gives the combined effect).[7]

IV. Superstar Effects and the Labor Share

Our estimates in Table 1 suggest that the labor share of a firm that adopts robots declines by 4 to 6.3 percentage points. The impact on the aggregate labor share of the economy is likely to be greater than this, however. This is because, as we have seen, firms adopting robots expand at the expense of their competitors, and this triggers a reallocation of economic activity towards firms with declining (and often lower) labor shares. This phenomenon is similar to what Autor et al. (2019) dub the "superstar effect"—the change in the covariance between the share of value added of a firm and the firm's labor share.[8] Autor et al. suggest that these changes may be due to markup and efficiency differences between expanding and contracting firms. Our data enable us to investigate whether similar trends are present in French manufacturing and whether automation's impact on the labor share and automation-induced reallocation of value added and employment across firms are (at least partially) responsible for these patterns.

Figure 2 presents a similar decomposition to Autor et al.'s for French manufacturing between 2010 in 2015. As in their US results, there is a significant decline in overall labor share, of 0.7 percentage point, and the "superstar effect" is the main driver of this change. In fact, the average within-firm change in the labor share is positive. We further decompose these effects between firms adopting robots and the rest to gauge the contribution of automation to these changes. Interestingly, while, analogously to the US, the labor share increases for firms not adopt-

[7]The Appendix decomposes the industry-level estimate into the own-firm effect, β_o, and the spillover effect on competitors, β_c. When a firm accounting for a share s of the market adopts a robot, employment in that firm increases by $s \cdot \beta_o$, while competitors' employment changes by $s \cdot \beta_c$. Hence, the total effect is $s \cdot (\beta_o + \beta_c)$. Our theoretical framework in the Appendix explains why, while β_o is positive, $\beta_c + \beta_o$ may be negative.

[8]Specifically, changes in an industry labor share, λ_i^ℓ, can be decomposed as $\Delta\lambda_i^\ell = \sum_f \Delta\lambda_f^\ell + \Delta\sum_f (\lambda_f^\ell - \bar{\lambda}_i^\ell) \cdot (s_{if}^v - \bar{s}_i^v)$, where λ_f^ℓ is the labor share in firm f, s_{if}^v the share of value added in industry i accounted for by firm f, and $\bar{\lambda}_i^\ell$ and $\bar{s}_i^v$ are their corresponding unweighted averages. The first term is the (*unweighted*) within component. The second term is the superstar effect. In this decomposition we are ignoring firm entry and exit since we focus on a balanced panel of firms. In Figure 2 this second term is further decomposed into the contribution of robot adoption and a residual superstar effect.

ing robots, it declines for robot adopters. Moreover, and more importantly, about two thirds (or -1.26 percentage points) of the superstar effect is accounted for by reallocation to firms adopting robots and experiencing declines in their labor shares due to automation. Finally, this -1.26 percentage point change is fully accounted for by the fact that the relative labor share of robot adopters declines and they account for a sizable share of value added, and is not due to adopters having lower labor shares at the outset. These results therefore provide a different interpretation of the "superstar effect," linked to automation.

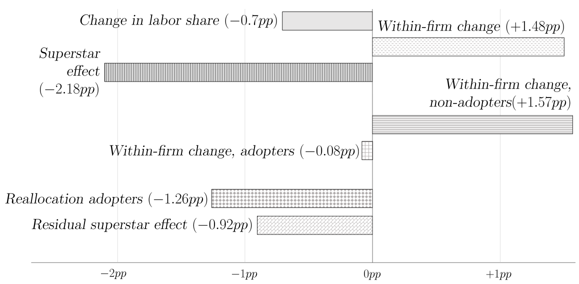

FIGURE 2: Changes in the labor share of French manufacturing industries for 2010-2015 decomposed as in Autor et al. (2019). The decomposition is extended to account for changes in the labor share within and the reallocation of activity towards robot adopters.

V. Conclusion

How firms change their production structure, employment, labor share, productivity and wages as they adopt automation technologies can help us understand the wide-ranging economic effects of automation. Nevertheless, firm-level effects do not correspond to the overall impact of automation technologies because firms that adopt such technologies will reduce their costs and expand at the expense of their competitors. In this paper, we estimate that French manufacturing firms that adopt robots reduce their labor share and share of production workers and increase their productivity, but also expand their operations and employment. Yet, this is more than accounted for by significant declines in their competitors' value added and employment. Overall, even though firms adopting robots tend to expand their employment, the market-level implications of robot adoption are negative. We also show that in the French manufacturing sector this reallocation of economic activity from non-robot-adopters towards firms adopting robots accounts for two thirds of Autor et al.'s (2019) "superstar effect"—the change in the covariance between firm-level value added and labor share.

