Multinationals, Robots, and the Labor Share

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Abstract

Using a panel of Spanish manufacturing firms covering the 1990-2017 period, I document new evidence about affiliates of multinational enterprises (MNEs): after being acquired, they exhibit a higher propensity to use robots, which leads to a reduction in their labor share. These effects are identified using a matched event-study design, which accounts for selection into multinational ownership and robot adoption. The findings are consistent with a model of robot adoption choices by heterogeneous firms and hold even after considering other explanations for the labor share decline. The estimates imply that without MNEs, the reduction in the manufacturing labor share over the sample period would have been 8% smaller. Multinational-induced robot adoption explains about one-third of the overall impact of multinational activity on the labor share.

JEL classifications: F23, F66, O33.
Keywords: Multinational Enterprises, Globalization, Robots, Labor Share.

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1 Introduction

Multinational enterprises (MNEs) have the potential to expand the production possibility frontier of host countries because of their superior technology (Harrison and Rodríguez-Clare, 2010). Indeed, affiliates of MNEs tend to employ more innovative production methods and effective management procedures than domestic firms (Bloom, Sadun and Van Reenen, 2012). However, since technological change is typically factor-biased, multinational activity may also reallocate income between production factors. The distributional outcomes of multinational investment concern policymakers as they can contribute to anti-globalization sentiment (Colantone, Ottaviano and Stanig, 2022).

In this paper, I provide evidence that firms acquired by MNEs experience a reduction in the labor share. Multinational takeovers generate fundamental changes for acquired firms. One dimension of this reorganization is the systematic adoption of industrial robots,[1] which enable affiliates to scale up production but reallocate income away from labor. I offer two contributions. First, I document a new channel through which MNEs can redistribute income between production factors, shedding light on the distributional implications of the technological change arising from multinational acquisitions. Second, I extend the argument that globalization and technological change are among the leading drivers of the observed labor share decline in many countries (see Grossman and Oberfield (2022) for a survey). Rather than alternative forces, I show that globalization (in the form of MNEs) and technological change (in the form of robots) interact and reinforce each other in driving the downward trend.

I document these results using the Survey on Business Strategies (ESEE), a representative panel of Spanish manufacturing firms from 1990 to 2017. The ESEE contains rich details about firm production and organizational choices. Crucially, it is among the few available data sources with information about ownership and robot adoption. I complement these data with cross-country industry-level information about multinational activity, labor share, and robot usage for 37 countries and 20 industries from 2005 to 2014.

I focus on two groups of Spanish firms. The first includes firms that stay under domestic ownership throughout their lifespan. The second contains firms that switch from domestic to multinational ownership, that is, they become multinational affiliates. While firms in the second group are only about 3% of the total, they account for a disproportionate share of production and employment, tend to be more innovative, and

[1] They are "automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (ISO 8372:2012). I refer to them whenever I mention robots.

are more involved in international trade than domestic firms.

I use the firm-level data to document two new facts about multinational affiliates. First, they have a lower labor share than domestic firms. Second, multinational affiliates systematically exhibit a higher rate of robot adoption than domestic firms which, in turn, is associated with a lower labor share. Using the cross-country industry-level data, I show that analogous patterns also apply beyond the Spanish manufacturing sector.

This evidence is consistent with a model of robot adoption choices by heterogeneous firms and reflects both selection and treatment effects. To disentangle them and triangulate the relationship between multinational acquisitions, robot adoption, and labor share dynamics, I use an event-study design and proceed in two steps. First, I examine whether firms acquired by an MNE experience a drop in their labor share after the acquisition. Second, I assess whether multinational acquisitions lead to an increased likelihood of affiliate firms investing in robots, and if these investments reduce their labor share.

The effects of multinational acquisitions are identified by comparing acquired firms with never and not-yet-acquired ones. Because multinational acquisitions are not random, I use nearest neighbor matching algorithm to create a group of domestic firms that is indistinguishable from those that are acquired in terms of several observable characteristics in growth and level. Additionally, I account for the staggered timing of acquisitions and their possible time-varying effects using the methodology proposed by Sun and Abraham (2021).[2] I apply a similar approach to identify the effects of robot adoption.

The estimates reveal that acquired firms experience an average labor share reduction of about 4 percentage points (7% relative to the sample average). After the acquisition, firms increase the probability of adopting robots by about 10 percentage points (30% relative to the sample average). In turn, robot adoption decreases the labor share by about 2 percentage points, half of the overall reduction following multinational acquisitions.[3]

An interesting question is why do multinational acquisitions lead to increased investment in robots. Using again a matched event-study design, I show that multinational parents grant their affiliates the possibility to expand into global markets through their networks. However, affiliates must scale up production to translate higher potential demand into actual sales. Adopting robots is one way to achieve this goal, but it reallocates income away from labor.

[2]See De Chaisemartin and D'Haultfoeuille (2022) for a review of the challenges that staggered treatment roll-out and time-varying effects pose in event-study designs.

[3]The richness of the ESEE data allows me to control for other factors identified in the literature that might contribute to labor share decline, e.g., factor-biased technological change, investment in intangibles, market power, and exposure to international trade. The impact of robot adoption on the labor share stays unchanged even after accounting for these additional, possibly complementary, mechanisms.

Finally, I use the reduced-form estimates to examine how changes at the firm level shape aggregate labor share dynamics. I consider two scenarios. In the first, I simulate how the Spanish manufacturing labor share would have evolved in the absence of multinational-induced robot adoption over the sample period. In the second, I completely turn off multinational acquisitions. The results suggest that in the absence of MNEs, the decline in the manufacturing labor share over the sample period would have been 8% smaller. Multinational-induced robot adoption accounts for about one-third of this effect. These findings offer new insights into how globalization (in the form of MNEs) and technological change (in the form of robots) interact and jointly contribute to the decline in the manufacturing labor share.

Related Literature. At its core, this paper contributes to the debate about the effects of multinational acquisitions on acquired firms. Previous literature shows that these firms are more productive (Griffith, 1999; Harris and Robinson, 2003; Arnold and Javorcik, 2009; Alfaro and Chen, 2018; Bircan, 2019; Fons-Rosen, Kalemli-Ozcan, Sørensen, Villegas-Sanchez and Volosovych, 2021), have easier access to credit (Harrison and McMillan, 2003; Desai, Foley and Hines Jr, 2004; Manova, Wei and Zhang, 2015), innovate more (Guadalupe, Kuzmina and Thomas, 2012), trade more (Hanson, Mataloni Jr and Slaughter, 2005; Ekholm, Forslid and Markusen, 2007; Ramondo, Rappoport and Ruhl, 2016; Conconi, Leone, Magerman and Thomas, 2024), pay higher wages (Almeida, 2007; Heyman, Sjöholm and Tingvall, 2007), and adopt better management practices (Bloom et al., 2012) than domestic firms. The literature also acknowledges that these improvements may be biased towards high-skilled labor (Feenstra and Hanson, 1997; Aitken, Harrison and Lipsey, 1996; Koch and Smolka, 2019; Setzler and Tintelnot, 2021) or capital (Sun, 2020). By focusing on robots, I shed light on a new channel through which multinational acquisitions can redistribute income within affiliates.

This article also contributes to the literature about the determinants of robot adoption. Recent literature using firm-level data for France (Acemoglu, Lelarge and Restrepo, 2020; Aghion, Antonin, Bunel and Jaravel, 2020; Bonfiglioli, Crinò, Fadinger and Gancia, 2022), Spain (Koch, Manuylov and Smolka, 2021), and Denmark (Humlum, 2021) shows that robot adopters tend to be large manufacturing firms. By showing that multinational acquisitions spur robot adoption on top of firm size, I add a new dimension to understanding why companies invest in robots.

Finally, this paper contributes to the debate about the determinants of the labor share decline across the world. Previous research identifies technological change and globalization as two major drivers of this trend (see Grossman and Oberfield, 2022, for a survey). Technological explanations include capital-biased technical change (Karabarbounis and Neiman, 2014), intangible and modern capital adoption (Koh, Santaeulàlia-Llopis and Zheng, 2020; Aghion, Bergeaud, Boppart, Klenow and Li, 2022), and automation (Acemoglu and Restrepo, 2018). The literature also shows that openness to trade (Elsby, Hobijn and Şahin, 2013; Leblebicioğlu and Weinberger, 2021; Panon, 2022) and multinational investment (Decreuse and Maarek, 2015; Adachi and Saito, 2020; Sun, 2020) may reduce the labor share. Most studies analyze these channels separately. Exceptions are Galle and Lorentzen (2022), who develop a quantitative framework to study the effects of the China shock and automation on US labor markets, and Faia, Laffitte, Mayer and Ottaviano (2021) and Stapleton and Webb (2022),[4] who provide evidence that offshoring and automation are complementary at the firm level. I contribute to the debate by showing how globalization (in the form of MNEs) and technological change (in the form of robots) interact and reinforce each other in driving down the labor share.

The paper unfolds as follows. Section 2 introduces the data. Section 3 presents preliminary evidence about the relationship between multinational acquisitions, robot adoption, and labor share dynamics. Section 4 addresses identification and contains the empirical results. Section 5 discusses the counterfactuals. Section 6 concludes.

2 Data

This section introduces the data used in this paper. See Appendix A for more details.

2.1 Firm-Level Data

The ESEE Survey. Firm-level data come from the Survey on Business Strategies (ESEE, or *Encuesta sobre Estrategias Empresariales*) administered by the SEPI Foundation in Madrid. The survey covers the period from 1990 to 2017 and is representative of the population of manufacturing firms with ten or more employees located in Spain. In 1990, the SEPI Foundation interviewed 2,188 firms divided into two categories. The first group contains firms with more than 200 employees. The second group is composed of a stratified sample of smaller firms employing 10-to-200 workers. From 1991 to 2017,

[4] A key difference between this paper and Stapleton and Webb (2022), who also use the ESEE data to study firm automation choices, is that I focus on Spanish firms acquired by foreign MNEs (inward FDI), while they focus on Spanish firms investing abroad (outward FDI).

the SEPI Foundation has surveyed about 1,800 firms each year and made an effort to minimize the sample deterioration due to either firm exit or missing response.

Firms are assigned to 20 two-digit manufacturing industries roughly matching the NACE review 2 classification, and the survey contains information about firm production process, sales, employment, technology adoption, and foreign trade. Crucially for my purposes, the ESEE survey is one of the few available data sources with information about firm ownership and robot adoption choices. Previous studies praise the reliability and accuracy of these data (Guadalupe et al., 2012; Garicano and Steinwender, 2016; Doraszelski and Jaumandreu, 2018; Koch and Smolka, 2019; Koch et al., 2021).

Sample Selection and Key Variables. Based on International Monetary Fund (2007), a firm is considered a multinational affiliate if a company headquartered outside Spain owns at least 10% of its capital.[5] I impose three sample selection criteria. First, I remove firms always owned by a multinational or switching ownership multiple times. This criterion excludes greenfield foreign direct investment (FDI) and firms already owned in 1990 for which I cannot determine the acquisition year. Second, I drop Spanish firms with equity shares in companies located abroad.[6] Third, I exclude firms involved in domestic mergers during the sample period. The final sample consists of two types of firms: those that are always under domestic control (i.e., "domestic firms") and those switching from domestic to multinational ownership after 1991 (i.e., "multinational affiliates").