References

Acemoglu, D., & Restrepo, P. (2019a) "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives.* 33(2): 3–30.

Acemoglu, D., & Restrepo, P. (2019b) "Robots and Jobs: Evidence from US Labor Markets" in press, *Journal of Political Economy.*

Autor, D., Dorn, D., Katz, L.F., Patterson, C., & Reenen, J.V. (2019) "The Fall of the Labor Share and the Rise of Superstar Firms," in press *Quarterly Journal of Economics.*

Aghion, P., Antonin, C., & Bunel, S. (2019) "Artificial Intelligence, Growth and Employment: the Role of Policy." Paris.

Bessen, J. E., Goos, M., Salomons, A., & Van den Berge, W. (2019) "Automatic Reaction-What Happens to Workers at Firms that Automate?" Mimeo. Boston University.

Bonfiglioli, A. Crinò, R., Fadinger, H., & Gancia, G. (2019) "Robot Imports and Firm Level Outcomes." Queen Mary University of London.

Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2019) "The Adjustment of Labor Markets to Robots." University of Würzburg.

Dinlersoz, E., & Wolf, Z. (2018) "Automation, Labor Share, and Productivity: Plant-Level Evidence from U.S. Manufacturing, " Census.

Dixen, J., Hong, B., & Wu, L (2019) "The Employment Consequences of Robots: Firm-level Evidence." Statistics Canada.

Graetz, G., & Michaels, G. (2018) "Robots at Work," *Review of Economics and Statistics,* 100(5): 753–768.

Humlum, A. (2019) "Robot Adoption and Labor Market Dynamics." Princeton University.

Kline, P., Petkova, N., Williams, H., Zidar, O. (2019) "Who Profits from Patents? Rent-Sharing at Innovative Firms." *The Quarterly Journal of Economics*, 134(3): 1343–1404.

Koch, M., Manuylov, I., & Smolka, M. (2019) "Robots and Firms." Aarhus University.

Online Appendix for "Competing with Robots"

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
≤ 10 workers	34,280	37	0.1%	0.2%	11	13	20
Total	55,384	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. These data only report imports from other countries in the European Union that exceed 460,000 Euros, which is the cost of approximately four or five industrial robots.
- 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 firms that are controlled by the State.

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 the total hours of work measure 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 the group of unskilled industrial workers (category 67 in the INSEE classification of professions) and unskilled artisanal workers (category 68 in the INSEE classifications 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, λ_f^{ℓ} and λ_f^m denote the share 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 ω, $e_{f\omega}$ denotes the export share of ω in firm f, and $\Delta \ln p_{\omega f}$ is the observed change in unit values for exports of firm f in product category ω.

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 present 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 as per hour, which we presented 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 wages share in sales share	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 their 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. Decomposing Changes in Employment

This section provides additional estimates for the extent of spillovers across competing firms and provides a decomposition for industry-level employment into own-firm effects and spillovers.

We provide two alternative strategies to identify spillovers across competing firms and discuss aggregation. Our first strategy exploits 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 the following variant of equation (1):

$$\Delta \ln \ell_{if} = \beta_c \cdot \text{Robot adoption}_i + \beta_o \cdot \text{Robot adopter}_f + \varepsilon_{if}, \tag{A.1}$$

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

Under the structure of spillovers assumed in (A.1), the estimate of $\beta_c + \beta_o$ corresponds to the industry-level estimate of robots on employment, at least to a first-order approximation. To see this, note that we can approximate changes in industry employment up to the first order as

$$\Delta \ln \ell_i \approx \sum_f s^{\ell}_{if} \Delta \ln \ell_{if},$$

where s^{ℓ}_{if} denotes the share of employment in industry i accounted by firm f, and $\Delta \ln \ell_f$ denote the change in employment at firm f. Substituting from equation (A.1) and simplifying, we obtain

$$\Delta \ln \ell_i \approx (\beta_c + \beta_o) \cdot \text{Robot adoption}_i + \varepsilon_i,$$

where $\varepsilon_i = \sum_f \lambda_{if} \varepsilon_{if}$. Hence, to a first-order approximation, $\beta_c + \beta_o$ coincides with an industry-level estimate of robot adoption on employment.