The survey asks firms if they use any of the following systems: (1) Computer-digital machine tools; (2) Robotics; (3) Computer-assisted design; (4) Combination of some of the above systems through a central computer (CAM, flexible manufacturing systems, etc.); (5) Local Area Network (LAN). Based on the response to this question, I create a binary indicator for whether a firm uses "Robotics" (system 2) in a given year.[7] Firms are asked this question in eight years (1990, 1991, 1994, 1998, 2002, 2006, 2010, and 2014). To match the yearly frequency of the other sample variables, I define an indicator variable equal to 1 since the first year a firm employs a robot. This definition is consistent with robot adoption being a lumpy investment (Humlum, 2021). I exclude firms already using robots in 1990 because I cannot determine the adoption year. I create binary indicators

[5] The ESEE data do not report if a firm is owned by a Spanish multinational. Nevertheless, I expect the conclusions of the empirical analysis in Section 4 to hold for these acquisitions as well.

[6] The ESEE data report outward FDI activity only from 2000 onward. Hence, I can only apply this criterion as of that year. However, if a firm born before 2000 starts investing abroad as of or after 2000, I exclude it from the sample.

[7] Koch et al. (2021) show that robot adoption patterns in the ESEE are consistent with the industry-level trends reported by International Federation of Robotics (2019).

for the other technologies following the same logic.

I define the labor share as the ratio of the wage bill (which consists of average labor costs, including salaries and social security contributions, multiplied by the number of employees) to variable production costs (which is the sum of the wage bill and expenditure on intermediate inputs, including raw materials, energy, and external services).

Sample Description. The final sample spans 1990 to 2014, the last year for which robot adoption information is available, and includes 3,128 firms. Among them, 102 are eventually acquired by an MNE. Table A.1 reports the number of acquisitions by year. Table A.2 shows summary statistics by ownership type, pooling together pre and post-acquisition periods for multinational affiliates. Firms acquired by MNEs outperform domestic ones in many respects. They are more productive, innovative, sell more, employ more workers, pay higher wages, and engage more in international trade. Figure A.1 shows that multinational affiliates perform better than firms that are always under domestic control already before the acquisition.

Although multinational affiliates represent only about 3% of all firms in the sample, they account for about 23% of production, 25% of exports, 15% of employment, and 30% of capital stock. These figures are consistent with what the literature has shown for other countries, such as Belgium (Conconi et al., 2024), Indonesia (Arnold and Javorcik, 2009), Turkey (Bircan, 2019), and the US (Antràs, Fadeev, Fort and Tintelnot, 2022).

2.2 Industry-Level Data

I complement the firm-level data with cross-country industry-level information about multinational activity, labor share, and robot adoption. Data about multinational affiliates' sales come from the Analytical Multinational Enterprises Database (AMNE) of the OECD. The income share accruing to labor is computed using the Socio-Economic Account (SEA) of the World Input-Output Database (WIOD). These data also contain information about employment, wages, fixed assets, exchange rates, and price deflators. The number of industrial robots adopted at the country-industry-year level is provided by the International Federation of Robotics (IFR), the most widely used source for robot adoption studies (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020).

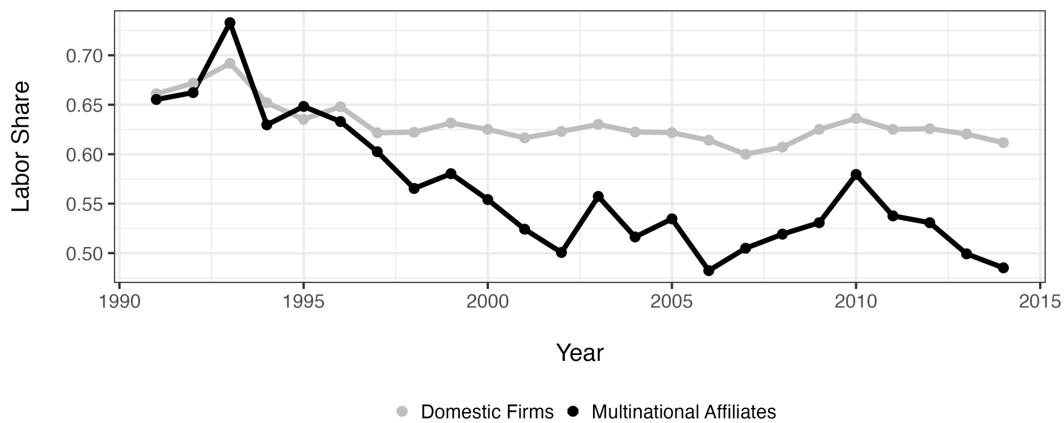
The final dataset includes 37 middle and high-income countries and 20 industries from 2005 to 2014. Industries are agriculture, mining, 15 two-digit manufacturing sectors, electricity and water supply, and construction. Table A.3 shows sample summary statistics.

3 Preliminary Evidence

This section provides preliminary evidence about the relationship between multinational ownership, robot adoption, and the labor share.

Fact 1. *Multinational affiliates have a lower labor share than domestic firms.*

Figure 1. Multinational Ownership and the Labor Share



Note: The figure shows labor share trends among domestic firms and multinational affiliates.

Figure 1 shows that the labor share declines during the sample period. However, multinational affiliates experience a sharper reduction (from 65% to 48%) than domestic firms (from 66% to 61%) and systematically have a lower labor share. As shown in Figure A.2, this pattern also holds conditional on firm size.

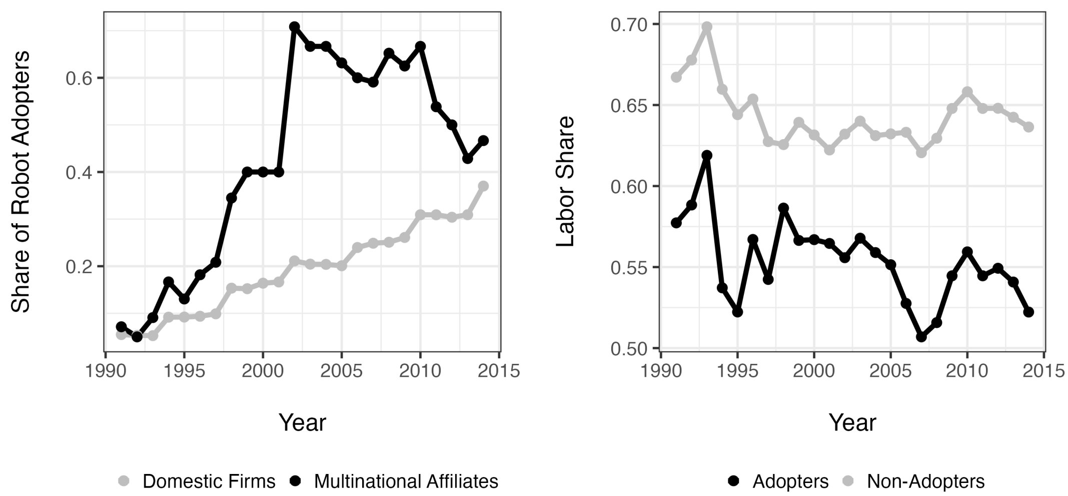
The trends in Figure 1 reflect both within-group changes in the labor share and between-group employment reallocation. Using the Olley and Pakes (1996) decomposition,[8] I find that the within-group margin accounts for 75% of the total labor share reduction. Therefore, understanding why multinational affiliates experience a declining labor share is crucial to explain industry-level labor share trends.[9]

Fact 2. *Multinational affiliates are more likely to adopt robots than domestic firms, and robot adopters have a lower labor share than non-adopters.*

[8] See Appendix B.1 for additional details about this decomposition.

[9] Among multinational affiliates, the reallocation of market shares from high to low labor share firms explains about 50% of the decline. The within-firm component is also negative, and explains about 40% of the reduction. The contribution of entry and exit is constant. This result is consistent with Autor, Dorn, Katz, Patterson and Van Reenen (2020) and Panon (2022), who show that the labor share decline in the US and France between the 1990s and 2000s is due to market share reallocation to "superstar firms" with low labor share. See Appendix B.2 for additional details about this decomposition.

Figure 2. Multinational Ownership, Robot Adoption, and the Labor Share



Note: The left panel shows the share of robot adopters among domestic firms and multinational affiliates. The right panel shows labor share trends among robot-adopting firms and non-adopters.

The left panel of Figure 2 shows that the share of robot adopters increases during the sample period. However, multinational affiliates experience a higher total increase (from 7% to 46%) than domestic firms (from 6% to 37%) and feature a systematically higher adoption rate. The left panel of Figure A.3 shows that this pattern also holds conditional on firm size. Because multinational affiliates represent about 3% of total firms in each year, the left panel of Figure 2 does not merely reflect changes in sample composition.

The right panel of Figure 2 shows that robot-adopting firms exhibit a stronger labor share reduction (from 57% to 52%) than non-adopters (from 66% to 63%) and have a lower labor share throughout the sample period. The right panel of Figure A.3 shows that this pattern holds even conditional on firm size.

Similarly to Figure 1, the right panel of Figure 2 subsumes both within-group changes in the labor share and between-group employment reallocation. Using again the Olley and Pakes (1996) decomposition, I find that 65% of the total labor share reduction is explained by within-group changes.

Discussion. Figure 1 shows that the drop in the manufacturing labor share is largely driven by changes within multinational affiliates. Figure 2 offers suggestive evidence as to why these firms have a falling labor share: multinational affiliates are more likely to adopt robots, which correlates with a lower labor share.

Clearly, this evidence alone does not identify treatment effects, as firms might self-select into multinational ownership and robot adoption. In Appendix B.3, I present a model of robot adoption choices by heterogeneous firms that is consistent with Facts 1 and 2 and rationalizes them as outcomes of both selection and treatment effects. In the next section, I propose a strategy to identify treatment effects beyond selection.

Apart from robot diffusion, the literature suggests various additional explanations for the labor share decline (Grossman and Oberfield, 2022). Thanks to the richness of the ESEE data, I can assess the role of robot adoption on top of these other mechanisms.

Beyond Spanish Manufacturing. Using the cross-country industry-level panel, Figure 6 shows that multinational production negatively correlates with the labor share (left panel) and positively correlates with the number of robots per thousand employees (middle panel), a standard measure of robot diffusion (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Additionally, the number of robots per thousand employees negatively correlates with the labor share (right panel). Correlations are shown after projecting each variable onto country-by-industry and year-level fixed effects. Overall, Figure 6 suggests that Facts 1 and 2 are general trends that apply beyond Spanish manufacturing.

4 Empirical Analysis

This section provides evidence that firms acquired by MNEs experience a labor share decline compared to similar domestic firms. A key driver of this effect is the higher propensity to use robots. I also investigate the role of other channels, why affiliates start using robots and other organizational changes brought about by the acquisition.

4.1 Multinationals and the Labor Share

Empirical Strategy. I estimate the following equation:

$$y_{ft} = \sum_{s=-\underline{k}}^{\bar{k}} \beta_s MNE_{ft}^s + \alpha_f + \alpha_t + \varepsilon_{ft}. \tag{1}$$

y_{ft} is the outcome of interest of firm f in year t. MNE_{ft}^s is a binary indicator that identifies the years before or after firm f is acquired by a multinational. $\underline{k}$ and $\bar{k}$ denote the first and last period for which MNE_{ft}^s can be defined. α_f and α_t are firm and year-level fixed effects, respectively. The coefficients β_s measure dynamic treatment effects.

I set $\beta_{-1} = 0$, which means that all other estimated coefficients are relative to the year prior to the acquisition. I cluster standard errors by firm.

Identifying β_s requires addressing two challenges. First, estimating event studies with a two-way fixed-effects estimator may not recover the treatment effect when the roll-out is staggered and treatment effects evolve over time. The problem arises because already treated units enter the control group for some cohorts, generating a "forbidden comparison" (Borusyak, Jaravel and Spiess, 2021). To deal with this issue, I use the method proposed by Sun and Abraham (2021) and estimate cohort-specific dynamic treatment effects, which I then aggregate using the size of each cohort as a weight.

Second, as shown in Section 2.1, better-performing self-select into multinational ownership. Absent exogenous variation in firms' corporate structure, I build upon previous literature and use a matching algorithm to identify treatment effects beyond selection (Arnold and Javorcik, 2009; Guadalupe et al., 2012; Koch and Smolka, 2019). The purpose of this procedure is to create a group of domestic firms that is indistinguishable from those that are acquired in terms of several observable characteristics. The identification assumption that, after matching and conditional on the fixed effects, never and not-yet-acquired firms are a credible counterfactual for acquired ones.

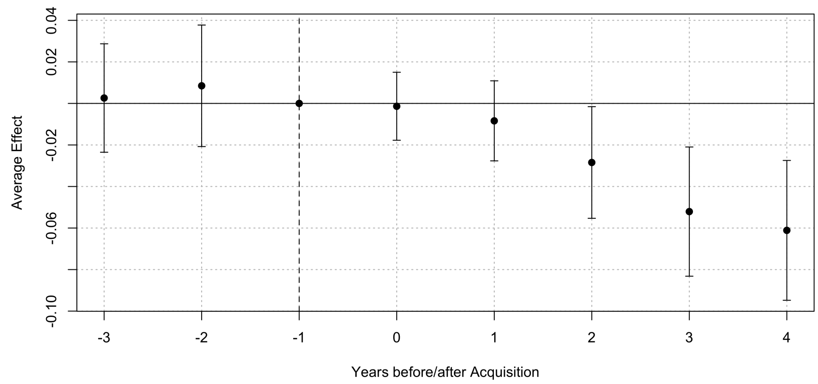
I proceed in two steps. First, using a nearest neighborhood algorithm, I match each acquired firm to the most similar five domestic firms in terms of observable characteristics in trends (to account for differences in growth) and levels (to account for differences in size).[10] Firms are matched based on their sales' growth rate, level of sales, value added, employment, labor costs, investment, fixed assets, R&D expenditure, export values, and number of export destinations. All variables refer to the year before the acquisition and, except the sales' growth rate, are in logs. In the second step, I estimate equation (1) on the matched sample.

The matched sample includes all the original multinational affiliates and 370 domestic firms. Table 1 shows the average characteristics for the two groups before and after treatment. Before matching, there are economically sizable average differences between the two groups. After matching, the two groups are indistinguishable in terms of growth, level of domestic activities, investment patterns, and international trade participation.

Results. I estimate equation (1) using the labor share as the outcome variable. Figure 3 shows that the labor share progressively decreases following multinational acquisitions.

[10] If the algorithm fails to find five matches, it selects the most similar $N < 5$ ones. I perform the matching without replacement. I obtain similar results when allowing for replacement, i.e., when control units can be matched to several treated units.

Figure 3. Multinational Acquisitions and the Labor Share



Note: The figure plots the estimates I obtain from equation (1) using the labor share as the dependent variable. The unit of observation is a firm-year pair. There are 4,165 observations. I cluster standard errors at the firm level and report 95% confidence intervals. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

There are no significant trends leading up to the acquisition. If anything, the pre-acquisition point estimates go in the opposite direction of the post-acquisition ones, reducing concerns about anticipation effects. Column 1 of Table 2 indicates that the average labor share reduction is about 4 percentage points, a 7% decrease relative to the mean labor share in the matched sample.

Columns 2 to 4 of Table 2 decompose the labor share into its components: (the log of) intermediate inputs, labor costs, and the number of employees. Wages do not significantly increase. Although acquired firms employ more workers after the acquisition (11%), the expenditure on intermediate inputs rises disproportionately more (26%), driving the labor share decline.

Table 3 replicates Table 2 on the unmatched sample. As expected, the estimated coefficients are larger in magnitude than those obtained post-matching.

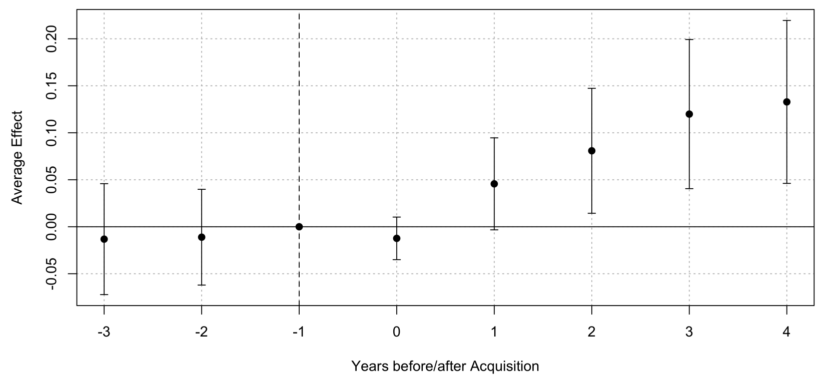
Robustness. The results in Figure 3 are robust to several alternative specifications. Figure A.4 shows that they are robust to replacing year fixed effects with industry-by-year fixed effects, to account for common changes across all firms within the same NACE 2 sector. Figure A.5 confirms the robustness of the baseline results when applying a one-to-three nearest neighbor matching algorithm. Figure A.6 indicates that the results hold even when redefining the labor share in terms of value added rather than production costs.

4.2 Mechanism

Overall Approach. To provide evidence that robot adoption is a driver of labor share reduction within acquired firms, I proceed in two steps. First, I document that multinational acquisitions make firms more likely to invest in robots. Second, I show that the adoption of robots leads to a reduction in the labor share.[11]

Multinationals and Robots. To test whether multinational acquisitions make firms more likely to adopt robots, I estimate equation (1) using a binary indicator equal to 1 since the first year firm f adopts a robot as the outcome variable. Figure 4 indicates that the probability of adopting robots gradually increases after the acquisition.

Figure 4. Multinational Acquisitions and Robot Adoption



Note: The figure plots the estimates I obtain from equation (1) using a binary indicator equal to 1 since the first year firm f adopts a robot as the outcome variable. The unit of observation is a firm-year pair. There are 4,165 observations. I cluster standard errors at the firm level and report 95% confidence intervals. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

Similarly to in Figure 3, there is no evidence of differential trends between groups before the acquisition. Column 1 of Table 4 shows that the average increase in the probability of adopting robots is about 10 percentage points, a 30% increase relative to the unconditional probability in the matched sample. Column 2 of Table 4 indicates that the estimates on the unmatched sample are larger in absolute value than the post-matching ones.

[11]See the model in Appendix B.3 for a theoretical foundation of this mechanism.

Robots and the Labor Share. To test whether robot adoption reduces the labor share, I modify equation (1) as follows:

$$y_{ft} = \sum_{s=-\underline{k}}^{\bar{k}} \beta_s R_{ft}^s + \alpha_f + \alpha_t + \varepsilon_{ft}. \tag{2}$$

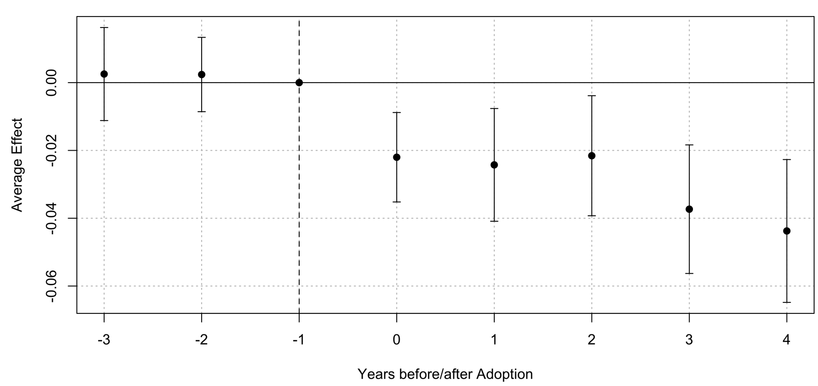
Notation follows from equation (1). However, MNE_{ft}^s is replaced by R_{ft}^s, which is a binary indicator that identifies the years before or after firm f adopts its first robot. As before, I estimate equation (2) using the method proposed by Sun and Abraham (2021).

I employ again a one-to-five nearest neighbor matching algorithm to account for firm self-selection into robot adoption. Firms are matched based on the same observable characteristics as in Table 1. However, since multinational acquisitions increase the likelihood of affiliates adopting robots, I perform matching by ownership status. Specifically, I match robot-adopting multinational affiliates with non-adopting multinational affiliates, and robot-adopting domestic firms with non-adopting domestic firms. After these matches are established, the two groups are combined into a single estimation sample.

The identification assumption is that, after matching and conditional on the fixed effects, firms that never adopt robots or have not yet done so serve as a credible counterfactual for those that do adopt robots. The matched sample includes 945 non-adopters and 376 adopters. Table 5 shows that matching makes the two groups indistinguishable.

I estimate equation (2) using the labor share as the outcome variable. Figure 5 shows that the labor share steadily decreases after the adoption of robots.

Figure 5. Robot Adoption and the Labor Share



Note: The figure plots the estimates I obtain from equation (2) using the labor share as the dependent variable. The unit of observation is a firm-year pair. There are 14,978 observations. I cluster standard errors at the firm level and report 95% confidence intervals. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

There is no evidence of differential labor share trends between groups before the event. Column 1 of Table 6 indicates that the average reduction in labor share is about 2 percentage points, a 3% decrease relative to the mean labor share in the matched sample. This number is about half of the overall reduction in Figure 3. Column 2 of Table 6 shows that the results on the unmatched sample are slightly larger in absolute value than those obtained post-matching.

Other Mechanisms. Robot adoption may not be the only channel through which firms experience a labor share reduction. Other—and possibly complementary—mechanisms are factor-biased technological change (Karabarbounis and Neiman, 2014), investment in intangible capital (Koh et al., 2020), process efficiency improvements (Aghion et al., 2022), exposure to international trade (Panon, 2022), and market concentration (Autor et al., 2020).

The richness of the ESEE data allows me to compute proxy variables for each of these mechanisms and compare their impact on the labor share with that of robot adoption. To proxy factor-biased technological change, I use the ratio of fixed assets to employees. For investment in intangible capital, I consider total R&D expenses. Process efficiency improvements are measured by value added in production, while exposure to international trade is measured by the ratio of export sales to total sales. Finally, I use a Paasche-type price index provided by the ESEE data which accounts for changes in output market concentration. All these variables are in logs and vary at the firm-by-year level.