Table A.5 presents estimates of (A.1). Column 1 presents estimates of (A.1) where we only include the average robot adoption in an industry as a regressor, thus obtaining an estimate of $\beta_c + \beta_o$. The estimate in column 1 indicates that a 10 percentage point increase in adoption is associated with an employment reduction of 0.82% (s.e.=0.0078). Consistent with our results in Table 2, column 2 show that this estimate is driven by a 1.17% decline in employment for firms that do not adopt robots and a 0.35% increase in employment at firms that do. As expected, the estimates in column 2 satisfy $\hat{\beta}_c + \hat{\beta}_o = 0.082$. Column 3 shows that our estimates are similar if we control for all of the baseline covariates in the main text, except that here we only control for 2-digit industry dummies since 4-digit industry dummies are collinear with average robot adoption in an industry. Finally, columns 4-6 reproduce the same estimates but using 95 3-digit industries rather than our 258 4-digit industries.

Our second strategy is the one we presented in the main text. It exploits differences in the overlap in sales across 4-digit industries with the sales of robot adopters. Here, we focus on the following variant of equation (1):

$$\Delta \ln \ell_{if} = \beta_c \cdot \text{Adoption by competitors}_f + \beta_o \cdot \text{Robot adopter}_f + \alpha_i + \varepsilon_{if}, \tag{A.2}$$

where Adoption by competitors$_f$ is as defined in the main text, and the α_i's denote the 4-digit industry fixed effects. This approach enables us to control for detailed industry covariates and exploit firm-level variation in the extent of competition from robot adopters, depending on a firm's distribution of sales across 4-digit industries. However, obtaining estimates for β_c and β_o is more complicated in this case, since the competition affects are not confined to a single industry.

Columns 7 and 8 in Table A.5 present estimates of equation (A.2). For comparison, column 4 first presents estimates using the same set of covariates as columns 3 and 6 (that is, controlling for 2-digit dummies rather than 4-digit industry dummies). The resulting point estimates for β_c and β_o are very

TABLE A.5—ADDITIONAL ESTIMATES OF SPILLOVERS ON EMPLOYMENT OF OTHER FIRMS.

	Dependent variable: Δ log employment (hours)							
	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			Adoption among competitors defined as in the main text	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot adoption by competitors	-0.082 (0.078)	-0.117 (0.081)	-0.061 (0.034)	-0.095 (0.084)	-0.128 (0.088)	-0.083 (0.046)	-0.110 (0.046)	-0.250 (0.107)
Robot adopter		0.035 (0.020)	0.054 (0.016)		0.033 (0.019)	0.052 (0.016)	0.046 (0.017)	0.035 (0.022)
R^2	0.005	0.007	0.154	0.006	0.008	0.152	0.155	0.190
Covariates:								
2-digit industry fixed effects			✓			✓	✓	✓
4-digit industry fixed effects								✓
Additional covariates			✓			✓	✓	✓

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 1-3 present estimates for the adoption of robots by firms in the same 3-digit industry. Columns 4-5 present estimates for the adoption of robots by firms in all the 4-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 3, 6, 7 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 4-6) industries are in parentheses.

similar to those in columns 3 and 6. Column 8 corresponds to the more demanding specification presented in the text, which goes one step further and controls for 4-digit fixed effects. The estimate for spillovers is more negative but less precise.

D. 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

$$\Delta\lambda_i^\ell = \Delta\bar{\lambda}_i^\ell + \Delta\sum_f (\lambda_f^\ell - \bar{\lambda}_i^\ell)\cdot(s_{if}^v - \bar{s}_i^v), \tag{A.3}$$

where λ_i^ℓ is the labor share in industry i, λ_f^ℓ 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*. The second term is the "*superstar effect"* 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 the equation (A.3) 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.

We next decompose the superstar effect in (A.3) 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 the reallocation of value added towards firms adopting robots, which are initially larger and have declining labor shares. The second line captures the residual of the overall superstar effect that is not explained by our automation measure (for example, due to the allocation of economic activity among robot adopters and separately among non-robot adopters). These terms capture all other economic forces generating a superstar effect and that are uncorrelated with the deployment of industrial automation technologies.