I assess the explanatory power of these variables for the decline in the labor share by including them as additional controls in a pooled version of equation (2). Table 7 shows the results. For reference, column 1 replicates the first column of Table 6. The other proxy variables are progressively added in the subsequent columns. As expected, robot adoption is not the only driver of falling labor share. Changes in input mix, higher R&D expenses, more exposure to international trade, and changes in output prices also contribute to the observed decline. However, the coefficient associated with robot adoption stays virtually unchanged as more regressors are included. Moreover, if robot adoption is accounted for, both the total and within R^2 increase only marginally as more regressors are added.

Overall, these results suggest that robot adoption is a key driver of the decline in labor share, and highlight its complementarity with other potential channels.

4.3 Why do Multinationals Adopt Robots?

Hypotheses. The results presented so far show that multinational acquisitions make firms more prone to adopt robots, which reduces their labor share. An interesting question is why multinational acquisitions spur robot investment. Adopting robots involves a fixed cost but reduces marginal costs. Firms with higher productivity or demand, or lower adoption costs, are more likely to make this investment (see the model in Appendix B.3).

Multinational acquisitions may make firms more likely to adopt robots due to improvements along each of these dimensions. For instance, firms acquired by a multinational may learn superior management practices that boost their productivity (Bloom et al., 2012) and gain increased access to foreign markets via their parents (Guadalupe et al., 2012; Conconi et al., 2024). Multinational parents may also reduce affiliates' investment costs, including in robots, by alleviating their credit constraints (Harrison and McMillan, 2003; Desai et al., 2004; Manova et al., 2015) or transferring them technological knowledge (Branstetter, Fisman and Foley, 2006; Keller and Yeaple, 2013; Bilir and Morales, 2020). The richness of the ESEE data allows me to distinguish among these hypotheses.

Testing the Hypotheses. To test if multinational acquisitions boost firm productivity, I inspect changes in firms' value added in production. To evaluate if multinational parents grant access to global markets to their affiliates, I exploit a survey question asking firms how they access export markets, if at all. The possible answers are that they export via their multinational parents (either using their distribution channel or directly selling to them), own means, specialized intermediaries, collective actions, or other means. To infer if acquired firms face lower investment costs, I test whether they increase external R&D expenditures per worker, an activity subject to credit constraints (Brown, Martinsson and Petersen, 2012), or purchase licenses and technical aid from abroad, possibly from their parents, which I use to proxy technology transfers.

Following the approach of Section 4.2, I proceed in two steps. First, I test if multinational takeovers lead to changes in any of these variables. Second, I assess the explanatory power of each channel for robot adoption. In both steps, I use the same matched sample as in equation (1).

Results. Table 8 shows the pooled estimates across all cohorts and post-acquisition periods. Multinational acquisitions make firms more likely to export via their foreign parents and more productive. Their sales and export values increase accordingly, as shown in Table A.4. There is no evidence that affiliates increase external R&D per employee and imports of foreign technology, dismissing the investment cost channel. Table 9 indicates that only the ability to export via the parental network has a statistically significant explanatory power for robot adoption. This results is consistent with previous work showing that foreign market access is a crucial driver of innovation (Lileeva and Trefler, 2010; Bustos, 2011; Guadalupe et al., 2012).

Altogether, there is evidence that affiliates can expand their customer base abroad thanks to their multinational parental network. However, they must scale up production to translate higher potential demand into actual sales. Robot adoption is one way to achieve this goal, but it reallocates income away from labor.

4.4 Other Changes in the Production Process

Robots are complex to operate, and multinational acquisitions trigger broader changes in the production process of their affiliates. For example, Table A.5 indicates that acquired firms are about 7 percentage points more likely than domestic firms to perform continuous manufacturing, a 24/7 large-scale production approach that requires automated production lines.

I also test if multinational affiliates direct investment towards technologies complementary to robots. To do so, I create binary indicators equal to 1 since the first year firms use computer-assisted design (CAD) manufacturing, a technology that facilitates computerized process design, or numerically controlled machines and flexible systems, which can execute specialized routine tasks. While CAD can complement robots, the other systems are inferior substitutes, unable to be reprogrammed without human supervision. Table A.6 shows that, post-acquisition, firms are about 8 percentage points more likely to adopt CAD and about 6 percentage points less likely to use any of the other two technologies.

5 Industry-Level Dynamics

This section quantifies the impact of multinational activity, and specifically multinational-induced robot adoption, on the decline of the manufacturing labor share.

5.1 Implementation

Consider the following pooled version of equation (1):

$$LS_{ft} = \beta_1 MNE_{ft} + \alpha_f + \alpha_t + u_{ft}. \tag{3}$$

LS_{ft} is the labor share of firm f in year t. The remaining notation follows from equation (1). This equation describes how multinational acquisitions affect the labor share at the firm level. Simulating it forward while shutting down the contribution of multinational ownership delivers counterfactual firm-level labor share paths, which I then aggregate at the industry level using firms' observed employment shares as weights.

I examine two scenarios. In the first, I shut down the impact of multinational acquisitions on the labor share through robot adoption. This is done by discounting multinational affiliates' $\widehat{\beta}_1$ and $\widehat{\alpha}_f$ by the coefficient in column 1 of Table 4, which is the robot adoption premium of multinational affiliates. In the second, I completely shut down multinational acquisitions by setting $MNE_{ft} = 0$ and removing the multinational premium from $\widehat{\alpha}_f$. Fixed effects are estimated using equation (3) on the full sample. For each counterfactual scenario, I simulate labor share changes using 1,000 bootstrap replications from the empirical distribution of $\widehat{u}_{ft}$ and report the average outcome across replications. See Appendix B.4 for more details.

5.2 Results

Figure 7 shows the results. There are two takeaways. First, without MNEs, the decline in the manufacturing labor share from 1990 to 2014 would have been 8% (1.5 percentage points) smaller. Second, multinational-induced robot adoption explains about 30% of the overall impact of multinational activity on the labor share.

While Figure 7 is only informative about partial equilibrium effects and is silent about welfare, it provides new insights into the decline in the manufacturing labor share. Grossman and Oberfield (2022) include globalization and automation among the leading explanations of this trend. Figure 7 reinforces and extends their argument. Rather than alternative forces, globalization (in the form of MNEs) and technological change (in the form of robots) interact and jointly shape the observed negative trend.

6 Conclusions

Using rich firm-level data for Spanish manufacturing, this paper provides evidence that firms acquired by multinational enterprises become more likely to employ robots in their production process. While this shift allows multinational affiliates to increase output and expand into global markets, it also leads to a reduction in their labor share. These findings are established after accounting for firm self-selection into both multinational acquisitions and robot adoption, are consistent with a model of robot adoption choices by heterogeneous firms, and hold even after considering other explanations for the labor share decline. The estimates imply that without multinationals, the drop in the labor share would have been 8% smaller by the end of the sample period. The adoption of robots driven by multinational acquisitions accounts for about one-third of this change.

Recent literature provides evidence that the impact of automation technology in general, and robots in particular, goes beyond labor markets and concerns, for instance, international trade patterns (Artuc, Paulo and Rijkers, 2018), public finance (Freeman, 2015), and electoral outcomes (Anelli, Colantone and Stanig, 2019). With this respect, the distributional implications of robot adoption induced by multinational acquisitions documented in this paper may be a lower bound to the economy-wide ones.

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Tables

Table 1. Goodness of Fit - Multinational Acquisitions (One-to-Five Nearest Neighbor Matching)

	Means Treated	Means Control (Pre)	Means Control (Post)	P-value (Pre)	P-value (Post)
Sales Growth Rate	0.05	-0.00	0.06	0.88	0.98
Lag Log Sales	16.76	14.58	16.78	0.16	0.99
Lag Log Value Added	15.61	13.55	15.62	0.19	1.00
Lag Log Employment	5.20	3.42	5.16	0.17	0.98
Lag Log Labor Costs	3.25	3.04	3.25	0.61	1.00
Lag Log Investment	11.84	7.71	12.16	0.34	0.94
Lag Log Fixed Assets	15.79	13.38	15.83	0.21	0.98
Lag Log RD Expenditure	6.91	1.96	7.21	0.45	0.96
Lag Log Exports	11.38	5.75	11.28	0.40	0.99
Lag Log Number of Export Markets	0.52	0.25	0.54	0.63	0.96

Note: The table shows the goodness of fit of the one-to-five nearest neighbor matching algorithm when comparing acquired firms to domestic ones. Each row corresponds to a variable I use for the matching. The first column shows the average for the treatment group. The second column shows the average for the control group before matching, whereas the third column shows the average after matching. The fourth column shows the p-value associated with the null hypothesis that the means in the first two columns are statistically equal. The fifth column shows the p-value associated with the null hypothesis that the means in the first and third columns are statistically equal.

Table 2. Multinational Acquistions and the Labor Share

Dependent Variables:	Labor Share$_{ft}$	Log(Intermediate Inputs)$_{ft}$	Log(Employees)$_{ft}$	Log(Wages)$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	-0.040**	0.263***	0.115**	0.035
	(0.016)	(0.066)	(0.047)	(0.022)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes	Yes
Observations	4,165	4,165	4,165	4,165

Note: The table shows the pooled estimates of equation (1). The unit of observation is a firm-year pair. In column (1), the dependent variable is the labor share of firm f in year t. In column (2), the dependent variable is Log(Intermediate Inputs)$_{ft}$, which is the log of the expenditure on intermediate inputs of firm f in year t. In column (3), the dependent variable is Log(Employees)$_{ft}$, which is the log of the number of employees of firm f in year t. In column (4), the dependent variable is Log(Wages)$_{ft}$, which are gross labor costs incurred by firm f in year t. MNE$_{ft}$ is a binary indicator equal to 1 if firm f is multinational-owned in year t and 0 otherwise. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table 3. Multinational Acquistions and the Labor Share (No Matching)

Dependent Variables:	Labor Share$_{ft}$	Log(Intermediate Inputs)$_{ft}$	Log(Employees)$_{ft}$	Log(Wages)$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	-0.062***	0.336***	0.129***	0.034
	(0.014)	(0.058)	(0.043)	(0.022)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Matched Sample	No	No	No	No
Observations	23,967	23,967	23,967	23,967

Note: The table shows the pooled estimates of equation (1) on the full sample (i.e., without matching). The unit of observation is a firm-year pair. In column (1), the dependent variable is the labor share of firm f in year t. In column (2), the dependent variable is Log(Intermediate Inputs)$_{ft}$, which is the log of the expenditure on intermediate inputs of firm f in year t. In column (3), the dependent variable is Log(Employees)$_{ft}$, which is the log of the number of employees of firm f in year t. In column (4), the dependent variable is Log(Wages)$_{ft}$, which are gross labor costs incurred by firm f in year t. MNE$_{ft}$ is a binary indicator equal to 1 if firm f is multinational-owned in year t and 0 otherwise. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table 4. Multinational Acquistions and Robot Adoption

Dependent Variable:	Robot Adoption$_{ft}$	
	(1)	(2)
MNE_{ft}	0.097***	0.171***
	(0.031)	(0.031)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Matched Sample	Yes	No
Observations	4,165	23,975

Note: The table shows the pooled estimates of equation (1). The unit of observation is a firm-year pair. The dependent variable is a binary indicator equal to 1 since the first year firm f uses a robot. MNE_{ft} is a binary indicator equal to 1 if firm f is multinational-owned in year t and 0 otherwise. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table 5. Goodness of Fit - Robot Adoption (One-to-Five Nearest Neighbor Matching)

	Means Treated	Means Control (Pre)	Means Control (Post)	P-value (Pre)	P-value (Post)
Sales Growth Rate	0.05	-0.01	0.04	0.81	0.95
Lag Log Sales	15.42	14.31	15.41	0.48	0.99
Lag Log Value Added	14.31	13.31	14.28	0.51	0.99
Lag Log Employment	4.02	3.25	3.98	0.53	0.98
Lag Log Labor Costs	3.15	2.99	3.16	0.70	0.98
Lag Log Investment	9.57	7.14	9.51	0.63	0.99
Lag Log Fixed Assets	14.50	12.96	14.48	0.41	0.99
Lag Log RD Expenditure	3.95	1.49	3.86	0.67	0.99
Lag Log Exports	8.25	4.95	8.42	0.64	0.98
Lag Log Number of Export Markets	0.35	0.22	0.36	0.77	0.98

Note: The table shows the goodness of fit of the one-to-five nearest neighbor matching algorithm when comparing robot adopters to non-adopters. Each row corresponds to a variable I use for the matching. The first column shows the average for the treatment group. The second column shows the average for the control group before matching, whereas the third column shows the average after matching. The fourth column shows the p-value associated with the null hypothesis that the means in the first two columns are statistically equal. The fifth column shows the p-value associated with the null hypothesis that the means in the first and third columns are statistically equal.