Finally, we can further decompose the contribution of robot adoption to the superstar effect 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. Hence, the covariance between value added and the labor share 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 at the same time as they reduce their labor share.

E. 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 θ_f denotes the extent of automation at firm f. We think of improvements in industrial automation technologies as generating an increase in θ_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 $\Gamma_k \cdot k^{1+\varepsilon_k}/(1+\varepsilon_k)$. Labor is supplied by households, who have quasi-linear preferences and face a disutility from working given by $\Gamma_\ell \cdot \ell^{1+\varepsilon_\ell}/(1+\varepsilon_\ell)$. These assumptions ensure that a competitive equilibrium maximizes

$$\begin{aligned} \max_{k,\ell,\{k_f,\ell_f\}_f} & \left(\sum_f \alpha^{\frac{1}{\sigma}} y_f^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} - \frac{\Gamma_k}{1+\varepsilon_k} k^{1+\varepsilon_k} - \frac{\Gamma_\ell}{1+\varepsilon_\ell} \ell^{1+\varepsilon_\ell} \\ \text{subject to: } & y_f = A_f \left(\frac{k_f}{\theta_f} \right)^{\theta_f} \left(\frac{\ell_f}{1-\theta_f} \right)^{1-\theta_f} \\ & \sum_f k_f = k \text{ and } \sum_f \ell_f = \ell. \end{aligned}$$

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

$$1 = \sum_f \alpha_f \cdot \left(\frac{r^{\theta_f} w^{1-\theta_f}}{A_f} \right)^{1-\sigma}; \tag{A.4}$$

- aggregate labor demand satisfies

$$w\ell = \sum_f (1-\theta_f) \cdot y \cdot \alpha_f \cdot \left(\frac{r^{\theta_f} w^{1-\theta_f}}{A_f} \right)^{1-\sigma}; \tag{A.5}$$

- aggregate capital demand satisfies

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

- aggregate labor supply satisfies

$$w = \Gamma_\ell \cdot \ell^{\varepsilon_\ell}; \tag{A.7}$$

- aggregate capital supply satisfies

$$r = \Gamma_k \cdot k^{\varepsilon_k}; \tag{A.8}$$

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, so that whenever it can, firm will adopt automation technologies and this would reduce its costs.

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

- Own-firm employment changes by

$$d \ln \ell_f = \left(-\frac{1}{1-\theta} + (\sigma - 1) \cdot \pi \right) d\theta_f + m, \tag{A.9}$$

  where m is common to all firms in the industry.

- Aggregate employment changes by

$$d \ln \ell = \frac{1}{\theta \varepsilon_k + (1-\theta)\varepsilon_\ell + \varepsilon_k \varepsilon_\ell} \left(-\frac{\varepsilon_k}{1-\theta} + (1+\varepsilon_k) \cdot \pi \right) \sum_f s_f^\ell \cdot d\theta_f, \tag{A.10}$$

  where s_f^ℓ denotes the share of employment accounted for by firm f.

- A necessary and sufficient condition for employment in firms experiencing increases in θ_f to expand, while aggregate employment contracts, is

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

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

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

which coincides with the formula in equation (A.9).

For aggregates, note that we can take a log derivative of (A.4), (A.5),(A.6),(A.7) and (A.8) to obtain a system of equations in $\{d\ln\ell, d\ln k, d\ln w, d\ln r, d\ln y\}$. When $\theta_f = \theta$ this system simplifies to

$$\begin{aligned} (1-\theta)d\ln w + \theta d\ln r = & \pi\sum_f s_f^{\ell} d\theta_f \\ d\ln w + d\ln \ell = & d\ln y - \frac{1}{1-\theta}\sum_f s_f^{\ell} d\theta_f \\ d\ln r + d\ln k = & d\ln y + \frac{1}{\theta}\sum_f s_f^{\ell} d\theta_f \\ d\ln w = & \varepsilon_{\ell} d\ln \ell \\ d\ln r = & \varepsilon_k d\ln k. \end{aligned}$$

Solving this system of equations yields the formula in equation (A.10) $\square$

Here, the assumption that initially $\theta_f = \theta$ is imposed for tractability. Suppose that θ_f and $d\theta_f$ are positive correlated with firm size, as seems to be the case in the data. In this case, because economic activity is being reallocated to firms that start with the lower labor share, aggregate employment is more likely to decline.