Table 6. ROBOT ADOPTION AND THE LABOR SHARE

Dependent Variable:	Labor Share$_{ft}$	
	(1)	(2)
Robot Adoption$_{ft}$	-0.022**	-0.024***
	(0.009)	(0.008)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Matched Sample	Yes	No
Observations	14,978	23,965

Note: The table shows the pooled estimates of equation (2). The unit of observation is a firm-year pair. The dependent variable is the labor share of firm f in year t. Robot Adoption$_{ft}$ is a binary indicator equal to 1 since the first year firm f uses a robot. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table 7. Other Mechanisms for the Falling Labor Share

Dependent Variable:	Labor Share$_{ft}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Robot Adoption$_{ft}$	-0.022**	-0.022**	-0.022**	-0.022**	-0.022**	-0.022**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Log(Fixed Assets/Employees)$_{ft}$		-0.022***	-0.022***	-0.022***	-0.023***	-0.023***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Log(R&D Expenses)$_{ft}$			-0.002***	-0.002***	-0.002***	-0.002***
			(0.0007)	(0.0007)	(0.0006)	(0.0006)
Log(Value Added)$_{ft}$				0.0004	0.0008	0.0009
				(0.005)	(0.005)	(0.005)
Log(Export/Sales)$_{ft}$					-0.051*	-0.050*
					(0.030)	(0.030)
Log(Price Index)$_{ft}$						-0.257***
						(0.049)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,978	14,978	14,978	14,978	14,978	14,978
R^2	0.83	0.84	0.84	0.84	0.84	0.84
Within R^2	0.03	0.04	0.04	0.04	0.04	0.05

Note: The table shows the pooled estimates of equation (2). The unit of observation is a firm-year pair. The dependent variable is the labor share of firm f in year t. Robot Adoption$_{ft}$ is a binary indicator equal to 1 since the first year firm f uses a robot. Log(Fixed Assets / Employees)$_{ft}$ is the log of fixed assets per employee of firm t in year t. Log(R&D Expenses)$_{ft}$ is the log of total R&D expenses of firm t in year t. Log(Value Added)$_{ft}$ is the log of value added of firm t in year t. Log(Export / Sales)$_{ft}$ is the log of the ratio of export sales over total sales of firm t in year t. Log(Price Index)$_{ft}$ is the log of the price index of firm t in year t. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table 8. Why Do Multinational Acquisitions Boost Robot Adoption? /1

Dependent Variables:	Exp. via Foreign Parent$_{ft}$ (1)	Log(Value Added)$_{ft}$ (2)	Log(Ext. R&D/Employees)$_{ft}$ (3)	Imp. of Foreign Tech.$_{ft}$ (4)
MNE$_{ft}$	0.356***	0.204***	0.169	0.008
	(0.037)	(0.072)	(0.325)	(0.038)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes	Yes
Observations	3,443	4,165	4,165	4,165

Note: The table shows the pooled estimates of equation (1). The unit of observation is a firm-year pair. In column (1), the dependent variable is a binary indicator equal to 1 if firm f exports via its multinational parental network in year t and zero if it uses an alternative channel (e.g., own means, specialized intermediaries, collective actions, or other means). This variable can only be defined for firms that export in a given year. In column (2), the dependent variable is the log of value added of firm t in year t. In column (3), the dependent variable is the log of the expenditure on external R&D per employee of firm f at time t. In column (4), the dependent variable is a binary indicator equal to 1 if firm f imports licenses and technical aid from abroad in year t and 0 otherwise. MNE$_{ft}$ is a binary indicator equal to 1 if firm f is multinational-owned in year t and 0 otherwise. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

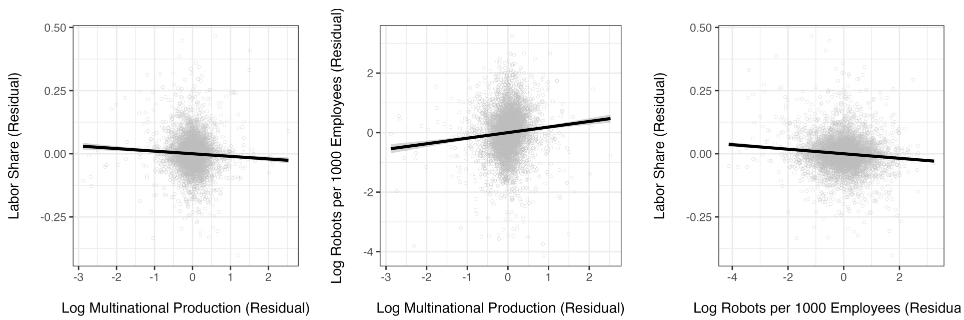
Table 9. Why Do Multinational Acquisitions Boost Robot Adoption? /2

Dependent Variable:	Robot Adoption$_{ft}$			
	(1)	(2)	(3)	(4)
Exp. via Foreign Parent$_{ft}$	0.132**	0.132**	0.133**	0.131**
	(0.061)	(0.061)	(0.061)	(0.060)
Log(Value Added)$_{ft}$		-0.002	-0.004	-0.005
		(0.017)	(0.017)	(0.017)
Log(Ext. R&D/Employees)$_{ft}$			0.005	0.004
			(0.003)	(0.003)
Imp. of Foreign Tech.$_{ft}$				0.037
				(0.035)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes	Yes
Observations	3,443	3,443	3,443	3,443

Note: The table shows the pooled estimates based on equation (1). The unit of observation is a firm-year pair. The dependent variable is a binary indicator equal to 1 since the first year firm f adopts a robot. Exp. via Foreign Parent$_{ft}$ is a binary indicator equal to 1 if firm f exports via its multinational parental network in year t and zero if it uses an alternative channel (e.g., own means, specialized intermediaries, collective actions, or other means). This variable can only be defined for firms that export in a given year. Log(Value Added)$_{ft}$ is the log of value added of firm t in year t. Log(Ext. R&D/Employees)$_{ft}$ is the log of the expenditure on external R&D per employee of firm f at time t. Imp. of Foreign Tech.$_{ft}$ is a binary indicator equal to 1 if firm f imports licenses and technical aid from abroad in year t and 0 otherwise. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

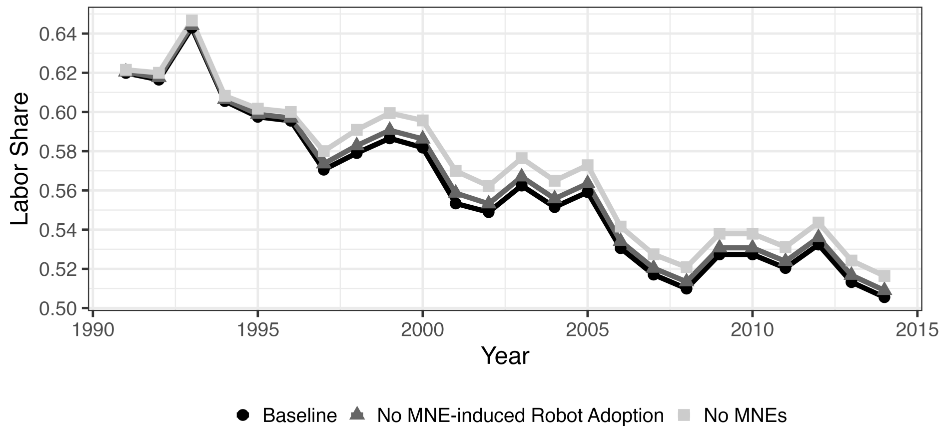
Figures

Figure 6. Multinational Production, Robot Adoption, and the Labor Share



Note: The left panel of the figure shows the correlation between the labor share and the log of multinational production in industry i of country c in year t. The middle panel shows the correlation between the log of the number of industrial robots per thousand employees and the log of multinational production in industry i of country c in year t. The right panel of the figure shows the correlation between the labor share and the log of the number of industrial robots per thousand employees in industry i of country c in year t. All variables are residualized after projecting out country-by-industry and year fixed effects. In each panel, 95% confidence intervals around the fitted values are computed using heteroscedasticity-robust standard errors. All correlations are significant at the 5% level.

Figure 7. Counterfactual Labor Share



Note: The figure shows industry-level labor share paths under three scenarios. The black line is the actual path. The dark gray line shows the counterfactual path absent multinational-induced robot adoption. The light gray line shows the counterfactual path absent multinationals enterprises.

Appendix

A Empirical Appendix

A.1 Firm-Level Data

The ESEE data also come with some limitations. First, firms do not disclose the identity of their multinational owners, which prevents distinguishing between vertical and horizontal FDI or assessing whether parents from countries where robots are highly diffused are more likely to encourage robot adoption. Second, the survey does not report if a firm is owned by a Spanish multinational. Finally, the survey does not report information about expenditure on robots (i.e., the intensive margin of robot adoption).

The data also contain missing values. I deal with them using a forward imputation criterion. If a binary indicator is missing, I impute its value with the first non-missing previous value. If a continuous variable is missing, I impute it with the average between two consecutive non-missing years. I only apply these criteria if the missing spell is less than three years. The table below describes the main variables.

Description of ESEE Variables

Variable	*Range/Unit*	*Frequency*	*Description*
Robot Adoption	[0, 1]	Q	= 1 if firm employs robot
Numerically Controlled Machines	[0, 1]	Q	= 1 if firm employs numerically controlled machines
CAD Manufacturing	[0, 1]	Q	= 1 if firm employs CAD manufacturing
Flexible Systems	[0, 1]	Q	= 1 if firm employs flex. systems
Batch Manufacturing	[0, 1]	Q	= 1 if firm performs batch manuf.
Mass Manufacturing	[0, 1]	Q	= 1 if firm performs mass manuf.
Continuous Manufacturing	[0, 1]	Q	= 1 if firm performs continuous manuf.
Mixed Manufacturing	[0, 1]	Q	= 1 if firm performs mixed manuf.
Investment	Euros	A	Value of investment in tangible assets
Total RD Expenses	Euros	A	Total research and development expenses
Internal RD	Euros	A	Internal research and development expenses
Sales	Euros	A	Value of firm sales (goods and services)
Value Added	Euros	A	Value of sales minus input purchases
Labor Costs	Euros	A	Gross labor costs (salaries, compensations, pension contribution)
Intermediate Inputs	Euros	A	Purchases of products, raw materials and other intermediates
Labor Share	Euros	A	Labor costs over intermediate inputs
Employees	$[0, \infty)$	A	Total number of employees
Fixed Assets	Euros	A	Value ot tangible fixed assets (no buildings and land)
Exporter	[0, 1]	A	= 1 If firm exports abroad
Export Value	Euros	A	Value of exports
No. of Export Markets	$[0, \infty)$	A	Number of foreign markets served
Price Index	$(-\infty, \infty)$	A	Paasche-type price index

Note: The table shows name, range or unit, frequency, and description of the ESEE variables I use in my analysis. A stands for “annual” and Q for “quadrennial”.

A.2 Cross-Country Industry-Level Data

Using the IFR data requires addressing two challenges. First, when constructing the stock of robots, the IFR assumes a depreciation rate of zero for the first twelve years of service. After that, they assume full depreciation. Instead, I follow Graetz and Michaels (2018) and employ a permanent inventory method to compute the stock of robots in each country-industry-year cell. Second, about 20% of the stock cannot be allocated to any industry. I follow Graetz and Michaels (2018) and allocate these robots proportionally to each sector based on their share of deployed robots across all sample years.

Merging data from AMNE, IFR, and WIOD SEA also requires tackling two challenges. First, one has to homogenize industry definitions. AMNE and WIOD follow the ISIC review 4 classification, whereas the IFR has its own system. However, since the IFR closely follows the ISIC review 4, it is feasible to match industries without ambiguity based on the industry description. Second, the three datasets use a different industry aggregation level. Because the AMNE data have the most aggregate industry classification, I group industries in the IFR and WIOD SEA to match the AMNE classification.

The final dataset contains: "A" (Agriculture, forestry and fishing), "B" (Mining and quarrying), "C1012" (Manufacture of food products, beverages and tobacco products), "C1315" (Manufacture of textiles, wearing apparel, leather and related products), "C16" (Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials), "C1718" (Manufacture of paper and paper products, printing and reproduction of recorded media), "C19" (Manufacture of coke and refined petroleum products), "C2021" (Manufacture of chemicals chemical products, pharmaceuticals, medicinal chemical and botanical products), "C22" (Manufacture of rubber and plastics products), "C23" (Manufacture of other non-metallic mineral products), "C24" (Manufacture of basic metals), "C25" (Manufacture of fabricated metal products, except machinery and equipment), "C26" (Manufacture of computer, electronic and optical products), "C27" (Manufacture of electrical equipment), "C28" (Manufacture of machinery and equipment), "C29" (Manufacture of motor vehicles, trailers and semi-trailers), "C30" (Manufacture of other transport equipment), "DE" (Electricity, gas, steam and air conditioning supply), "F" (Construction), "P" (Education and R&D).

The final dataset includes the following countries: Australia, Austria, Belgium, Bulgaria, Brazil, Switzerland, China, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Great Britain, Greece, Croatia, Hungary, Indonesia, India, Ireland, Italy, Japan, South Korea, Lithuania, Latvia, The Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovakia, Sweden, Slovenia, Turkey and the USA.

A.3 Additional Tables

Table A.1. MULTINATIONAL ACQUISITIONS BY YEAR

Year	Number of New Acquisitions
1991	14
1992	11
1993	5
1994	1
1995	8
1996	4
1997	4
1998	5
1999	5
2000	3
2001	4
2003	1
2004	3
2005	1
2006	8
2007	3
2008	2
2009	3
2010	2
2011	4
2012	1
2013	4
2014	5

Note: The table reports the number of Spanish firms acquired by a foreign MNE in each year.

Table A.2. Summary Statistics (ESEE Data)

	Domestic		Multinational	
	Mean	St. Dev.	Mean	St. Dev.
Panel A: Automation Technology				
Robot	0.15	0.36	0.28	0.45
Numerically Controlled Machines	0.37	0.48	0.52	0.50
CAD Manufacturing	0.26	0.44	0.38	0.49
Flexible Systems	0.23	0.42	0.39	0.49
Panel B: Type of Manufacturing				
Batch Manufacturing	0.52	0.50	0.25	0.44
Mass Manufacturing	0.34	0.47	0.54	0.50
Continuous Manufacturing	0.10	0.31	0.17	0.38
Mixed Manufacturing	0.04	0.19	0.03	0.18
Panel C: Innovation and Research and Development				
Investment	0.28	1.40	4.08	21.40
Total RD Expenses	0.07	1.45	1.10	2.80
Internal RD	0.05	0.93	0.80	2.04
Panel D: Other Characteristics				
Sales	9.05	41.41	107.31	333.93
Value Added	2.56	9.62	27.62	76.04
Labor Costs	22.43	10.19	30.90	12.93
Intermediate Inputs	6.64	34.05	81.96	269.48
Labor Share	0.63	0.27	0.57	0.25
Employees	64.29	199.36	559.31	1204.01
Fixed Assets	4.67	22.10	89.27	364.80
Exporter	0.45	0.50	0.82	0.38
Export Value	2.24	16.08	32.14	106.73
No. of Export Markets	0.43	0.81	1.16	1.18
Price Index	1.00	0.06	0.99	0.06

Note: The table reports the mean and standard deviation of firm-level characteristics by type of ownership. Variables in Panel A and Panel B are binary indicators. Variables in Panel C are in millions of current Euros. Variables in Panel D are in millions of current Euros, except for labor costs, which are in thousands of current Euros, the labor share, the number of employees and export markets, the exporter variable, which is a binary indicator, and the price index.

Table A.3. Summary Statistics (Industry-Level Data)

Variable	N	Mean	St. Dev.	Q25	Median	Q75
Log Multinational Production	6514	7.69	1.98	6.48	7.85	9.04
Labor Share	6514	0.57	0.19	0.44	0.59	0.71
Log Robot Stock	6514	3.01	3.50	1.04	3.18	5.39
Log Employees	6514	4.66	2.05	3.24	4.51	5.88
Log Capital Stock	6514	9.33	1.97	8.09	9.30	10.73
Log Wages	6514	7.98	1.84	6.79	7.90	9.25
Log Interest Rate	6514	7.62	1.95	6.37	7.67	8.90

Note: The table shows summary statistics for the cross-country industry-level data.

Table A.4. Multinational Acquisitions, Sales, and Export Values

Dependent Variables:	Log(Sales)_{ft}	Log(Exports)_{ft}
	(1)	(2)
MNE_{ft}	0.196**	0.903*
	(0.087)	(0.543)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Matched Sample	Yes	Yes
Observations	4,165	4,165

Note: The table shows the pooled estimates of equation (1). The unit of observation is a firm-year pair. In column (1), the dependent variable is the log of total sales of firm f in year t. In column (2), the dependent variable is the log of export values of firm f in year t. MNE_{ft} is a binary indicator equal to 1 if firm f is multinational-owned in year t and 0 otherwise. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table A.5. Type of Manufacturing

Dependent Variables:	Batch Manuf.$_{ft}$	Mass Manuf.$_{ft}$	Mixed Manuf.$_{ft}$	Continuous Manuf.$_{ft}$
	(1)	(2)	(3)	(4)
MNE$_{ft}$	-0.080	-0.014	0.011	0.072***
	(0.073)	(0.075)	(0.026)	(0.028)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Matched Sample	Yes	Yes	Yes	Yes
Observations	4,128	4,128	4,128	4,128

Note: The table shows the pooled estimates based on equation (1). The unit of observation is a firm-year pair. In column (1), the dependent variable is a binary indicator equal to 1 if firm f performs batch manufacturing in year t and 0 otherwise. In column (2), the dependent variable is a binary indicator equal to 1 if firm f performs mass manufacturing in year t and 0 otherwise. In column (3), the dependent variable is a binary indicator equal to 1 if firm f performs mixed manufacturing in year t and 0 otherwise. In column (4), the dependent variable is a binary indicator equal to 1 if firm f performs continuous manufacturing in year t and 0 otherwise. These activities are mutually exclusive. MNE$_{ft}$ is a binary indicator equal to 1 if firm f is multinational-owned in year t and 0 otherwise. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

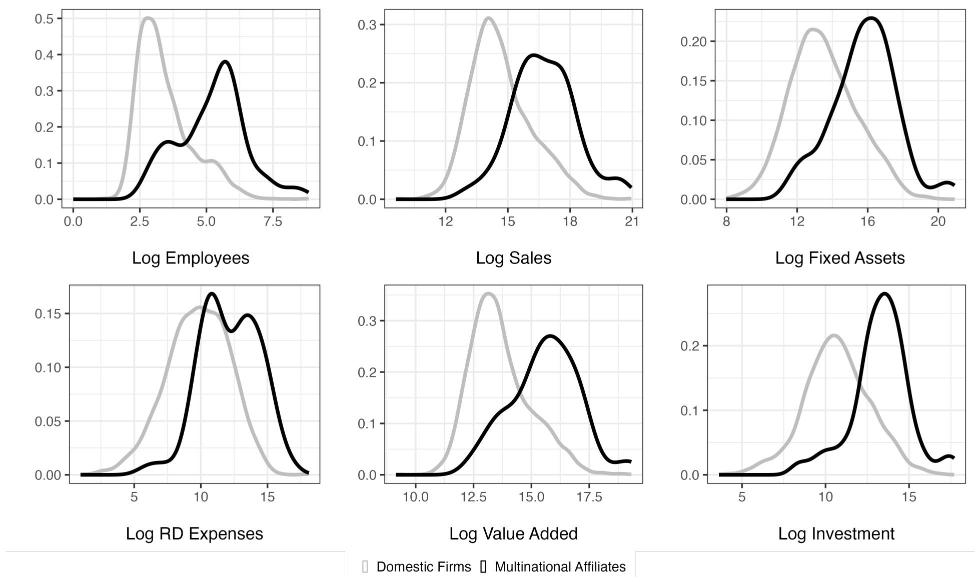
Table A.6. Other Types of Automation

Dependent Variables:	Other Automation$_{ft}$	CAD Manufacturing$_{ft}$
	(1)	(2)
MNE$_{ft}$	-0.057**	0.082**
	(0.027)	(0.040)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Matched Sample	Yes	Yes
Observations	4,163	4,163

Note: The table shows the pooled estimates based on equation (1). The unit of observation is a firm-year pair. In column (1), the dependent variable is a binary indicator equal to 1 since the first year firm f uses flexible systems or numerically controlled machines. In column (2), the dependent variable is a binary indicator equal to 1 since the first year firm f uses CAD manufacturing. These activities are not mutually exclusive. MNE$_{ft}$ is a binary indicator equal to 1 if firm f is multinational-owned in year t and 0 otherwise. Cluster standard errors at the firm level in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

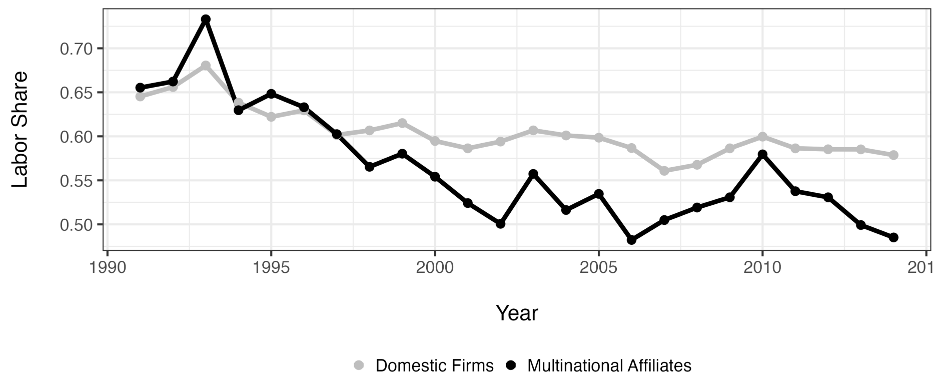
A.4 Additional Figures

Figure A.1. Density Plots by Ownership



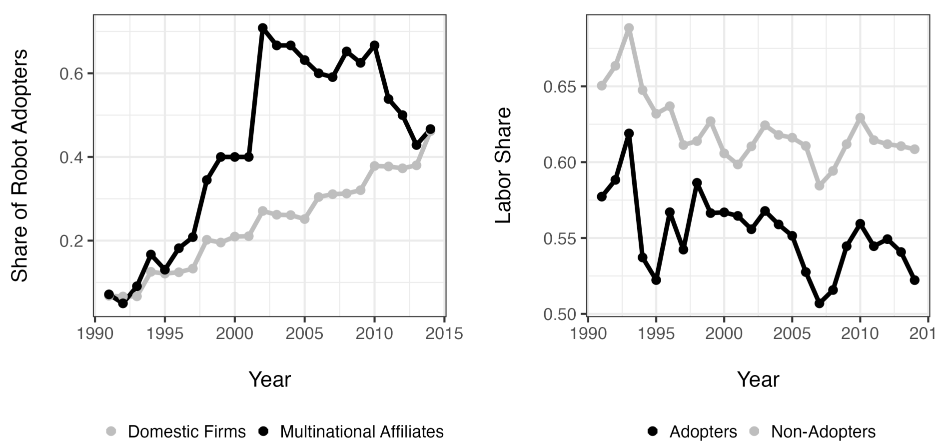
Note: The figure shows the empirical probability density function (pdf) of the log of employees, sales, fixed assets, R&D expenses, value added, and investment by ownership type. I estimate the empirical pdf for domestic-owned firms based on their lifetime characteristics. I estimate it only for the years before the acquisition date for multinational affiliates.

Figure A.2. Multinational Ownership and the Labor Share - Conditional on Firm Size



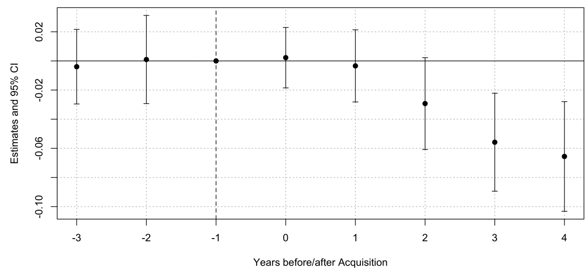
Note: The figure shows the labor share trends by ownership. Differently from Figure 1, I only include domestic firms with employment level above the sample median.

Figure A.3. Multinational Ownership, Robot Adoption, and the Labor Share - Conditional on Firm Size



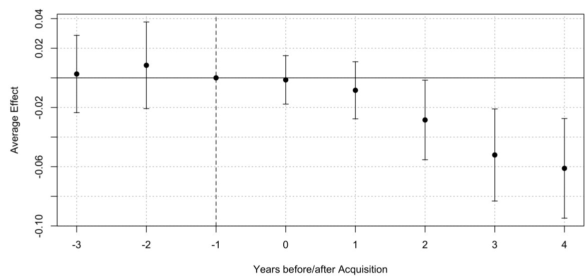
Note: The left panel of the figure shows the share of robot adopters among domestic firms and multinational affiliates. The right panel shows labor share trends among robot-adopting firms and non-adopters. Unlike Figure 2, the left panel considers only domestic firms with employment level above the sample median. The right panel of the figure includes only non-adopting firms with employment level above the sample median.

Figure A.4. Multinational Acquisitions and the Labor Share - Robustness 1



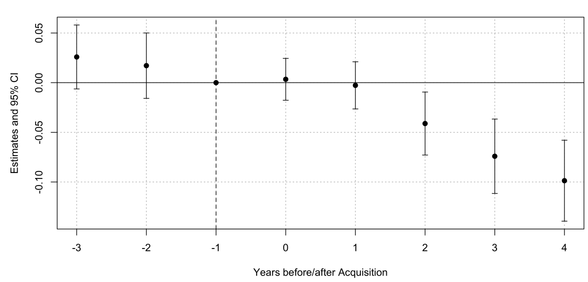
Note: The figure reproduces Figure 3 replacing year fixed effects with industry-by-year fixed effects. The unit of observation is a firm-year pair. There are 4,171 observations. I cluster standard errors at the firm level and report 95% confidence intervals. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

Figure A.5. Multinational Acquisitions and the Labor Share - Robustness 2



Note: The figure reproduces Figure 3 using a one-to-three nearest neighbor matching algorithm. There are 3,169 observations. I cluster standard errors at the firm level and report 95% confidence intervals. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

Figure A.6. Multinational Acquisitions and the Labor Share - Robustness 3



Note: The figure reproduces Figure 3 replacing the labor share relative to production costs with the labor share relative to total value added. The unit of observation is a firm-year pair. There are 4,171 observations. I cluster standard errors at the firm level and report 95% confidence intervals. I report the estimates for $[\underline{k}, \bar{k}] = [-3, 4]$.

B Theoretical Appendix

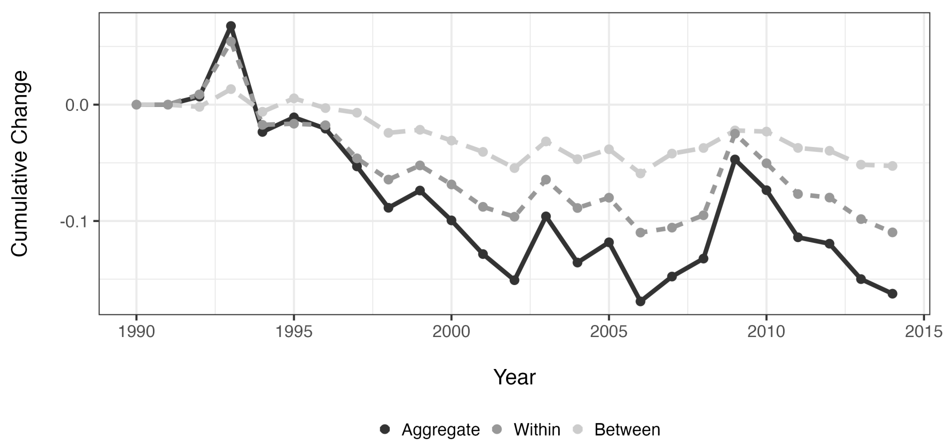
B.1 Olley and Pakes Decomposition

Building upon Olley and Pakes (1996), I express changes in the manufacturing labor share between year $t-1$ and t as follows:

$$\Delta LS_t = \Delta \overline{ls}_t + \Delta cov(s_{it}, ls_{it}), \quad i \in \{\text{domestic firms, multinational affiliates}\}. \tag{B.1}$$

Changes in the labor share can be attributed to the sum of changes in the unweighted mean of the labor share ($\overline{ls}_t$), which reflects within-group dynamics, and changes in the covariance between the market share of each group (s_{it}) and its labor share (ls_{it}), which captures between-group reallocation. Figure B.1 shows that the within-group component accounts for 75% of the total labor share reduction, indicating that changes among multinational affiliates are key drivers of manufacturing labor share dynamics.

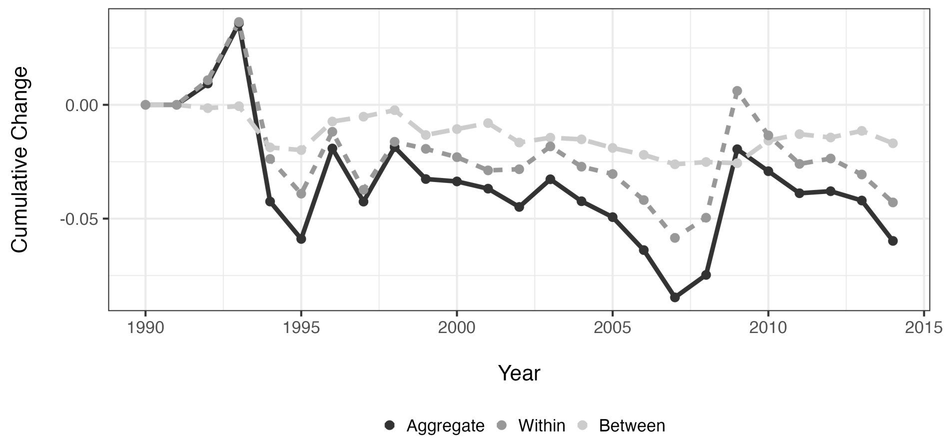
Figure B.1. Labor Share Decomposition - Olley and Pakes /1



Note: The figure shows the cumulative change in the Spanish manufacturing labor share and its two components in equation (B.1) over time. The black solid line is the total cumulative change. The dark gray dotted line shows the within-group change, whereas the dashed light gray line is the between-group change. Groups are multinational affiliates and domestic firms.

I also apply the labor share decomposition in equation (B.1) to the group of robot adopters and non-adopting firms. Figure B.2 shows that the within-group component accounts for 65% of the total labor share reduction, suggesting that robot adoption is also a key driver of changes in the manufacturing labor share.

Figure B.2. Labor Share Decomposition - Olley and Pakes /2



Note: The figure shows the cumulative change in the Spanish manufacturing labor share and its two components in equation (B.1) over time. The black solid line is the total cumulative change. The dark gray dotted line shows the within-group change, whereas the dashed light gray line is the between-group change. Groups are robot adopters and non-adopting firms.

B.2 Melitz and Polanec Decomposition

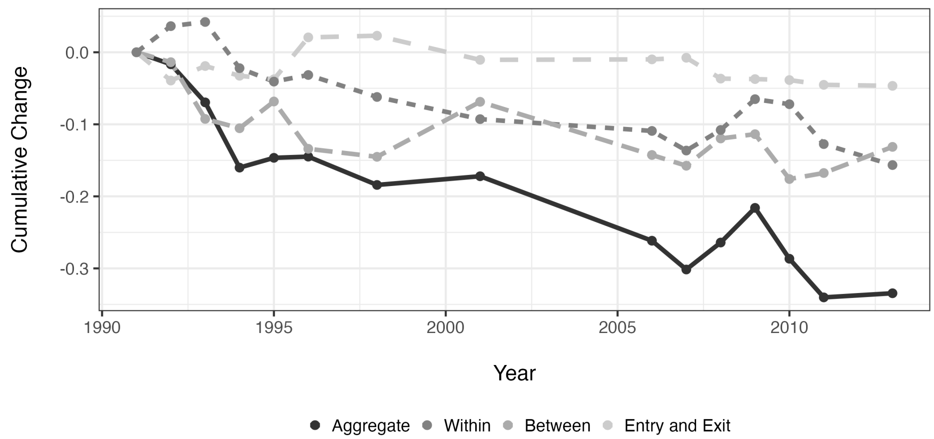
Following Autor et al. (2020), I express the changes in the manufacturing labor share between year $t-1$ and t as follows:[12]

$$\Delta LS_t = \Delta \overline{ls}_{St} + \Delta cov(s_{St}, ls_{St}) + s_{Et}(\overline{ls}_{Et} - \overline{ls}_{St}) + s_{Xt-1}(\overline{ls}_{St-1} - \overline{ls}_{Xt-1}) \tag{B.2}$$

The index St denotes firms that survive between $t-1$ and t. Et denotes firms that enter the sample in year t, while Xt denotes firms that exit the sample in year t. $s_{Gt} = \sum_{i \in G} s_{it}$ is the market share of group G in year t. $ls_{Gt} = \sum_{i \in G}(s_{it}/s_{Gt}) ls_{it}$ is the group's average labor share. Changes in the labor share equal the sum of four elements: (1) changes in the unweighted labor share mean of survivors, (2) market share reallocation between survivors, (3) the labor share of new entrants and exiting firms relative to survivors (see Melitz and Polanec (2015) for a discussion). In Figure B.3, I apply equation (B.2) to the sub-sample of multinational affiliates. The reallocation of market shares from firms with higher to those with lower labor share explains about 50% of the total decline among multinational affiliates. The within-firm change is also negative, and explains about 40% of the total reduction. The contribution of entry and exit is stable over time.

[12] Melitz and Polanec (2015) originally proposed this decomposition for productivity.

Figure B.3. Labor Share Decomposition - Melitz Polanec



Note: The figure shows the cumulative change in the manufacturing labor share of multinational affiliates and its components in equation (B.2) over time. The black solid line is the total cumulative change. The dark gray dotted line shows the within-group change, whereas the dashed gray line is the between-group change. The long-dashed light gray line is the entry-exit component.

B.3 Model

This section outlines a model consistent with Facts 1 and 2. Similarly to Koch et al. (2021) and Bonfiglioli et al. (2022), the model features firm heterogeneity as in Melitz (2003) within a model of robot adoption as in Acemoglu and Restrepo (2018). However, while these papers exclusively load firm heterogeneity onto firm productivity, I also allow for differences in demand shocks and fixed costs of robot adoption. The richness of the ESEE data allows me to disentangle these two channels from productivity. Similarly to Guadalupe et al. (2012), firms can be owned by multinational parents, and I explicitly model firm selection into multinational ownership.

Set Up

There is a large number of heterogeneous mono-product firms, each denoted by f, living for infinitely many periods, each denoted by t. Within each period, firms make two choices. First, they decide whether to use robots or not. If they do, they keep them forever. Second, firms produce and sell output. Firms can also be acquired by foreign firms. I assume that multinational acquisitions are irreversible.

Production Technology. Firms carry out a unit measure of tasks i to produce output:

$$Y_{ft} = z_{ft} \left(\int_0^1 y_{ft}(i)^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}, \quad y_{ft}(i) = \mathbf{1}\{i \leq \bar{\iota}_{ft}(R_{ft})\}\gamma_{ft}(i)M_{ft}(i) + L_{ft}(i). \quad \text{(B.3)}$$

z_{ft} denotes Hicks-neutral productivity, $y_{ft}(i)$ is the output of each task, and $\sigma > 1$ is the elasticity of substitution between tasks. R_{ft} is a binary indicator equal to 1 if firm f employs robots in year t. $M_{ft}(i)$ and $L_{ft}(i)$ are the quantity of material inputs and labor employed in each task, and $\gamma_{ft}(i)$ is their relative productivity level. Equation (B.3) states that inputs are perfect substitutes in any task $i \leq \bar{\iota}(R_{ft})$. However, only labor can perform tasks $i > \bar{\iota}_{ft}(R_{ft})$. I introduce the following standard assumption:

Assumption 1. *$\partial\gamma_{ft}(i)/\partial i < 0$ and $r_t/w_t > \gamma_{ft}(\bar{\iota}_{ft})$. Moreover, $\bar{\iota}_{ft}(1) > \bar{\iota}_{ft}(0)$.*

Firms take wages and robot prices, denoted by w_t and r_t respectively, as given. Assumption 1 states that labor has a strict comparative advantage in tasks indexed by a higher i. This assumption ensures that there exists a unique $\bar{\iota}_{ft}(R_{ft})$. Tasks below this threshold are carried out by material inputs, whereas tasks above it are performed by labor. The condition $\bar{\iota}_{ft}(1) > \bar{\iota}_{ft}(0)$ ensures that robot adoption reduces the set of tasks performed by labor. Firms' unit production costs can be expressed as:

$$c_{ft}(R_{ft}) = \frac{1}{z_{ft}} \left(\alpha_{ft} r_t^{1-\sigma} + \beta_{ft} w_t^{1-\sigma}\right)^{\frac{1}{1-\sigma}}, \tag{B.4}$$

where $\alpha_{ft} = \int_0^{\bar{\imath}_{ft}(R_{ft})} \gamma_{ft}(i)^{\sigma-1} d\omega$ and $\beta_{ft} = 1 - \bar{\iota}_{ft}$ Under Assumption 1, robot adoption reduces marginal costs.

Demand and Market Structure. Each firm produces a single variety and faces a downward-sloping demand curve $q_{ft} = D_t \psi_{ft} p_{ft}^{-\theta}$, $\theta > 1$. q_{ft} and p_{ft} denote quantity demanded and firms' prices, respectively. D_t is a demand shifter common to all firms, whereas ψ_{ft} is a firm-level time-varying demand shock. Firms are monopolistically competitive and charge a fixed markup over marginal costs:

$$p_{ft} = \frac{\theta}{\theta - 1} c_{ft}. \tag{B.5}$$

Firm revenues can be expressed as:

$$\pi_{ft}(R_{ft}) = \Omega_t \psi_{ft} c_{ft}(R_{ft})^{1-\theta}, \tag{B.6}$$

being $\Omega_t = D_t \theta^{-\theta} (\theta - 1)^{\theta-1}$.

Robot Adoption. Let the the expected discounted profit stream of firm f in year t be:

$$V_{ft}(R_{ft}) = \sum_{s=t}^{\infty} \beta^{s-t} \mathbb{E}_s \left[\pi_{fs}(R_{ft})\right] - FC_{ft}(R_{ft}) \tag{B.7}$$

Firms have rational expectations over z_{ft} and ψ_{ft}, and $\beta \in (0, 1)$ is the discount rate. FC_{ft} denotes the cost that firm f must pay when adopting robots in year t. Firms pay the fixed cost of robot adoption in year t if and only if the expected discounted profit stream they earn by undergoing the investment exceeds what they garner otherwise:

$$V_{ft}(1) \geq V_{ft}(0). \tag{B.8}$$

Multinational Acquisitions. Let W_{mt} be the net present value of multinational parent m in year t. I assume that this value is weakly increasing with the value of each affiliate f. Firm f is acquired by m if and only if the net present value of multinational parent m

in year t when owning f is greater than its net present value without f:

$$W_{mt}^{f} - K_{ft} \geq W_{mt}^{-f}. \tag{B.9}$$

$W_{mt}^{f} - K_{ft}$ is net present value of multinational parent m in year t when owning f, being K_{ft} the cost of acquiring firm f in year t. W_{mt}^{-f} denotes the net present value of multinational parent m in year t without f.

Multinational acquisitions can boost the value of affiliate f by enhancing its productivity (z_{ft}), granting greater (and positive) demand shocks (ψ_{ft}), or lowering the costs associated with robot adoption (FC_{ft}).

Model Predictions

The model delivers the following testable predictions:

Prediction 1. *Firms with higher z_{ft} and ψ_{ft}, or lower FC_{ft} and K_{ft}, are more likely to be acquired by a multinational parent.*

Prediction 2. *Firms with higher z_{ft} and ψ_{ft}, or lower FC_{ft}, are more likely to adopt robots.*

Prediction 3. *Robot-adopting firms have a lower labor share than non-adopters.*

Overall, better-performing firms (i.e., with higher z_{ft} and ψ_{ft}, or lower FC_{ft} and K_{ft}) are more likely to be acquired by multinational parents and to adopt robots. If foreign parents improve the performance of their subsidiaries, multinational affiliates are more likely to adopt robots than domestic firms. In turn, robot adoption is associated with a lower labor share.

These predictions imply that identifying the impact of multinational acquisitions on the labor share through robot adoption requires addressing firm selection. Section 4 empirically tackles this challenge.

B.4 Counterfactuals' Implementation

I consider the following equations:

$$LS_{ft} = \widehat{\beta}_1 \times MNE_{ft} + \alpha_f + \alpha_t + u_{ft}, \tag{B.10}$$

$$R_{ft} = \widehat{\beta}_2 \times MNE_{ft} + \delta_f + \delta_t + v_{ft}. \tag{B.11}$$

LS_{ft} is the labor share of firm f in year t. R_{ft} is an indicator equal to 1 since the first year firm f adopts robots. MNE_{ft} is an indicator equal to 1 if firm f is multinational-owned in year t. α_f, δ_f, α_t, and δ_t are firm and year-level fixed effects. I use $\widehat{\beta}_1$ and $\widehat{\beta}_2$ from column 1 of Table 2 and Table 4, respectively. Fixed effects are estimated using equations (B.10) and (B.11) on the full sample. I consider two counterfactual scenarios:

- **Scenario 1 (no multinational-induced robot adoption)**: The counterfactual firm-level labor share is:

$$LS_{ft}^{(1)} = \widehat{\beta}_1 \times (1 - \widehat{\beta}_2) \times MNE_{ft} + (1 - \widehat{\beta}_2) \times \widehat{\alpha}_f^{(1)} + \widehat{\alpha}_t + \widehat{u}_{ft}. \tag{B.12}$$

  Where:

$$\widehat{\alpha}_f^{(1)} = \widehat{\alpha}_f - (\mathbb{E}[\widehat{\alpha}_f | MNE_{ft} = 1] - \mathbb{E}[\widehat{\alpha}_f | MNE_{ft} = 0]) \times MNE_{ft}. \tag{B.13}$$

  In words, if $MNE_{ft} = 1$, I discount $\widehat{\beta}_1$ by $\widehat{\beta}_2$. I also discount $\widehat{\alpha}_f$ by $\widehat{\beta}_2$ after subtracting from it the multinational premium.

- **Scenario 2 (no multinationals)**: The counterfactual firm-level labor share is:

$$LS_{ft}^{(2)} = \widehat{\alpha}_f^{(1)} + \widehat{\alpha}_t + \widehat{u}_{ft}. \tag{B.14}$$

  In words, I set $MNE_{ft} = 0$ and subtract the multinational premium from $\widehat{\alpha}_f$.

In each scenario, I use 1,000 bootstrap replications from the empirical distribution of $\widehat{u}_{ft}$ and report the average counterfactual LS_{ft} across replications.